Exploring the Landscape of Teacher Applications

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This version: *August 2026. This paper is a revised version of "Exploring the Landscape of Teacher Applications" (CALDER Working Paper No. 329-1025 / CEDR Working Paper 07222025-1, October 2025) and supersedes it. The earlier version remains available at https://caldercenter.org/publications/exploring-landscape-teacher-applications for reference.*

The revised version was reorganized following peer review and differs in several respects from the October 2025 version: (1) the analysis of application volume over the hiring season has been removed, as applications-per-opening is not well suited to cross-organization comparison; (2) a new analysis of applicant characteristics (demographics, experience, education, and measures of applicant quality) has been added; (3) the paper has been reorganized to foreground the comparison between traditional school districts and charter organizations; (4) inference is now based on the delete-one-cluster (CV3) jackknife variance estimator (MacKinnon, Nielsen, and Webb, 2023), given the small number of clusters. Under this approach some relationships reported in the earlier version — most notably the positive salary–applicant supply association among districts — are no longer statistically significant, though point estimates are essentially unchanged; (5) the small number of observations from 2019 are excluded from the analytic sample.

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Abstract

Despite widespread concern about teacher shortages, there is little evidence on when teaching positions are posted and how many people apply for them. Using detailed job-posting and application data on nearly 57,000 applicants from 19 traditional school districts and 24 charter organizations, we provide descriptive evidence on the timing of job postings, the supply of applicants, and the characteristics of applicants, emphasizing how each varies across organizations and between the district and charter sectors. We find that late hiring is less prevalent than prior single-district studies suggest—about 11% of openings are posted late—but varies widely across organizations. Applicant supply differs widely across organizations and by sector: districts average 3.3 applicants per opening, versus 6.1 for charters. We also find sectoral differences in applicant pool composition; compared to charters, district applicant pools have higher percentages of White applicants and applicants with prior teaching experience.

1. Introduction

Teacher staffing has been a persistent policy concern in the United States, and the current moment is no exception. Recent estimates put nationwide teacher vacancies at nearly 40,000 and positions filled by less-than-fully-qualified teachers at about 280,000 (Nguyen et al., 2024). Longer-run trends—declining satisfaction, prestige, and interest in the profession (Kraft and Lyon, 2024) and a steep fall in teacher preparation enrollment over the past decade (NCES, 2022)—are also concerning. However, an important piece of context that is missing from our understanding of the teacher labor market is evidence on the supply of individuals *applying* for teaching positions and how supply varies across the K-12 landscape.

Over the past decade, a series of district-level studies of teacher hiring has generated information about the number of applicants per opening (Bruno and Strunk, 2019; Chi and Lenard, 2023; Goldhaber, Grout, and Huntington-Klein, 2017; Jacob et al., 2018; James et al., 2023; Sajjadiani et al., 2019). However, each of the studies was conducted in a mid-size to large urban school district and may not generalize to large segments of the U.S. teacher labor market (Grout, 2025). This lack of information hampers policy debate on several fronts. First, discussions of teacher shortages typically focus on unfilled vacancies and on the prevalence of underqualified teachers but offer little visibility into the upstream supply pipeline—how many applicants districts have to choose from when filling open positions. Second, current policy initiatives aimed at strengthening teacher hiring are difficult to evaluate in part because the baseline supply of applicants in different settings is poorly documented. Third, as discussed below, there are reasons to expect differences in applicant supply to charter schools versus traditional public schools, but we have no direct information about applicants to charter schools, a rapidly growing sector of the K-12 teacher labor market. This paper provides descriptive evidence on each of these dimensions.

We describe teacher job posting and application patterns across a variety of public school districts and charter organizations. We use novel data obtained through a data sharing agreement with Nimble PBC (henceforth "Nimble"), a K-12 hiring platform that provides applicant tracking system services to school systems.[1] Nimble's data allow us to observe deidentified information about Nimble clients' *job openings*, *applicants* and *applications*. We leverage this detailed application data to address the following questions:

1. How does the seasonality of job postings, including the prevalence of "early" and "late" postings, vary across organizations?
2. How does the supply of applicants vary across organizations?
3. How do applicant characteristics vary across organizations?

To the best of our knowledge, this is the first study to systematically look at applicant pools across multiple organizations with varied student-body demographics. A key area of comparison in our analysis is that between traditional school districts and charter organizations. Little evidence exists regarding the supply of teacher applicants to charter organizations and there are reasons to expect differences compared to traditional school districts driven by differential licensure requirements, compensation, working conditions, and the distinctive missions and instructional models of many charter organizations.

2. Background Literature

A small but growing literature aims to describe the supply of labor in the teaching profession. Evidence garnered from teacher vacancy data has been used to study how the supply of teachers varies across and within localities. Edwards et al. (2024) used data on unfilled teaching positions in Tennessee to show that unfilled vacancies are concentrated in particular

[1] For more information about Nimble, see https://www.hirenimble.com.

schools such that shortages and surpluses within a single district often coexist. Using job posting data from California and Washington state to analyze teacher vacancy patterns, Goldhaber et al. (2020) and Goldhaber et al. (2024) find that hiring needs and challenges vary over the course of the school year and are correlated with district type (rural districts have higher needs), student characteristics (schools serving more historically marginalized students have higher needs) and subject areas (greater needs for special education and STEM teachers).

Several studies have analyzed how the preferences of teachers influence the supply of candidates. Using data from the state of New York, Boyd et al. (2013) found that teachers prefer to be closer to home and prefer to teach in classrooms with lower numbers of minority students. Similarly, two recent analyses of vacancy postings and teacher applications using data from single school districts found that applicants exhibited preferences for schools serving fewer disadvantaged students and with shorter commute times (Laverde et al., 2023; Bates et al., 2025).

The theoretical and empirical relationships between wages and labor supply are well studied (Blundell and MaCurdy, 1999). While empirical evidence from the public education sector is relatively limited, several studies show that the supply of teachers is responsive to compensation.[2] Hough and Loeb (2013) found that salary increases in San Francisco USD improved both the size and quality of the teacher applicant pool. Biasi (2021) found that the structure of compensation has implications for the composition of the teacher workforce; districts were able to attract high-quality teachers from other districts following a policy reform in Wisconsin that allowed districts to implement more flexible compensation schemes. Compensation levels have also been found to improve retention. Rumberger (1987) found that the size of salary differentials between math and science teachers and engineers was related to

[2] For a general discussion of teacher compensation, see Biasi (2025).

the extent of teacher shortages and Clotfelter et al. (2008) found that annual bonuses targeted at math, science, and special education teachers reduced turnover among those teachers by 17%.

The most direct evidence on the supply of teachers comes from studies that observe both job postings and applications. Contrary to the way the teacher labor market is often described,[3] a series of recent district-level analyses have found that districts often have multiple unique applicants per open position, ranging from 5 to 9 per opening (Goldhaber et al., 2017; Jacob et al., 2018; Bruno and Strunk 2019; Sajjadiani et al., 2019; Chi and Lenard, 2023; James et al., 2023; Goldhaber and Grout, 2026). In the study that is most similar to our current paper, James et al. (2023) used job application data from Boston Public Schools to model the hiring process across 129 schools. The study provides evidence on how the supply of applicants varies across subject areas, schools, and the stage of the hiring season. Similar to the district-level analyses noted above, James et al., (2023) found a ratio of applicants to openings of 9:1; they also found that the supply of applicants varied substantially across schools and subject areas. For example, there were 5.7 applicants per science opening compared to 15.8 applicants per social studies opening.

In addition to school characteristics and subject areas, the timing and seasonality of job postings are also likely to influence the supply of applicants and student outcomes. Because schools and districts compete with one another for candidates, hiring earlier will tend to correspond with greater choice among applicants and higher-quality hires (James et al., 2023). Additionally, hiring that occurs during summer vacation is more likely to be information poor since applicants have less opportunity to interact with multiple staff members and students (Liu

[3] For example, in 2022 the Washington Post remarked that, "The teacher shortage in America has hit crisis levels—and school officials everywhere are scrambling to ensure that, as students return to classrooms, someone will be there to educate them" (Natanson, 2022).

and Johnson, 2006). There is also evidence that late hiring is common (after the start of the school year) and detrimental to student achievement (Papay and Kraft, 2016). Among first-year teachers surveyed in four states, one in three reported being hired after the start of the school year (Liu and Johnson, 2006) and district-level analyses found that 18% and 26% of teachers were hired after school started (Kraft et al., 2020; Papay and Kraft, 2016). Finally, in an analysis of web-scraped job posting-data from Washington state, Goldhaber et al. (2025) found that 10% of positions were posted in the fall.

