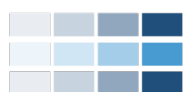


What Do Teacher Job Postings Tell Us about School Hiring Needs and Equity?

Dan Goldhaber
Grace Falken
Roddy Theobald

March 2023

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CALDER
National Center for Analysis of
Longitudinal Data in Education Research



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Dan Goldhaber

*American Institutes for Research / CALDER
University of Washington*

Grace Falken

University of Washington

Roddy Theobald

American Institutes for Research / CALDER

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CALDER • American Institutes for Research
1400 Crystal Drive 10th Floor, Arlington, VA 22202
202-403-5796 • www.caldercenter.org

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Abstract

Several decades of research using school administrative data show that teacher quality is inequitably distributed across schools. But these estimates may understate teacher-related inequities if they do not account for how teacher vacancies or late hires are distributed across schools. We investigate these hiring issues using data on a direct proxy of school hiring needs: teacher job postings collected from public school district websites. These data allow us to document how, over the course of the school year, hiring needs vary across districts, schools, and subject areas. We find that schools serving more students of color have greater hiring needs throughout the hiring cycle. We also find that hiring needs for special education and STEM positions are consistently higher than hiring needs for elementary positions. Schools with growing enrollments, as well as schools and subjects with higher prior attrition rates, also tend to have more job postings. Postings for schools in towns and rural areas tend to stay open longer than for schools in suburban and urban areas. Finally, we validate that job postings, which can be obtained quickly and inexpensively, are a good indicator of school and district needs in that they closely line up with eventual teacher hires.

1. Introduction

Longstanding evidence shows that teacher quality, as measured by factors like experience, advanced degrees, and value-added measures, is distributed across schools in ways that harm students of color and low-income students (Goldhaber et al., 2015; Lankford et al., 2002; Rodriguez et al., 2023). This issue is so pervasive that improving systems for teacher hiring, support, and retention has become a national priority and target of federal grant programs (Wellington et al., 2023). But these accounts may misstate (and likely understate) teacher-related inequity in the system because the static measures of teacher quality they use fail to capture the fact that schools often struggle to staff classrooms throughout the year in ways that are not distributed evenly across students. Despite their likely inequitable effects on students, teaching vacancies that go unfilled or are filled during the school year are not captured by studies that focus on the characteristics of classroom teachers.¹

A lack of information about vacancies and hiring delays is not just a problem for research. States often lack concurrent information to help them tackle staffing challenges in real time; annual state staffing reports and administrative data are usually available too late to inform policy debates or decision making. In short, there is often not enough detailed and timely data about the state of the teacher labor market to provide nuanced information in the service of informing policy decisions (Bleiberg & Kraft, 2023; Nguyen et al., 2022; Putman, 2023).

Information collected from school and district job postings offers a possible answer to the lack of timely data on school staffing challenges. For instance, recent work (Goldhaber, Brown, et al., 2022) characterizes the dynamics of school hiring needs over a full year and across

¹ Several studies document that late-hiring is not only a relatively frequent phenomenon (Liu & Johnson, 2006) but also has negative impacts on student achievement (Kraft et al., 2020; Papay & Kraft, 2016). One recent study in Boston Public School District finds that late-hiring schools tend to hire lower-performing candidates relative to those schools initiating hiring well in advance of the fall (James et al., 2022).

different district characteristics using job postings scraped from school system websites. The scraped postings data have the major advantage of being a direct measure of the demand side of the teacher labor market—that is, they represent schools’ *preferences* for hiring (i.e., the market demand) rather than their realized hires. Job postings data can also be observed in real time to identify hiring difficulties, sidestepping the time-related problems associated with administrative staffing data. There is some question, however, whether job postings data accurately reflect open positions (we elaborate on this in Section 3).

In this paper, we use data on job postings scraped from school system websites in Washington state to describe the number and type of teacher job postings at *individual schools*, the extent to which postings vary across school and district characteristics, the degree to which these postings translate into new hires, and the extent to which postings are associated with special circumstances, including the unprecedented influx of federal dollars received through the Elementary and Secondary School Emergency Relief (ESSER) fund.² Specifically, we answer the following research questions:

1. How accurately do job postings predict new hires?
2. How do new teacher job postings vary across subject areas, across school districts, within school districts, and how are they related to school and district characteristics?
3. To what extent are new postings predicted by prior teacher attrition, changes in student enrollment, and ESSER funding?
4. How long are job postings typically visible online before they are filled, and how does duration vary by subject and school system characteristics?

² In total districts have received about \$190 billion in ESSER funding as part of the American Rescue Plan. For more details on this funding, see <https://oese.ed.gov/offices/education-stabilization-fund/elementary-secondary-school-emergency-relief-fund/>.

In answering these questions, we make four primary contributions. First, and arguably most importantly, we link rates of job postings in 2021-22 to rates of new hiring in 2022-23 to validate the extent to which this measure accurately captures realized hiring. This is important given that the job-scraping method of obtaining information about hiring needs provides timely information at a relatively low cost and is a promising area for new research on hiring challenges in schools. Second, while several studies (Goldhaber et al., 2020; Goldhaber, Brown, et al., 2022; Goldhaber, Gratz, et al., 2023; James et al., 2022) examine the distribution of job postings across districts and schools, ours is the first to use statewide, *school-level* information about postings, giving us the ability to observe the equity implications of unfilled job postings both within and between school districts. Third, this is the first paper we know of that assesses the degree to which staffing changes at the school-level are attributable to the unique policy environment of ESSER funding relative to other factors, such as prior school attrition. This is important given that the ESSER funding is time-limited, meaning surges in hiring funded by ESSER will likely not reflect a steady state. Finally, our consideration of the duration of job postings is a novel contribution given that most administrative data only provide snapshots in time and do not reflect the administrative and financial costs of prolonged job searches.

Not surprisingly, we find that schools serving more students of color (used interchangeably with underrepresented minority students or “URM”) have greater hiring needs throughout the hiring cycle, including after the school year has begun. Additionally, hiring needs for special education and STEM positions are consistently higher than for elementary positions. ESSER funding is a significant predictor of more job postings, but not when we account for the fact that districts that received more ESSER funding also have schools with more students of color. Together, our findings and the initial validation suggest that states and districts could use

these data to intervene in real-time in ways that could benefit students who are currently disadvantaged by these trends.

2. Background on Teacher Quality Distribution

This study touches on several strands of literature. As we describe below, a well-developed literature on teacher quality suggests the extent to which teacher vacancies are filled as well as how long it takes to fill them has important implications for educational outcomes and equity. But school staffing has also taken on a special urgency in the wake of the COVID-19 pandemic. Districts and schools must help large numbers of students recover academically and socially from pandemic-related disruptions while dealing with a tight labor market, teacher burnout, and concerns about staff morale (Zamarro et al., 2022). Meanwhile, ESSER support has brought an infusion of resources, increasing the system's capacity to act while raising pressing questions about what districts should do, how, and based on what information.

2.1 *Teacher quality and distribution*

An extensive literature shows that teachers and their attributes are inequitably distributed across students. This literature has documented inequity in measures of experience and credentials over several decades (Clotfelter et al., 2005; Clotfelter, Ladd, & Vigdor, 2007; Clotfelter, Ladd, Vigdor, et al., 2007; Darling-Hammond, 2004; Lankford et al., 2002; Rodriguez et al., 2023). More recent work also considers the distribution of value-added measures of teacher contributions to student test scores (Goldhaber et al., 2015, 2018; Isenberg et al., 2022; Mansfield, 2015) and school climate (Backes et al., 2022).

These inequities do not have a single explanation. There is evidence, for instance, that all else equal, teachers prefer employment in schools that serve more advantaged students, as illustrated by patterns of attrition, transfers, and initial applications to teaching jobs (Clotfelter et al., 2011; Hanushek et al., 2004; James et al., 2022; Lankford et al., 2002). This may reflect

compensation differences across schools (Baker, 2017; Chambers & Fowler Jr., 1995; Clotfelter et al., 2011; Imazeki, 2005), differences in working conditions or leadership (Borman & Dowling, 2008; Horng, 2009), preferences for teaching certain student demographics (Fairchild et al., 2012), or teacher preferences about location, e.g., proximity to teacher education programs (Boyd et al., 2005; Krieg et al., 2016; Reininger, 2012). Some of these factors are outside the direct control of school systems. James and Wyckoff (2022), for instance, find a meaningful association between the degree of segregation between and across districts in the same metropolitan areas and the distribution of teacher experience in schools. But school system hiring practices themselves may also be important. Indeed, research finds that decisions about when and how schools screen for applicants influences the pool of individuals considered and which candidates are ultimately selected (Bruno & Strunk, 2019; James et al., 2022; Papay & Kraft, 2016).

Inequities in teacher distribution across students may also be shaped by one or more of the staffing actions described by Clotfelter et al. (2011): attrition from teaching, transfers, and the initial hiring of candidates. While all these actions can influence the distribution of teachers across schools, some evidence suggests that hiring and intra-district mobility may be particularly important to teacher distribution inequities (Goldhaber, Kasman, et al., 2023).³ This is buttressed by recent empirical work showing how significant variation in hiring practices across schools influences gaps in teacher quality (James et al., 2022; Kraft et al., 2020). As for intra-district mobility, there is some debate about the equity implications of providing seniority preference in

³ Goldhaber, Kasman, et al. (2023) use data from Washington to simulate the degree to which gaps in teacher quality across schools are related to teacher attrition from the state teaching workforce, teacher mobility between teaching positions, and teacher hiring for open positions. They find that eliminating inequities in teacher mobility and hiring across different schools would close gaps between schools in the proportion of novice teachers within 5 years, while just eliminating inequities in teacher hiring would close gaps within 10 years. On the other hand, eliminating inequities in teacher attrition without addressing mobility and hiring does little to close gaps.

teacher transfer policies (Grissom et al., 2014; Koski & Horng, 2014), but evidence suggests that seniority preference tends to exacerbate the transfer of more experienced teachers to schools serving more advantaged students (Anzia & Moe, 2014; Goldhaber et al., 2016; Koski & Horng, 2007).⁴ Internal and external staffing dynamics are also inter-dependent; for example, the way school systems handle teacher transfers within districts can have implications for the timing of external hiring efforts (Levin & Quinn, 2003).

