Research/Empirical

Front End to Back End: Teacher Preparation, Workforce Entry, and Attrition

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Abstract

We use a database of over 15,000 teacher candidates from 15 teacher education programs in Washington state to investigate the connections between specific teacher preparation experiences and the likelihood that these candidates enter and stay in the state's public teaching workforce. As has been found in prior research, candidates with endorsements in hard-to-staff subjects like math and special education are more likely to enter the public teaching workforce than other candidates. We also find large differences in hiring rates over time, as candidates who graduated in the years prior to and during the Great Recession are far less likely to be hired than candidates in recent years. Finally, teacher candidates hired into the same school type (elementary, middle, or high school) or into schools and classrooms with similar student demographics as their student teaching placement are more likely to stay in the teaching workforce than candidates who experience less alignment.

Keywords

teacher education preparation, field experiences, quantitative research, recruitment and retention

Introduction

Student teaching internships provide prospective teachers with their first formalized teaching experiences before entering the workforce and are regularly touted as the most important component of teacher training (Anderson & Stillman, 2013; National Council for Accreditation of Teacher Education, 2010). Mounting quantitative evidence has buttressed the notion that student teaching experiences influence teachers' inservice outcomes. Recent findings discussed in the next section suggest that characteristics of the student teaching school, the effectiveness of the cooperating teacher who supervised the student teaching placement, and the alignment between student teaching and early-career teaching experiences are all predictive of both the value added and inservice evaluations of teacher candidates once they enter the workforce (e.g., Bastian et al., 2020; Goldhaber et al., 2020a; Matsko et al., 2020; Ronfeldt, Brockman, & Campbell, 2018; Ronfeldt, Matsko, et al., 2020).

A much smaller body of literature focuses on connections between student teaching and the probability that teacher candidates become teachers and are subsequently retained in their positions (e.g., Goldhaber et al., 2014; Ronfeldt, 2012). There are, however, good reasons to consider the connections between teacher candidates' preparation experiences and their future career paths. Aspects of teacher preparation have been found to be predictive of teacher candidates' perceptions of their readiness to teach (e.g., Matsko et al., 2020), which may influence their probability of entering the workforce. Furthermore, the connections between teacher preparation and teacher effectiveness discussed above may imply connections to teacher attrition since more effective teachers are less likely to leave the workforce (e.g., Feng & Sass, 2017; Goldhaber et al., 2011).

This article contributes in several ways to understanding the role that student teaching may play in teacher workforce participation (both initial employment in public schools as a teacher and attrition from teaching). Specifically, we combine data from Washington state's Office of the Superintendent of Public Instruction (OSPI) on public school students and teachers with data on student teaching placements provided by a group of 15 teacher education programs (TEPs) training the vast majority of the new teachers trained in Washington state. The data we employ include far more detailed information about cooperating teachers and student teaching

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classrooms than has been previously considered. The sample of over 15,000 teacher candidates that we utilize is also far larger than that in prior studies, allowing us to estimate relationships between student teaching and teacher labor market outcomes with considerable precision. Finally, this is the first article to investigate the extent to which the alignment between student teaching experiences and first job experiences is predictive of teacher attrition. In particular, we link specific characteristics of cooperating teachers and student teaching classrooms to the teacher workforce participation of teacher candidates and investigate two broad research questions:

1. **Research Question 1 (RQ1):** What preservice characteristics of teacher candidates (e.g., related to their qualifications or student teaching placements) predict which candidates enter the state's public teaching workforce?
2. **Research Question 2 (RQ2):** Among teacher candidates who enter the state's public teaching workforce, what preservice characteristics predict which candidates remain in the teacher workforce?

Each of these research questions is an important contribution to the existing literature on teacher preparation and the teacher labor market. First, while some prior research has compared the characteristics of college students who do and do not become teachers (e.g., Bacolod, 2007; Goldhaber & Liu, 2003; Hanushek & Pace, 1995; Ingersoll & Perda, 2010; Podgursky et al., 2004), relatively few studies (e.g., Goldhaber et al., 2014) make comparisons between college students who have already completed teacher preparation and the requirements for teacher licensure. Our investigation of RQ1 is therefore important for determining which preservice experiences may influence the workforce participation of students who are already pursuing teaching as a career. Second, teacher turnover is costly, both in terms of dollars (e.g., Barnes et al., 2007) and student achievement (e.g., Hanushek et al., 2016; Ronfeldt, Loeb and Wyckoff, 2013). There are fewer studies linking teacher preparation to teacher retention, but given the costs of turnover, this is also an important outcome and motivates RQ2. More generally, these research questions are motivated by theory on the importance of student teaching for later workforce outcomes (e.g., Anderson & Stillman, 2013), and the evidence from these research questions can directly inform policy as states set policies around student teaching placements (e.g., minimum years of experience for cooperating teachers) and TEPs have a great deal of discretion over making placements within these broad guidelines.

Our descriptive findings on workforce entry document the dramatic impact of the Great Recession on teacher labor market entry, as candidates who graduated in the years prior to and during the Great Recession were far less likely to be hired than graduates in recent years. Importantly, a smaller percentage of these graduates entered the workforce even within a decade of graduation than the percentage of recent graduates who have entered the workforce within 3 years, suggesting that many graduates from eras with slack labor markets are ultimately lost to the system after not initially securing a teaching job.

The findings from our analytic models of workforce entry are consistent with those of prior literature (Bardelli & Ronfeldt, 2020; Goldhaber et al., 2014) showing that teacher endorsement area is by far the strongest predictor of teacher candidates' participation in the teacher labor market. Teachers with endorsements in hard-to-staff areas like science, technology, engineering, and math (STEM) and special education are 5 to 15 percentage points (or 6% to 14%) more likely to be observed in Washington public schools after completing student teaching than teachers with an elementary education endorsement, all else being equal. Few other characteristics of candidates, student teaching schools, or cooperating teachers are significantly predictive of workforce entry.

When we use these same measures to predict retention, we again find few significant relationships between student teaching experiences and the likelihood that teachers are retained in public schools for more than 2 years. But measures of the *alignment* between student teaching and first-job characteristics are predictive of retention. In particular, teachers who teach in the same school type (elementary, middle, or high) as their student teaching placement are considerably less likely to leave the workforce than early-career teachers who teach in a different school type than their student teaching placement. Likewise, teachers whose classrooms and schools have similar student demographics as their student teaching placements are less likely to leave the workforce than teachers who are teaching in very different settings than their student teaching placement. Both findings suggest that alignment between training and workforce experiences is important for the longer term stability of the teacher workforce.

The models we employ include a rich set of control variables, and the findings are robust to the inclusion of TEP, school, and district fixed effects. Still, we are cautious about interpreting our findings as causal given the likelihood that unobserved preservice characteristics of teacher candidates or their experiences could be correlated with labor market participation. Thus, we also follow Altonji and colleagues (2005) and Oster (2017) to estimate the amount of additional sorting on unobservables necessary to explain away the same school alignment finding. While not definitive, we conclude that our alignment finding is robust to extreme assumptions of sorting on unobservables (e.g., Altonji et al., 2005).

Background Literature

This study seeks to contribute to three different existing literatures: research on teacher preparation and student teaching, research on teacher workforce entry, and research on teacher retention. This is the first study, to our knowledge, to unify these three different strands of literature.

As discussed above, a growing body of literature suggests the importance of teacher candidates' student teaching preparation and student teaching for their early-career effectiveness. Characteristics of the *schools* in which teacher candidates student taught, such as teacher turnover and collaboration, are predictive of the value added of teacher candidates who become teachers (Ronfeldt, 2012, 2015). Measures of the alignment between student teacher and early-career teaching experiences have also been shown to be predictive of teacher effectiveness in the workforce, though not uniformly (Boyd et al., 2009; Goldhaber et al., 2017; Henry et al., 2013; Krieg et al., 2020a; Ronfeldt, 2015). For example, teachers are more effective (as measured by value added) when they are teaching in a classroom with similar student demographics as their student teaching classroom or in the same grade in which they student taught (Krieg et al., 2020a), but several studies have found that teaching *in the same school* as student teaching is not significantly predictive of value added (Goldhaber et al., 2017; Henry et al., 2013; Krieg et al., 2020a; Ronfeldt, 2015).

There is also a growing body of evidence suggesting that the inservice teacher supervising student teaching experiences (referred to as the "cooperating" teacher) influences the inservice outcomes of those candidates who themselves become teachers. Specifically, both the effectiveness (as measured by value added) and instructional performance (as measured by inservice performance evaluations) of cooperating teachers have been found to be associated with the future effectiveness and instructional performance of their teacher candidates who themselves become teachers (Bastian et al., 2020; Goldhaber et al., 2020b; Matsko et al., 2020; Ronfeldt, Brockman, & Campbell, 2018; Ronfeldt, Matsko, et al., 2020). Three recent experimental studies build on this observational work by providing evidence that candidates randomly assigned to "better" student teacher placements (as proxied by cooperating teacher experience and value added and school value added) report better preparedness (Ronfeldt, Goldhaber, et al., 2018; Ronfeldt, Bardelli,et al., 2020) and receive better preservice clinical observation ratings (Goldhaber, Ronfeldt, Matsko et al., 2020) than candidates randomly assigned to "worse" placements.

Despite this rapidly growing evidence base on preservice predictors of teacher effectiveness, few prior studies have connected these same measures to patterns of teacher workforce entry and retention. There are, however, reasons to think that preservice factors could influence workforce participation. Miller and Youngs (2021), for instance, describe person–environment fit theory that predicts that the degree of congruence between the values and goals of employees and their organizations should improve the likelihood of retention. They also find empirical evidence that teachers who report better fit with their jobs (colleagues, teaching assignments, and student populations) are more likely to remain in their schools. Similarly, Bartanen and Kwok (2020) find that preservice teachers with higher clinical observation scores were significantly more likely to find employment in the same school in which they completed their student teaching. These findings echo prior work on teacher labor markets (e.g., Boyd et al., 2013) and a broader labor economics literature on the importance of job matches (e.g., Jovanovic, 1979a, 1979b; Ju & Li, 2019; Merz, 1999; Munasinghe, 2005).

Only a small amount of literature uses preservice teacher candidate characteristics and experiences to predict workforce participation. In terms of teacher workforce entry, research finds candidates' subject-area endorsements are the greatest predictors of workforce entry, with candidates in hard-to-staff areas like STEM and special education more likely to be hired as teachers than teachers with an elementary education endorsement (Bardelli & Ronfeldt, 2020; Goldhaber et al., 2014; Theobald et al., 2021). Recent work has also found that teacher candidates with higher observational scores during student teaching are more likely to enter the teaching profession (Vagi et al., 2019).