Compared to the large body of research on teachers in traditional public schools, less attention has been paid to the charter school sector of the teacher labor market. An important difference is that teachers in charter schools are not necessarily required to be certified. States differ considerably in whether they require charter-school teachers to hold a standard teaching license. According to the Education Commission of the States' review of charter statutes (Education Commission of the States, 2020), among the 45 states and the District of Columbia with charter-school laws, roughly half require charter teachers to meet the same certification requirements as teachers in traditional public schools, while about eight impose no certification requirement at all and roughly a dozen take an intermediate approach — requiring that a specified share of a charter's teachers be certified. Where charters face looser requirements, the set of individuals eligible to teach in a charter school can be substantially broader than the set eligible to teach in a traditional public school.

A few studies suggest how the charter sector of the teacher labor market differs compared to the traditional public school sector. In an analysis of teacher hiring and retention in Massachusetts charter schools, Bruhn et al. (2022) found results consistent with a model where teachers initially seek employment in charter schools and higher-performing teachers move to traditional public schools once they obtain certification while lower-performing teachers tend to exit the public education workforce. Relatedly, Gulosino et al. (2019) apply segmented labor market theory to newly hired teachers in Utah and find that those entering the charter sector are more likely to exit teaching and less likely to transfer to another school than newly hired teachers in traditional public schools — evidence of differential mobility between the two sectors. Finally, Barrett et al. (2022) compared retention in the highly deregulated teacher labor market of New Orleans with retention in surrounding districts. They found retention was more closely tied to performance in New Orleans but did not result in an advantage in teacher performance because new teachers in the city were of lower quality than in neighboring districts.

Our study builds upon the existing literature by assessing variation in postings and teacher supply using novel data that tracks job postings, applicants, and applications across multiple school districts and charter school organizations.

3. Data

3.1 Data Sources

Our primary source of data is job application records generated in the applicant tracking system (ATS) operated by Nimble. Nimble serves a wide range of traditional public school districts, charter organizations, preschools, and private schools.[4] These organizations use Nimble's platform to post job openings, receive applications, and manage the hiring process from intake and initial screening of applications through hiring and onboarding. We focus on public K-12 educational settings and exclude private schools and preschools. This enables us to link each posting to detailed information about the characteristics of the associated public K-12 school and organizations via the Common Core of Data (CCD).

[4] Nimble clients that are charter organizations include both charter management organizations and independent charter schools. For the purposes of our analyses, we combine these two groups.

The Nimble data include de-identified job posting and job application data from the period from January 2020 to September 2024. The job posting data include the date the posting was created, job title, the number of openings (i.e., FTE) associated with the job posting, and organization identifiers. Each job posting (a position description) may be associated with one or more openings (job that needs filling) at one or more schools. The application data include identifiers that allow us to distinguish between *applications* linked to specific job postings and *applicants*—distinct individuals who may apply to multiple jobs and organizations. Together, these data allow us to discern when a job is posted, the number of openings and applications associated with the job, and the number of unique applicants associated with different types of jobs and organizations.

The job application data also includes information about applicant characteristics. Applicants are given the opportunity to volunteer demographic information including race, ethnicity and gender, and Nimble's ATS collects a detailed education work history from each candidate. The information is used to determine whether a candidate has an advanced degree, prior teaching experience and the number of years of experience. The Nimble ATS employs models and parameters from Sajjadiani et al. (2019) and the work history infromation to generate predictions of candidate effectiveness measured by value-added and retention. These predictions are visible to hiring managers as "Nimble Candidate Insight" (NCI) scores.

In addition to the records maintained by Nimble, we integrate data from the Common Core of Data (CCD). Using name and location information, we link Nimble client organizations to annual district-level data from the CCD. [5] These include information about the racial and

[5] These include the Directory, Membership, Staffing, and Free and Reduced Lunch, and Geographic files are available at https://nces.ed.gov/ccd/files.asp (accessed March 18, 2024).

ethnic composition of the student body, the percentage of students receiving free or reduced-price lunch (FRPL), district size, and the ratio of students to teachers.

3.2 Analytic Sample and Measures

As noted above, we focus on public K-12 educational settings. The organizations in our analytic sample are a convenience sample comprising the universe of public K–12 organizations that pay to use the Nimble platform and receive a certain minimum tier of training and support from Nimble. These client organizations are the most likely to make consistent use of the ATS for teacher recruitment activities.[6] With these restrictions in place, our study uses job posting and application data from 19 school districts and 24 charter organizations located in a wide range of states.[7]

To assess how the schools in our analytic sample compare to the broader population of U.S. K–12 schools, we use The Generalizer (Tipton & Miller, 2026), a web-based tool that estimates the similarity between a sample and one or more inference populations on a set of moderating covariates drawn from the CCD and the American Community Survey. The tool reports a generalizability index between 0 and 1, with values above 0.9 indicating "very high generalizability" and values between 0.7 and 0.9 indicating "high generalizability." Submitting school-level NCES identifiers for the traditional school districts and charter organizations in our analytic sample separately, we obtain national generalizability indices of 0.81 for the district sample and 0.91 for the charter sample.

[6] Nimble is available to a large number of clients with a lower-touch support model under state-level contracts that provide a basic level of service at no cost to education organizations in the state. Among these clients, a majority have never recorded an applicant to a classroom teaching position as hired (only 1 client with their standard support model has never recorded an applicant as hired).

[7] The states and jurisdictions represented in the analytic sample are Arizona, California, Connecticut, the District of Columbia, Idaho, Illinois, Indiana, Louisiana, Missouri, New Jersey, Ohio, Oklahoma, Tennessee, Texas, Utah, and Washington.

The analytic sample is anchored by job postings for classroom teaching positions. We distinguish between teaching positions and other types of job postings using job titles and the Occupational Information Network (ONET) codes that are included in the job data. The sample is restricted to job postings with an ONET code prefix of "25-", though we exclude a subset of these positions where the hired applicant would not be primarily involved in the instruction of students in a classroom setting (e.g., *instruction coordinator*, t*eaching assistants*, or *library workers*).[8] We also use keywords to exclude non-classroom teaching positions such as *counselor*, *coach*, and *therapist*, as well as extra-curricular, virtual learning, summer school, pre-K, and substitute positions. Job postings that are classified as *internal only*, meaning that only existing staff may apply for them, are also excluded.

Measuring *when* jobs are posted and the *number of openings* associated with each job are central to our analysis. Regarding when a job opening is posted, we are interested in whether it is posted *early* or *late*. While there are no clear markers for what constitutes early or late job posting,[9] we characterize each job posting date as *early* or *late* based on its relation to each organization's academic calendar.[10] Specifically, we classify postings as *early* if they are posted two or more weeks prior to the end of the school year. We choose a period of two weeks because it would allow for a candidate selection process that involved visiting the hiring school while it was in session and interactions with multiple staff members and students. In contrast, a job

[8] ONET codes can be accessed at https://www.onetonline.org/find/all (accessed July 15, 2024).
[9] There is some precedent for using the start and end of the school year as a reference point. Studies on the impacts of late hiring tend to define a late hire as one that occurs after the start of the school year (e.g., Papay and Kraft, 2016; Kraft et al., 2020). In their survey of newly hired teachers, Liu and Johnson (2006) asked respondents to indicate whether they were hired more than one month before school started, the month before school started, or after the school year started. There is less precedent regarding what constitutes early hiring, but Liu and Johnson (2006) argue that hiring that occurs in the summer (when students and staff are not present) is an impediment to more interactive and information-rich hiring.
[10] We determine each organizations start and end dates to the school year based on web searches for academic calendars for the 2024-25 school year. Hence, we are assuming that start and end dates are roughly consistent year-to-year.

posted closer to the end of the school year or during the summer would be more likely to involve interactions with a single administrator. Similarly, we classify job postings as *late* if they are posted fewer than two weeks prior to (or after) the start of the school year. In these cases, the hired teacher would have little time to prepare for the start of the school year or face the challenge of taking over a classroom after school has started.

The *early* and *late* job posting periods are represented in **Figure 1** for a representative school district where the school year begins on September 1st and ends on June 15th. Note that in analyses related to the timing of job postings, we exclude job openings posted outside of the hiring season, defined as the period four months prior to the end of the school year to one month after the start of school. We impose this restriction because a challenge in classifying the timing of job postings as early or late is that postings do not consistently identify the school year with which a job is associated. During the period from October to December, there appears to be a combination of hiring for the current school year and hiring for the subsequent school year. Therefore, broadly classifying jobs posted from October to December as *late*, for instance, will tend to overstate the proportion of late postings.[11] By restricting our analysis of early and late job posting to the defined hiring season, we seek to avoid conflating one for the other.