More closely related to our work, inequitable distribution of teachers may be related to staffing challenges. Recent evidence finds that staffing challenges measured by job openings are more prevalent in districts serving higher proportions of students of color, rural districts, and for some specific subjects (Goldhaber, Brown, et al., 2022). For example, districts in Washington in the top quartile of percent of under-represented minority (URM) students have 20 percent higher rates of new weekly postings per pupil relative to districts in the bottom quartile of percent URM students.⁵ Rural districts in the state have almost double the total postings per pupil for teaching positions as districts in cities. Across subjects, STEM positions experience double the vacancy rate of elementary teaching positions, and special education positions are vacant at quadruple the rate of elementary positions (Goldhaber, Brown, et al., 2022).

Regardless of its source, teacher-related inequity harms students. Teachers impact a wide range of student outcomes, including college-going and earnings in adulthood (Chetty et al., 2014). As students move through school, gaps in teacher quality that seem minor can accumulate over time, resulting in meaningful effects on a student's academic trajectory (Goldhaber, Theobald, et al., 2022). Beyond the distribution of teacher quality, research has also shed light on

⁴ The presence of collective bargaining also shapes the structure and flexibility of teacher compensation. For instance, exploiting the expiration of CBAs in Wisconsin, Biasi (2021) finds that flexible pay structures, relative to seniority pay structures, increase salaries for high-performing teachers and increases average teacher quality.

⁵ In this paper, URM includes students who are Black, Hispanic, and American Indian/Alaska Native.

how disruptions to teacher continuity in the classroom harms students' learning, either through the churn of teachers across positions within a school (Atteberry et al., 2017), spillovers from teacher turnover (Ronfeldt et al., 2013), or late hiring during the school year (James et al., 2022; Liu & Johnson, 2006; Papay & Kraft, 2016).

2.2 *Staffing during the pandemic*

Although empirical evidence about COVID-19's impact on the teaching profession is still emerging, assertions and anecdotes about the pandemic's negative effects on teachers are widespread. "The teachers were just dropping like flies," reports one CNN article, quoting a tenth grader in Wisconsin (Marsh, 2023).⁶ Survey research suggests that the move to virtual or hybrid instruction was associated with higher self-reported rates of burnout and interest in leaving the profession among teachers in the 2020-21 school year (Zamarro et al., 2022). Teacher attrition during the pandemic has also been widely reported in the media as problematic and at "crisis levels" (Maxouris & Zdanowicz, 2022). Recent evidence from a variety of contexts resonates with these anecdotal concerns, finding increases in teacher attrition after the third year of the COVID-19 pandemic (Barnum, 2023; Diliberti & Schwartz, 2023; Goldhaber & Theobald, 2023).⁷ For instance, in Washington state, the setting of this study, teacher attrition in the 2021-22 school year was recently found to be higher than at any point over the last three decades (Goldhaber & Theobald, 2023). Nevertheless, whether public education faces the 'mass exodus' or 'crisis' that has been portrayed in the media remains debatable (Maxouris & Zdanowicz, 2022; Rahman, 2022).

⁶ The article goes on to say that "In addition to having to deal with low pay, high student-to-teacher ratios, poor working conditions, post-pandemic learning loss, school shootings and social or emotional issues with students, teachers across the nation are also grappling with culture wars over what they can and cannot teach in the classroom" (Marsh, 2023).

⁷ Evidence from several states also suggests that attrition increased by a few percentage points from the first to the second year of the pandemic (Bacher-Hicks et al., 2021, 2022; Bastian & Crittenden Fuller, 2023; Camp et al., 2022; Goldhaber & Theobald, 2022a, 2022b).

School staffing needs depend on several factors, including attrition, changes in educational programs, enrollment, and funding levels. Goldhaber and Theobald (2022b), for example, find that teacher turnover rates at the district level predict vacancy rates, though the relationship is not terribly strong ($r = 0.23$).⁸ Prior work on district-level job postings in Washington finds that subject-area district attrition rates are significantly predictive of district job postings rates the following year (Goldhaber, Brown, et al., 2022).

One challenge associated with predicting school staffing needs is the large infusion of ESSER funding. With ESSER, schools received about a quarter the value of total annual spending on K12 education—roughly \$190 billion—to implement a variety of COVID-19 academic recovery programs, many of which entail increases in school staffing (Sparks, 2022). Because ESSER funding is allocated according to district Title I eligibility, the effect on financial capacity varies greatly across districts. Moreover, recent research highlights that local factors are the most important predictors of vacant teaching positions, even though school staffing is also governed by nested labor markets at the town-, region-, and state-level (Edwards et al., 2022). ESSER funding may further complicate our ability to observe these local factors in the data. A recent analysis of districts' ESSER spending plans illustrates that financial priorities also vary across ESSER recipients (Jordan & DiMarco, 2022b). Investment in teachers and instructional staff—\$390 per pupil on average—is second only to investments in air ventilation and climate-control systems, which were \$394 per pupil on average (Jordan & DiMarco, 2022a).

⁸ We find that this correlation is similar at the school-level ($r = 0.25$).

3. Data and Summary Statistics

3.1 Job posting data

The primary source of data for this analysis is job posting data collected via automated web scraping of 242 of the 295 school district websites in Washington. The districts we exclude from this process serve about 1.5% of all Washington students.⁹ We exclude these districts because they did not have active, observable job posting sites at the time of the study. In districts that had web-based job postings, we conducted an initial pilot of web-scraping postings in the fall of 2021. Following the pilot, we scraped district sites twice-weekly, usually on Mondays and Fridays, from early December 2021 through the end of December 2022. This cadence gave us a relatively consistent picture of district hiring challenges for the entire 2022 calendar year. Our web-scrapers assigns unique IDs to each job posting the first time it is observed, allowing us to distinguish each unique position posted and track how long that position remains online.

Importantly, there are several potential limitations to using job postings as a measure of school hiring needs. First, postings for a teaching job may underrepresent the number of positions that a district seeks to hire (e.g., districts may post a generic elementary teaching position but seek to hire multiple elementary teachers). In the case of postings indicating that there are “multiple positions,” we conservatively count the posting as two positions. We do not know the degree to which this assumption understates the true number of positions being filled. Second, internal transfers within districts may not appear as job postings, or alternatively a teacher moving from one school to another could create two job postings (for both hiring school and departing school) for a single internal move. Third, it is possible that schools and districts

⁹ Unobserved districts are 90% in rural areas, 8% in towns, and 2% in suburbs; no unobserved districts are in cities. Observed districts serve 14 times more students, on average, than unobserved districts. Unobserved districts serve slightly higher proportions of white students and American Indian students. Lastly, unobserved districts received higher total ESSER funding per pupil.

may not advertise or try to staff positions if they do not expect to attract enough applicants. Fourth, website administrators may not or may be slow to remove postings, leading us to believe that there are slots to be filled even when that is not the case, or conversely may remove postings that have not been filled (leading us to incorrectly think a posting has been filled). Finally, while the web scraping collects the school's name from the online postings when available, not all job postings identify the specific school for which the position is being hired.¹⁰

To address our first research question and validate postings as a measure of hiring, our posting data includes posts from the initial pilot of this web-scraping endeavor collected in the fall of 2021 (Goldhaber, Gratz, et al., 2023) and posts from December 2021 through October 2022.¹¹ We total the number of posts removed from district websites between the fall of 2021 and October 1, 2022, both by school and by district.¹² This measure of posts assumes that positions removed from district websites have been filled. We are then able to compare these “filled posts” to the number of new teaching staff we observe both overall and by subject using methods described below.

¹⁰ We use fuzzy matches to connect school names to unique Washington public school IDs. For posts that clarify the schooling level (e.g., elementary) in districts that only have one school at that level, we assume the post is attributable to the individual elementary school. Similarly, for districts with only one school we assign posts to that school. Importantly, in some rural districts more than one school shares a physical location and school name but operates under distinct school codes in our administrative data. In these cases, even if a school name is included in the posting, if the grade level is not clarified we cannot assign the post to a specific school.

¹¹ This time range allows our validation to span postings that occurred throughout the 2021-22 school year. We piloted this web scraping process in the fall of 2021, which provides a point of comparison for total post volume to fall of 2022 but the pilot data are not used in our primary analyses. For further detail on the pilot data, see Goldhaber, Gratz, et al., (2023). We only reference these data as a point of comparison for the vacancy rates we observe in fall 2022.

¹² Our fall 2021 data initially scraped websites as of October 26th, so if any positions were filled between October 1, 2021, and October 26th, 2021, we would undercount the number of posts relative to new hires that we observe as of October 1, 2022. Similarly, the last date we scraped district websites before October 1, 2022, was September 29, 2022; this means that if a post was filled between those dates we do not count it as such and may undercount the number of filled positions relative to new hires. These dates are the closest we observe to the October 1, 2021, and October 1, 2022, staffing snapshots provided by WA administrative data and should capture almost all positions hired for between staffing snapshots.

One reason we construct our validation measures for both the school and district level is that not all postings attribute the position to a specific school. We elaborate on the differences of this school-identified subsample below, but for the remainder of our research questions, our school-level analysis limits our sample only to postings which have an identifiable school. We also limit our analysis for RQ2 through RQ4 to posts observed in the 2022 calendar year. Because we observe bi-weekly posting data for December 2021 and the entirety of 2022, we can observe postings as they initially appear in the 2022 sub-sample, allowing us to avoid left censoring (i.e., we know that a post is new if it is observed in January 2022 and was not on a district website in December 2021).

We group job postings into categories according to keywords found in job titles and focus only on classroom teaching positions in this analysis.¹³ Teaching positions are classified into the following mutually exclusive subject areas: special education; science, technology, and math (STEM); elementary; English-language learner; and “other”. We selected these categories because the first four are the most common areas of subject endorsement in Washington and thus allow us to compare posting volume to staffing volume across subject areas, which we explain below. Using these five teaching categories, we aggregate our posting data to the school-subject-month level to observe how the volume of new postings varies within districts, across subjects, and over the course of the calendar year. In our primary analysis, each posting is assigned to the month in which we first observe it on a district website, meaning the time categories are mutually exclusive. In our duration analysis we investigate the number of weeks that different postings stay open by disaggregating to the post-by-week level.

