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The Special Education Teacher Pipeline: Teacher Preparation, Workforce Entry, and Retention

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Abstract

We use data on the teacher preparation experiences and workforce outcomes of more than 1,300 graduates of special education teacher education programs in Washington to provide a descriptive portrait of special education teacher preparation, workforce entry, and early career retention. We find high rates of workforce entry for special education candidates (over 80%), but we document considerably lower rates of entry into special education classrooms for candidates who hold a dual endorsement in special education and another subject. We also find that special education teachers who are dual endorsed and begin their careers teaching in special education classrooms are less likely stay in these classrooms. Both sets of findings are supported by an instrumental variable analysis that exploits passing score cutoffs on required licensure tests to provide plausibly causal evidence that obtaining a dual endorsement significantly reduces the likelihood that special education candidates teach in special education classrooms.

1. Introduction

Ample evidence suggests that school systems across the country have struggled to fill special education teaching positions for many decades (e.g., Cowan, Goldhaber, Hayes, & Theobald, 2016; Mason-Williams et al., 2019; McCleskey, Tyler, & Flippin, 2004; Sutcher, Darling-Hammond, & Carver-Thomas, 2019). The situation in Washington State, the setting of this study, is similar, as prior work has documented special education teacher shortages in the state as measured by the number of applications to open teaching positions (Goldhaber, Grout, & Huntington-Klein, 2014), rates of workforce entry (Goldhaber, Krieg, & Theobald, 2014), overall teacher production and attrition (Goldhaber, Krieg, Theobald, & Brown, 2015), and emergency teaching credentials (Goldhaber, Krieg, Naito, & Theobald, 2019). Much of this staffing challenge is driven by lower retention rates for special education teachers (e.g., Brunsting, Sreckovic, & Lane, 2014), which research has connected to the unique demands and working conditions in these class assignments (Billingsley & Bettini, 2019). Another potential explanation for these lower retention rates may be related to the preparation that special education candidates receive before entering the teaching profession.

Unfortunately, there is relatively little empirical evidence about the relationship between the preparation of special education teachers and their workforce outcomes. For instance, there is no large-scale empirical evidence about the predictors of whether special education teacher *candidates* actually become teachers. Likewise, while prior research documents the disproportionate attrition of special education teachers from the teaching profession, there is limited evidence about specific factors that make it more likely for special education teachers to stay in the profession and in special education classrooms in particular.

This paper represents what we believe is the first analysis connecting the preparation of special education teachers to their entry into and retention in the public teaching workforce and special education classrooms. This analysis leverages a longitudinal data set from Washington State that combines data about preservice teacher candidate experiences with information about K–12 teachers and their students, along with novel survey data of special education faculty from these teacher education programs (TEPs) and special education directors from the state's school districts. This data set allows us to characterize aspects of the preparation of individual teacher candidates, such as teaching endorsements, student teaching placements, and measures of the alignment between candidates' teacher preparation and student teaching experiences. We then connect these teacher preparation measures to the workforce outcomes of special education teacher candidates.

We find high rates of workforce entry for special education candidates (over 80%) and annual workforce retention for candidates who go on to teach in special education classrooms (over 90%). However, we document considerably lower rates of entry into and retention in special education classrooms for candidates who hold a dual endorsement in special education and another subject relative to teachers who hold only an endorsement in special education. As a result, many more teachers in the state workforce are endorsed to teach special education than are actually teaching special education.

These findings are based on observational data and not terribly surprising given that candidates who choose to get a dual endorsement may be less interested in teaching in special education classrooms than candidates who choose to get only a special education endorsement. However, exploiting licensure test passing score cutoffs for additional endorsement areas, we also provide plausibly causal evidence that obtaining a dual endorsement reduces the likelihood that special education candidates teach in special education classrooms. This has potential implications for state policy given that special education endorsement requirements are an active area of policy in Washington, and the state just transitioned to requiring dual endorsements for all special education teacher candidates (Dual endorsement requirement, 2018).

Finally, we find little evidence that other measures of special education teacher preparation are predictive of workforce entry and retention. One exception is that special education candidates who student teach with a cooperating teacher endorsed in special education are more likely to enter special education classrooms, all else equal. This finding could be driven by candidates more interested in teaching special education being more likely to student teach with a cooperating teacher endorsed in special education. But given that this result is conditional on the candidates' own endorsements and other measures of their student teaching placement, including whether the student teaching position was in a special education classroom, it provides preliminary evidence that the preparation of cooperating teachers may matter in their student teachers' career decisions.

2. Prior Literature

About a decade ago, a National Research Council (2010) report concluded that we know relatively little about how specific approaches to teacher preparation, including coursework and student teaching, are related to later outcomes for teacher candidates. Although the subsequent years have seen the development of a growing literature relating teacher education experiences to teacher outcomes in general, little of this literature contains a specific focus on special education teachers and their workforce entry or retention.