To measure the *number of openings* associated with each job posting we rely on the total FTE associated with it. A challenge with working with job posting data generated by multiple organizations is that there appears to be some irregularity in how information is recorded. Among the 5,262 job postings in our analytic sample, 182 do not have any specific number of

[11] We investigate this issue by looking at postings that *do* identify the school year with which the job is associated (e.g., *Grade 2 Teacher, 2021-22*). We can do this for 70% of the job postings in our analytic sample. Among these, 22% of those posted in October are for the subsequent school year, as are 48% of the jobs posted in November, 67% in December and 68% in January. During the period from February to September, the jobs posted are more consistently associated with the next school year (between 87% and 99%).

openings attached.[12] In these cases, we assume that the posting is associated with one opening, or two if the job title indicates multiple openings. Finally, if the number of hired applicants recorded for a job posting is greater than the preceding measures of openings (779 jobs), we use the hired number of applicants as the measure of openings.[13] We are ultimately left with a degree of uncertainty in measuring the number of openings associated with each job posting, but the information is more detailed and multifaceted than what is typically available in multi-district analyses of job openings—such as those relying data obtained by web-scraping job posting sites or self-reported vacancy levels.[14]

An aspect of applicant supply we analyze is its relationship to the level of compensation offered by an organization. Nimble job posting data include variables reporting minimum and maximum salary. We focus on minimum salary because it is reported for a larger proportion of jobs in our sample (54% vs. 47%) and is more comparable across organizations since the number of steps in different salary schedules is likely to vary.[15] In most cases, values consistent with annual salary levels are reported but about 5% of jobs with salary data list smaller values, which we adjust to be consistent with annual salaries.[16] To increase coverage we calculate the average minimum salary at the organization-year level, which gives us a measure of salary for 135 of 144

[12] A job may be unlinked to school-level openings or have a value of 0 FTE in the school openings data if a district is seeking to hire candidates and determine where to place them at a later point in time. It is also possible that in some cases, clients were not using the functionality of the ATS as intended.

[13] Among the job postings in the analytic sample, 40% are not associated with a recorded hire. Discussions with Nimble engineers indicated that the presence of no-hire jobs was mostly due to users not using the system as intended and failing to record hires. However, we cannot precisely distinguish between jobs with unmarked hires and jobs postings that were removed.

[14] Goldhaber, Falken, and Theobald (2025) provide a useful external validation of opening counts derived from job postings. Using web-scraped postings and state personnel records from Washington, they report a district-level correlation greater than 0.90 between the number of openings implied by job postings and the number of teachers new to a district.

[15] Among the jobs in our analytic sample that report both minimum and maximum salary, the correlation between the two is 0.79.

[16] Values that appear to be hourly wages (e.g., $15 to $40) are multiplied by 1,080 hours, a typical number of hours in a year-long teacher contract. Similarly, values that appear to be daily and monthly wages are multiplied by 180 days (a typical number of days in a teacher contract) and 12 months, respectively.

organization-year combinations. For the remaining 9 organization-year combinations, we use average salaries from years where it is reported or look up compensation information for the organization online.

We present the observation levels in our analytic sample in **Table 1**. Overall, we observe 85,904 applications to 5,262 job postings that are associated with 13,282 openings in 43 organizations. These applications were submitted by 56,898 unique applicants, corresponding to 1.5 applications per applicant and 4.3 unique applicants per opening. The number of job postings is roughly evenly split between school districts and charter organizations, though we observe substantially more openings among school districts and more of a tendency to post jobs associated with multiple openings.[17] As measured by the number of unique applicants per opening, we observe a smaller supply of applicants to school districts (3.3 per opening) than for charter organizations (6.1 per opening).

4. Descriptive Analyses

We organize our descriptive analyses around the three questions posed above: the timing of teacher hiring (Section 4.1), the supply of applicants (Section 4.2), and the characteristics of applicants (Section 4.3), throughout emphasizing how each varies across organizations and, in particular, between traditional school districts and charter organizations.

4.1 The Timing of Teacher Hiring

We begin in **Figure 2** by showing the distribution of posted FTE by calendar month and organization type. To ensure even coverage across months, we exclude the first year an organization appears in our data if the observed job posting activity in that year begins after January, and we exclude 2024 because the data were extracted in September of that year.

[17] This pattern may be driven by the school districts in our sample being comprised of relatively large urban school districts rather than the differential tendencies of school districts and charter organizations.

Among traditional districts, posting activity picks up at the start of the calendar year, peaks in March, and remains steady through August before tapering in September and October. About 70% of district openings are posted within what James et al. (2023) refer to as the "hiring season" — the March–October period of calendar year *y* when organizations hire for the school year starting in year *y* and ending in year *y+1*. The pattern among charter organizations is broadly similar but differs in one notable respect: a sizable share of charter FTE is posted in December — well above the corresponding district share for that month — and only 54% of charter openings fall within the March–October window.

We are not aware of prior evidence documenting a December concentration of charter hiring activity, and the underlying mechanism is not obvious from our data.[18] That said, conversations about this pattern with Nimble representatives provide anecdotal evidence that charter management organizations tend to post all of their talent pools by the end of December based on their projected vacancies. In general, a fuller exploration of the prevalence of "off-season" hiring is a useful direction for future work.

As noted in section 3.2, we characterize each job posting as *early*, normal, or *late* based on its relation to the posting organization's academic calendar. Recall that because the organizations in our study have a wide range of start and end dates, we define the hiring season as the period within four months prior to the end of a school year and one month after the start of the subsequent school year.[19] Within this hiring season, the overall proportions of openings

[18] We explored the opening of new schools as a potential explanation for the December concentration of hiring. Specifically, we used longitudinal CCD records to classify each organization based on whether it had any school newly opened during the study period and re-plotted the monthly FTE shares with charter organizations split by that flag. Among charter organizations, the share of December FTE coming from organizations with newly opened schools (62.4%), which is essentially identical to the share of non-December FTE coming from those organizations (63.1%).

[19] This roughly corresponds to the March 1 to October 31 hiring season defined by James et al. (2023) vis-à-vis the school year calendar of Boston Public Schools (early September to mid-June), the setting of their analysis. However, our hiring season extends one month (rather than two) past the start of the school year.

falling into each classification are 60% *early*, 29% normal, and 11% *late*.[20] The 11% figure is the lower end of the range found in prior studies (between 10% and 26%). It is possible that organizations have made efforts to reduce late hiring in response to increased awareness (and research) about the downsides associated with late hiring. While we do not find strong evidence of a downward trend in late hiring in our data, we cannot rule out a shift in behavior that preceded the study period.[21]

We observe a substantial degree of variation across organizations in the degree to which jobs are posted early or late, particularly for early postings. We present the distribution of organization-level percentages of early and late job postings for districts and charters in Figure 3. Panel A shows the distribution of the percentage of postings classified as early, and Panel B shows the corresponding distribution for late postings. The organization-level percentage of early postings is widely distributed between roughly 40% and 80%, with only a handful of organizations falling above or below that range. The distribution of the percentage of late postings is more concentrated, with most organizations falling between 0% and 20%. Although charter organizations cluster slightly toward higher early-posting shares and slightly lower late-posting shares, the two sector distributions overlap substantially.

Given the variation in the prevalence of early/late hiring evident in Figure 3, we also examine whether the timing of an organization's job postings is systematically related to its characteristics. We estimate the relationship between the share of early and late postings and organizational size, the percentage of students eligible for free or reduced-price lunch (FRL), the

[20] Here, we include jobs posted in 2024, which were excluded from Figure 2. There are seven districts for which the 2024 hiring season is truncated by the September 22 data extraction date. Among these districts, the hiring season is truncated by between 3 and 14 days, and average of 7 days. Therefore, the extent of late job posting may be slightly understated among these districts.

[21] Among the 27 organizations with at least three in-sample years, the mean trend in the percentage of late job postings is roughly flat (-0.34 pp/year) but the SD is large (12.43), limiting our ability to draw strong conclusions.

percentage of underrepresented-minority (URM) students, locale, average minimum salary, and charter status. In our regression results (a full description of the regression approach and output are available in the appendix), we find no robust relationships between organization characteristics and the shares of early and late job postings.