¹³ For more information on other areas of postings, such as for paraeducators, transportation, or administrator positions, see Goldhaber, Brown, et al. (2022). While we do not limit our analysis to certain ranges of position FTE posted, only 1% of postings are for positions less than 0.5 FTE and omitting these postings does not affect our overall results.

Observing the duration of postings allows us to disentangle the volume of postings over time from the length of time posts remain online. We interpret the removal of a post from a district website as the filling of that position. As noted above, we record job postings that newly appear on school district websites in January 2022 and categorize the initial date of the posting as corresponding with the date that the websites are scraped. While there is limited concern about left censoring, as we discussed above, our duration measures are right censored because we do not observe the full duration of postings that remain open as of the most recent scraping collection in December 2022. Additionally, all postings exhibit interval censoring where we do not necessarily observe the exact day the post appears or disappears but instead observe the first time the post was online when we ran the web-scraper. We address how our analytic methods account for these sources of censoring in Section 4 below.

3.2 *Additional measures*

We supplement the job posting data described in the prior section with details on districts, schools, and teachers obtained through a data sharing agreement with the Washington State Office of Superintendent of Public Instruction (OSPI). The publicly available data include school- and district-level student enrollment, testing, and demographic data. We use these data to create controls in our models—such as the percent of students who are from underrepresented minority groups (URM: American Indian/Alaska Native, Black, and Hispanic) and students eligible for free/reduced-priced lunch (FRL)—to calculate changes in student enrollment across school years, and to account for average student test achievement on the fall 2021 state assessment. Given prior evidence linking school staffing difficulties with proximity to teacher education programs (TEPs) and district urbanicity, we also include a measure of the distance from each teacher’s school to the nearest TEP and the urbanicity (city, suburb, town, or rural) of each school.

Our analyses also use a comprehensive dataset of public education staff in Washington state, called the S-275. We link the S-275 to schools and districts to identify staffing levels and prior year attrition rates by endorsement area. The S-275 also contains teacher salary information, which allows us to calculate the average salary in 2021–22 of full-time first-year teachers with a bachelor’s degree in each district as an additional control. One important limitation of the S-275 is that it depicts a snapshot of public-school employment in Washington as of October 1st of each school year. So, while we can observe year-to-year changes in employment we cannot discern any information about hiring timing or within-year turnover (Redding & Henry, 2018). Implicitly, this also eliminates our ability to observe positions which are filled and again turnover between October 1st of each year.

We supplement these publicly available data with additional data on educator credentials and endorsements provided by OSPI. These data provide the specific subject areas in which every teacher in the state is endorsed to teach. We assign endorsements into our job posting categories — STEM, special education, ELL, elementary, and other—to identify the number of teachers credentialed in each subject area and school.¹⁴ These counts come from the most recent available FTE data (October 2021) in each school-subject area cell and form the denominators for the job postings/FTE proportions described in the next section.¹⁵

Particularly relevant for our analyses, we also observe district-level ESSER funds distributed for ESSER I (spring 2020), ESSER II (winter 2021), and projections for ESSER III

¹⁴ See Appendix A for the specific endorsements mapped into each of these categories.

¹⁵ Because teachers can be endorsed in more than one subject area (e.g., elementary and special education) and we cannot yet determine from available data what subjects these teachers are actually teaching, we double count teachers endorsed in more than one subject area when calculating these sums (i.e., the sums represent the total number of teachers with an endorsement to teach a subject area, but these sums don’t add to the total number of teachers in the school).

(summer 2021) from public OSPI data.¹⁶ For our analyses, we pool across all three funding cycles to calculate total ESSER funds per pupil in a district.¹⁷ ESSER funding needs to be considered relative to typical levels of funding in individual districts, so we also include measures of per pupil expenditures from the National Center for Education Statistics. Finally, to account for differential employment opportunities outside of education that may predict school staffing difficulties, we include county-level unemployment rates as a final control.

3.3 Summary statistics

Before describing our analytic approach, we first check one of the primary limitations of our analysis (i.e., that not all job postings identify the school for which the position is open) and then provide some descriptive data on the inequity in job postings across schools and subjects.

Table 1 reports sample statistics for selected job posting and district characteristics by whether postings can be assigned to individual schools. Column 1 reports the means for the full sample of postings. Column 2 reports the subsample in which individual schools are identified in the postings. Column 3 reports the subsample where schools are not identified. Schools are identified in about 75 percent of the postings, which represent the 182 districts and 1,519 schools that form our primary analytic sample.¹⁸

The sample statistics clarify that the postings where we can identify the school have different characteristics than those where we cannot. For instance, the average duration of observing a job post online is far longer for postings in which schools are not identified,

¹⁶ States' departments of education are responsible for distributing funds within the following timeframes: May 11, 2020 through September 30, 2021 (ESSER I); March 15, 2021 through September 30, 2022 (ESSER II); and May 24, 2022 through September 30, 2023 (ESSER III). If states do not distribute funds they are forfeited back to the federal government.

¹⁷ As we describe above, the ESSER funding formula is tied to Title I allocations, meaning that distributions across districts are meaningfully different. For example, in our sample the tenth percentile of per pupil total ESSER funds received by a district—about \$862—is dwarfed by the \$4,838 received by districts at the 90th percentile.

¹⁸ Note that of the 242 districts we observe, there are 157 (65%) in which some postings identify schools and some do not.

compared to postings in which schools are identified.¹⁹ Additionally, postings for which we can identify the schools are more likely to be posted in the summer and fall of 2022 than postings with no school identified. Postings for elementary level positions are much more likely to identify schools. There are also differences in the types of districts whose postings tend to identify schools. Postings that do not identify schools are much more likely to be in smaller, rural school systems that serve a whiter student population. Because these school systems are usually smaller, and generally have only one school per grade level, identifying the school in the job posting may be unnecessary.

We begin with some descriptive information about school-level posting rates. In a typical month, the average school in our sample posted about one position per 100 staffed FTE in the school (or about 12 postings per 100 FTE over the course of the year), although the distribution of school average posts per FTE per month is positively skewed, as illustrated in Figure 1. To further explore the variation in hiring challenges across subject areas and over time, Figure 2 groups schools into quartiles by percent URM students and describes average differences in total new posts, scaled by total teaching staff. This figure illustrates meaningful post volume spikes in the late spring and summer months and begins to capture the inequities in hiring challenges across different school types over time. In every month, schools in the top quartile of the percent of URM students had more postings per FTE than schools in the bottom quartile. These posting gaps were the greatest in the spring months when postings signal anticipated staffing needs for the next school year.

¹⁹ Note that the duration for some postings is censored based on the last time that we scraped district sites in 2022 (December 29th), because we do not observe when these posts were removed from district sites. In these cases, we assign this date as the end of the duration seen for the purposes of Table 1. We explain how we overcome this issue in our analytic approach, below.

We further disaggregate these gaps by subject area in Figure 3. Beyond the obvious differences in posting volume (scaled here by subject staff FTE in October 2021), we observe striking differences in job postings/FTE across subject areas and school poverty. Elementary teaching positions, for example, exhibit the smallest gaps between the highest and lowest quartile URM schools—an average of .14 posts per 100 FTE in 2022. The smaller gaps here likely reflect the fact that elementary education credentialed job candidates are relatively plentiful, making elementary education positions relatively easy to fill. In contrast, the staffing challenge gaps in special education and ELL are far larger, especially in the spring months when schools in the top quartile of the percent of URM students are seeking to hire over twice as many special education and ELL teachers per FTE than schools in the bottom quartile of the percent of URM students. Over the 2022 calendar year, the average gap between the top and bottom quartiles in ELL posts per 100 FTE is 1.06 positions, or over seven times the gap for elementary positions. We explore these inequities further in the analytic models described in the next section.

4. Analytic Approach

First, we seek to understand the degree to which job postings are an accurate reflection of new hires (RQ1). To gauge this, we consider both the number of total job postings and the number of job postings that appear to have been filled (i.e., are taken down) by school and district. Specifically, for each school and district, we assign the count of total positions and filled positions between October 1, 2021, and October 1, 2022, the dates when the S-275 data provide snapshots of school level teacher employment. We then correlate these counts from the postings data with various categories of new hires from the S-275 (i.e., new to school, new to district, and new to workforce) and explore how well the number of job postings in a given school or district predict the number of new hires the following year in that school or district.

We use these different measures of new hires because, while postings would ideally be a proxy for the number of teachers new to their *school* in the following year, it is likely that many internal district transfers are not hired through formal job postings. This is consistent with aggregate counts in our data: while 8,205 posts appear to be filled between October 1, 2021, and October 1, 2022, 8,842 teachers end up switching schools the following year. We therefore also create a measure of the number of teachers new to the district, all of whom were likely hired through a formal job posting, though this is an undercount (6,654 teachers new to district relative to 8,205 posts filled) because it omits all within-district transfers. For completeness, we also create a measure of teachers new to the state altogether, though this results in substantial undercounting (5,324 teachers new to state relative to 8,205 posts filled).

When we do this at the district level, we can also include postings not linkable to a specific school, which is one important source of error in the school-level estimates. In this dataset, the total number of postings filled (10,684) is very similar to the number of teachers new to their school in the following year (10,629), suggesting that (at least in the aggregate) the number of postings is a reasonable proxy for the number of new school hires.

For our analysis of patterns of posting and inequities, we begin by presenting simple descriptive information about the share of new job postings by job category, month, and various school and district characteristics. The estimates from these models address RQ2 and questions of equity (How do new teacher job postings vary across subject areas and across and within school districts, and how are they related to school and district characteristics?) and RQ3 (To what extent are new postings predicted by prior teacher attrition, changes in student enrollment, and ESSER funding?). For comparability, we scale new postings relative to the FTE in each endorsement area at the school-level. Scaling by subject-specific staffing allows us to account for

variation in staffing levels by specialty and accompanying differences in the number of jobs posted. For instance, there were over 32,000 teachers in the state endorsed in elementary education and fewer than 10,000 endorsed in special education in 2021-22, so an equivalent number of postings for special education and elementary teachers would imply that staffing needs in special education are over three times larger.