A small body of literature finds some connections between teacher education and the attrition of teachers. Ingersoll and colleagues (2012), Papay and associates (2012), and Ronfeldt and colleagues (2014) each find positive effects of more extensive teacher training on teacher retention, while Goldhaber and colleagues (2011) and Feng and Sass (2017) find that more effective teachers are more likely to remain in the workforce. Ronfeldt (2012, 2015) finds that teachers who student taught in schools with lower rates of annual teacher turnover and higher levels of collaboration are less likely to leave the teaching workforce. Finally, Vagi and associates (2019) find that teacher candidates with higher observational scores during student teaching are more likely to stay in the profession within the first 2 years after graduation. We are unaware of prior research that considers information about cooperating teachers or the alignment between student teaching and early-career experiences as predictors of teacher retention.

Data and Setting

Data Sources

The data we use combine student teaching data supplied by 15 Washington TEPs participating in the Teacher Education Learning Collaborative (TELC)[1] with K–12 administrative data provided by OSPI in Washington state. The 15 TEPs participating in this study are all university-based TEPs, and with one exception (Western Governors University) were operating continuously in the state during the range of years we consider. Many of these TEPs also operate multiple programs (e.g., bachelor's and master's programs), though as described below, we can account for these different programs in the analyses.

Specifically, in addition to program and certification data, the TELC data include information about when and where each teacher candidate's student teaching occurred, as well as the classroom teacher who supervised their internship. In the case of TEPs that require two student teaching placements, we use the most recent student teaching placement for each candidate as this is typically used to satisfy the state's student teaching requirement. A key feature of the data is that we only observe student teaching placements for teachers who graduate from one of the TEPs participating in TELC. This excludes in-state teachers from other TEPs and all new teachers trained out of state. Recent studies using the same data set have shown that new teachers in the TELC data are not particularly representative of all new teachers in the state; for example, TELC programs prepare over 90% of all new in-state teachers west of the Cascade Mountains but only about 60% of new in-state teachers in the eastern half of the state (Krieg et al., 2020b). Thus, the results of this analysis should only be generalized to graduates of the 15 TEPs that participated in this study.

We focus on school years 2007–2008 to 2018–2019, since these are the years in which we can both match teachers to students in individual classrooms and follow student teaching candidates into the state's teaching workforce (the most recent year of available data is 2019–20). Also, to account for censoring, we limit observations to candidates who completed their student teaching prior to the 2018–2019 school year. Over this 11-year time span, we observe 17,626 teacher candidates who graduated from TELC institutions and can be linked to their student teaching placements. Of these candidates, 13,915 (79%) are later observed in a teaching position in a Washington public school.

The OSPI data consist of three types: building-level information, student data, and teacher personnel records. The building data contain information used to replicate prior studies focused on student teaching schools (e.g., Goldhaber et al., 2017), including geographic information, aggregated program participation (e.g., gifted programs, free or reduced-price lunch [FRL], and special education), and aggregated student demographics. The student-level data include annual standardized test scores, demographic information, and program participation for all K–12 students in the state. The data also include a variable enabling the linking of students to their teachers so that the value added of cooperating teachers can be estimated (as discussed in "Student-Level Data" section).[2]

We merge these three data sets with the TELC data using the classroom certification number and building information to identify the students in the classrooms where candidates student taught as well as in their classrooms after being hired into their first teaching jobs. Thus, we can create public school employment histories for each teacher in the state.

Student-Level Data

The student-level data from OSPI include annual standardized tests scores in math and English language arts (ELA) that can be linked to the TELC data set through unique teacher identification numbers for the cooperating teacher. We use these standardized test scores to calculate the value added of the cooperating teacher, which we later use as a predictor of future candidate outcomes (e.g., likelihood of hiring).

We calculate cooperating teachers' value added in two ways. The first approach relies on the Chetty and colleagues (2014a) "leave out" approach to value added, in which we regress student standardized test scores on prior student test scores and student/classroom characteristics with teacher fixed effects. One advantage of this leave-out specification is that it has been validated as an out-of-sample predictor of both short- and long-term student outcomes (Chetty et al., 2014a, 2014b). This approach also takes advantage of as many years of data as possible while still removing any endogenous contribution of the teacher candidate to student test scores by removing the year of student teaching from the estimation.

There is some evidence, however, that serving as a cooperating teacher has developmental impact on teacher effectiveness, that is, teacher value added is increased after serving as a cooperating teacher (Goldhaber et al., 2020b). Given the potential that teacher value added could be endogenous to a teacher's role as a cooperating teacher, we also calculate cooperating teachers' value added a second way, using data *for all years prior to the student teaching placement* in generating the value-added measure. This "pre-student teaching" approach allows us to remove the endogeneity of the student teachers' impact on student performance both in the year that they are hosted (Ronfeldt, Brockman, and Campbell, 2018) *and* in the years following the student teaching placement (Goldhaber et al., 2020b).

Importantly, we use the student-level standardized test scores *only* to calculate the cooperating teacher value added. All of our remaining analyses either focus on all candidates (i.e., our hiring data set as described in "Hiring Data Set" section) or candidates who are hired (i.e., our attrition data set as described in "Attrition Data Set" section).

Hiring Data Set

The summary statistics describe the data set we utilize to investigate RQ1 (predicting teacher workforce entry). Tables 1 and 2 provide summary statistics for teacher candidates for the years in which we have TELC data, broken out by hiring outcome, first for variables we observe for the all candidates (Table 1), and then for variables we observe only for a subset of candidates (Table 2). Specifically, we only observe student teaching average classroom prior performance for candidates who student taught in Grades 4 to 9 (because the state's annual tests are in Grades 3 to 8, we only observe candidate ethnicity from a subset of participating TEPs, and the value added samples consist only of math and ELA teachers in Grades 4 to 8). The *t* tests reported in the tables

Table 1. Teacher Candidate and Student Teaching Characteristics, by Hiring Outcome (Full Sample).

Candidate sample	All candidates $N = 17{,}466$	Public teaching role $n = 13{,}768$	Public non-teaching role $n = 147$	Not observed hired $n = 3{,}551$
Age	29.07	29.10**	32.22***	28.79
	(8.200)	(8.109)	(10.14)	(8.438)
Female	0.765	0.765	0.762	0.768
	(0.424)	(0.424)	(0.428)	(0.422)
STEM endorsement	0.157	0.169***	0.0397***	0.113
	(0.364)	(0.375)	(0.196)	(0.316)
Special education endorsement	0.132	0.153***	0.106***	0.0529
	(0.339)	(0.360)	(0.309)	(0.224)
ELL endorsement	0.0956	0.105***	0.113***	0.0586
	(0.294)	(0.306)	(0.317)	(0.235)
Elementary endorsement	0.583	0.595***	0.589	0.537
	(0.493)	(0.491)	(0.494)	(0.499)
Other endorsement	0.346	0.353***	0.517***	0.312
	(0.476)	(0.478)	(0.501)	(0.463)
Number of endorsements	1.314	1.375***	1.364***	1.073
	(0.589)	(0.591)	(0.638)	(0.511)
CT Experience	14.76	14.70*	14.45	15.00
	(8.760)	(8.715)	(8.685)	(8.936)
CT Female	0.775	0.780***	0.755	0.757
	(0.417)	(0.414)	(0.432)	(0.429)
CT Non-White	0.0894	0.0910	0.0596	0.0848
	(0.285)	(0.288)	(0.238)	(0.279)
CT Master's degree	0.785	0.788*	0.768	0.774
	(0.411)	(0.409)	(0.423)	(0.418)
CT Gender match	0.748	0.749	0.715	0.748
	(0.434)	(0.434)	(0.453)	(0.434)
CT Endorsement match	0.879	0.897**	0.854	0.809
	(0.326)	(0.304)	(0.354)	(0.393)
CT Institution match	0.234	0.232	0.199	0.243
	(0.424)	(0.422)	(0.400)	(0.429)
ST Standardized class % FRL	−0.100	−0.0887***	0.0555*	−0.155
	(0.977)	(0.978)	(1.128)	(0.965)

Note. Significance levels for two-sided t-test in columns 2 and 3 relative to last column. Standard deviations in parenthesis. STEM = science, technology, engineering, and mathematics; ELL = English language learner; CT = cooperating teacher; FRL = free or reduced-price lunch.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

indicate some significant differences between those hired into public teaching and non-teaching roles as compared with those who are not hired. The largest differences are for teacher endorsement areas, with candidates endorsed in hard-to-staff areas much more likely to be hired. Although candidates whose cooperating teacher held the same subject-area endorsement were more likely to be hired into teaching positions, we find few differences in the student teaching experience associated with differential workforce entry outcomes.

Attrition Data Set

We next present the summary statistics for our attrition sample—that is, the sample we use to investigate predictors of teacher attrition (RQ2)—in Tables 3 and 4. The attrition subsample is limited only to candidates who were hired into teaching positions in public school and only includes data for the first 2 years in the workforce after completing student teaching to isolate the impact of the preparation experiences on early attrition from the profession; importantly, our measure of attrition only captures movement out of Washington public schools and could include teachers who move to private schools, move to another state, or leave the teaching profession altogether. Table 3 (variables observed for all hired candidates) and 2b (variables observed only for a subset of hired candidates) break out the attrition sample by timing of workforce attrition: after 1 year, after 2 years, and those who remain in the workforce longer than 2 years. Approximately 12% of teachers leave public education after

Table 2. Teacher Candidate and Student Teaching Characteristics, by Hiring Outcome (Subsamples).

Candidate sample	All candidates	Public teaching role	Public non-teaching role	Not observed hired
ST Classroom Test Sample	n = 6,610	n = 5,220	n = 41	n = 1,313
ST Standardized average classroom prior performance	0.0284	0.0124***	−0.0965**	0.0970
	(0.607)	(0.617)	(0.742)	(0.556)
Race/ethnicity sample	n = 8,506	n = 6,975	n = 64	n = 1,467
White/non-White	0.141	0.141	0.172	0.142
	(0.348)	(0.348)	(0.380)	(0.349)
CT White/non-White match	0.808	0.809	0.766	0.808
	(0.394)	(0.393)	(0.427)	(0.394)
Value Added Sample (Leave Out)	n = 2,699	n = 2,117	n = 20	n = 556
CT Value Added (Leave Out)	0.00644	0.00628	0.00274	0.00720
	(0.116)	(0.116)	(0.120)	(0.114)
Value Added Sample (Pre ST)	n = 3,023	n = 2,384	n = 21	n = 610
CT Value Added (Pre ST)	0.00820	0.00777	−0.0161	0.0107
	(0.143)	(0.144)	(0.116)	(0.144)

Note. Significance levels for two-sided t test in columns 2 and 3 relative to last column. Standard deviations in parenthesis. CT = cooperating teacher; ST = student teaching.
*$p < .05$. **$p < .01$. ***$p < .001$.

their first year, while another 10% of the remaining teachers leave after their second year. Together, approximately 20% of teachers in the sample leave within 2 years of entering the workforce. These attrition rates are higher than previously reported annual attrition rates of 7% to 8% across the whole state (Goldhaber & Cowan, 2014) but are consistent with national estimates for first- and second-year teacher attrition (Gray & Taie, 2015).