Several existing empirical analyses address the factors that influence the decision to obtain a teaching degree or the decision to enter the teaching workforce (Bacolod, 2007; Boyd, Goldhaber, Lankford, & Wyckoff, 2007; Goldhaber & Liu, 2003; Hanushek & Pace, 1995; Ingersoll & Perda, 2010; Podgursky, Monroe, & Watson, 2004). Importantly, much of the existing literature offers little to no information on the effects of teacher education experiences or special education teachers in particular. One study (Goldhaber, Krieg, et al., 2014) found that teacher candidates with an endorsement to teach special education are far more likely to end up employed in the teacher workforce than teachers without this endorsement, all else equal. This same study found that about 20% of all special education teacher candidates in the data set never enter the state's public teaching workforce. This finding is surprising given the well-documented shortage of special education teachers both in Washington (e.g., Goldhaber et al., 2015) and nationally (e.g., Brunsting et al., 2014; McCleskey et al., 2004). Follow-up work by Krieg, Theobald, and Goldhaber (2016) also found that the location of a candidate's student teaching placement is more predictive of where candidates enter the teaching workforce than the location of their TEP or high school.

A large body of research has investigated the factors that determine whether and when teachers choose to leave the public teaching workforce, and it has found that teachers are more likely to leave more disadvantaged schools and districts (e.g., Boyd, Grossman, Lankford, Loeb, & Wyckoff, 2008; Brewer 1996; Goldhaber, Gross, & Player, 2011; Krieg, 2006; Scadifi, Sjoquist, & Stinebrickner, 2007). Papers that have considered the special education placement of a teacher (e.g., Boe, 2006; Brunsting et al., 2014; Ingersoll, 2001; McCleskey et al., 2004) consistently have found that special education teachers are more likely to leave the teaching workforce than other teachers. The majority of recent studies that have sought to explain the lower retention rates of special education teachers have highlighted the demands and working conditions that are unique to special education teaching positions (Billingsley & Bettini, 2019).

In connecting teacher education experiences to special education teacher retention, we build on a small literature that has found some connections between teacher education and teacher retention (but not specifically for special education teachers). For example, Ingersoll, Merrill, and May (2012); Papay, West, Fullerton, and Kane (2012); and Ronfeldt (2014) has found positive effects of more extensive teacher training on teacher retention. Ronfeldt (2012) has found that teachers who did their student teaching in schools with lower rates of annual teacher turnover are less likely to leave the teaching workforce; this finding was replicated in recent work in Washington State (Goldhaber, Krieg, & Theobald, 2017). One study that has connected teacher education to special education teacher preparation (Connelly & Graham, 2009) found that first-year special education teachers in the Schools and Staffing Survey and Teacher Follow-Up Survey data with at least 10 weeks of student teaching experience were more likely to stay in the workforce than first-year special education teachers with less student teaching experience.

One measure of teacher preparation that we consider is the endorsements that special education candidates receive on their initial teaching credentials. Prior work from Florida (Feng & Sass, 2013) and North Carolina (Gilmour, 2019) have connected special education teacher credentials to learning outcomes of students with disabilities, but we are not aware of prior evidence connecting them to the career paths of special education teachers. There is also recent evidence (e.g., Boyd, Grossman, Lankford, Loeb, & Wyckoff, 2009; Goldhaber, Krieg, & Theobald, 2017, 2020; Ronfeldt, 2012, 2015; Ronfeldt, Brockman, & Campbell, 2018) on the relationship between the student teaching experiences of teacher candidates and the achievement of their students after they enter the workforce.

Finally, this analysis considers the alignment between a special education teacher candidate's teacher education experiences, student teaching experiences, and early-career teaching experiences. This focus is motivated by a small empirical literature (Boyd et al., 2008; Goldhaber et al., 2017) and a broader qualitative literature (Darling-Hammond, 2000; Feiman-Nemser & Buchmann, 1983; Grossman, Hammerness, McDonald, & Ronfeldt, 2008) suggesting that this alignment may have important implications for teacher and student outcomes, although little of this literature contains a specific focus on special education teachers. One exception is Powell (2015), who argues for a closer connection between the instructional strategies taught to special education teacher candidates and the "specialized nature" of instruction by special educators in schools.

3. Data

We combine data from three sources for this study: data on K–12 students and teachers provided by the Washington State Office of the Superintendent of Public Instruction (OSPI); data on teacher candidates collected as part of the Teacher Education Learning Collaborative (TELC); and data collected through surveys of special education TEP faculty and district special education directors in Washington.

3.1 OSPI Data

The data on in-service teachers and students used in this study come from data sets maintained by OSPI. First, the state's S-275 database provides annual employment information for all public school employees in the state. We use this data set to identify individuals in public school teaching positions and further use the activity codes in the data set to identify teachers whose primary responsibilities are in special education. Second, the S-275 can be linked to the state's Credential and Endorsement database, which contains a complete history of all teaching credentials (i.e., the credentials necessary for any public school teaching position) and teaching endorsements (i.e., the subject areas teachers are endorsed to teach) in the state. As described in the next subsection, we use this database to define our analytic sample (i.e., individuals who received a Washington teaching credential with an endorsement in special education), as well as to identify candidates who also receive an endorsement in something other than special education (i.e., are "dual endorsed"). The credential and endorsement data also include the teacher licensure test scores on the tests required for licensure and endorsements, including the Washington Education Skills Tests—Endorsement (WEST-E, required since 2009) and the tests in the National Evaluation Series (NES, that replaced some WEST-E tests in 2016). Candidates must pass these tests in each area in which they are seeking a teaching endorsement (e.g., every candidate endorsed in special education since 2009 has passed the WEST-E or NES special education test, while dual-endorsed candidates since 2009 have also passed a WEST-E or NES test in the area of their additional endorsement). These tests play a central role in an extension to our primary analysis that exploits the passing thresholds on these tests.