We estimate binomial regressions predicting the proportion of open postings in each school-subject area-month cell:

$$\log\left(\frac{P_{sijt}}{1-P_{sijt}}\right) = a_0 + a_1S_i + a_2D_j + a_3PriorAtt_{si} + a_4f(ESSER_j) + \gamma_s + \gamma_t \quad (1)$$

In (1), P_{sijt} is the proportion of job postings relative to prior FTE in subject area s , school i , in district j , in month t .²⁰ Our base model includes just subject and month fixed effects γ_s and γ_t to explore variation in postings across subjects and time, but then we add controls for school, S_i , and district, D_i , including characteristics such as student demographics, enrollment and changes in enrollment, funding, and geographic and urbanicity measures to account for differences in hiring challenges across school systems. We also include attrition by subject area between the fall of 2020 and fall of 2021 to account for the need to replace teachers that left, as well as a function of ESSER funding allocations (linear and squared terms in our primary results) to account for increased staffing related to implementing COVID-19 recovery programs. Finally, in some models we include district and school fixed effects to explore variation across districts, across schools within the same district, and across subject areas within the same school. We cluster all standard errors by district to account for correlation across multiple observations from the same district in these models.

²⁰ We use the October 2021 S-275 staffing data to determine prior FTE. Note that for 0.03 percent of our school-subject-month sample, this proportion exceeds 1. For those observations we cap the proportion at the closest possible value to 1, by replacing the denominator with the number of postings plus 1.

We convert all estimated logit coefficients from Equation 1 to average marginal effects that can be interpreted as the expected increase in the proportion of job posting associated with a one unit increase in each predictor variable. We then use the results from Equation 1 and the methodology outlined in Gelbach (2016) to decompose the overall difference in teacher postings per FTE between different types of schools (e.g., high- and low-URM). This methodology allows us to partition differences in postings because of factors like ESSER funding while accounting for the covariance between the controls in the model.²¹

To explore the factors predicting posting *duration* (RQ4), we estimate discrete-time hazard models at the *weekly* posting level while accounting for the censoring issue described above.²² Specifically, let w' represent the week that a specific position is first posted, and let w index subsequent weeks. We define P_{psijw} as the probability that position p in subject s , school i , and district j remains open in week w conditional on not having already been filled by week $w-1$. The discrete-time hazard model takes the following form:

$$\log\left(\frac{P_{psijw}}{(1-P_{psijw})}\right) = \beta_0 + \beta_1 S_i + \beta_2 D_j + \beta_3 \text{PriorAtt}_{si} + \beta_4 f(\text{ESSER}_j) + \beta_s + \beta_{w'} + \beta_{w-w'} \quad (2)$$

Many of the terms in the model in Equation 2 are identical to Equation 1. The differences are that the model in Equation 2 is estimated at the posting-by-week level (i.e., each posting is in the data for each subsequent week until the posting is closed) and includes indicators for the week the posting was *first* posted ($\beta_{w'}$) and the number of weeks the job has been already posted

²¹ As Gelbach shows, other means of decomposing differences across groups, such as sequentially adding variables to a model, can lead to erroneous conclusions due to the correlations between added variables.

²² For instance, imagine two schools that post jobs at the beginning of the month. In one school, postings are typically filled in 28 days, on average; in the other, postings are typically filled in five days. Our analysis of first-time postings would not capture this dimension of need and a month-level analysis of the total postings online would also fail to capture this granularity.

$(\beta_{w-w'})$.²³ This latter term distinguishes this as a discrete-time hazard model that accounts for right censoring in the data; that is, each observation is only compared to other observations that have been open for the same number of weeks (Allison, 1982; Singer & Willett, 1993). Postings are therefore included in the regression data until they are filled or right censored.

As in Equation 1, we convert all logit coefficients to average marginal effects that can be interpreted as the expected change in the probability that a given position remains open associated with a one unit change in each predictor variable. In some specifications, we estimate the models separately for postings that occur after September 2022 (when most districts in Washington began the 2022-23 school year) to isolate the relationships between observable school characteristics and the probability that vacant positions in fall 2022 remain open each week.²⁴

5. Results

5.1 *Assessing how accurately job postings predict new hires*

Before characterizing the dynamics of hiring needs within and across districts, we want to assess the extent to which job postings during the 2021-22 school year predict new hires in fall 2022. In other words, are job postings a good measure of staffing needs? In Table 2, we correlate the number of job postings filled in a given school (first column) or district (second column) with three different measures of new teacher hiring in fall 2022 in the same school.²⁵ The first of these, “teachers new to school,” is the number of teachers in a given school who were not

²³ We keep the aggregation at the week level to avoid interval censoring, though there is still the possibility of missing posts that go up after our initial scrape in a week (typically on Mondays) and come down before our second scrape in that week (typically on Fridays).

²⁴ Note that school system start dates do vary somewhat, e.g., the Issaquah School District started 9/30/2022, but most districts started on or before 9/7/2022. See <https://www.k12.wa.us/about-ospi/about-school-districts/2022%E2%80%9323-school-breaks>.

²⁵ Note we have also calculated these correlations for the total count of unique postings observed in a school, which reports substantively similar correlations to our hiring outcomes. The correlation between unique posts observed and unique posts filled at a school is 0.9782.

teaching in the same school the previous year (including teachers who were not teaching in Washington public schools last year at all). The second, “teachers new to district,” is the number of teachers in the school who were not teaching in the same district last year (again including teachers who were not teaching in Washington public schools last year at all). The final measure (for completeness) is just those teachers in the school who were not teaching in Washington public schools last year at all.

Focusing first on the school-level estimates, we find that the number of postings filled in a given school during the 2021-22 school year is moderately predictive (i.e., correlations between .55 and .61) of these various hiring measures from fall 2022. The strongest correlations are with the measure of teachers who are new to the district, which is consistent with the notion that teachers hired into a school, but not new to the district, might have been hired through processes that do not entail formal job postings (e.g., internal transfers). We illustrate the relationships between these posting and hiring measures in Figure 4, where we see that the scatterplot of teachers new to the district against posts filled in a given school is roughly linear and distributed relatively evenly around the 45-degree line in the figure.

A major source of error in these school-level estimates, discussed in Section 3, is that we cannot connect all job postings to specific schools (as a result, it is not surprising that our various school-level posting measures tend to undercount the number of new hires in a given school). We therefore repeat this exercise at the district level and include all job postings regardless of whether we can connect the posting to a specific school. We find that the correlations are much stronger at around 0.9, and again are more correlated with the measure of teachers new to a given district. We take this as evidence that job postings are at least a reasonable proxy for school and district hiring needs.

Finally, in Figure 5, we show the number of new hires by quartile of the school percent of students of color. The trend in Figure 5 (i.e., schools serving more students of color tend to have considerably more new teachers in fall 2022) is consistent with our conclusions from the job postings data observed over the course of the 2021-22 school year. This suggests that postings provide reasonable estimates of *equity* in hiring needs across different kinds of schools.

5.2 Factors predicting job postings per FTE

In Table 3 we report select coefficient estimates for various specifications of the model in Equation 1, where we predict the proportion of new job postings in a school-subject-month, scaled by the associated school-subject-level staffing FTE in fall of 2021. The coefficients in Table 3 can be interpreted as the predicted change in the proportion of posted teacher positions in a given school, subject, and month associated with a one-unit change in each predictor variable. The specifications in columns 1-3 of Table 3 address RQ2 and focus on school and district demographic and location variables. We estimate separate specifications with district and school fixed effects, in each case dropping district and/or school-level predictors that are collinear with these fixed effects.

While not reported in Table 3, the coefficients on specific months in these regressions show that posts tend to be more frequent in the “traditional” teacher hiring season between March and August and lower in the off seasons between January and March and between October and December. Turning to the specific subject areas in Table 3, posting rates in special education, STEM, and other subjects are consistently higher than for elementary positions, the baseline monthly rate for which is 0.0065 postings per FTE. Importantly, this is true whether comparisons are made across the whole state (column 1), across different schools within the same district (column 2), or across different subjects within the same school (column 3).

Consistent with the evidence presented in Section 3, the models also show that schools serving higher proportions of students of color tend to have higher rates of postings, whether comparisons are made across the state or across schools within the same district. We also find that larger schools tend to have fewer postings, all else equal, and we document no significant differences in posting rates by district urbanicity or distance to the nearest TEP, all else equal. The overall conclusion for RQ2 is that the overall trends documented in the descriptive figures in the previous section—i.e., that posting rates tend to be higher in schools serving more students of color and in high-demand subjects like special education and STEM—hold in the “all else equals” framework of these regressions.

5.3 Attributing job postings to teacher attrition, enrollment changes, and ESSER

In columns 4-9 of Table 3, we add three sets of variables to the regressions from columns 1-3: enrollment changes, district funding variables (including ESSER funding), and attrition rates by school and subject area. It is important to note that the primary conclusions from RQ2—i.e., that posting rates tend to be higher in schools serving more students of color and in high-demand subjects—hold even when we control for these additional variables in columns 4-6, but not when we limit the data to just fall 2022 (i.e., after the start of the 2022-23 school year). The coefficient on school % URM attenuates somewhat in the model in column 5 with all three sets of controls and district fixed effects. Accordingly, we perform a Gelbach (2016) decomposition of this change and find that the attenuation is mostly explained by including attrition rates and enrollment growth, both of which are highly significant predictors of posting rates in the models in columns 4-6 of Table 3. Notably, subject-area attrition rates are highly predictive of posting rates even in models with school fixed effects (column 6), meaning that schools that experience

high attrition rates in a given subject area are more likely to post more positions in that subject area than in other subject areas, all else equal.