We then compare the characteristics of those who attrit after 1 year and 2 years (columns 2 and 3) with those who remain in the workforce longer than 2 years (column 4). We find some differences by teacher endorsement area, with teachers with STEM and other endorsements more likely to leave and teachers with special education and elementary endorsements less likely to leave. In addition, teachers with a higher percentage of FRL students at their internship school appear less likely to leave the workforce. The analytic models described in the next section are intended to explore these differences further.

Finally, in Table 5, we examine measures of the alignment between candidates' student teaching placements and first jobs. Column 1 summarizes all hired teachers and shows that, consistent with prior research (Krieg et al., 2020a), about 25% of candidates are hired into the same grade, about 80% are hired into the same school type (elementary, middle, or high school), 16% are hired into the same school, and 40% are hired into the same district as their student teaching placement. The average teacher also begins their career in a classroom with 6 percentage points more FRL students in their classroom and in a school with 3 percentage points more FRL students in their school than experienced during their student teaching.

Also consistent with Krieg et al. (2020a), there is substantial variation in alignment across teachers who begin their careers in different school levels (columns 2–5 of Table 5). For example, while over 90% of elementary teachers in the sample also student taught in an elementary school and about 80% of high school teachers student taught in a high school, only 45% of middle school teachers student taught in a middle school. This suggests that fewer candidates student-teach in middle school than are hired into middle schools. We explore this further in Figure 1, which plots the proportion of candidates from each internship year who student taught (dashed line) and are hired (solid line) in each school level. Panel B shows that while only about 12% to 16% of all candidates student-teach in middle schools over the years of available data, 18% to 22% are hired into middle schools. Interestingly, in the early years of data (2010–13), more candidates student taught in elementary schools than were hired into these schools, while in high school the misalignment is in the later years of data (2013–2018, in which more candidates student taught in high schools than were hired into these schools).

Empirical Strategy

Our analysis considers a series of binary outcomes (entrance into the workforce and attrition from the workforce), so our primary analytic approach consists of a series of logistic regression models. First, to investigate predictors of workforce entry, we define $E_{ikt'}$. as a binary indicator for whether candidate i who graduated from institution k in year t' enters the public teaching workforce. The models that consider workforce entry take the following form:

$$\log\left(\frac{Pr\left(E_{ikt'}=1\right)}{Pr\left(E_{ikt'}=0\right)}\right)=\alpha_0+\alpha_1 X_i+\alpha_{t'}+\varepsilon_{ik}. \quad (1)$$

The model in Equation 1 predicts the log odds of workforce entry as a function of observable characteristics of the candidate (X_i) , including all the preservice characteristics summarized

Table 3. Teacher and Student Teaching Characteristics for Hired Teachers, by Attrition Type (All).

	All hired	Left after 1 year	Left after 2 years	Stayed 2+ years
Candidate sample	n = 13,915	n = 1,699	n = 1,184	n = 11,032
Teacher attrition (within 2 years of hire)	0.207	1	1	0
	(0.405)	(0)	(0)	(0)
Teacher Age	29.15	30.13***	29.46**	28.96
	(8.152)	(9.137)	(8.339)	(7.958)
Teacher Female (male ref.)	0.765	0.736***	0.739***	0.772
	(0.424)	(0.441)	(0.439)	(0.419)
Teacher Graduate degree	0.351	0.347	0.351	0.352
	(0.477)	(0.476)	(0.478)	(0.478)
STEM endorsement	0.168	0.169	0.179	0.167
	(0.374)	(0.375)	(0.384)	(0.373)
Special education endorsement	0.152	0.129***	0.141	0.157
	(0.359)	(0.336)	(0.348)	(0.364)
ELL endorsement	0.105	0.0865***	0.0971	0.109
	(0.307)	(0.281)	(0.296)	(0.311)
Elementary endorsement	0.596	0.489***	0.476***	0.625
	(0.491)	(0.500)	(0.500)	(0.484)
Other endorsement	0.356	0.420***	0.424***	0.339
	(0.479)	(0.494)	(0.494)	(0.473)
Number of endorsements	1.377	1.293***	1.318***	1.397
	(0.590)	(0.550)	(0.557)	(0.598)
Number of years until hire	1.825	2.053***	1.851	1.787
	(1.609)	(1.833)	(1.608)	(1.568)
CT Age	45.59	46.07**	45.67	45.51
	(10.30)	(10.27)	(10.33)	(10.30)
CT Experience	14.70	15.37***	14.84	14.58
	(8.717)	(8.942)	(8.707)	(8.679)
CT Female (male ref.)	0.779	0.721***	0.740***	0.793
	(0.415)	(0.449)	(0.439)	(0.405)
CT Non-White	0.0908	0.0800*	0.0896	0.0926
	(0.287)	(0.271)	(0.286)	(0.290)
CT Graduate degree	0.787	0.790	0.785	0.787
	(0.409)	(0.407)	(0.411)	(0.409)
CT Gender match	0.749	0.716***	0.721***	0.756
	(0.434)	(0.451)	(0.449)	(0.429)
CT Endorsement match	0.898	0.876***	0.899	0.901
	(0.303)	(0.329)	(0.301)	(0.299)
CT Institution match	0.231	0.230***	0.231	0.232
	(0.422)	(0.421)	(0.422)	(0.422)
ST Standardized class % FRL	−0.0885	−0.101	−0.174**	−0.0782
	(0.979)	(0.971)	(0.962)	(0.982)

Note. See Table 1.

in Tables 1 and 2. We estimate these models with and without institution effects, α_k, because one potential source of confounding (discussed below) is that there may be variation in both preparation experiences and hiring rates across different institutions. Models without an institution fixed effect make comparisons across all candidates in the sample (i.e., any differences in hiring rates across institutions gets attributed to the variables in X_i), while models with an institution fixed effect make comparisons between candidates from the same institution (i.e., removing all variation at the institution level). We include internship year effects α_t in all specifications to account both for time trends in the data and for right censoring of some observations from the later years of TELC data.

Next, to investigate predictors of teacher retention, we define A_{iklt} as a binary indicator for whether candidate i from institution k who is teaching in district l in year t leaves the teacher workforce the following year. As described in "Data and Setting" section, we drop all data after

Table 4. Teacher and Student Teaching Characteristics for Hired Teachers, by Attrition Type (Subsamples).

Candidate sample	All hired	Left after 1 year	Left after 2 years	Stayed 2+ years
ST Classroom Test Sample	n = 5,220	n = 670	n = 491	n = 4,059
ST Standardized average classroom prior performance	0.0113	0.0594**	0.0561**	−0.00207
	(0.618)	(0.585)	(0.652)	(0.618)
Race/ethnicity sample	n = 13,723	n = 1,678	n = 1,169	n = 10,876
Non-White	0.113	0.109	0.0992*	0.116
	(0.317)	(0.312)	(0.299)	(0.320)
CT White/non-White match	0.835	0.847	0.845	0.832
	(0.371)	(0.360)	(0.362)	(0.374)
CT Value Added Sample (LO)	n = 2,117	n = 247	n = 166	n = 1,704
CT Value Added (LO)	0.00564	0.00114	−0.000332	0.00688
	(0.116)	(0.107)	(0.110)	(0.118)
CT Value Added Sample (Pre ST)	n = 2,384	n =276	n = 192	n = 1,916
CT Value Added (Pre ST)	0.00715	−0.00545	0.00417	0.00927
	(0.143)	(0.142)	(0.137)	(0.144)

Note. See Table 2.

Table 5. School Alignment Summary Statistics, by Teacher Type.

Teacher Sample	(1) All teachers	(2) Elementary teachers	(3) Middle school teachers	(4) High school teachers	(5) Other school teachers
Same Grade	0.252	0.278	0.178***	0.263	0.164***
	(0.434)	(0.448)	(0.383)	(0.440)	(0.371)
Same School Type	0.780	0.926	0.454***	0.779***	0.0847***
	(0.414)	(0.262)	(0.498)	(0.415)	(0.279)
Same School	0.160	0.167	0.113***	0.197***	0.0621***
	(0.367)	(0.373)	(0.316)	(0.398)	(0.242)
Same District	0.403	0.447	0.390***	0.330***	0.220***
	(0.491)	(0.497)	(0.488)	(0.471)	(0.416)
Classroom % FRL Difference	5.993	5.282	8.212***	6.271	2.958
	(30.14)	(32.17)	(28.09)	(26.34)	(28.50)
School % FRL Difference	2.945	3.351	5.053***	0.493**	−1.828**
	(25.15)	(26.56)	(24.39)	(21.82)	(24.45)
Observations	7,583	4,167	1,489	1,725	177

Note. P values calculated from *t* tests relative to column 2. FRL is free or reduced-price lunch.
**p* < .05. ***p* < .01. ****p* < .001.

each teacher's second year *in the workforce* based on prior evidence that teacher preparation effects tend to "fade out" the longer teachers are in the workforce (e.g., Goldhaber et al., 2013, 2017) and that a disproportionate amount of teacher attrition occurs in teachers' first 2 years in the workforce (e.g., Goldring et al., 2014). The attrition models are discrete-time hazard models of the following form:

$$\log\left(\frac{Pr\left(A_{ilkt}=1\right)}{Pr\left(A_{ilkt}=0\right)}\right)=\beta_0+\beta_1 X_i+\beta_2 X_{it}+\beta_t+\varepsilon_{ilt}. \quad (2)$$

The model in Equation 2 predicts the log odds of attrition from the workforce as a function of time-invariant observable characteristics of the candidate (X_i), including the same variables considered for Equation 1 and time-variant observable characteristics (X_{it}), such as teacher experience and the characteristics of the teacher's current school or classroom. As described previously, we estimate these models with and without institution (β_l) effects to account for sorting across different institutions in the sample. As robustness checks, we also estimate models with and without district fixed effects (β_k) to account for an additional source of bias discussed below, the nonrandom sorting of teacher candidates to hiring districts. We include year effects β_t in all specifications to account for time trends in attrition rates. We account for multiple observations per teacher by clustering the standard errors at the teacher level. Finally, we estimate versions of the model in Equation 2 in which R_{ilkt} is a binary