Starting in 2009–10 through the most recent year of available data, 2017–18, these databases can be connected to the state's CEDARS data system that allows teachers to be linked to their students through unique course identifiers.[1] Our primary use of the CEDARS database in this analysis is to identify teachers for whom at least 50% of their students are receiving special education services. This process allows us to define teachers in special education classrooms as teachers who *either* are in a special education position as identified in the S-275 or, following

[1] 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.

Feng and Sass (2013), whose classes contain at least 50% students with disabilities.[2] This cutoff is relatively arbitrary, but as shown in **Figure 1**, it is also largely inconsequential given that the majority of classrooms in the state have fewer than 40% or more than 90% students with disabilities. As a result (and as represented by the vertical lines in Figure 1), the mean percentage of students with disabilities in non–special education classrooms under this definition is about 10%, while the mean in special education classrooms is more than 90%.

The databases above also are linkable to publicly-available information about school-level student demographics, including the percent of students within each race/ethnicity category, the percent of students receiving free or reduced priced lunch, and the percent of students receiving special education and foster services. These variables are important because previous research has connected the proportion of traditionally disadvantaged students in a teacher's school to patterns of teacher attrition (e.g., Goldhaber et al., 2011; Hanushek, Kain, & Rivkin, 2004; Scafidi et al., 2007). Note that our analysis does not consider classroom-level demographics because many special education teachers in the state (e.g., resource teachers) are not linked to student rosters in the CEDARS data.

Before discussing the analytic data set below, we use the broader Washington data to provide some descriptive information about the special education teacher workforce in Washington. **Figure 2** shows the number of teachers in the state's public teaching workforce who have an endorsement to teach special education in each year of available data, as well as the number of teachers who teaching in special education classrooms according to our definition presented previously. In each year, the number of teachers with a special education endorsement

[2] This definition captures both special education teachers without classroom responsibilities (through the activity codes) and classroom teachers whose positions may not be funded through special education but who primary serve students with disabilities.

is more than 50% larger than the number of teachers in special education classrooms in the state. In other words, thousands of teachers in the state each year are deemed eligible by the state (in terms of their qualifications) to teach in special education classrooms but are not staffing these classrooms.

Teachers are identified in the OSPI data as leaving the workforce only if they leave the state's public school workforce; teachers who stay in a teaching position are identified as retained, while teacher-year observations in which teachers move into other public school positions (e.g., administrator or instruction coach) are censored because these types of outcomes are conceptually different from leaving the workforce altogether. **Figure 3** plots attrition rates of special education teachers in each year of data, and it contrasts these attrition rates with the comparable attrition rate of elementary teachers in the state. Between 7% and 10% of special education teachers in the state leave the public teaching workforce each year, which is consistently higher (by 1–2 percentage points) than the comparable attrition rate of elementary teachers in the state.

3.2 Teacher Education Learning Collaborative Data

Data on the preservice experiences of teachers have been assembled as part of TELC, a partnership with 15 TEPs in Washington designed to explore the effects of teacher education experiences on in-service teacher and student outcomes.[3] The TELC data set is unique because it includes comprehensive student teaching data (such as the specific in-service teacher, or "cooperating teacher," with whom teacher candidates did their student teaching) for these teacher

[3] The institutions participating in TELC and that provided data for this study include Central Washington University, City University, Evergreen State College, Gonzaga University, Northwest University, Pacific Lutheran University, St. Martin's University, Seattle Pacific University, Seattle University, University of Washington Bothell, University of Washington Seattle, University of Washington Tacoma, Washington State University, Western Governors University, and Western Washington University. The six institutions that are not participating in TELC include only one relatively (for Washington) large public institution in terms of teacher supply, Eastern Washington University, and five smaller private institutions—Antioch University, Heritage University, University of Puget Sound, Walla Walla University, and Whitworth University.

candidates and allows us to track them into the state's K–12 public school workforce. We focus on student teaching data from 2009–10 to 2015–16 because we can identify whether candidates did their student teaching in a special education classroom in these years (i.e., if their cooperating teacher was a special education teacher in that year according to the definition above). We can also observe other characteristics of the cooperating teachers from the S-275, such as their teaching experience and whether they have a master's degree or special education endorsement.

We combine the TELC data with the OSPI data above to define the analytic sample and outcomes for the analysis. We define the sample as all graduates of TELC programs between 2009–10 and 2015–16 for whom we observe student teaching data and who graduate with an endorsement to teach special education; there are 1,351 such candidates in the TELC data. These candidates are identified as entering the workforce if they ever appear in a teaching position in the S-275. **Figure 4** shows the percentage of special education candidates who enter the state's public teaching workforce within 3 years of graduation for each graduating cohort: More than 75% of special education candidates from each graduating cohort enter the state's public teaching workforce within 3 years of graduation. For reference, we include the comparable figures for candidates in the TELC data with only an elementary education endorsement; the comparison between those with a special education endorsement and those with only an elementary education endorsement shows that the hiring rates of special education candidates have been higher for every cohort but were dramatically higher near the end of the Great Recession (i.e., in 2010 and 2011).