Consistent with the null regression results, we find little correlation between the current and 1-year lagged values of the proportion of jobs that are posted early ($r = 0.179$) and late ($r = 0.011$). In other words, organizations that post more job openings early or late one year do not systematically tend to do so the following year. And while our data cover the pandemic period, which might be hypothesized to have affected teacher hiring patterns, we do not find much evidence of this driving the result.[22]

4.2 Applicant Supply

As discussed in section 2, there is little direct evidence on the supply of applicants to teaching positions. Here, we expand the body of evidence by looking at job application levels across a wide range of districts. Since applicants often submit applications to multiple job postings, using *applications* to measure supply will tend to overstate the number of individuals seeking employment. Therefore, to measure the quantity of supply, we count the unique number of *applicants* per opening, as opposed to the number of *applications* per opening.[23]

We present the unique number of applicants per opening by subject area and sector (district and charter) in **Figure 4**. We derive subject areas from the interpretation of the job title.

[22] To account for the potential of pandemic-era irregularities, we also calculate correlations comparing 2023 and 2024 to lagged values from 2022 and 2023. Here, we find stronger, but still modest correlations between the proportions of jobs that are posted early (r=0.257) and late (r=0.089). When we estimate the regression models in Table A1 restricting the sample to the period 2022 to 2024, we still find little relationship between district characteristics and the timing of job postings.

[23] We treat applicants who submit applications in different years and/or to different organizations as distinct. Applicant IDs allow us to track individuals across Nimble client organizations. In our analytic sample, fewer than 5% of applicants have applications associated with more than one Nimble client in a given year. Note that the data only covers client organizations, not all local competitors.

The *Elementary* category includes grade teachers and positions involving primary subject areas (*Math*, *Reading*, and *Science*) while more specialized elementary positions (*Arts*, *Health/PE*, and *SPED)* are categorized as such. The most striking pattern in Figure 4 is that supply is greater in charter organizations than in school districts. The overall number of applicants per opening among charters is 6.1 versus 3.3 among districts. We also observe considerable variation in the supply of applicants across subject areas. Among districts, special education positions have the smallest supply of applicants per opening (2.4) and among charters, math (5.4), special education (5.0), and science (5.7) positions have the smallest supplies of applicants. Interestingly, and counter to some other measures of staffing challenges (e.g., Goldhaber et al., 2015; Cowan et al., 2016; Edwards et al., 2024), among school districts, we observe greater numbers of applicants per opening for math and science positions (3.8-4.0) than for elementary positions (3.7).[24]

At the organization level, the number of applicants per opening ranges from 1.5 to 20.7, but the great majority (84%) average between 3 and 12 applicants per opening (see **Figure 5**). The outliers at the upper end of the distribution (> 15) are generally medium-to-small-sized charter organizations serving roughly 150 to 2,400 students.[25] The range of applicants-per-openings values is broader than has been previously documented. As discussed in Section 2, other studies using detailed job application data (in different years) indicated between 5 and 9 applicants per opening (Goldhaber et al., 2017; Jacob et al., 2018; Bruno and Strunk 2019; Sajjadiani et al., 2019; Chi and Lenard, 2023; James et al., 2023; Goldhaber and Grout, 2024).

[24] Recall that we classify job postings for elementary math and science positions as belonging to the elementary subject area category.
[25] The average school district in our sample serves about 12,500 students whereas the average charter organization serves about 2,400 students.

To understand how the supply of applicants is related to organizational characteristics, we estimate a series of linear regressions predicting applicants per opening at the district-year-subject area level.[26] Specifically, we estimate the following equation:

$$ApplicantsPerOpening_{its} = D_{it}\beta_1 + W_{it}\beta_2 + S_{is}\beta_3 + \tau Y_t + \varepsilon_{its}\,, \qquad (1)$$

where $ApplicantsPerOpening_{its}$ is the number of applicants per opening in organization i, year t, and subject area s, D_{it} is a vector of district characteristics including the number of students in the district, the percentage of students eligible for free or reduced-price lunch (FRL), the percentage of under-represented minorities (URM) students, categorical controls for locale type, and an indicator for whether the district is a charter organization. W_{it} is a vector of work environment measures—average minimum salary and student-to-teacher ratio, S_{si} is a vector of subject area indicators, τY_t is a vector of year indicators, and ε_{its} is an error term. The model is estimated as a weighted regression using the total FTE posted in each organization-year-subject area bin as analytic weights. Because our analytic sample contains a small number of clusters — 19 districts and 24 charters — conventional cluster-robust standard errors can understate sampling uncertainty (Cameron et al., 2008). We therefore base inference on the cluster (delete-one-cluster) jackknife variance CV3 estimator (MacKinnon et al., 2023), clustering at the organization level.

To accommodate potential sectoral differences in the relationship between supply and organization characteristics, we estimate separate models for districts and charters. **Table 2** reports estimates from a series of specifications that progressively add controls. Among districts

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[26] Note that counting the number of unique applicants within a subject area requires us to treat applicants as distinct when they apply to jobs in different categories. Therefore, the total number of unique applicants is somewhat larger here than under our district-level calculations. About 12% of applicants apply to positions in multiple subject areas.

(Panel A), applicant supply is descriptively lower in organizations serving more economically disadvantaged and more underrepresented-minority students: entered on its own, a 10 percentage-point increase in the share of FRL-eligible students is associated with roughly 0.6 fewer applicants per opening (column 1), and a comparable negative association holds for the URM share (column 2). These two simple associations are the only relationships in Table 2 that are statistically significant. When the two student-body measures are entered jointly (column 3), or when organizational size, locale, and working-condition controls are added (columns 4 and 5), no individual coefficient is statistically significant. The point estimate on FRL is nonetheless stable at roughly −0.06 across columns 1 through 4 and falls by about 60 percent, to −0.024, once average minimum salary is included (column 5) — a pattern consistent with higher-FRL districts tending to offer lower salaries. Salary itself enters positively (a $1,000 increase associated with about 0.15 more applicants per opening), though this association, too, is not statistically significant.

The descriptive pattern among charter organizations (Panel B) differs in sign: entered on their own, higher FRL and URM shares are associated with somewhat *more* applicants per opening (columns 1 and 2), the opposite of the district pattern. None of the charter coefficients, however, is statistically distinguishable from zero in any specification. We also test directly whether the district and charter slopes differ, using sector interactions in a pooled model: none of the differences is statistically significant. We therefore describe the apparent contrast across sectors in how student-body composition and pay relate to applicant supply as suggestive.

4.3 Applicant Characteristics

The supply differences documented above raise the question, do districts and charter organizations draw on different pools of applicants? As noted above, there are reasons to expect differences in the charter sector driven by differential licensure requirements, compensation, and working conditions, as well as the mission-driven orientation of many charter organizations. These differences could shape not only how many candidates apply but who applies. The composition of the applicant pool is consequential for hiring since organizations can only hire the teachers who apply. In this section, we first compare the characteristics of district and charter applicant pools and then examine how applicant characteristics vary across organizations within each sector.

We observe three groups of applicant characteristics: self-reported demographics (gender and race/ethnicity); experience and education (prior teaching experience, years of experience, and advanced degrees); and two quality indices generated by Nimble's candidate-screening models (the NCI performance and turnover scores) based on the prediction models in Sajjadiani et al. (2019). We structure the data at the applicant level and consistent with the analyses above, treat applicants who apply to different organizations or in different years as distinct.

Table 3 reports unweighted within-sector means of each characteristic alongside the adjusted charter-minus-district difference — the coefficient on a charter indicator from a pooled regression with subject-area and year fixed effects — with cluster (delete-one-cluster) jackknife standard errors clustered at the organization level. The clearest differences between the sectors concern experience. Applicants to charter organizations are about 20 percentage points less likely to report prior teaching experience than applicants to districts (52.5% versus 72.2%) and average nearly two fewer years of measured teaching experience (6.7 versus 8.5). Charter applicants also score somewhat lower on Nimble's NCI turnover score (1.00 versus 1.09). Each of these differences is statistically significant at the 1% level.

Demographic differences are less precisely estimated. The share of applicants who are White is about 18 percentage points lower in charter pools (31.4% versus 48.8%), and the Black and Hispanic shares are higher (+7.9 and +4.2 percentage points, respectively), but only the White difference is statistically significant. The share of female applicants is about four percentage points lower among charters, a difference that is marginally significant. We find no sector differences in the shares of Asian applicants or applicants holding advanced degrees, or in the NCI performance score.

We also observe considerable *within-sector* variation across organizations in the racial and ethnic composition of their applicant pools. **Figure 6** plots, for each organization, the share of applicants of each racial/ethnic group against the corresponding share of students. In both sectors, applicant composition tracks student composition: organizations serving more Asian, Black, Hispanic, or White students receive correspondingly more applications from teachers of the same group. The fitted lines for Black and Hispanic applicants lie well below the 45-degree line, however, indicating that applicant pools are generally less Black and less Hispanic than the student bodies of the organizations to which those candidates apply.