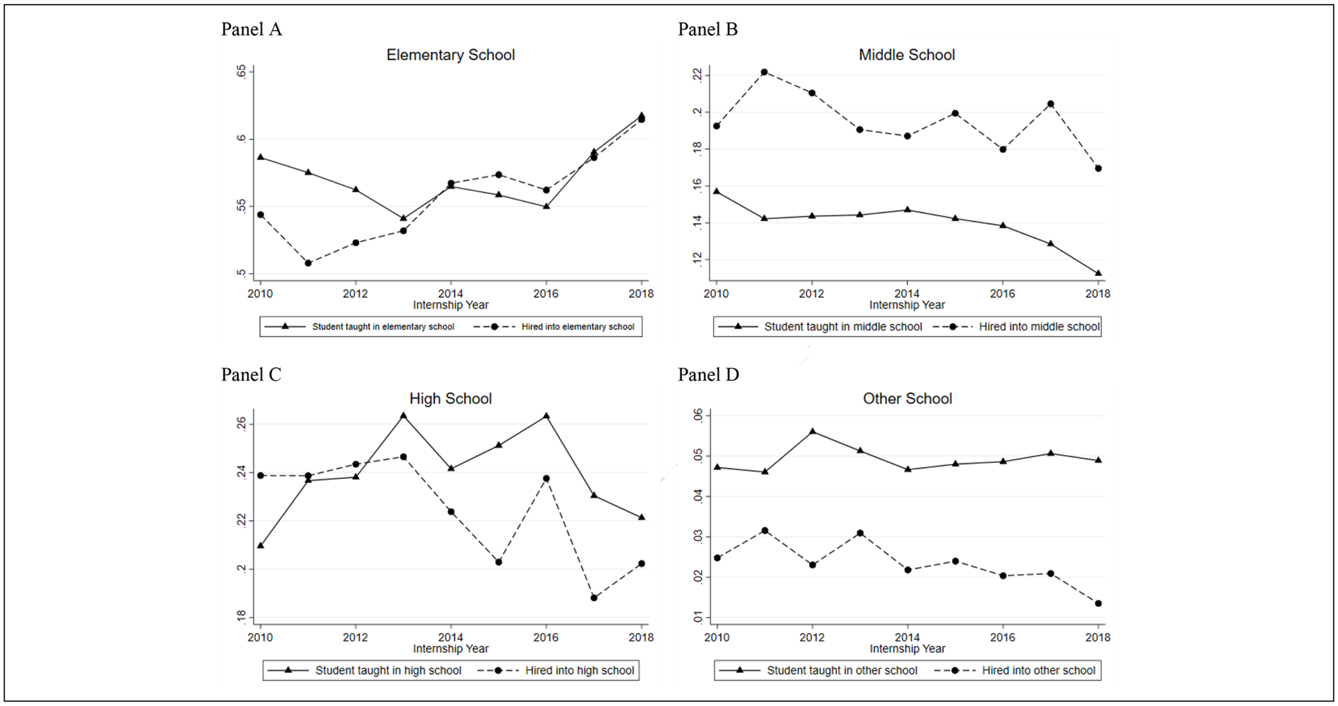

Figure 1. Student teaching and inservice school type comparisons: Panel A: Elementary school; Panel B: Middle school; Panel C: High school; Panel D: Other school.

indicator for attrition from a specific school or district, respectively.

We build on the attrition model (Equation 2) to explore the importance of alignment between student teaching and early-career teaching positions in two ways. First, we include four binary measures of alignment as part of the vector of time-variant observable characteristics in X_{it}: teaching in the same grade as student teaching, teaching in the same school level (elementary, middle, or high) as student teaching, teaching in the same school as student teaching, and teaching in the same district as student teaching. The "same grade" variable is calculated from student-level data linked to teachers' student teaching and current placements, and equals one if the modal student grade taught in student teaching (i.e., the most common grade among the students in the cooperating teacher's classrooms) is the same as the modal student grade in the teacher's current classrooms.

Second, we consider the alignment between the student demographics of a teacher's current school/classroom and their student teaching school/classroom. Following Goldhaber et al. (2017) and Krieg et al. (2020a), we focus on the percentage of students receiving FRL in a teacher's classroom or schools and include flexible polynomials for the differences between the first classroom and their student teaching experience in the attrition model in Equation 2. Specifically, let FRL_{jt} be the percentage FRL of teacher j's current classroom/school, and let $\text{FRL}_{jt'}$ be the percentage FRL of that teacher's student teaching classroom/school. We construct flexible polynomial models of the difference between the FRL status in the teacher's first year and the FRL status when they served as a student teacher and add the following terms to the model in Equation 2:

$$\gamma_1 FRL_{jt} + \sum_{k=1}^{3} \gamma_{k+1} \left(FRL_{jt} - FRL_{jt'} \right)^k + FRL_{jt} \sum_{k=1}^{3} \gamma_{k+4} \left(FRL_{jt} - FRL_{jt'} \right)^k . \tag{3}$$

The first term in Equation 3 is the main effect of the FRL on teacher retention, the second term is a polynomial of the match between current and internship experiences, and the third term interacts this polynomial with the main effect of the current characteristics. Instead of reporting the coefficients from these models, we use the estimates from these models to create heat maps of predicted rates of teacher attrition for each combination of school/classroom current and student teaching FRL.

The logit coefficients in Equations 1 and 2 are difficult to interpret, so we calculate average marginal effects of all coefficients of interest. These can be interpreted as the expected change in the probability of a given outcome associated with a one-unit change in the given predictor variable for the average teacher in the sample. Importantly, despite the extensive controls in these analytic models, we do not interpret these marginal effects as causal effects on candidate outcomes given that candidates nonrandomly sort into

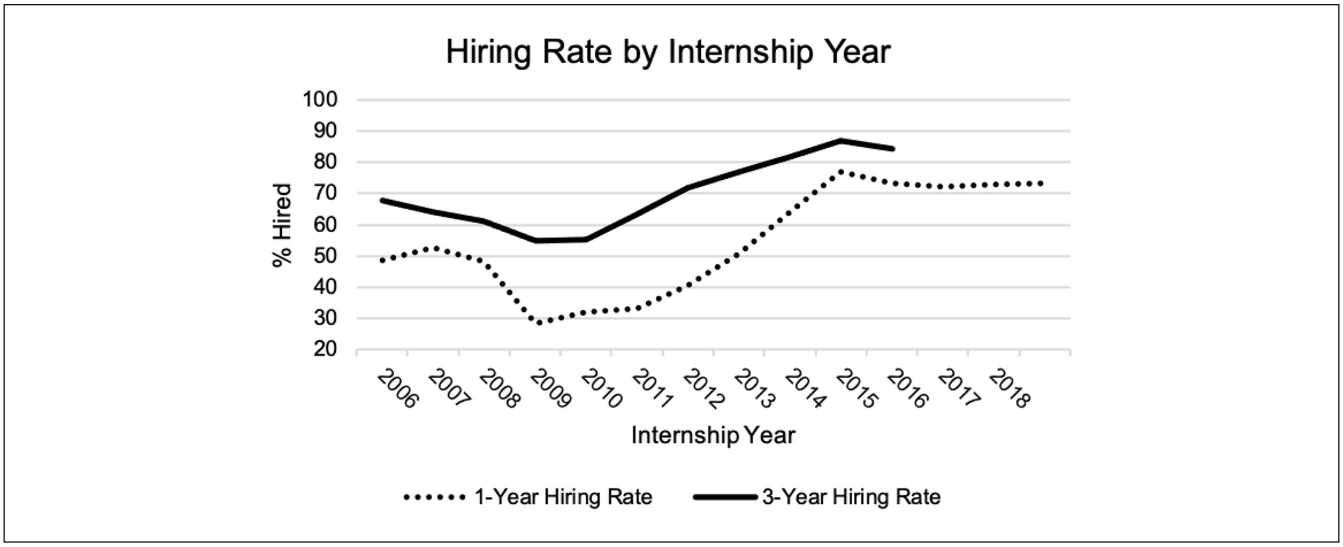

Figure 2. Hiring rates in Washington state, by internship year over time.

different teacher preparation institutions and school districts. We therefore pursue a number of robustness checks of our primary results. Our primary robustness checks are the fixed-effects specifications described in Equations 1 and 2 that remove variation across different institutions and districts, but even within institutions and districts, it is likely that candidates nonrandomly sort to specific preparation experiences and school settings. We therefore pursue one additional robustness check outlined in Altonji and colleagues (2005) and further developed by Oster (2017) that quantifies the amount of nonrandom sorting on unobservables that would be necessary to explain away some of the noteworthy empirical relationships that we discuss below.

Results

Labor Market Participation Trends Over Time

We begin by presenting simple trends in the labor market in Washington state over time. Figure 2 reports the trends over time in the 1-year and 3-year hiring rates (defined as the proportion of candidates who are teaching in a Washington public school within 1 year and within 3 years of student teaching) for the teacher candidates in the TELC sample. These hiring rates increased dramatically in the years since the Great Recession: Less than 30% of TELC candidates who student taught in 2009 were hired into a Washington state public school within 1 year of completing their student teaching in 2009, compared with over 70% of candidates who completed their student teaching in 2015. It is notable that many of the teacher candidates who are not hired in periods of slackness in the labor market appear lost to the teaching profession. For instance, as shown in Figure 3, we observe only about 67% of those teacher candidates who completed student teaching in the "pre-recession" period in the labor market in any of the next 3 years. And, if we continue to follow this cohort all the way to the 2018–2019 school year, only an additional 9% of the original sample of teacher candidates are employed as a public school teacher in any of the subsequent years. Put another way, the 3-year window we use to assess whether a teacher candidate in these years will show up as an employed public school teacher captures 88% of the teacher candidates who would be observed in the labor market over the next 13 years.

Now consider a much tighter teacher labor market in later years. For instance, we observe about 84% of the "post-recession" cohort of teacher candidates in the labor market in the next 3 years. If one makes the assumption that the desire to become a teacher among teacher candidates is not radically different between these cohorts, the above figures imply that we might expect that at least an additional 17% (the difference between 84% and 67%) of the pre-recession cohort of teacher candidates desired to get a job but were unable to find one. Yet, as noted above, only 9% of those show up over the next decade. This suggest that a significant number of individuals received a credential to teach in the state, and had an interest in teaching, but likely became engaged in other sectors of the workforce when they failed to find a teaching job during the period of slack demand for new teachers.