Figure 5 breaks the 3-year hiring rates for special education candidates from Figure 4 into hiring rates into special education and general education classrooms. The majority of special education candidates in each cohort enter special education classrooms, but a significant and growing share begin their careers in general education classrooms. As a result, fewer than 70% of special education candidates in each cohort enter special education classrooms in the state's public teaching workforce.

Figure 6 tracks one cohort of special education candidates (the 2010 graduating cohort); we focus on this cohort because we can track all candidates in this cohort who enter the workforce within 3 years for up to 6 years in the workforce, but the results are qualitatively similar for other cohorts. The yellow line in Figure 6 represents the percentage of this graduating cohort who are teaching in public schools in each subsequent year, while the blue line represents the percentage who are teaching in special education classrooms. The initial drop from the full sample to the first year of experience is identical to what is reported in the first bar of Figure 5, but then the remainder of the figure illustrates the cumulative effects of teacher attrition from the workforce and from special education classrooms over time. Most notably, while more than half of this graduating cohort reaches their sixth year of teaching by the end of our data panel, only about 40% are still teaching in special education classrooms in this year.

3.3 Survey Data

Finally, to investigate the alignment between special education teacher candidates' teacher education and hiring district experiences, we designed and administered surveys to special education faculty from the 13 TELC institutions with special education TEPs, and parallel surveys for special education directors of school districts in the state. The surveys were developed by an Expert Planning Team of special education TEP faculty and former special education district administrators.[4] Questions were primarily derived from the Council for Exceptional Children Initial Level Special Educator Preparation Standards, but the Expert Planning Team also consulted with an Advisory Board of additional TEP and district personnel

[4] The Expert Planning Team consisted of two faculty from special education TEPs in the state and two former special education directors of districts in the state.

to determine instructional practices currently prevalent *for use with students with high-incidence disabilities* (i.e., emotional/behavioral disorder, health impairment, or specific learning disability) in TEP instruction and school districts. Although the survey contained questions addressing knowledge and skills necessary such as classroom management and preparing IEPs, for the purposes of this analysis, we primarily focus on two questions from this survey that focus on instructional practices: one that asks faculty and directors to select all *literacy* instructional practices for students with high-incidence disabilities emphasized or used in their TEP or district; and another in which they select all *mathematics* instructional practices for students with high-incidence disabilities emphasized or used in their TEP or district. The final response rate across all questions on the TEP survey was 100%, while we have complete district responses for 87% of the candidates in the analytic sample. As a result, we estimate models that consider these survey measures on a subset of the full data set.

Before investigating the implications of alignment for workforce entry and attrition, we first describe the faculty and director survey responses about literacy and mathematics instructional practices emphasized in their TEP or district.[5] **Figure 7** presents survey responses to the literacy question ("Select all practices currently used/emphasized in special education in your coursework/district"). The instructional practices are ordered from top to bottom in order of their frequency in the *TEP responses* (the red bars), and then the yellow and blue bars represent the percentage of candidates in the sample that student taught and started their teaching careers, respectively, in districts that emphasize the given instructional method. Perhaps the most notable finding is in Figure 5 for instructional methods (near the bottom of the figure). While about 80%

[5] These survey summary statistics are produced after merging with candidate data from our analytic sample, as this provides a direct look at the extent to which individual candidates experience alignment. Consequently, some survey responses (e.g., from large TEPs or districts) are more heavily weighted in these figures. We chose to do this given that larger TEPs, for instance, are responsible for more teachers in the state's workforce than others.

of candidates' student teaching and first districts report that they emphasize sight word instruction and guided reading, for example, these practices are emphasized by fewer than 30% of candidates' TEPs.

We repeat this exploration of alignment for the mathematics survey responses in **Figure 8**. Interestingly, much of the misalignment in mathematics is in the other direction, as practices like mental math, number talks, and community math walks are all far more likely to be emphasized in candidates' TEPs than in their hiring districts. But generally, we tend to observe greater alignment across the board (again, with some exceptions) in the mathematics survey responses than in the literacy survey responses.

4. Analytic Approach

We first report the results of a factor analysis of the two survey questions we use for this analysis, outline how we use this analysis to create measures of alignment at the individual candidate level, and then conclude this section by describing our analytic approach to investigating teacher workforce entry and retention.

4.1 Factor Analysis

Table 1 summarizes the results of a factor analysis of responses *to the district director surveys*. We perform the factor analysis on the director surveys because of the considerably larger sample sizes (relative to the TEP surveys), and because we believe the director survey likely better represent the full range of instructional philosophies across the state. Panel A of Table 1 summarizes the factor analysis for the literacy question, while Panel B does the same for the math question. In each case, the factor analysis identified four principal components. On the literacy question, we label the four principal components "Guided and Close Reading," "Fluency and Phonics," "Reading and Writing," and "Balanced Literacy" to reflect the instructional practices that load most positively onto these factors (all factor loadings with an absolute value of at least 0.3 are bolded in Table 1). For the math question, the four principal components are "Manipulatives and Fact Fluency," "Vocabulary and Visualization," "Number Talks and Walks," and "Problem Solving," again reflecting the practices that load most positively onto these factors.