Also notable in Table 3 is that we find no significant evidence (in either direction) of a relationship between any of our financial characteristics, including ESSER funding and starting teacher salaries, and posting rates except for per pupil funding in column (7). The null relationship with ESSER funding is particularly surprising. As noted above, there is evidence that districts are spending some ESSER resources on staffing teacher positions (Sparks, 2022), and there are 631 teaching positions statewide that are recorded in the S-275 as being funded by ESSER. It is the case from a naïve district-level regression that ESSER funding significantly predicts job postings per FTE, but not when we control for the other variables in Table 3.²⁶

As a check, we perform a Gelbach (2016) decomposition of the change in the ESSER coefficient between a null model of year and subject fixed effects and the full model in Table 2. As noted above, while ESSER funding per pupil is a significant predictor of staffing challenges in the null model, the attenuation of this relationship in magnitude and significance is predominantly driven by controlling for school percent URM. In sum, because the ESSER funding mechanism is tied to school characteristics such as Title I eligibility, how variation in ESSER funding explains variation in posting behaviors is hard to disentangle from other school characteristics that are related to both ESSER allocations and staffing challenges.

5.4 *The Factors Predicting Job Posting Duration*

We now turn to the factors predicting the *duration* that specific job postings remain open. Descriptively, Figure 6 and Figure 7 present the Kaplan-Meier survival models of posts

²⁶ As an additional test, we have also estimated these models at the district-subject-month-level, which allows us to include those postings not matched to a school, and we find similarly null results of associations between ESSER funding and posting rates.

disaggregated by academic subject and school URM quartile, respectively. We see elementary posts fill more quickly relative to other subject areas, with about 60 percent of posts being removed from district job boards within two weeks of their appearance. By the eighth week of a post being online, only 11 percent of elementary positions are still posted compared to 25 percent in special education. Gaps across school URM quartiles are much smaller by comparison, although schools in the top quartile appear to have slower rates of filling over most periods. By the eighth week of posts being online, 80 percent of posts in the top quartile URM are filled relative to 82 percent in the bottom quartile URM.

More formally, we estimate the relationships from the weekly discrete-time hazard model described in Equation 2. The coefficients in Table 4 can be interpreted as the predicted change in the probability that a given position remains open for one additional week associated with a one unit change in each predictor variable. Across all specifications (i.e., without district and school fixed effects) and across the whole year (columns 1-3) and just in fall 2022 (columns 4-6), elementary postings are filled much more quickly than postings in other subject areas. The probability that a specific posting remains open for an additional week is, compared to postings in elementary education, about 7-9 percentage points higher in STEM and other subjects, about 12 percentage points higher in ELL, and about 15 percentage points higher in special education.

Turning to the school and district predictors of posting duration, we see that larger schools and schools with greater enrollment gains tend to have postings that remain open longer, as do schools in town and rural districts (relative to urban districts). We also find some relationship between ESSER funding and the duration of postings, with the linear relationship being negative and the squared relationship positive. This implies that growth in ESSER funding

in the lower end of the distribution predicts quicker hiring while growth in ESSER funding at the higher end of the distribution predicts slower hiring.

6. Discussion and Conclusions

Recent accounts of school shortages across subjects and schools during the COVID-19 pandemic highlight the lack of detailed and up-to-date information on staffing challenges to help inform policy decisions. Our analysis contributes to a nascent literature suggesting that district and school job postings offer a plausible solution to this problem. Specifically, job postings are available in close to real time and provide a clear and timely signal of school staffing needs. The importance of timeliness cannot be overstated. As has been pointed out (Bleiberg & Kraft, 2023; Bruno, 2023; Putman, 2023), there are major deficiencies in the data needed to understand the scope of challenges in the teacher labor market and their equity implications.

Our job scraping method appears to be a low-cost strategy (particularly relative to surveys or other labor-intensive means of collecting data on shortage areas) that states could employ to understand their staffing needs better and more quickly. Indeed, we believe that the most important result of our research is the validation of job postings as a measure of staffing needs based on actual hires. To our knowledge, ours is the first evidence showing the degree to which school- and district-level postings are tied to new teacher hires. Not surprisingly, we find evidence that schools and districts that post more jobs hire more new teachers. However, as we discussed above, these relationships are not one-to-one, particularly at the school level where we are unable to match all job postings to the specific school for which the job is posted. Even accounting for this, postings still tend to understate actual hiring, with implications not only for state-level analyses but also for attempts to estimate teacher vacancies nationwide (e.g., Nguyen et al., 2022).

Validating the relationship between job postings and actual hires also provides information about teacher-related inequity in public schools. Importantly, the degree to which postings at different types of schools (e.g., high shares of students of color) predict hiring differentials across schools lends support to the use of postings as measure of equity. It also illustrates the need for nuanced approaches to teacher staffing challenges, which differ across different contexts. Decades of research show that teacher attrition is higher for schools and districts serving higher shares of underserved students (e.g., students of color and those receiving free- or reduced-price lunch). There is less evidence, however, about how these disparities translate into hiring needs. Our findings show, for the first time at the *school level*, that teacher postings per FTE are higher in schools serving more students of color and that these schools also tend to have a greater duration of job postings, including after the start of the school year. In short, job postings data highlight inequities in teacher hiring needs that go beyond what are captured in administrative data.

The job postings data may also forecast future inequity in the distribution of teacher experience across students, a well-established feature of the teacher labor market (Goldhaber et al., 2015, 2018; James & Wyckoff, 2022). Given that schools serving more disadvantaged students are more likely to hire inexperienced teachers (Goldhaber, Kasman, et al., 2023), the job postings disparities we report are likely to reinforce and perpetuate inequities in the distribution of teacher experience across students.

Finally, postings data provide useful information that help us understand how circumstances related to the COVID-19 pandemic are contributing to school hiring needs across different kinds of schools. Perhaps surprisingly, district ESSER funding does not appear to be a significant predictor of school job postings. On the one hand, this is perhaps good news because,

had schools and districts relied on this funding heavily to hire teachers, it might raise the specter of layoffs as this infusion of federal funding is phased out. But we do not yet know whether these funds are disproportionately funding non-teaching positions, or the extent to which they are funding actual hires (as opposed to just postings), so we plan to investigate this in future work. That said, in a state and era in which some districts are careening from staffing shortages to potentially laying off teachers heading into the 2023-24 school year (Velez, 2023), better understanding the connections between district funding and staffing challenges will be a critical issue to navigate in both policy and research in the months and years ahead.

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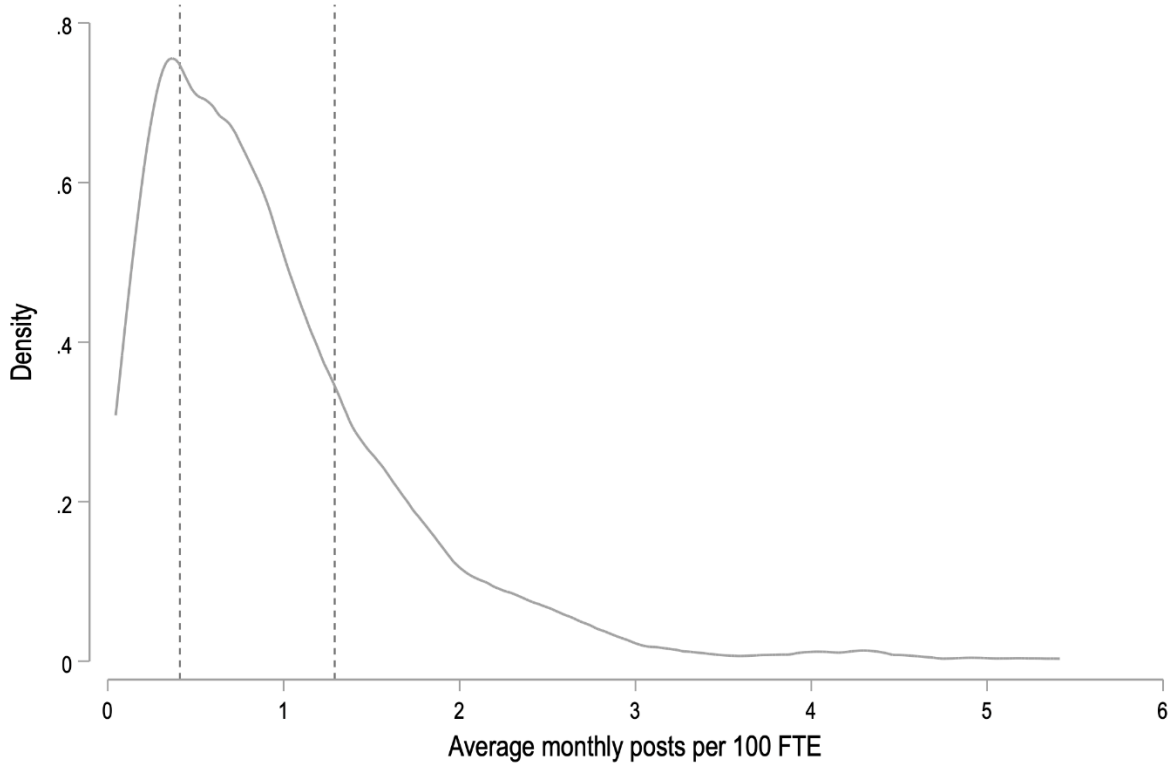
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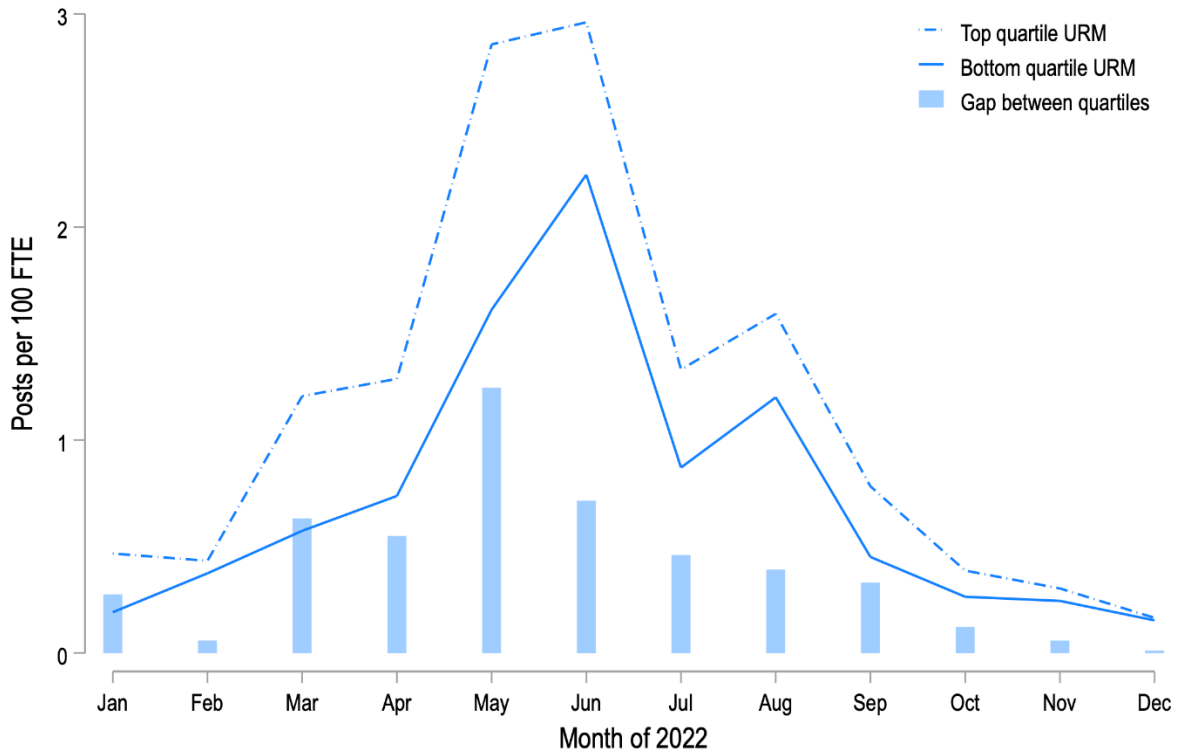
Figures and Tables