It is also striking to focus on the trends for teacher candidates who have different teaching endorsements. In Figure 4, we break out the figures reported in Figure 2 (the 1- and 3-year hiring rates) by endorsement category over time. Consistently over the years of data—but particularly in periods with lower rates of teacher hiring (e.g., during the recession)—candidates with endorsements in STEM and special education are more likely to enter the state's public teaching workforce within 1 year than candidates with other endorsements. These differences are less stark in 3-year hiring rates, which may be due to the delayed teacher hiring illustrated in Figure 3.

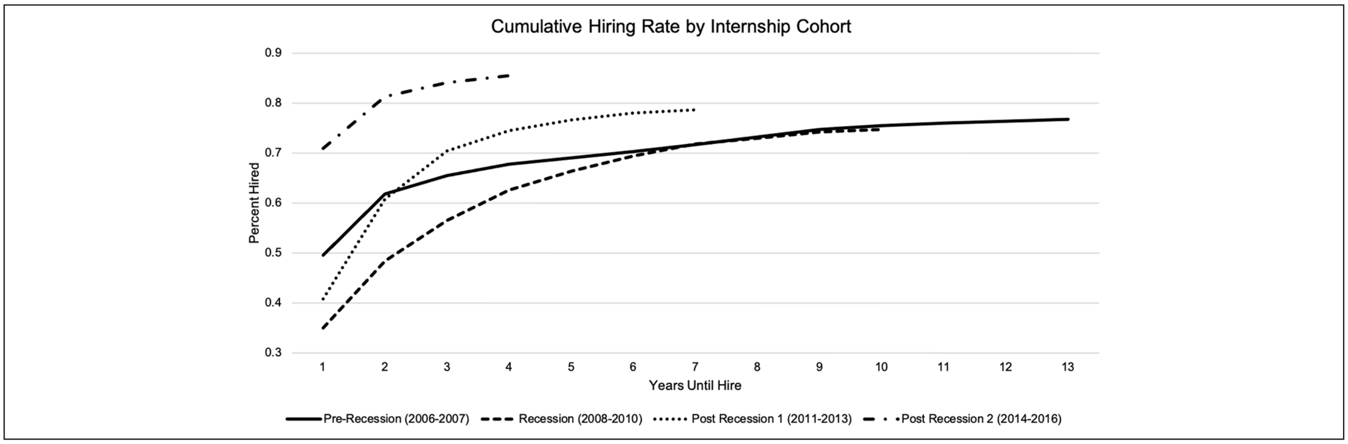

Figure 3. Cumulative hiring rates, by internship cohort.

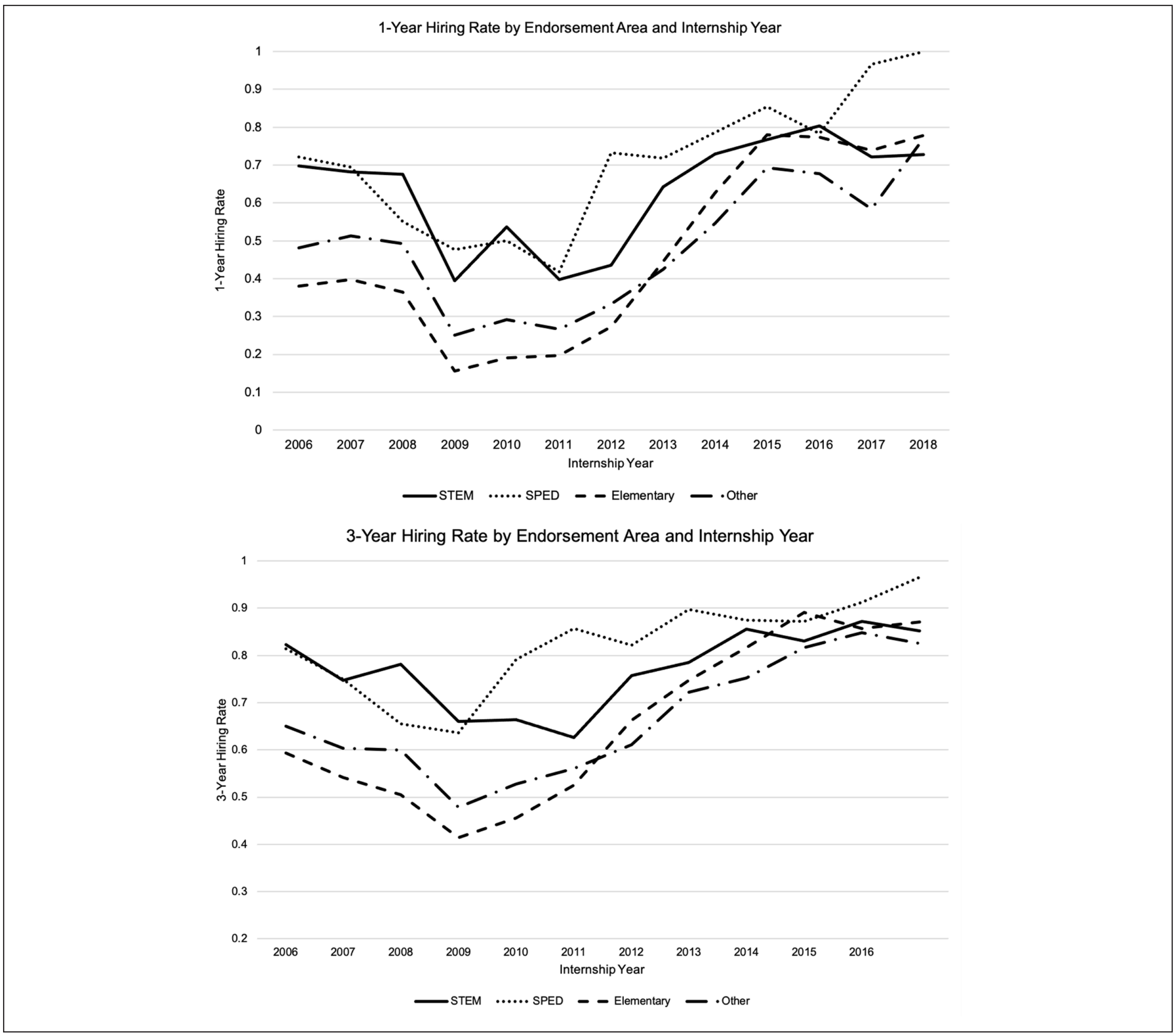

Figure 4. One- and 3-year hiring rates, by endorsement category over time.

Factors Predicting Teacher Labor Market Participation

The previous subsection describes the overall trends for workforce entry. In this subsection, we turn to describing estimates from the analytic models (discussed in "Empirical Strategy" section) for in-state public school teacher workforce entry (RQ1). Table 6 presents the marginal effects of the various teacher preparation variables: Column 1 of the table presents models that include variables observed for all candidates in the sample; column 2 adds measures of prior test performance of students in the student teaching classroom observed only for a subset of candidates; and column 3 adds cooperating teacher value added from the leave-out specification described in "Empirical Strategy" section (though results are similar for the pre-student teaching measure).

Consistent with prior work in Washington (Goldhaber et al., 2014), we find that candidates with endorsements in hard-to-staff areas like STEM and special education are considerably more likely to enter the workforce than candidates with just an elementary endorsement. All else being equal, candidates with a STEM endorsement are 4.4 percentage points more likely to enter the workforce than candidates with just an elementary endorsement, while candidates with a special endorsement are 11.8 percentage points more likely to enter the workforce than candidates with just an elementary endorsement.

These models also include interactions between endorsement areas and an indicator for whether the candidate holds multiple endorsements. The interaction terms are difficult to interpret and are not reported in Table 6; instead, we plot the predicted probability of workforce entry for the eight most comment endorsement combinations in Figure 5. These estimates differ from the earlier descriptive figures because they hold all other variables in the models constant. Candidates with only an elementary or a subject-area ("Other") endorsement are the least likely to enter, while candidates with a special education endorsement (either only special education or a dual endorsement in elementary and special education) are the most likely to enter, all else being equal. In fact, candidates with only an elementary endorsement are more than twice as likely not to enter the workforce than candidates with both an elementary endorsement and a special education endorsement.

While candidate endorsement areas are by far the greatest predictor of workforce entry, a few other findings (significant and otherwise) are potentially important. For example, we find that the probability of workforce entry decreases with candidate age. We also find no more significant relationships than we would expect by random chance between characteristics of the cooperating teacher (including their value added) and the probability that the candidates they supervise enter the workforce. It is worth noting that the standard errors of these estimates are very small (generally less than 1 percentage point) due to the large sample sizes, so we can rule out even relatively modest relationships between cooperating teacher characteristics and the probability of workforce entry.

Table 6. Marginal Effects Predicting Entry Into Public Teaching Role.

Column Number	(1)	(2)	(3)
Candidate Age	−0.001**	−0.002**	−0.001
	(0.000)	(0.001)	(0.001)
Candidate Female (male ref.)	−0.014	−0.008	−0.024
	(0.008)	(0.010)	(0.022)
Candidate Non-White	0.017	0.031	0.036
	(0.019)	(0.031)	(0.051)
Candidate STEM endorsement (ref. Elementary)	0.044***	0.029	0.022
	(0.011)	(0.015)	(0.029)
Candidate SPED endorsement (ref. Elementary)	0.118***	0.125**	0.27
	(0.022)	(0.042)	(0.145)
Candidate ELL endorsement (ref. not ELL)	0.015	0.014	0.006
	(0.017)	(0.026)	(0.041)
Candidate Other endorsement (ref. Elementary)	0.005	−0.003	0.002
	(0.008)	(0.013)	(0.026)
CT Experience	−0.001	−0.001	−0.001
	0.000	(0.001)	(0.001)
CT Female (male ref.)	0.016*	0.011	0.053*
	(0.008)	(0.010)	(0.022)
CT Non-White	0.011	0.008	−0.028
	(0.011)	(0.018)	(0.029)
CT Master's degree	0.009	−0.001	0.009
	(0.007)	(0.012)	(0.021)
CT Gender match	0	0.002	−0.011
	(0.007)	(0.010)	(0.022)
CT Endorsement match	−0.004	−0.024	−0.041
	(0.010)	(0.018)	(0.028)
CT Institution match	−0.002	0.006	0.001
	(0.007)	(0.011)	(0.020)
CT White/non-White match	0.012	0	−0.014
	(0.018)	(0.028)	(0.045)
ST Classroom Standardized % FRL	0.002	0	0.015
	(0.004)	(0.007)	(0.012)
ST Standardized average classroom prior performance		−0.007	0.021
		(0.011)	(0.026)
CT Value Added (Leave Out)			−0.034
			(0.070)
N	17,275	6,884	2,197