4.2 Measures of Alignment

The factor analysis described in Section 4.1 allows us to calculate values for each candidate in the sample of the extent to which their district emphasizes instructional approaches aligned with each of the four factors in each subject. Specifically, let F_{ijs}^{DIST} be the value for candidate *I* for factor *j* (*j* = 1, … 4) in subject *s* (literacy or math) for their hiring district. We can then use the factor loadings in Table 1 to create analogous measures for the candidate's student teaching district, F_{ijs}^{ST}, and—by applying the factor loadings in Table 1 to the responses from the TEP faculty surveys—for each candidate's TEP, F_{ijs}^{TEP}. Conceptually, these measures provide information about the extent to which each candidate's TEP, student teaching district, and hiring district emphasize the instructional practices aligned with each of the factors in Table 1.

We then create measures of (mis)alignment for each candidate in the sample by applying the Euclidean distance formula to the measures discussed previously. These measures can be between a candidate's TEP and hiring district, between their TEP and student teaching district, or between their student teaching district and hiring district. Likewise, these measures can be more literacy coherence only, math coherence only, or pooled between the two subjects. To make these calculations concrete, the subject-specific misalignment measure for candidate *i* in subject *s* between A and B (where A and B can be TEP, ST, or DIST) can be expressed as:

$$S_{is}^{A/B} = \sqrt{\sum_{j=1}^{4}\left(F_{ijs}^{A} - F_{ijs}^{B}\right)^{2}} \qquad (1)$$

Likewise, the pooled misalignment measure for candidate *I* between A and B be expressed as:

$$S_{i}^{A/B} = \sqrt{\sum_{s}\sum_{j=1}^{4}\left(F_{ijs}^{A} - F_{ijs}^{B}\right)^{2}} \qquad (2)$$

To turn these into interpretable measures of alignment, we standardize these measures across all candidates and multiply by –1 so that increasing values indicate greater alignment. As shown in the summary statistics in **Table 2**, this results in all of these measures having a mean of 0 and a standard deviation of 1 across the largest sample of candidates for whom we can calculate the measure. It allows us to make comparisons between measures of misalignment for candidates who experience different outcomes. These comparisons are formalized in the analytic models described in the next section.

4.3 Analytic Models

Our analysis considers a series of binary outcomes (entrance into the workforce/special education classrooms and attrition from the workforce/special education classrooms, summarized in Panel A of Table 2), so our primary analytic approach consists of a series of logistic regression models. First, define E_{ik} as a binary indicator for whether candidate *i* from institution *k* enters the workforce. The models that consider workforce entry take the form:

$$\log\left(\frac{Pr(E_{ik}=1)}{Pr(E_{ik}=0)}\right) = \alpha_0 + \alpha_1 X_i + \alpha_2 S_i^{TEP/ST} (+\, \alpha_k) + \varepsilon_{ik} \qquad (3)$$

The model in equation 3 predicts the log odds of workforce entry as a function of observable characteristics of the candidate (X_i), including indicators for whether they hold a dual endorsement, their gender, and the characteristics of their student teaching school and cooperating teacher (summarized in Panel B of Table 2). We can also consider the alignment between each candidate's TEP and student teaching experiences as an additional predictor, and we estimate these models with and without institution effects, α_k. Finally, we estimate versions of the model in equation 3 in which E_{ik} is a binary indicator for whether candidate *i* from institution *k* enters a special education classroom, conditional on entering the workforce at all.

Next, to investigate predictors of teacher retention, we define R_{ikt} as a binary indicator for whether candidate *i* from institution *k* who is teaching in district *l* in year *t* stays in the teacher workforce the following year. The retention models are discrete-time hazard models of the form:

$$\log\left(\frac{Pr(R_{ilkt}=1)}{Pr(R_{ilkt}=0)}\right) = \beta_0 + \beta_1 X_i + \beta_2 X_{it} + \beta_3 S_i^{A/B} (+\beta_l)(+\beta_k) + \beta_t + \varepsilon_{ilt} \quad (4)$$

The model in equation 4 predicts the log odds of retention in the workforce as a function of time-invariant observable characteristics of the candidate (X_i), including the same variables discussed for equation 3; time-variant observable characteristics such as teacher experience and the characteristics of the teacher's current school (described in Section 3.1); and measures of alignment S_i. As described previously, we estimate these models with and without institution (β_l) effects, and we estimate models with and without district fixed effects (β_k). We include year effects β_t in all specifications to account for time-trends in the data. 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 4 in which R_{ilkt} is a binary indicator for retention in a special education classroom, conditional on staying in the teaching workforce the following year.

The logit coefficients in equations 3 and 4 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 and fixed effects in these analytic models, we do not interpret these marginal effects as causal effects on candidate outcomes given that candidates nonrandomly sort into different teacher preparation experiences; for example, candidates who are more committed to teaching special education may seek out different endorsements and student teaching placements than candidates who are less committed. We therefore describe the results from the models above in descriptive terms in Section 5.1, but then we pursue an extension in Section 5.2 that seeks to generate causal estimates for one variable of interest (dual endorsement in special education and another subject).