Figure 1. Distribution of school average posts in a month scaled by 100 FTE



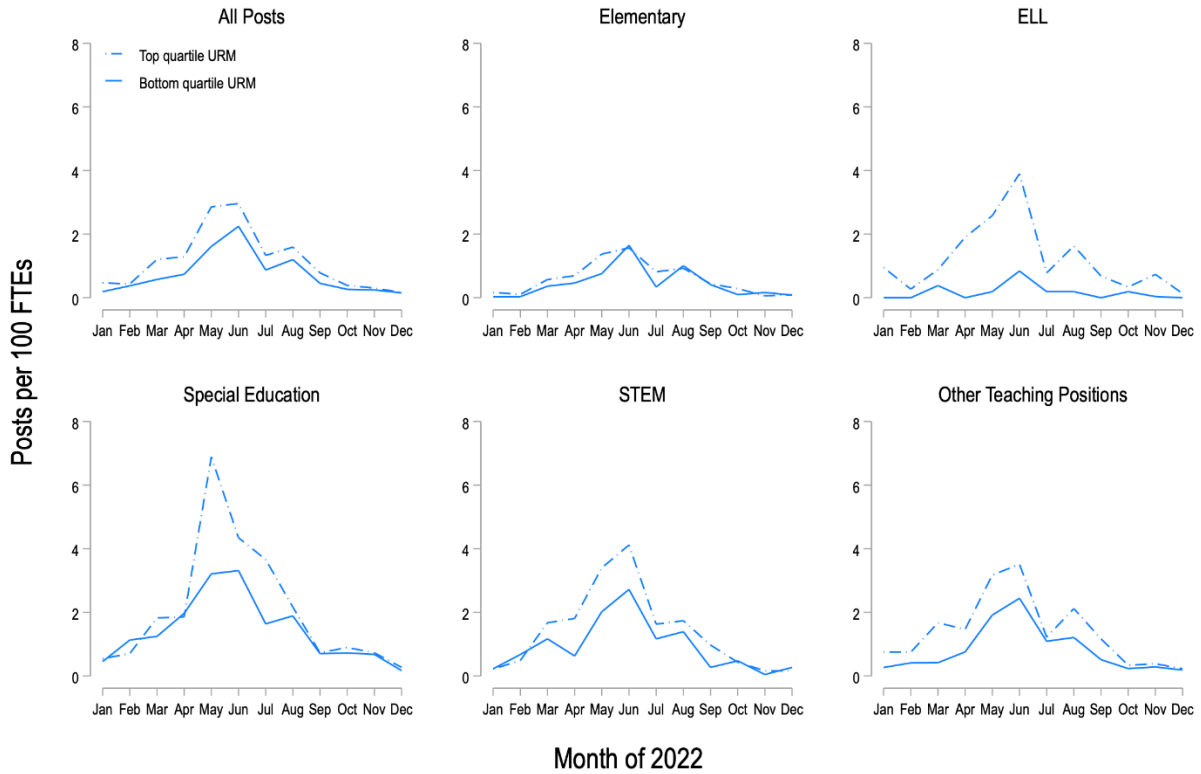
Notes: Graph presents density of new job postings per 100 total staff FTE averaged across all months of 2022 for each school. The vertical lines demarcate the 25th and 75th percentiles in the distribution (0.41 and 1.29, respectively). Posts not attributed to a school are excluded.

Figure 2. Month average new posts per 100 FTE by URM quartile



Notes: Dashed and solid lines above represent group averages of new postings by month for schools within the top (fourth) and bottom (first) quartiles of school percent under-represented minority, respectively. We scale new posting volume by total full-time equivalent teachers in that school as of October 1, 2021.

Figure 3. Subject-specific monthly new posts per 100 subject FTE, by URM quartile



Notes: Dashed and solid lines above represent group averages of new postings by month for schools within the fourth (highest) and first (lowest) quartiles of school percent under-represented minority, respectively. We scale new posting volume by total full-time equivalent teachers in that school as of October 1, 2021.

Figure 4. School-level job postings in 2021-22 as predictors of school-level new teachers in 2022-23