Note. All models control for teaching roles prior to and concurrently with internship placement, the quarter of internship, internship year, and interactions between endorsement areas and an indicator for multiple endorsements. STEM = science, technology, engineering, and mathematics; SPED = special education; ELL = English language learner; CT = cooperating teacher; ST = student teaching; FRL = free or reduced-price lunch.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

We next turn to predictors of teacher attrition from the public school teacher workforce (RQ2) in Table 7. The columns of this table add student teaching classroom prior performance and cooperating teacher value added in additional columns as in Table 6. Although we do not report these estimates due to

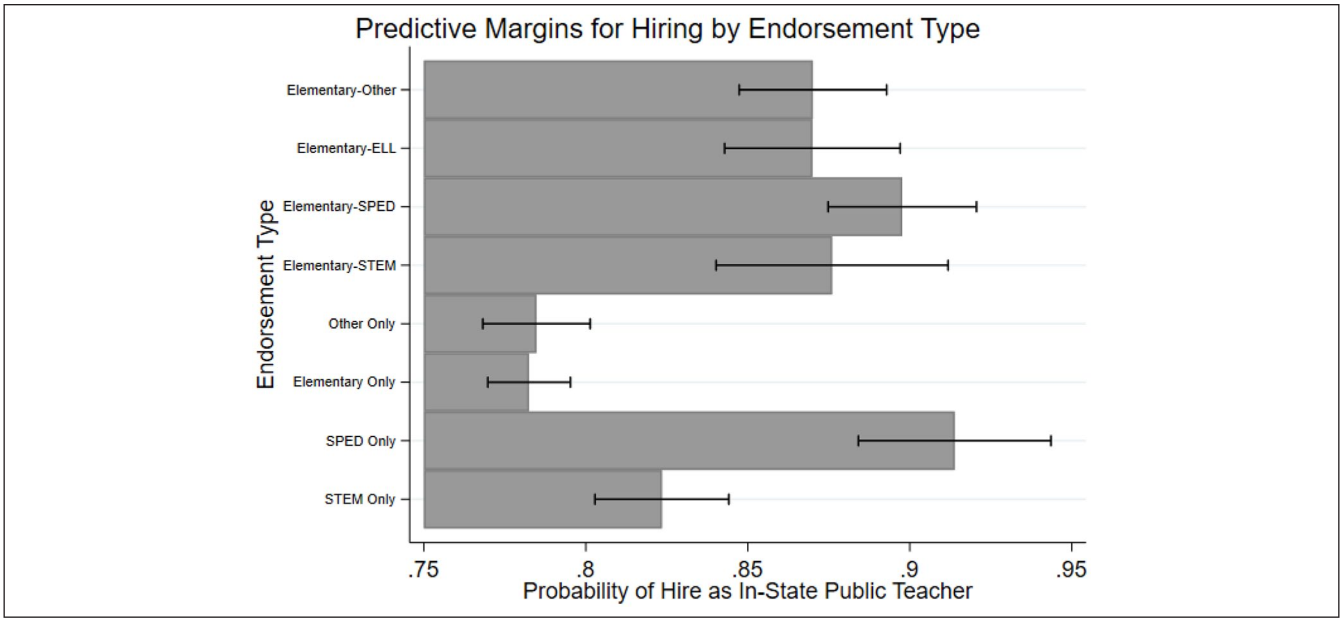

Figure 5. Predicted probabilities of hire as in-state public school teacher, by endorsement area.

space constraints, we again find some variation across teacher endorsement areas, this time as predictors of teacher attrition; teachers with a STEM endorsement, an English language learner (ELL) endorsement, and a subject-area ("Other") endorsement are all more likely to leave the workforce than teachers with an elementary endorsement, all else being equal. Older teachers and teachers who took longer to enter the workforce are both more likely to leave the workforce, while teachers with a graduate degree are less likely to leave.

When we turn to the cooperating teacher characteristics reported in Table 7, though, we again find little evidence that observable characteristics of cooperating teachers are predictive of the future attrition of the student teachers they supervise. Candidates with a female cooperating teacher are less likely to leave the workforce, though this is the only one of the nine cooperating teacher characteristics that is significantly predictive of teacher attrition, which is not much more than we would expect by random chance. We also find little evidence in column 3 that cooperating teacher value added is predictive of teacher attrition.

Measures of the alignment between candidates' student teaching and current teaching positions (discussed in "Empirical Strategy" section) are more predictive of attrition. Specifically, while being hired into the same school or district as student teaching is not significantly predictive of early-career attrition, we find evidence that alignment in terms of school type (i.e., elementary, middle, and high) is predictive of teacher attrition; these teachers are about 5 percentage points less likely to leave the workforce, even controlling for other measures of alignment between student teaching and current placements. To further explore the school type match finding, we plot the predicted probabilities of attrition for each combination of current school type and student-teaching school type in Figure 6. Within each cluster of current school types (i.e., each set of three estimates), teachers who student taught at the same school level are the least likely to leave the workforce. Thus, this finding is related to school type matches at all three school levels; in other words, regardless of whether early-career teachers are teaching in an elementary, middle, or high school, they are less likely to leave the teaching workforce if they also student taught at that same school level, all else equal.

We also estimate specifications that include measures of the alignment between the percentage of students eligible for FRL of the teachers' student-teaching classroom/school and current classroom/school. The coefficients from these models based upon Equation 3 are difficult to interpret directly and not reported due to space constraints; instead, we present these results as heat maps in Figure 7. The colors in Figure 7 represent the predicted probability of attrition for each combination of student-teaching classroom (Panel A) and school (Panel B) FRL on the x-axis and current classroom/school FRL on the y-axis. The negative signs indicate combinations of student-teaching and first-job demographics where the predicted probabilities of attrition are statistically significantly lower than the average probability of attrition.

In both panels of the figure, there is evidence that having a student-teaching experience with students who demographically match the students that teachers have in a first job reduces attrition (see the negative signs in the areas along the 45-degree line). This looks to be particularly important for *school-level* measures of FRL alignment; teachers in a school with student poverty levels similar to those at their student teaching school (i.e., near the 45-degree line in

Table 7. Discrete Time Hazard Models of Attrition Marginal Effects, Limited to First 2 Years in the Workforce.

Column Number	(1)	(2)	(3)
Number of years until hired	0.006***	0.009**	0.009*
	(0.001)	(0.003)	(0.004)
CT Age	0	−0.001	−0.001
	(0.000)	(0.001)	(0.001)
CT Experience	0.001	0.001*	0.001
	(0.000)	(0.001)	(0.001)
CT Female (male ref.)	−0.012*	−0.016*	0.004
	(0.005)	(0.007)	(0.016)
CT Non-White	−0.004	0.01	0.015
	(0.009)	(0.014)	(0.021)
CT Graduate degree	0	0	0.017
	(0.005)	(0.009)	(0.015)
CT Gender match	−0.004	−0.002	−0.037*
	(0.005)	(0.007)	(0.016)
CT Endorsement match	0.001	0.017	0.009
	(0.007)	(0.013)	(0.018)
CT Institution match	−0.003	−0.005	−0.012
	(0.005)	(0.008)	(0.014)
CT White/non-White match	−0.001	0.004	−0.002
	(0.009)	(0.014)	(0.020)
ST Standardized class % FRL	0.001	−0.006	0.01
	(0.003)	(0.005)	(0.008)
Grade match	−0.009	−0.004	−0.023
	(0.009)	(0.012)	(0.020)
School type match	−0.043***	−0.042***	−0.028
	(0.009)	(0.011)	(0.018)
School match	−0.016	−0.028	0.005
	(0.013)	(0.018)	(0.029)
District match	−0.006	−0.005	−0.029
	(0.009)	(0.011)	(0.019)
ST Standardized average class prior performance		0.006	0.021
		(0.008)	(0.017)
CT Value Added (Leave Out)			−0.005
			(0.048)

Note. All models control for teaching roles prior to and concurrently with ST placement, the quarter of internship, inservice school characteristics, and school year. The models also control for teacher age, gender, non-White indicator, graduate degree, limited/no certification, endorsement areas, and interactions with an indicator for multiple endorsements. STEM = science, technology, engineering, and mathematics; SPED = special education; ELL = English language learner; CT = cooperating teacher; ST = student teaching; FRL = free or reduced-price lunch.
*$p < .05$. **$p < .01$. ***$p < .001$.

Figure 6, panel B) are considerably less likely to leave the workforce than teachers in schools with very different student poverty levels than their student teaching school (i.e., the top left and bottom right corners in the figure). These findings for alignment and teacher attrition are large in magnitude (e.g., 10% predicted attrition near the 45 degree line in panel B compared to over 20% in the corners of panel B) and are directionally consistent with findings relating these same measures to teacher value added in Goldhaber et al. (2017).

Nonrandom Sorting Robustness Checks

As discussed earlier, we have to be cautious about interpreting the above findings as reflecting causal relationships between preservice teacher candidate characteristics and experiences and teacher workforce participation outcomes. As a first set of robustness checks, we estimate a series of models with institution and/or district fixed effects. These account for time-invariant institution-, school-, or district-level confounders that could be correlated with the variables of interest and that could influence both entry and retention decisions. While not reported due to space constraints, all significant results discussed in "Factors Predicting Teacher Labor Market Participation" section—perhaps most notably, the relationship between the alignment between student teaching school level and current school level and the probability of attrition—are robust to the inclusion of these fixed effects.

We may still worry that the estimated relationships could be biased by unobserved factors associated with nonrandom sorting of teacher candidates/students into student teaching and inservice school or classroom types (e.g., if more committed candidates are more likely to be hired into the same school level in which they student taught). As a first check on this possibility in the context of the same school type finding, we examine the distribution of teacher licensure test scores across our measures of preservice-inservice alignment. And we do find a significant difference in basic skills licensure test scores between teachers who do and do not experience a match in terms of their school level. While not dispositive, this finding suggests that sorting of teachers into schools/classrooms along unobserved dimensions is a concern.