5. Results

5.1 Descriptive Models

Table 3 presents estimates from different specifications of the model in equation 3 in which the outcome is whether each candidate enters the state's public teaching workforce. As shown in Table 2, 89% of all candidates in the sample eventually become public school teachers in the state, which is higher than was reported previously for Washington (Goldhaber et al., 2014) and is not surprising given that the earlier analysis corresponded with a time period when teacher hiring was limited by the Great Recession. We find little evidence in Table 3 of a relationship between any of the measures of the preparation of special education candidates and the probability of entering the state's public teaching workforce. Importantly, these findings are precisely estimated; for instance, for all of the binary measures of teacher candidate preparation, we can rule out effects of greater than about 6 percentage points in either direction. These null findings are not surprising given that the overall rates of workforce entry are so high.

Table 4 limits the sample to teachers who enter the workforce and presents estimates from the model in equation 3 in which the outcome is whether each candidate begins their career in a special education classroom. Here, we find two variables are consistently predictive of this outcome across model specifications. First, dual-endorsed candidates are dramatically (about 20 percentage points, all else equal) less likely to enter special education classrooms than candidates with only an endorsement in special education. This finding is not surprising given that the state's licensure policies imply that only dual-endorsed teachers should be eligible to teach outside of special education classrooms and the likelihood that teacher candidates who are dual endorsed are more likely to be interested in broader assignments. Moreover, candidates who are more committed to teaching special education may be less likely to pursue a dual endorsement in another subject, so part of this relationship may be due to nonrandom sorting into these different endorsement areas. Nonetheless, but the magnitude of the result is striking, and we pursue an extension in Section 5.2 that seeks to provide a causal estimate of this relationship for a subset of candidates.

Second, special education candidates who student teach with a cooperating teacher endorsed in special education are more likely to enter special education classrooms, all else equal. This also could reflect patterns of non-random sorting, in this case into student teaching positions (e.g., candidates who are more interested in teaching special education may be more likely to student teach with a cooperating teacher endorsed in special education). The relationship is conditional on the candidates' own endorsements and other measures of their student teaching placement (including whether this student teaching placement is in a special education classroom). We thus interpret this result as suggestive evidence supporting the view (e.g., Anderson & Stillman, 2013) that student teaching experiences, and the preparation of cooperating teachers in particular, may matter in their student teachers' career decisions.

In **Table 5**, we report estimates from the discrete-time hazard models from equation 4 that predict workforce retention of special education teachers in the sample. As with workforce entry in Table 3, we find little evidence that measures of the preparation of special education teachers are predictive of whether they stay in the state's public teaching workforce. Finally, **Table 6** limits the sample to teachers in special education classrooms who stay in the workforce and presents estimates from the model in equation 3 in which the outcome is whether each teacher stays in a special education classroom (relative to moving to a general education classroom). Again, with one notable exception, we find little evidence relating the various measures of teacher candidate preparation to the retention of special education teachers in special education classrooms. The notable exception is that dual-endorsed teachers in special education classrooms are considerably more likely to move to general education classrooms that teachers with only an endorsement in special education.

5.2 Instrumental Variables (IV) Models

The most notable and consistent result discussed above is that special education candidates who are dual endorsed in another subject are considerably less likely to be hired into and stay in special education classrooms than candidates without a dual endorsement. Yet it is unclear whether dual endorsements actually reduce, in a causal sense, the likelihood that special education candidates teach in special education classrooms. For example, it is likely that candidates who are less committed to teaching special education classes exclusively would be more likely to seek a dual endorsement; thus, to some extent the descriptive relationships described above may be driven by the desires of the teacher candidates pursuing specific endorsements rather than the availability of those endorsements. This distinction is important for policy purposes; as discussed in the introduction, the state has recently introduced a policy requiring dual endorsements for all special education candidates, and the extent to which this policy might influence the staffing (or lack thereof) of special education classrooms is a function of whether these dual endorsements actually impact candidates' career paths.

We therefore pursue an extension that leverages the fact that candidates since 2009 have been required to pass specific licensure tests (referred to as the WEST-E or NES licensure tests in Washington) in each subject in which they want to be endorsed. These tests have a sharp passing cutoff; candidates who score below a given score (240 on the WEST-E or 220 on the NES) cannot get an endorsement in that area without retaking and passing the test. Therefore, special education candidates who fail a WEST-E or NES test in a subject other than special education should be less likely to get dual endorsed than special education candidates who pass one of these tests. This provides an opportunity to exploit this passing score and use IV methods to estimate the local average treatment effect (LATE) of dual endorsement on the career paths of these candidates. In this context, the LATE is the treatment effect for the sample of candidates who would have become dual endorsed if they had passed the WEST-E/NES and not become dual endorsed if they had failed the WEST-E NES test; we return to the limitations of this sample in the conclusion.

Before describing the IV models, it is important to note that the sample for this extension differs from the sample used in Tables 1–6. First, we expand the sample of teacher candidates in our analytic dataset beyond those that are included in the TELC data. We do this in an effort to improve the statistical power of these IV models; specifically, we include all special education candidates who passed the WEST-E or NES in special education (i.e., all special education candidates since 2009) but not necessarily in a different content area. This process limits the number of control variables we can include in these models, but it more than doubles the sample sizes from the previous tables. Second, these models are necessarily restricted to special education candidates who attempted at least one WEST-E or NES test in a subject other than special education. In some ways, this is an advantage, as it provides a signal of which candidates were interested in a dual endorsement in the first place.