In **Table 4** we analyze how applicant characteristics relate to organizational characteristics. Each cell of the table reports a separate regression, estimated within sector at the applicant-by-organization-by-year level, of each applicant characteristic (in rows) on a single organizational characteristic (in columns) — the percentage of FRL-eligible students, the percentage of URM students, or the average minimum salary — with subject-area and year fixed effects and CV3 standard errors clustered on organization. Because each cell contains a single organizational characteristic, and these characteristics are themselves correlated, the estimates should be read as descriptive associations.

Two patterns stand out. First, the demographic gradients visible in Figure 6 appear in both sectors: organizations serving higher shares of FRL-eligible and URM students have significantly more Black applicants (roughly +0.4 percentage points per percentage point of FRL or URM among districts, and +0.3 per percentage point of URM among charters), and the share of White applicants declines significantly with the URM share in both sectors (and with the FRL share among charters). Second, the sectors diverge on experience. Among districts, organizations serving more FRL-eligible and URM students have somewhat more experienced applicant pools (+0.027 and +0.025 years per percentage point, respectively), and the share of applicants with advanced degrees rises with the URM share. Among charters, the gradient runs the other way: average years of experience declines with both the FRL (−0.022) and URM (−0.020) shares, and the share of applicants with prior teaching experience falls by about 0.2 percentage points per percentage point of FRL.

5. Discussion and Conclusion

In this paper, we expand the limited evidence base on a critical and understudied aspect of the teacher labor market: the interface between job postings and the submission of applications by prospective teachers. Using proprietary data on job openings and applications from 19 school districts and 24 charter organizations, we examine how the timing of job postings, the quantity of supply, and applicant characteristics vary across organizations and between the traditional public and charter sectors of the K-12 teacher labor market. The data allow us to observe patterns for almost 57,000 unique teacher applicants. To our knowledge, this is the first study to use detailed job application data to explore these patterns across a broad set of school districts and charter organizations.

Regarding timing, we find that 11% of jobs are posted late—that is, within two weeks of the school year or later. This figure falls at the lower end of the range reported in prior studies that examined teacher hiring timelines (e.g., Liu & Johnson, 2006; Papay et al., 2016; Kraft et al., 2020) but aligns closely with Goldhaber et al.'s (2025) finding that 10% of jobs were posted in the fall. However, we observe substantial variation across organizations, with many posting between 10% and 20% of their job openings late in the season, suggesting room for improvement. Organizational characteristics generally did not predict the timing of job postings. These findings, and the weak correlation in districts' late hiring across years, run counter to the narrative that urban districts always hire late. This may reflect real change since the original wave of work on the topic though as noted above, the mean trend in the percentage of late job postings in our sample is roughly flat.

Our analysis of applicant supply—measured by the number of unique applicants per opening—reveals stark differences between districts and charters. Districts attract an average of 3.3 applicants per opening, considerably fewer than the 5 to 9 reported in prior district-level studies using similar data. Charters, by contrast, receive an average of 6.1 applicants per opening, with some attracting 10 to 20 applicants per opening. This may be related to differences between sectors in licensure requirements and is broadly consistent with Bruhn et al.'s (2022) finding that individuals may initially seek employment in charter schools before moving to traditional public schools.[27] We also uncover interesting sectoral differences in how applicant supply relates to student demographics. Among districts, student disadvantage (FRL% and URM%) is negatively predictive of applicant supply while among charters, the relationship is positive and statistically insignificant.

Turning from how many apply to *who* applies, we find systematic differences in the applicant pools of districts and charters. The clearest gap is experience: charter applicants are

[27] As noted above, in many states, charter school teachers are partially or fully exempt from certification requirements applied to teachers in traditional public schools. We find that charters in states with no licensure requirement attract somewhat more applicants per opening than charters in states with same-as-traditional-public-school rules. However, the conditional relationship is essentially zero once we control for organizational size, locale, salary, subject mix, and student demographics.

about 20 percentage points less likely to report prior teaching experience (52.5% versus 72.2%) and average two fewer years of experience than district applicants. Charter applicants are also significantly less White (31.4% versus 48.8%). These descriptive patterns show that differences in the quantity of supply come with meaningful differences in who applies.

In sum, this study adds to the limited existing evidence on the upstream supply of applicants and how it varies across the K-12 landscape by focusing on when organizations post jobs, how many candidates organizations have to choose from, and the characteristics of those candidates. Three themes emerge: late hiring is less pervasive, and more variable across organizations, than the prevailing narrative suggests; the supply of applicants to districts is lower and more variable than has been previously documented, and is lower than the supply to charters; supply differences are accompanied by differences in the composition of applicant pools—applicants to districts are more experienced and less diverse. Although descriptive, these patterns offer a baseline against which policymakers and researchers can weigh teacher-shortage claims and evaluate efforts to strengthen hiring.

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Note: During the preparation of this work, the authors used Claude AI for assistance in writing Stata do-files, reading log files and editing the manuscript. The authors reviewed and edited output as needed and take full responsibility for the content of the published article.

Tables and Figures

Table 1. Observation Levels

	All Organizations	School Districts	Charter Organizations
Organizations	43	19	24
Schools	624	474	150
States and Jurisdictions	16	6	10
Job Postings	5,262	2,720	2,542
Openings (FTE)	13,282	8,219	5,063
Unique Applicants	56,898	26,531	30,367
Applications	85,904	47,526	38,378

Notes: Jobs may be associated with multiple openings and applicants often submit applications to multiple jobs. Applicants who submit applications in different hiring seasons and/or districts or charter organizations are treated as distinct.

Table 2. Organization Characteristics and Applicant Supply

Dependent variable: unique applicants per opening (district-year-subject level)

	(1)	(2)	(3)	(4)	(5)
Panel A. Traditional school districts					
% FRL-eligible	-0.059**		-0.051	-0.056	-0.024
	(0.023)		(0.040)	(0.045)	(0.088)
% URM		-0.048**	-0.012	-0.005	-0.022
		(0.021)	(0.024)	(0.033)	(0.051)
ln(Students)				-0.605	-0.531
				(1.022)	(1.214)
Avg. min. salary ($1,000s)					0.151
					(0.182)
Student–teacher ratio					-0.082
					(0.209)
Locale controls	No	No	No	Yes	Yes
Subject-area FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	421	421	421	421	421
Clusters	19	19	19	19	19
R-squared	0.204	0.162	0.207	0.215	0.230
Panel B. Charter organizations					
% FRL-eligible	0.054		0.035	0.007	0.013
	(0.050)		(0.065)	(0.075)	(0.082)
% URM		0.045	0.018	-0.011	-0.020
		(0.045)	(0.053)	(0.048)	(0.056)
ln(Students)				-1.839	-1.550
				(1.549)	(1.771)
Avg. min. salary ($1,000s)					0.058
					(0.097)
Student–teacher ratio					-0.108
					(0.121)
Locale controls	No	No	No	Yes	Yes
Subject-area FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	558	558	558	558	558
Clusters	24	24	24	24	24
R-squared	0.105	0.104	0.106	0.156	0.161

Notes: FRL = free or reduced-price lunch; URM = underrepresented minority. Each column of Panels A and B is a separate weighted OLS regression of unique applicants per opening at the district-year-subject level, weighted by the number of openings. Standard errors in parentheses are cluster (delete-one-cluster) jackknife CV3 standard errors, clustering by organization. Stars denote *** p<0.01, ** p<0.05, * p<0.10. All models include subject-area and year fixed effects; districts and charters are estimated separately in Panels A and B.