Thus, to further address the concern of nonrandom sorting, we utilize methods developed by Altonji and colleagues (2005) and Oster (2017) that quantify the amount of sorting on unobservables that would be necessary to explain away the relationship between the alignment between student teaching school level and current school level and the probability of attrition; this methodology is a computationally different but related approach to that of Frank et al. (2013) to quantify the sensitivity of a given regression result to nonrandom sorting on unobservables. We calculate that the amount of sorting on unobservables would need to be 1.82 times the amount of sorting on observables for the true relationship between school-level match and attrition to be zero. This level of sorting on unobservables is unlikely (i.e., it exceeds the recommended benchmark of 1 suggested by Altonji et al., 2005), implying in turn that the statistically significant findings are unlikely due to selection on unobservables.

Conclusion

One unique contribution of this article is the consideration of long-run labor market participation trends *among teacher candidates who completed formal teacher preparation and received a credential to teach in the state.* The dramatic

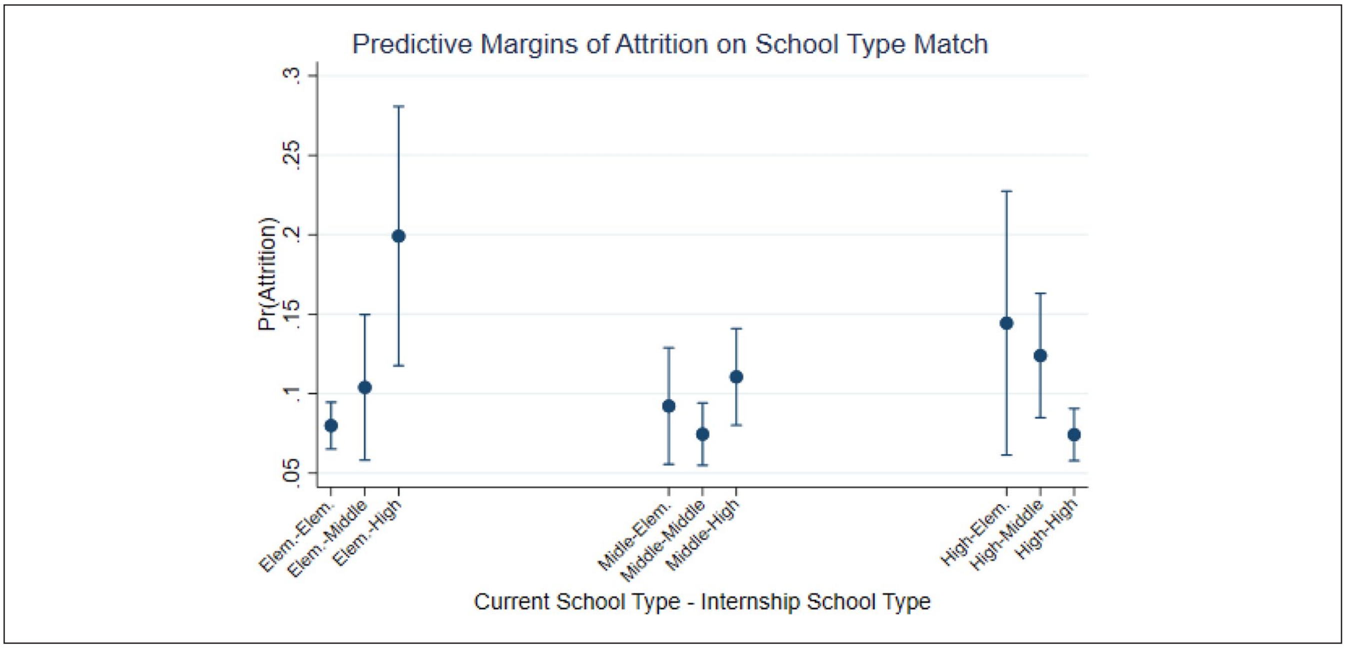

Figure 6. Probability of attrition based on school type match between current and internship school type.

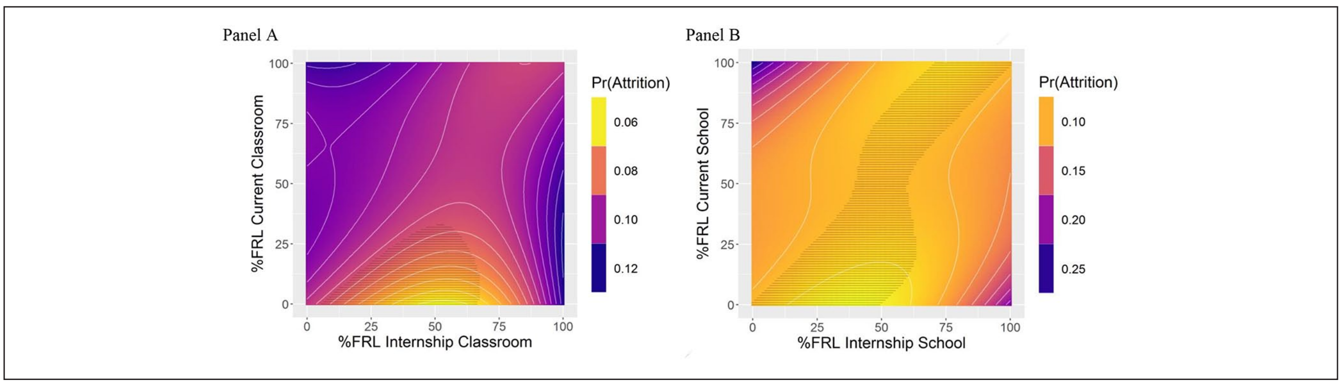

Figure 7. Predicted attrition from the workforce by % FRL in student teaching and first job placements: Panel A: Classroom level; Panel B: School level.

Note. + indicates regions statistically significantly greater than zero; − indicates regions statistically significantly less than zero.

variation in hiring rates over time, combined with associated analysis suggesting that many candidates who aren't hired in eras with slack teacher labor markets are simply lost to the system (i.e., they do not enter the Washington public school labor market over the next 13 years), suggests that school systems might want to consider ways to keep candidates engaged with the system even when they are not hired immediately when labor markets are slack, so that they do not face a hiring crunch when teacher labor markets are tight. For example, as schools consider new models of instruction following the COVID-19 pandemic (Hill & Jochim, 2020), they could also consider new types of positions for candidates who have not immediately been hired as teachers due to associated district budget cuts across the state.

The formal analysis of teacher workforce entry and retention is novel for three reasons: (a) We consider information about cooperating teachers as predictors of teacher career paths, (b) the data set we utilize is far larger than that in prior studies connecting teacher preparation to workforce entry and retention, and (c) this is the first article to investigate the extent to which the alignment between student teaching experiences and first job experiences is predictive of teacher retention.

We draw several broad conclusions aligned with these contributions of the article. First, we replicate prior findings (e.g., Goldhaber et al., 2014) about the large differences in hiring rates between teacher candidates with different teaching credentials. For example, all else being equal, candidates with a special education endorsement are over 10 percentage points more likely to enter the state's public teaching workforce than candidates with an elementary endorsement. This likely reflects the high demand for special education teachers, both in Washington state (e.g., Theobald et al., 2021) and across the country (e.g., Mason-Williams et al., 2019). Thus, it may make sense for the state to consider other means of encouraging teacher candidates to acquire the skills during training that line up with school system needs. For instance, this might include differential pay for difficult-to-staff classrooms or better information about likely future job prospects.

Second, despite mounting evidence about the importance of cooperating teachers for future candidate *effectiveness* (e.g., Bastian et al., 2020; Goldhaber et al., 2020a; Ronfeldt et al., 2018), we find little evidence that characteristics of cooperating teachers (including their value added) are predictive of teacher candidates' future career paths (either the probability of workforce entry or attrition). These null results are estimated with considerable precision due to the large sample sizes, so we can rule out even relatively modest relationships between cooperating teacher characteristics and workforce entry and retention. This, of course, does not necessarily mean that cooperating teachers are not playing important roles in candidates' career paths, but perhaps that these roles are not proxied by the cooperating teacher characteristics we consider. Future research could explore this issue further by leveraging surveys of teacher candidates or new teachers (e.g., Bastian et al., 2018; Boyd et al., 2009; Matsko et al., 2020; Ronfeldt, Matsko, et al., 2020) that ask about the role that cooperating teachers play in candidate career decisions.

Finally, we find that early-career teachers who are teaching in the same school type (elementary, middle, or high), and whose classrooms and schools have similar student demographics as their student teaching experience, are considerably less likely to leave the workforce than early-career teachers who do not experience these types of alignment between student teaching and their first job. While descriptive, this is consistent with a growing body of evidence (e.g., Boyd et al., 2009; Goldhaber et al., 2017; Henry et al., 2013; Krieg et al., 2020b; Ronfeldt, 2015) suggesting that candidates may benefit from learning to teach in a setting that is similar to the setting in which they begin their teaching careers. This is also important given that we also document substantial misalignment between student teaching placements and first teaching jobs; for example, less than half of first-year middle school teachers student taught in a middle school. Only about 3% of teachers host student teachers each year (Goldhaber, Krieg, et al., 2020), implying both that there is tremendous scope for change in student teaching assignments and that trying to ensure better alignment between student teaching placements and first teaching jobs could be a low-cost strategy for improving teacher retention. Given that much of the misalignment between student teaching and early-career placements are related to disproportionate student teacher placements in elementary and high schools and disproportionate teacher hiring in middle schools, a good place to start might be placing more student teachers in middle school settings, as this would likely improve the alignment between student teaching and early-career placements in the aggregate.

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Notes

1. At the time of data collection between 2014 and 2016, there were 21 total TEPs in Washington. Nine additional TEPs have been certified since then.
2. The state's CEDARS data system, introduced in 2009–2010, allows classroom teachers to be linked to their classrooms

and students through unique course identifiers. CEDARS data include fields designed to link students to their individual teachers based on reported schedules. However, limitations of reporting standards and practices across the state may result in ambiguities or inaccuracies around these links.

References

Altonji, J. G., Elder, T. E., & Taber, C. R. (2005). Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools. *Journal of Political Economy*, *113*(1), 151–184.

Anderson, L. M., & Stillman, J. A. (2013). Student teaching's contribution to preservice teacher development: A review of research focused on the preparation of teachers for urban and high-needs contexts. *Review of Educational Research*, *83*(1), 3–69.

Bacolod, M. (2007). Who teaches and where they choose to teach: College graduates of the 1990s. *Educational Evaluation and Policy Analysis*, *29*(3), 155–168.

Bardelli, E., & Ronfeldt, M. (2020). *Workforce outcomes of program completers in high-needs areas* [Working paper]. Tennessee Education Research Alliance. https://peabody.vanderbilt.edu/TERA/files/TERA_Working_Paper_2020-01.pdf

Barnes, G., Crowe, E., & Schaefer, B. (2007). *The cost of teacher turnover in five school districts: A pilot study*. National Commission on Teaching and America's Future.