We begin by providing some figures that illustrate this analytic approach. **Figure 9** plots the probability that candidates eventually pass a given WEST-E/NES test as a function of candidates' first score on the test, centered so that the passing score for each test is 0 on the *x* axis. Clearly, every candidate who scores at the passing score or above eventually passes the test, while a substantial number of candidates who do not pass the test on the first attempt eventually pass the test through retakes. There is a clear discontinuity at the passing score; that is, candidates who narrowly fail the test on the first attempt are about 20 percentage points less likely to eventually pass the test than candidates who pass on the first attempt.

Not surprisingly, this difference translates into differences in dual endorsement rates for candidates with different scores the first time they take the test. **Figure 10** plots the probability that candidates receive a dual endorsement in a given area as a function of candidates' first score on the WEST-E/NES test in that area. This figure illustrates the first stage of the IV regression described below, and it shows that candidates who pass the test on the first attempt are about 10 percentage points more likely to receive a dual endorsement than candidates who fail the test on the first attempt, conditional on the candidates' continuous scores. This exogenous change in the likelihood of receiving a dual endorsement is then the instrument in the second-stage regression predicting candidate outcomes.[6] As a falsification check on an outcome that we would not expect this instrument to influence, **Figure 11** plots candidates' first score on the WEST-E/NES special

[6] We experiment with formal regression discontinuity (RD) models that focus on the area just around the cut score in Figure 10, but found that the estimates are under-powered at the optimal bandwidth of 0.3 and sensitive to the choice of bandwidth. We therefore expand the bandwidth substantially to 2.0 and describe these models as IV (rather than RD) models.

education test (eventually passed by all candidates in the sample) a function of candidates' first score on the WEST-E/NES content area test. We do not observe a discontinuity at the passing score on the content area test, suggesting that this covariate is balanced across the cutpoint.[7]

These trends motivate our use of IV models to generate plausibly causal estimates of the impact of dual endorsement on the probability of teaching in a special education classroom. Specifically, for each candidate and year they appear in the workforce, we predict the probability that the candidate teaches in a special education classroom as a function of their dual endorsement status and other observable characteristics prior to workforce entry.[8] This essentially combines the workforce entry and retention analyses described above, and it is intended to estimate the overall impact of dual endorsement on special education classroom staffing. Specifically, we estimate the following model:

$$\mathrm{f}\big(Pr(R_{it} = 1)\big) = \gamma_0 + \gamma_1 D_i + \gamma_2 X_i + \gamma_3 S_i * 1(S_i < 0) + \gamma_4 S_i * 1(S_i \geq 0) + \gamma_t + \varepsilon_{it} \quad (4)$$

Our preferred parameterization of the outcome variable $Pr(R_{it} = 1)$, the probability that candidate *i* is teaching in a special education classroom in year *t*, is a probit that bounds fitted values of this probability between 0 and 1.[9] We model this outcome as a function of the variable of interest, whether the candidate is dual endorsed (D_i), and control for candidate characteristics X_i (gender, degree level, content area test type, and first score on the special education WEST-E/NES test), the candidate's first score on the content area test (S_i, interacted with whether the score is before or after the cutpoint), and year effects γ_t. We cluster all standard errors at the teacher level to account for multiple observations per teacher.

[7] We perform formal balance tests on this and the other covariates (gender and degree level) and do not find evidence that these variables are unbalanced across the cutpoint.
[8] We also estimate IV models of the entry and retention models described in Section 5.1, but these models are underpowered (and are available from the authors on request).
[9] We also experiment with a linear parameterization and find that results are similar but less precise.

Columns 1-5 of **Table 7** provide results from this descriptive model for different subsets of data). Column 1 illustrates that, across the entire sample of special education candidates in the OSPI data, dual-endorsed candidates are about 39 percentage points less likely to teach in special education classrooms than candidates without a dual endorsement. This relationship is smaller both in the TELC data (column 2) and especially for candidates who attempted the WEST-E test in another subject (column 3); this finding makes intuitive sense since this sample drops all candidates who never pursued a dual endorsement and were likely more committed to teaching in special education classrooms (and thus disproportionately contributed to the negative relationship in column 1). This relationship is consistent for the relatively small sample of TELC candidates in this group (column 4) and is robust to controlling for candidates' WEST-E scores (column 5).

We now turn to the IV models, for which we estimate the following first-stage regression in a two-stage least squares IV framework:

$$D_i = \theta_0 + \theta_1 1(S_i \geq 0) + \theta_2 X_i + \theta_3 S_i * 1(S_i < 0) + \theta_4 S_i * 1(S_i \geq 0) + \theta_t + \varepsilon_{it} \quad (5)$$

In equation 5, the indicator for whether the candidate passed the WEST-E/NES content area test on the first attempt ($1(S_i \geq 0)$) is the IV; column 6 in Table 7 illustrates that special education candidates who pass the WEST-E/NES test are about 8 percentage points more likely to be dual endorsed, all else equal.[10] This finding is quite consistent with the first-stage picture in Figure 10.