Table 3. Mean Applicant Characteristics in School Districts vs. Charter Organizations

	Districts (1)	Charters (2)	Difference (3)
Demographics			
% Female	64.8	60.5	-3.87*
			(2.05)
% Asian	14.4	14.1	-0.03
			(5.57)
% Black	17.3	25.3	+7.94
			(6.29)
% Hispanic	8.8	12.4	+4.25
			(4.06)
% White	48.8	31.4	-17.80**
			(8.52)
Observations	26,531	30,367	
Experience and education			
% Prior teaching experience	72.2	52.5	-20.30***
			(3.82)
Years of experience	8.5	6.7	-1.85***
			(0.43)
% Advanced degree	42.1	41.1	-0.70
			(3.41)
Observations	26,531	30,367	
Quality (NCI)			
NCI performance	0.026	0.036	+0.0016
			(0.0257)
NCI turnover	1.090	1.002	-0.0906***
			(0.0119)
Observations	20,321	16,053	

Notes: Statistics calculated at the applicant-by-organization-by-year level. The Districts and Charters columns report unweighted within-sector means. The Difference column reports the charter-minus-district coefficient on a sector indicator in a pooled regression of the applicant characteristic on the indicator with subject-area and year fixed effects, with the cluster (delete-one-cluster) jackknife CV3 standard error in parentheses; asterisks correspond to two-sided t-tests (*** p<0.01, ** p<0.05, * p<0.10). Demographic and experience measures span all applicants (N = 26,531 districts / 30,367 charters; 43 clusters in the pooled regression). Years of experience is missing for a small share of applicants and is imputed rather than dropped: applicants with no prior teaching experience are recoded to zero years, and applicants with prior experience are assigned the within-sector (district or charter) mean of observed years of experience. This adjustment affects 311 applicant-by-organization-by-year cells (102 districts / 209 charters); all other measures are unimputed. The NCI-based measures are available only for a subset of applicants.

Table 4. Applicant Characteristics and Organizational Characteristics

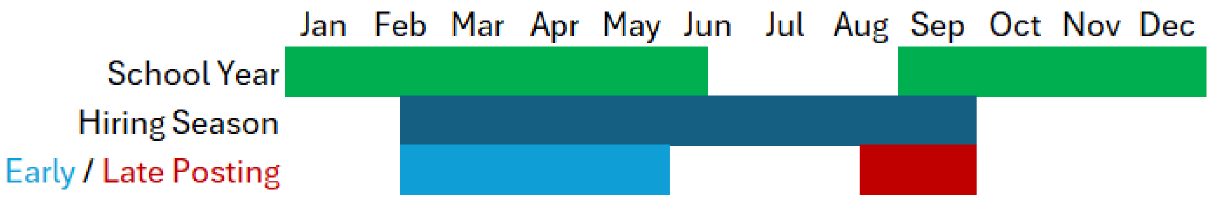
Each cell is a separate regression.

Organization:	**Student % FRL**	**Student % URM**	**Salary ($1,000s)**
Panel A. Districts			
Applicant Demographics			
% Female	+0.017	-0.006	-0.143
	(0.078)	(0.061)	(0.194)
% Asian	-0.167	-0.020	+1.387
	(0.281)	(0.127)	(0.815)
% Black	+0.423***	+0.403***	-0.599
	(0.049)	(0.053)	(0.475)
% Hispanic	-0.069	+0.028	+0.425*
	(0.128)	(0.056)	(0.207)
% White	-0.104	-0.416***	-1.487***
	(0.409)	(0.135)	(0.405)
Experience and education			
% Prior teaching experience	+0.006	+0.031	+0.096
	(0.049)	(0.064)	(0.167)
Years of experience	+0.027**	+0.025***	-0.019
	(0.010)	(0.006)	(0.016)
% Advanced degree	+0.146	+0.229**	+0.549
	(0.193)	(0.099)	(0.384)
Quality (NCI)			
NCI performance	-0.0002	+0.0007	+0.0055*
	(0.0013)	(0.0007)	(0.0029)
NCI turnover	-0.0008	-0.0005	-0.0003
	(0.0007)	(0.0009)	(0.0007)
Panel B. Charters			
Applicant Demographics			
% Female	-0.081	-0.096***	-0.438**
	(0.091)	(0.031)	(0.198)
% Asian	+0.005	+0.016	+0.486*
	(0.035)	(0.043)	(0.254)
% Black	+0.287	+0.335***	-0.050
	(0.206)	(0.106)	(0.812)
% Hispanic	+0.168**	+0.117	+0.725**
	(0.075)	(0.071)	(0.279)
% White	-0.494**	-0.507***	-1.304**
	(0.195)	(0.087)	(0.589)
Experience and education			
% Prior teaching experience	-0.196**	-0.228	-0.119
	(0.092)	(0.164)	(0.462)

Organization:	Student % FRL	Student % URM	Salary ($1,000s)
Years of experience	-0.022***	-0.020***	-0.045
	(0.006)	(0.004)	(0.031)
% Advanced degree	-0.028	-0.019	+0.216
	(0.108)	(0.076)	(0.181)
Quality (NCI)			
NCI performance	-0.0004	-0.0004	+0.0021
	(0.0012)	(0.0008)	(0.0019)
NCI turnover	-0.0002	-0.0002	+0.0004
	(0.0006)	(0.0004)	(0.0010)

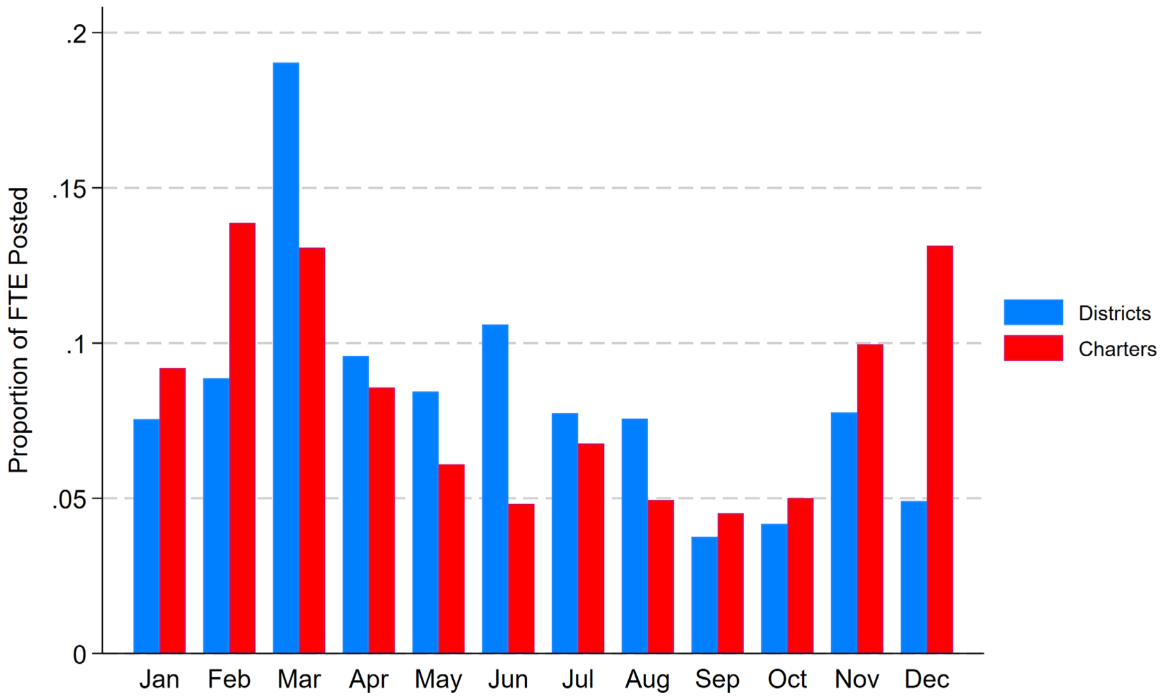
Notes: FRL = free or reduced-price lunch; URM = underrepresented minority. Each cell reports the coefficient on the organizational characteristic from a separate regression of the applicant characteristic on that characteristic, with subject-area and year fixed effects, estimated at the applicant-by-organization-by-year level and clustered by organization. Standard errors in parentheses are cluster (delete-one-cluster) jackknife CV3 standard errors; *** p<0.01, ** p<0.05, * p<0.10. Demographic and experience measures are available for essentially all applicants (N = 26,531 districts / 30,367 charters). The NCI-based measures are available for a subset of applicants (N = 20,321 / 16,053).