Bartanen, B., & Kwok, A. (2020). *Pre-service teacher quality and workforce entry* (Ed working paper: 20-223). Annenberg Institute at Brown University. https://doi.org/10.26300/jvss-mr72

Bastian, K. C., Patterson, K. M., & Carpenter, D. (2020). Placed for success: Which teachers benefit from high-quality student teaching placements? *Educational Policy*. https://doi.org/10.1177/0895904820951126

Bastian, K. C., Sun, M., & Lynn, H. (2018). What do surveys of program completers tell us about teacher preparation quality? *Journal of Teacher Education*, *72*(1), 11–26.

Boyd, D. J., Grossman, P. L., Lankford, H., Loeb, S., & Wyckoff, J. (2009). Teacher preparation and student achievement. *Educational Evaluation and Policy Analysis*, *31*(4), 416–440.

Boyd, D. J., Lankford, H., Loeb, S., & Wyckoff, J. (2013). Analyzing the determinants of the match of public school teachers to jobs: Disentangling the references of teachers and employers. *Journal of Labor Economics*, *31*(1), 83–117.

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014a). Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates. *American Economic Review*, *104*(9), 2593–2632.

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014b). Measuring the impacts of teachers II: Teacher value-added and student outcomes in adulthood. *American Economic Review*, *31*(4), 2633–2679.

Feng, L., & Sass, T. R. (2017). Teacher quality and teacher mobility. *Education Finance and Policy*, *12*(3), 396–418.

Frank, K. A., Maroulis, S. J., Duong, M. Q., & Kelcey, B. M. (2013). What would it take to change an inference? Using Rubin's causal model to interpret the robustness of causal inferences. *Educational Evaluation and Policy Analysis*, *35*(4), 437–460.

Goldhaber, D., & Cowan, J. (2014). Excavating the teacher pipeline: Teacher preparation programs and teacher attrition. *Journal of Teacher Education*, *65*(5), 449–462.

Goldhaber, D., Gross, B., & Player, D. (2011). Teacher career paths, teacher quality, and persistence in the classroom: Are public schools keeping their best? *Journal of Policy Analysis and Management*, *30*(1), 57–87.

Goldhaber, D., Krieg, J. M., Naito, N., & Theobald, R. (2020). Making the most of student teaching: The importance of mentors and scope for change. *Education Finance and Policy*, *15*(3), 581–591.

Goldhaber, D., Krieg, J. M., & Theobald, R. (2014). Knocking on the door to the teaching profession? Modeling the entry of prospective teachers into the workforce. *Economics of Education Review*, *43*, 106–124.

Goldhaber, D., Krieg, J. M., & Theobald, R. (2017). Does the match matter? Exploring whether student teaching experiences affect teacher effectiveness. *American Educational Research Journal*, *54*(2), 325–359.

Goldhaber, D., Krieg, J. M., & Theobald, R. (2020a). Effective like me? Does having a more productive mentor improve the productivity of mentees? *Labour Economics*, *63*, Article 101792.

Goldhaber, D., Krieg, J. M., & Theobald, R. (2020b). Exploring the impact of student teaching apprenticeships on student achievement and mentor teachers. *Journal of Research on Educational Effectiveness*, *13*(2), 213–223.

Goldhaber, D., Liddle, S., & Theobald, R. (2013). The gateway to the profession: Evaluating teacher preparation programs based on student achievement. *Economics of Education Review*, *34*, 29–44.

Goldhaber, D., & Liu, A. (2003). Occupational choices and the academic proficiency of the teacher workforce. *Developments in School Finance*, *2001*, 253–275.

Goldhaber, D., Ronfeldt, M., Cowan, J., Gratz, T., Bardelli, E., Truwit, M., & Mullman, H. (2020). *Room for improvement? Mentor teachers and the evolution of teacher preservice clinical evaluations* (CALDER working paper no. 239-0620). https://caldercenter.org/publications/room-improvement-mentor-teachers-and-evolution-teacher-preservice-clinical-evaluations

Goldring, R., Taie, S., & Riddles, M. (2014). *Teacher attrition and mobility: Results from the 2012–13 teacher follow-up survey—First look* (NCES 2014-077). U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics. https://nces.ed.gov/pubs2014/2014077.pdf

Gray, L., & Taie, S. (2015). *Public school teacher attrition and mobility in the first five years: Results from the first through fifth waves of the 2007–08: Beginning Teacher Longitudinal Study—First look* (NCES 2015-337). U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics. https://nces.ed.gov/pubs2015/2015337.pdf

Hanushek, E. A., & Pace, R. R. (1995). Who chooses to teach (and why)? *Economics of Education Review*, *14*(2), 101–117.

Hanushek, E. A., Rivkin, S. G., & Schiman, J. C. (2016). Dynamic effects of teacher turnover on the quality of instruction. *Economics of Education Review*, *55*, 132–148.

Henry, G. T., Campbell, S. L., Thompson, C. L., Patriarca, L. A., Luterbach, K. J., Lys, D. B., & Covington, V. M. (2013). The predictive validity of measures of teacher candidate programs and performance: Toward an evidence-based approach to teacher preparation. *Journal of Teacher Education*, *64*(5), 439–453.

Hill, P., & Jochim, A. (2020). *Can public education return to normal after the COVID-19 pandemic?* Brown Center Chalkboard.

Ingersoll, R., Merrill, L., & May, H. (2012). Retaining teachers: How preparation matters. *Educational Leadership*, *6*(8), 30–34.
Ingersoll, R. M., & Perda, D. (2010). Is the supply of mathematics and science teachers sufficient? *American Educational Research Journal*, *47*(3), 563–594.
Jovanovic, B. (1979a). Job matching and the theory of turnover. *Journal of Political Economy*, *87*(5), 942–990.
Jovanovic, B. (1979b). Firm-specific capital and turnover. *Journal of Political Economy*, *87*(6), 1246–1260.
Ju, B., & Li, J. (2019). Exploring the impact of training, job tenure, and education-job and skills-job matches on employee turnover intention. *European Journal of Training and Development*, *43*(3/4), 214–231.
Krieg, J. M., Goldhaber, D., & Theobald, R. (2020a). *Disconnected development? The importance of specific human capital in the transition from student teaching to the classroom* (CALDER working paper no. 236–0520). https://eric.ed.gov/?id=ED605737
Krieg, J. M., Goldhaber, D., & Theobald, R. (2020b). Teacher candidate apprenticeships: Assessing the who and where of student teaching. *Journal of Teacher Education*, *71*(2), 218–232.
Mason-Williams, L., Bettini, E., Peyton, D., Harvey, A., Rosenberg, M., & Sindelar, P. T. (2019). Rethinking shortages in special education: Making good on the promise of an equal opportunity for students with disabilities. *Teacher Education and Special Education*, *43*(1), 45–62.
Matsko, K. K., Ronfeldt, M., Nolan, H. G., Klugman, J., Reininger, M., & Brockman, S. L. (2020). Cooperating teacher as model and coach: What leads to student teachers' perceptions of preparedness? *Journal of Teacher Education*, *71*(1), 41–62.
Merz, M. (1999). Heterogeneous job-matches and the cyclical behavior of labor turnover. *Journal of Monetary Economics*, *43*(1), 91–124.
Miller, J. M., & Youngs, P. (2021). Person-organization and first-year teacher retention in the United States. *Teacher and Teacher Education*, *97*, Article 103226.
Munasinghe, L. (2005). Expectations matter: Job prospects and turnover dynamics. *Labour Economics*, *13*(5), 589–609.
National Council for Accreditation of Teacher Education. (2010). *Transforming teacher education through clinical practice: A national strategy to prepare effective teachers* [Report of the Blue Ribbon Panel on Clinical Preparation and Partnerships for Improved Student Learning]. https://eric.ed.gov/?id=ED512807
Oster, E. (2017). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, *37*(2), 187–204.
Papay, J. P., West, M. R., Fullerton, J. B., & Kane, T. J. (2012). Does an urban teacher residency increase student achievement? Early evidence from Boston. *Educational Evaluation and Policy Analysis*, *34*(4), 413–434.
Podgursky, M., Monroe, R., & Watson, D. (2004). The academic quality of public school teachers: An analysis of entry and exit behavior. *Economics of Education Review*, *23*(5), 507–518.
Ronfeldt, M. (2012). Where should student teachers learn to teach? Effects of field placement school characteristics on teacher retention and effectiveness. *Educational Evaluation and Policy Analysis*, *34*(1), 3–26.
Ronfeldt, M. (2015). Field placement schools and instructional effectiveness. *Journal of Teacher Education*, *66*(4), 304–320.
Ronfeldt, M., Bardelli, E., Truwit, M., Mullman, H., Schaaf, K., & Baker, J. C. (2020). Improving preservice teachers' feelings of preparedness to teach through recruitment of instructionally effective and experienced cooperating teachers: A randomized experiment. *Educational Evaluation and Policy Analysis*, *42*(4), 551–575.
Ronfeldt, M., Brockman, S., & Campbell, S. (2018). Does cooperating teachers' instructional effectiveness improve preservice teachers' future performance? *Educational Researcher*, *47*(7).
Ronfeldt, M., Goldhaber, D., Cowan, J., Bardelli, E., Johnson, J., & Tien, C. D. (2018). *Identifying promising clinical placements using administrative data: Preliminary results from ISTI placement initiative pilot* (CALDER working paper no. 189). American Institutes for Research.
Ronfeldt, M., Loeb, S., & Wyckoff, J. (2013). How teacher turnover harms student achievement. *American Educational Research Journal*, *50*(1), 4–36.
Ronfeldt, M., Matsko, K. K., Greene Nolan, H., & Reininger, M. (2020). Three different measures of graduates' instructional readiness and the features of preservice preparation that predict them. *Journal of Teacher Education*, *72*(1), 56–71.
Ronfeldt, M., Schwartz, N., & Jacob, B. A. (2014). Does preservice preparation matter? Examining an old question in new ways. *Teachers College Record*, *116*, 1–46.
Theobald, R., Goldhaber, D., Naito, N., & Stein, M. (2021). The special education teacher pipeline: Teacher preparation, workforce entry, and retention. *Exceptional Children*. https://caldercenter.org/publications/special-education-teacher-pipeline-teacher-preparation-workforce-entry-and-retention
Vagi, R., Pivovarova, M., & Miedel Barnard, W. (2019). Keeping our best? A survival analysis examining a measure of preservice teacher quality and teacher attrition. *Journal of Teacher Education*, *70*(2), 115–127.

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