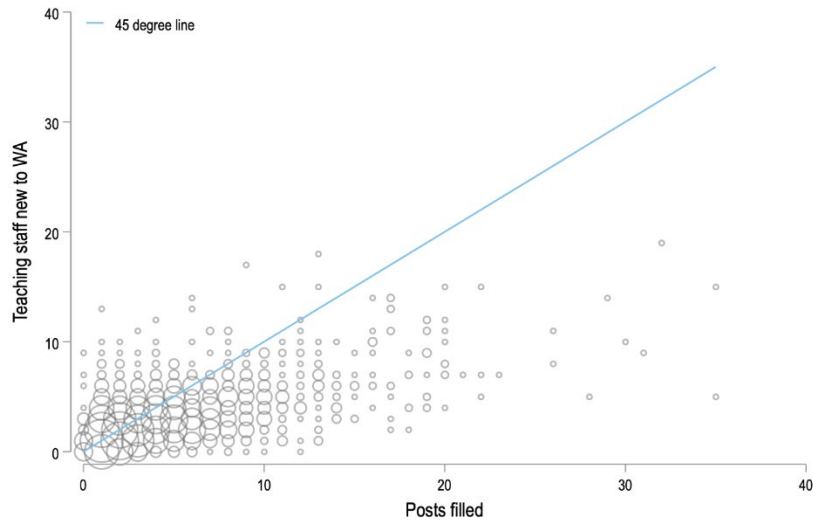
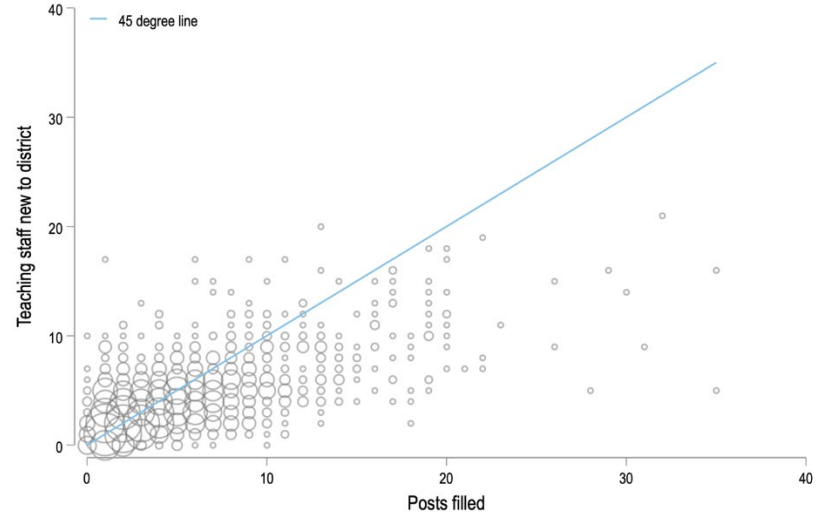
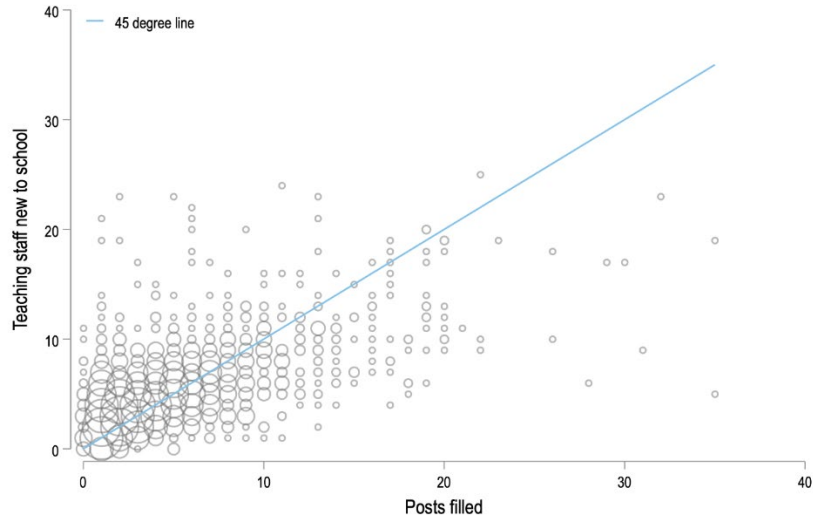
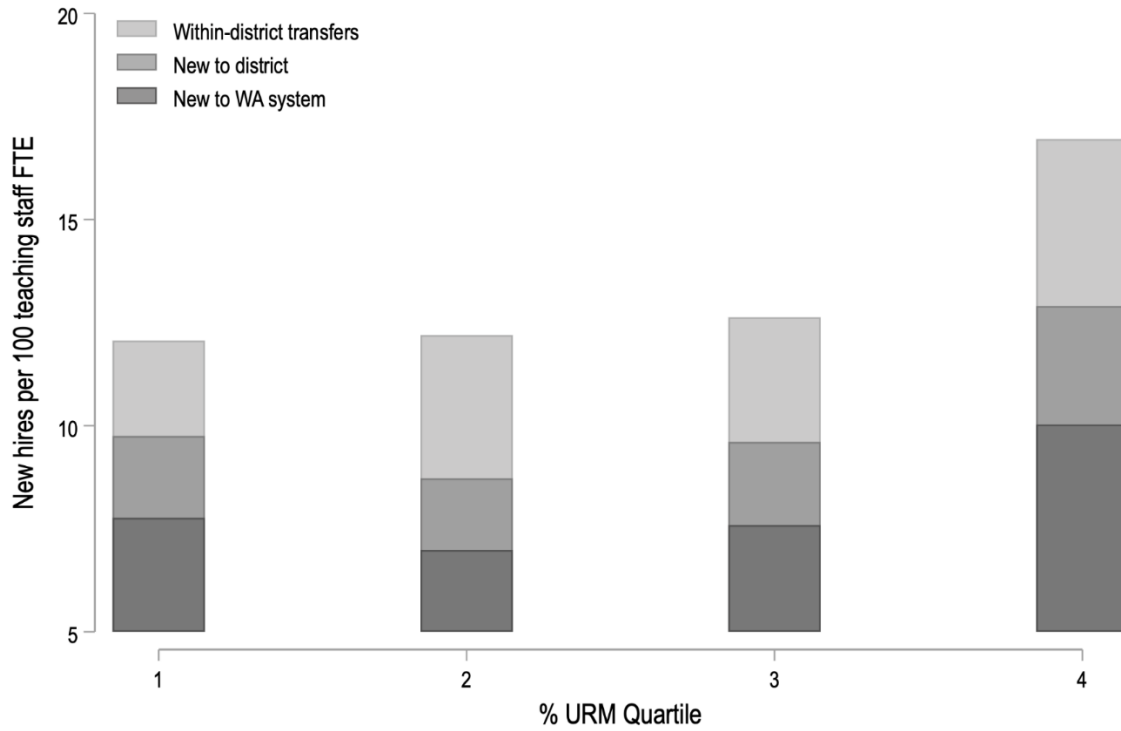
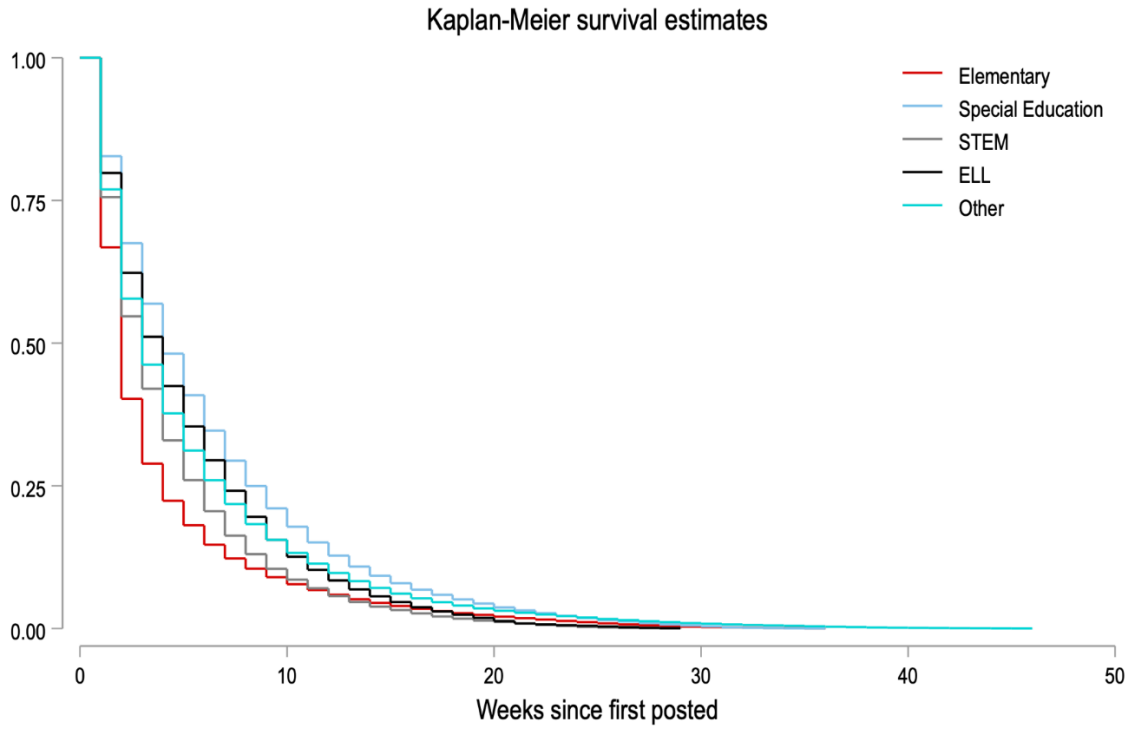


Figure 5. Average composition and level of new hires per 100 teacher staff FTE in schools by % URM quartile



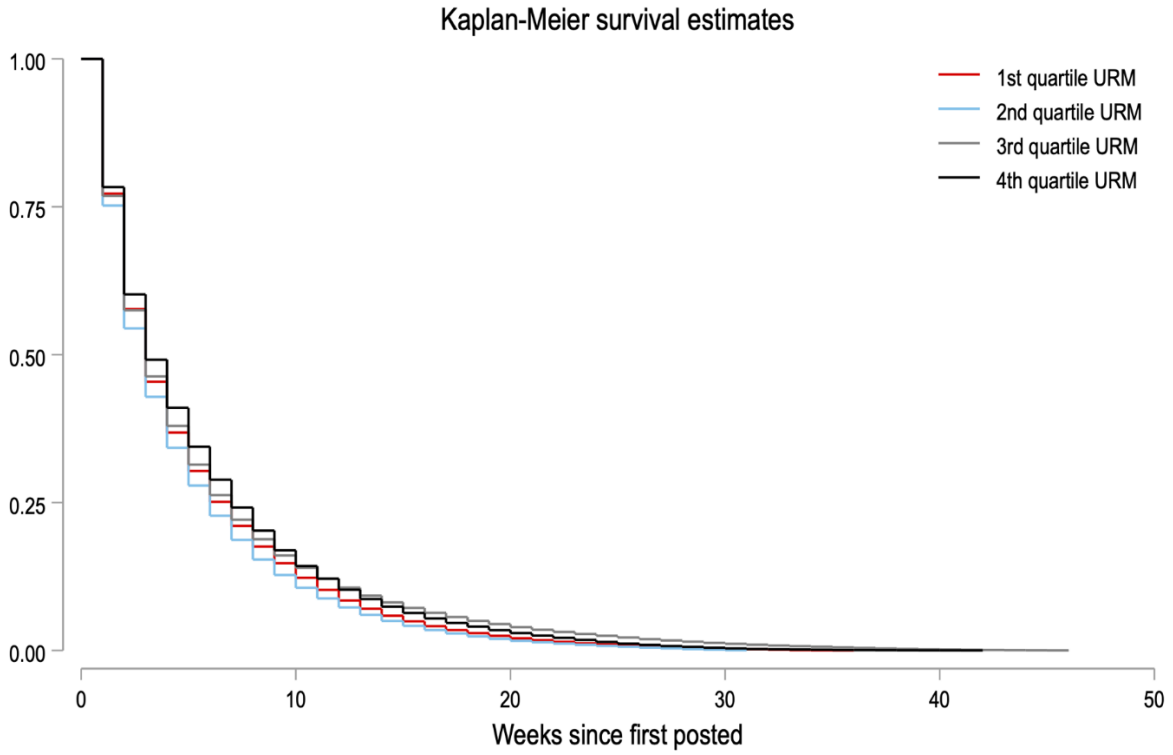
Notes: New hires include all teaching staff in the school irrespective of subject and are scaled as a percent of total teaching staff in the year prior. Hires are disaggregated into intra-district transfers, inter-district transfers, and those hired from outside of the Washington public school system. URM quartiles are ordered from lowest to highest percent URM.

Figure 6. Kaplan-Meier duration of posts by subject area



Notes: Plots show proportion of postings within each subject area still unfilled a given number of weeks after first posted.

Figure 7. Kaplan-Meier duration of posts by school URM quartile



Notes: Plots show proportion of postings within each school category still unfilled a given number of weeks after first posted.