Figure 1. Early and Late Job Posting for a Representative District



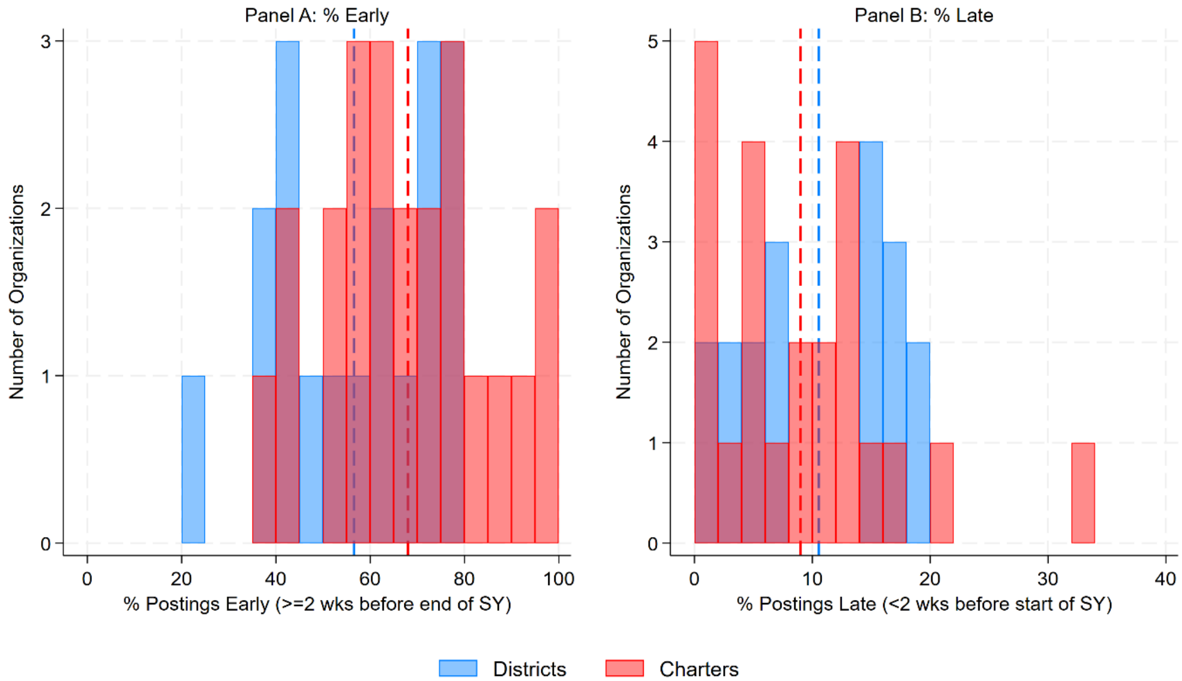
Notes: In this example, school year t ends on June 15th and school year $t+1$ begins on September 1st. The hiring season is the period four months prior to the end of school year t (February 15th) to 1 month after the start of school year $t+1$ (October 1st). Early job posting is defined as occurring 2 weeks prior to the end of the school year t or earlier and late job posting is defined as occurring 2 weeks prior to the start of school year $t+1$ or later.

Figure 2. The distribution of job openings posted by month and organization type



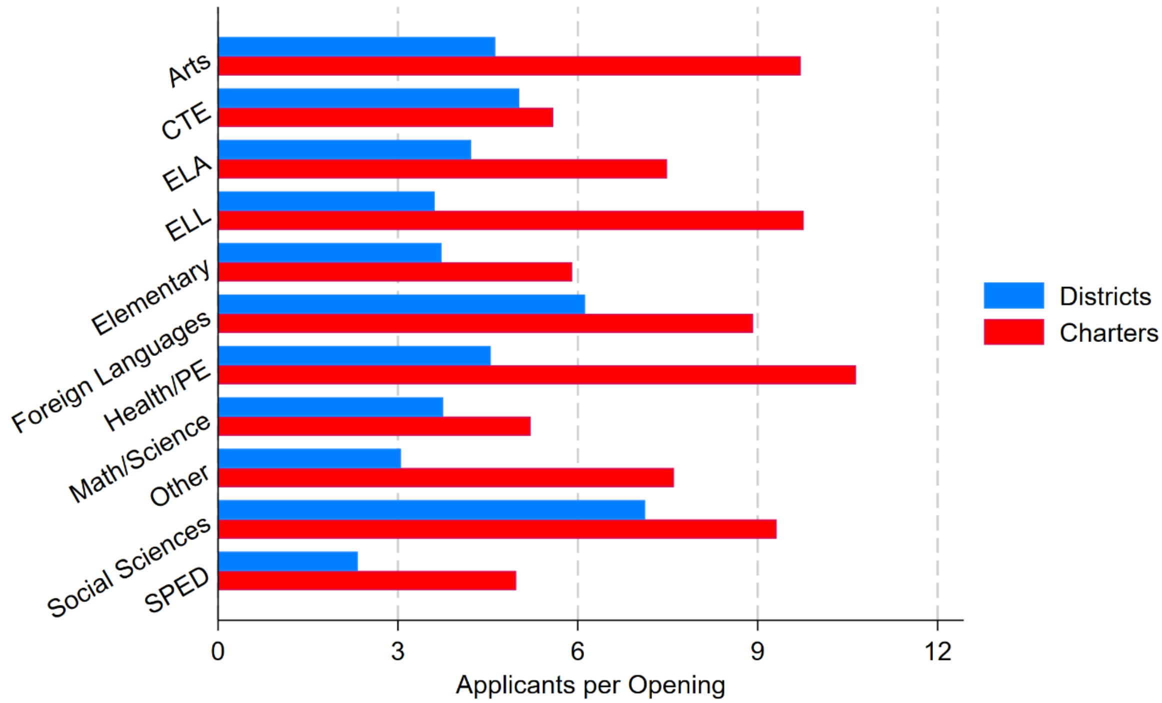
Notes: To ensure even coverage of job posting activity across months, we exclude the first year an organization appears in the data if observed job posting activity in that year begins after January. We also exclude job posting activity from 2024 because the data were extracted mid-year, in September 2024. This reduces the number of district-year observations from 138 to 91 and total posted FTE from 13,212 to 9,865.

Figure 3. The timing of job openings posted by organization (within hiring season)



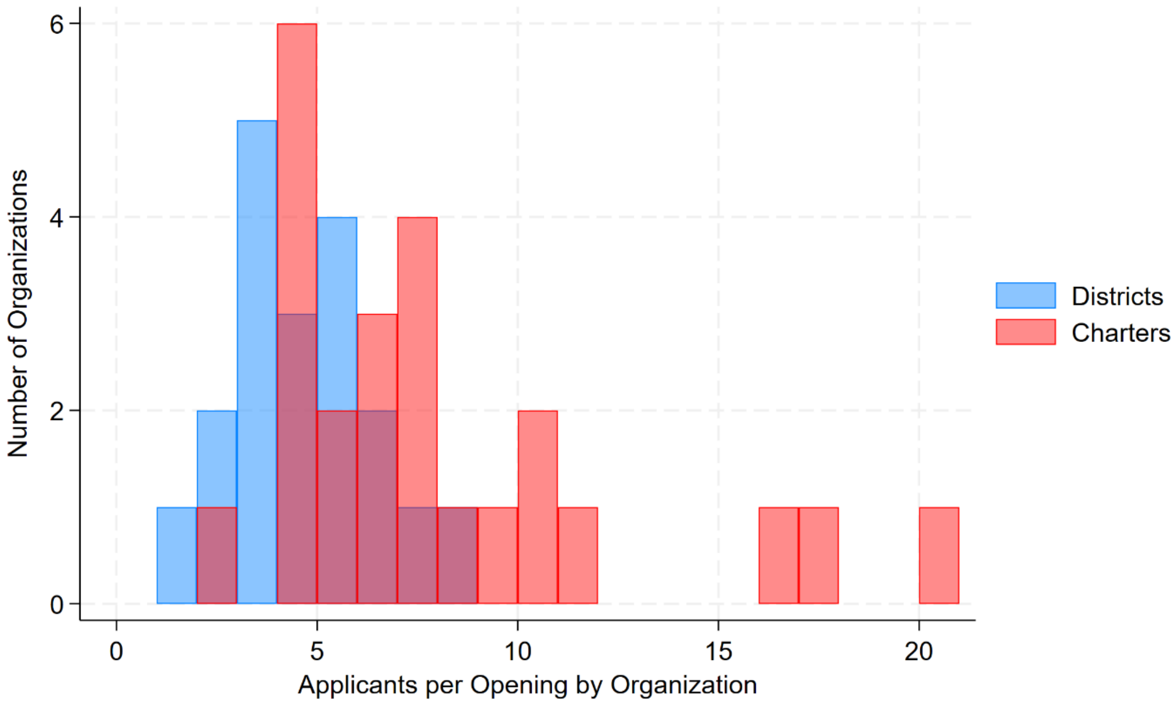
Notes: Each histogram shows the distribution across organizations of the percentage of job postings classified as "early" (Panel A) or "late" (Panel B), with sector overlay. Districts are shown in blue and charter organizations in red; bin widths are 5 percentage points in Panel A and 2 percentage points in Panel B, reflecting the more concentrated distribution of the late share. The sample is restricted to job postings within each organization's hiring season — defined in Section 3.2 as the period within four months prior to the end of a school year and one month after the start of the subsequent school year — and excludes the first year an organization appears in the data if observed posting activity in that year begins after January. Forty-one organizations are represented (18 districts, 23 charter organizations); two organizations whose only observed activity falls in a truncated first year are excluded. Dotted lines show means calculated at the organization level.

Figure 4. Applicants/Opening by Subject Area



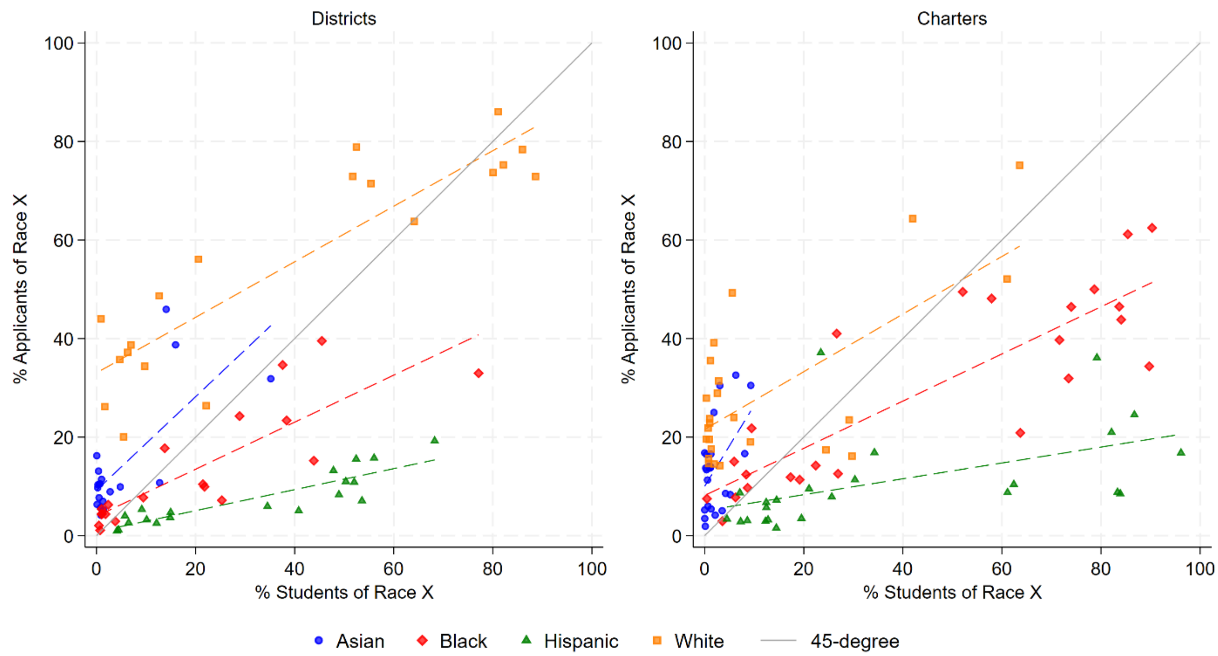
Notes: The figure shows the average number of unique applicants per opening by subject area, separately for traditional school districts (blue) and charter organizations (red). Within each subject area and sector, applicants per opening is computed as the total number of unique applicants — counted once within each organization, year, and subject area — divided by the total number of openings in that subject area and sector, pooled across all years in our analytic sample. Subject areas are derived from job titles. The Elementary category includes general grade-level positions and primary subject areas (Math, Reading, and Science).

Figure 5. Distribution of Unique Applicants per Opening by Organization



Notes: For each organization, applicants per opening is computed as the total number of unique applicants — counted once per organization and year — divided by the total number of openings observed for that organization across all years in our analytic sample (N = 43; 19 districts and 24 charter organizations).

Figure 6. Applicant Race Shares vs. Student Race Shares by Organization



Notes: Each marker is an organization. For each race-ethnicity group (Asian, Black, Hispanic, and White), the organization-level percentage of applicants of that race — computed across unique applicant-organization-year cells, pooled across all years in our analytic sample — is plotted against the percentage of students of that race, averaged across in-sample years. Dashed lines are race-specific linear fits; the solid gray line marks the 45-degree line of perfect demographic alignment. Districts and charter organizations are shown in separate panels (N = 43; 19 districts and 24 charter organizations).
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Appendix

To explore the relationship between early/late hiring and organization characteristics, we estimate linear regression models specified as follows:

$$Timing_{it} = \alpha_0 + D_{it}\alpha_1 + Y_t\alpha_2 + \varepsilon_{it} \,, \tag{1}$$

where $Timing_{it}$ is the proportion of job openings in organization i and year t that are either *early* or *late*, D_{it} is a vector of district characteristics including the number of students in the district, the percentage of students eligible for free or reduced-price lunch (FRL), the percentage of under-represented minorities (URM) students, categorical controls for locale type, and an indicator for whether the district is a charter organization. Y_t is a vector of year indicators and ε_{it} is an error term.[28] We estimate standard errors using the cluster (delete-one-cluster) jackknife (CV3) described in Section 4.2.

We present results from regressions predicting the proportion of job postings classified as early (Panel A) or late (Panel B) in Table A1. Each panel introduces the variables of interest incrementally: FRL alone in column 1, URM alone in column 2, FRL and URM jointly in column 3, with size and locale controls added in column 4, and finally with average district minimum salary in column 5. The sample is restricted to jobs posted during the hiring season and excludes the first year an organization appears in the data if observed posting activity in that year begins after January. The most consistent pattern across specifications is a negative point estimate on the percentage of FRL-eligible students in the models for late postings (Panel B), with magnitudes ranging from approximately −0.11 to −0.20 percentage points of late hiring per one-percentage-point increase in the FRL share. Although the conventional cluster-robust

[28] Since the dependent variable is an average calculated for each district-year, we estimate weighted regressions using total openings at the district-year level as analytic weights.

standard errors would suggest this association is statistically significant in several specifications, the few-cluster-robust CV3 standard errors are substantially larger and none of these associations is statistically significant. Indeed, no coefficient in Table A1 reaches conventional significance levels under CV3 inference.[29]

[29] We also estimate fully-interacted models to test whether the relationships between organizational characteristics and posting timing differ between traditional school districts and charter organizations. Although point estimates differ across sectors in some cases — most notably on the percentage of FRL-eligible students and the average minimum salary — differences are not statistically significant.

Table A1. Organization Characteristics and the Timing of Job Postings

	FRL	*URM*	*FRL + URM*	*+ size, locale*	*+ salary*
	(1)	(2)	(3)	(4)	(5)
Panel A. Dependent variable: % of postings classified as Early					
% FRL	0.004		0.149	0.182	0.020
	(0.269)		(0.438)	(0.546)	(0.544)
% URM		-0.057	-0.167	-0.195	-0.121
		(0.156)	(0.292)	(0.425)	(0.423)
Log(students)				1.944	1.201
				(4.777)	(5.186)
Avg. min. salary					-0.713
					(0.949)
Charter	5.805	6.029	6.658	10.321	9.688
	(7.180)	(6.231)	(7.103)	(12.949)	(13.823)
Observations	114	114	114	114	114
R-squared	0.081	0.086	0.096	0.106	0.138
Clusters	41	41	41	41	41
Panel B. Dependent variable: % of postings classified as Late					
% FRL	-0.114		-0.188	-0.199	-0.162
	(0.106)		(0.128)	(0.183)	(0.199)
% URM		-0.053	0.086	0.081	0.064
		(0.081)	(0.093)	(0.127)	(0.132)
Log(students)				0.543	0.710
				(2.840)	(3.040)
Avg. min. salary					0.161
					(0.196)
Charter	0.694	1.051	0.257	0.941	1.084
	(2.896)	(3.766)	(2.854)	(7.260)	(8.103)
Observations	114	114	114	114	114
R-squared	0.135	0.075	0.154	0.209	0.216
Clusters	41	41	41	41	41

Notes: FRL = free or reduced-price lunch; URM = underrepresented minority. Each column reports a separate weighted OLS regression of the indicated organization-year posting share (Panel A: % early; Panel B: % late) on the listed organizational characteristics, with total within-window FTE postings as analytic weights. All specifications include year fixed effects; specifications 4 and 5 add locale-type indicators (urban, suburban, town/rural). The Charter row reports the coefficient on a charter indicator. Standard errors in parentheses are cluster (delete-one-cluster) jackknife standard errors (CV3; MacKinnon, Nielsen, and Webb, 2023), clustered on organization (G = 41), with significance assessed against the t(G−1) reference distribution; *** p<0.01, ** p<0.05, * p<0.10. The sample comprises 114 organization-year observations from 41 organizations within the hiring season window defined in Section 3.2. No coefficient is statistically significant at conventional levels.