Table 1. Job posting and district characteristics by school identification (post-level)

	Full Sample	School Identified	School Unidentified	
Job Posting Characteristics	% Teacher category elementary	17.82	19.01***	14.12
	% Teacher category ELL	4.43	4.30	4.81
	% Teacher category special education	19.63	19.47	20.13
	% Teacher category STEM	13.62	14.61***	10.58
	% Teacher category other	44.50	42.61***	50.36
	% First posted winter 2022	7.94	6.53***	12.33
	% First posted spring 2022	38.10	35.86***	45.03
	% First posted summer 2022	42.50	45.52***	33.13
	% First posted fall 2022	9.93	10.57***	7.96
	% First posted winter 2023	1.52	1.52	1.55
	Post online duration (days)	29.84	22.55***	52.42
District Characteristics	% City	41.79	43.55***	36.36
	% Rural	9.30	6.78***	17.10
	% Suburb	34.70	35.76***	31.42
	% Town	14.21	13.91	15.12
	Total student enrollment (1,000s)	14.83	15.75***	11.99
	% American Indian	1.37	1.24***	1.80
	% Asian	7.99	8.12***	7.57
	% Black	5.09	5.52***	3.77
	% Hawaiian / Pacific Islander	1.43	1.50***	1.21
	% Hispanic	27.13	27.78***	25.13
	% Multiracial	8.84	9.06***	8.17
	% White	48.13	46.78***	52.33
	% ELL	13.33	13.81***	11.86
	% Disabled	14.54	14.58***	14.41
	% Low-income	48.55	48.75*	47.94
	ESSER Funds per pupil (\$1,000)	2.61	2.64***	2.54
	Spending per pupil (\$1,000)	16.06	15.99***	16.29
	Number of schools in the district	27.52	27.61***	16.22
Number of postings	10,299	7,785	2,514	
n unique districts	242	182	217	

Table 2. Raw correlations between postings and hired staff counts

	School-Level Posts Filled	District-Level Posts Filled
Any Teachers New to School	0.5676	0.8985
Teachers New to Both School and District	0.6087	0.9046
Teacher New to WA Only	0.5553	0.8966
N Total Postings	8,205	10,684

Notes: Correlations are between the number of job postings filled from October 2021 to October 2022 in a given school (first column) or district (second column) and three different measures of new teacher hiring from October 2021 to October 2022.

Table 3. Marginal effects on proportion of new school-level job postings relative to current staffing (selected coefficients reported)

	All Months						Fall 2022		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SPED (ref. Elem)	.01122*** (.00129)	.01119*** (.00117)	.01138*** (.00124)	.01086*** (.00124)	.01076*** (.00114)	.01101*** (.00118)	.00514*** (.00104)	.00556*** (.00106)	.01225*** (.00238)
STEM (ref. Elem)	.00652*** (.00068)	.00658*** (.00063)	.00658*** (.00062)	.00661*** (.00068)	.00665*** (.00065)	.00651*** (.00063)	.00169*** (.00045)	.00190*** (.00046)	.00432*** (.00090)
ELL (ref. Elem)	.00163 (.00101)	.00158 (.00099)	.00144 (.00096)	.00149 (.00099)	.00147 (.00098)	.00139 (.00095)	.00076 (.00048)	.00077 (.00051)	.00173 (.00107)
Other (ref. Elem)	.00597*** (.00053)	.00604*** (.00052)	.00624*** (.00057)	.00604*** (.00053)	.00610*** (.00053)	.00616*** (.00057)	.00244*** (.00051)	.00277*** (.00055)	.00627*** (.00129)
School % URM	.00683*** (.00159)	.00517* (.00224)		.00807*** (.00183)	.00558* (.00227)		.00278 (.00168)	.00304 (.00186)	
School Prior Student Test Score	-.00341 (.00230)	-.00583* (.00261)		-.00279 (.00222)	-.00506* (.00244)		-.00110 (.00203)	.00050 (.00223)	
School Enrollment (2021-22)	-.00142** (.00045)	-.00078 (.00045)		-.00069 (.00045)	-.00007 (.00046)		-.00060 (.00036)	-.00073* (.00037)	
District Suburb (ref. City)	-.00091 (.00099)			-.00059 (.00078)			.00009 (.00044)		
District Town (ref. City)	.00009 (.00098)			-.00008 (.00096)			.00034 (.00068)		
District Rural (ref. City)	.00089 (.00128)			.00130 (.00098)			.00116 (.00066)		
District Log distance to nearest TEP	.00013 (.00033)			.00006 (.00034)			-.00017 (.00017)		
School Enrollment Change SDs (2021-22)				.00063** (.00023)	.00067** (.00021)		.00019 (.00013)	.00046*** (.00013)	
County Unemployment Rate				-.04258 (.04949)			-.03360 (.02929)		
District Bach. Degree Salary No Experience (\$1000s)				-.00005 (.00010)			-.00004 (.00006)		
District ESSER Funding (\$1k/student)				-.00048 (.00088)			-.00022 (.00048)		
District ESSER Funding (\$1k/student) squared				.00009 (.00011)			-.00003 (.00007)		
District Per-pupil Expenditures (2020-21)				-.02655 (.31727)			.67217*** (.12874)		
School Attrition Rate (same subject)				.00770*** (.00109)	.00783*** (.00099)	.00687*** (.00114)	.00369*** (.00085)	.00465*** (.00085)	.01114*** (.00210)
District FE		X			X			X	
School FE			X			X			X
N (school-subject-months)	90,420	90,420	90,240	90,420	90,420	90,420	30,140	26,460	11,500

Notes: * p<.05, ** p<.01, *** p<.001. Estimates come from binomial regressions of the proportion of postings per baseline staffing counts in each subject, school, and month. Standard errors in parentheses are clustered by district. All models also include month fixed effects.

Table 4. Marginal effects for probability of posts remaining open next week (selected coefficients reported)

	All Months			Fall 2022 Only		
	(1)	(2)	(3)	(4)	(5)	(6)
SPED (ref. Elem)	.15187*** (.01321)	.17743*** (.01112)	.19780*** (.016)	.19581*** (.03384)	0.29254*** (0.035)	.35364*** (.062)
STEM (ref. Elem)	.07820*** (.01237)	.09757*** (.01067)	.09038*** (.015)	.12965*** (.03886)	0.23172*** (0.040)	.28443** (.097)
ELL (ref. Elem)	.12326*** (.01554)	.13129*** (.01588)	.14084*** (.024)	.18533*** (.03590)	0.24564*** (0.040)	.33210*** (.079)
Other (ref. Elem)	.08681*** (.01197)	.10280*** (.01112)	.10179*** (.016)	.09861** (.03790)	0.19907*** (0.038)	.18819** (.070)
School % URM	.07159 (.04638)	.06915 (.07011)		.07312 (.08986)	0.06998 (0.192)	
School Prior Student Test Score	-.00012 (.00044)	.00013 (.00075)		.00053 (.00089)	0.00063 (0.002)	
School Enrollment (2021-22)	.00002* (.00001)	.00002** (.00001)		.00005** (.00002)		
School Enrollment Change SDs 2021-22	.00963** (.00304)	.00624 (.00361)		.01642 (.01178)	0.01518 (0.014)	
District Suburb (ref. City)	.02753 (.01480)			-.00061 (.02043)		
District Town (ref. City)	.07378*** (.02004)			.05209 (.03831)		
District Rural (ref. City)	.06491*** (.01845)			.05730 (.04927)		
District Log distance to nearest TEP	.00120 (.00069)			.00287* (.00144)		
County Unemployment Rate	-1.54529 (.81696)			-3.43972* (1.47159)		
District Bach. Degree Salary No Experience (\$1000s)	-.00000 (.00000)			.00000 (.00000)		
District ESSER Funding (\$1k/student)	-.03064* (.01332)			-.03785 (.02543)		
District ESSER Funding (\$1k/student) squared	.00461** (.00150)			.00760* (.00322)		
District Per-pupil Expenditures (2020-21)	.00332 (.00444)			.00336 (.01062)		
School Attrition Rate (same subject)	.01790 (.02118)	.03414 (.01744)	.01112 (.024)	.05266 (.03556)	0.02693 (0.041)	-.39025 (.231)
District FE		X			X	
School FE			X			X
N	33927	33926	33876	3630	3611	3419
N unique posts	7782	7781	7731	874	870	768

Notes: * p<.05, ** p<.01, *** p<.001. Estimates come from discrete-time hazard models estimated at the posting-week level predicting the probability that a given posting remains open for an additional week. Standard errors in parentheses are clustered by district. All models also include indicators for week of first posting and the number of weeks the job has already been posted.

Appendix A

Teaching endorsements were categorized as follows.

STEM includes: Mathematics; Mathematics - Primary; Mathematics - Supporting; Middle Level Math/Science; Middle Level Mathematics; Middle School Mathematics; ELEMENTARY MATHEMATICS SPECIALIST; MATHEMATICS APPLIED (V610000); Natural Sciences; Biological Science; Physics; Earth Sciences; General Science; Science; Biology; Chemistry; Earth Science; Physics; Science - Primary; Biology - Primary; Chemistry - Primary; Earth Science - Primary; Physics - Primary; Biology - Supporting; Chemistry - Supporting; Earth Sciences - Supporting; Physics - Supporting; Middle Level Math/Science; Middle Level Science; Science; Designated Science: Biology; Designated Science: Chemistry; Designated Science: Earth Sciences; Designated Science: Physics; Designated Science: Earth; Physical Science; Middle School Science; Secondary Education: Biology; Natural Science; Geology; Environmental Science; SCIENCE APPLIED (V620000); STEM TECHNOLOGY (V141000)

ELL includes: Bilingual Education; English as a Second Language; Bilingual Education - Supporting; English Language Learner

Elementary includes: Early Childhood; Elementary Education; Early Childhood Education; Elementary Education - Primary; Early Childhood Education - Primary; Early Childhood Education - Supporting; Early Childhood/Elementary Education; Multiple Subjects; Elementary/Middle School; Prekindergarten; MIDDLE LEVEL-PRIMARY

Special Education includes: Special Education; Early Childhood Special Education; Communication Disorders; Special Education - Primary; Early Childhood Special Education; Special Education; Deaf Education; Early Childhood Special Education; Varying Exceptionalities; Special Education: LD/BH; Special Education II; Mild/Moderate Impairments; Orientation and Mobility; Vision Impairments; Early Childhood Intervention: Special Education; Special Education: Learning Disabilities; Emotionally Handicapped; Emotionally Handicapped; Learning Disabilities; Behavioral Disorders; Educable Mentally Handicapped; Behavioral/Mental Disability; Specialty Area: Visual Impairment; Specialty Area: Orientation and Mobility; SPECIAL EDUCATION-LEARNING HANDICAPPED

Other includes: all other endorsements not previously assigned to the above