We then use the fitted value $\widehat{D_i}$ in place of D_i in equation 4 to produce the IV estimate of the relationship between dual endorsement and the probability of teaching in a special education

[10] This estimate is statistically significant at conventional levels, but the resulting F-statistic is only 7.11, which is relatively weak for the first stage of an IV regression. This is another reason we interpret these results with caution.

placement.[11] **Figure 11** illustrates that there is a corresponding discontinuity in the resulting second stage regression (of about –4 percentage points); as shown in column 7 of Table 7, this translates into a LATE of –43.5 percentage points on the probability that special education candidates teach in special education classrooms. This relationship is larger than the analogous descriptive estimate for the same sample (Column 5), but quite similar to the unadjusted estimate for the full sample (Column 1). This finding provides plausibly causal evidence that obtaining a dual endorsement reduces the probability that special education candidates eventually teach in a special education classroom, at least among candidates who attempt to get a dual endorsement and would be induced to get this endorsement by passing the required test.

6. Discussion and Conclusions

This analysis of special education teacher workforce entry and retention is, to our knowledge, the first study of its kind that leverages statewide data on special education teacher candidates and their workforce outcomes. Importantly, thousands more teachers in the state are endorsed to teach special education than are actually teaching in special education classroom. This finding is consistent with the notion that there may not actually be a special education teacher shortage, but rather there is a shortage of special education teachers teaching special education. At a high level, this suggests that policymakers and practitioners struggling to staff special education classrooms may want to consider policies (such as differential pay) to entice these teachers who are already in the public teaching workforce to move into these difficult-to-staff classrooms.

[11] These estimates are produced by the ivprobit command in STATA, which corrects standard errors in the second stage for uncertainty in the first-stage estimates.

We find little evidence that various aspects of the preparation of teacher candidates, such as their student teaching experiences and the alignment between their coursework and student teaching experiences, are predictive of overall workforce entry. However, completing student teaching under the supervision of a cooperating teacher endorsed in special education is predictive of special education teachers beginning their careers in special education classrooms. This finding is important because, while Washington does have some requirements for candidates' student teaching placements (e.g., the cooperating teacher must have at least 3 years of teaching experience), we are not aware of any requirements about the types of classrooms in which different candidates can student teach or the endorsements that cooperating teachers must hold. Indeed, only 66% of the special education candidates in our sample actually student taught in a special education classroom, and only 61% were supervised by a cooperating teacher who was endorsed in special education. This analysis provides preliminary evidence that the endorsements of the cooperating teacher can matter for special education candidates' future career decisions, and that special education TEPs may want to prioritize student teaching placements for special education candidates with cooperating teachers endorsed in special education.

Finally, we find strong evidence that, among those teacher candidates employed in public schools, being dual endorsed in special education and another subject is related to the likelihood that they teach in special education classrooms. Candidates who pass a required licensure test in a second area are both less likely to initially be assigned to teach in special education classrooms, and, conditional on first being assigned to these classrooms, more likely to leave them if they do receive a second endorsement. This suggests that the state's new dual endorsement requirement

(Dual endorsement requirement, 2018) could have unintended consequences for special education teacher entry into and mobility out of special education classrooms.

The dual endorsement findings also highlight an aspect of education policy that has received very little empirical attention: the role that states may play in influencing within-profession mobility through credentialing requirements.[12] While credentialing is generally framed as a means of ensuring proper preparation, it also serves to restrict the grades and subjects that prospective and current teachers are eligible to teach. The dual endorsement policy in Washington is not framed as an attempt to change the subjects teachers are allowed to teach—e.g., the policy was cited in the state's equity plan as addressing the special education teachers' "need for expertise in content area(s) and… special education program(s)" (Pauley, 2015, p. 62)—but our results suggest that the policy may also influence the hiring and mobility patterns of teachers as well.

That said, we are cautious about drawing strong inferences about how endorsements affect the special education teacher pipeline or mobility, given that the IV results are generalizable to an entirely different subset of candidates than would likely be affected by the state's dual endorsement policy. Specifically, while the IV estimate is only generalizable to teacher candidates who have demonstrated an interest in a content area endorsement and would become dual endorsed if they pass the content area test, the subgroup of candidates most impacted by a dual endorsement policy is candidates who would not have pursued a dual endorsement under the current system in the first place. We therefore cannot say how changes to policy, such as the new dual endorsement requirement, might impact this group of candidates.

[12] There is, by contrast, significant policy debates and empirical evidence on the effects of licensure on who opts to teach and the effectiveness of teachers in the profession; see, for instance, Boyd et al. (2007) for a review.

We are also cautious because we do not know how the requirement and associated training will affect the front end of the teacher pipeline (i.e., who pursues a teaching license or special education endorsement in the first place) or, ultimately, student achievement. The requirement could, for example, induce more candidates to pursue a special education endorsement, and could lead to better instruction in both general education and special education classrooms. So, while our findings raise concerns about potential unanticipated effects of a dual endorsement requirement on the state's ability to staff special education classrooms, future research that explicitly studies this policy change is necessary to establish whether these concerns will play out in practice.

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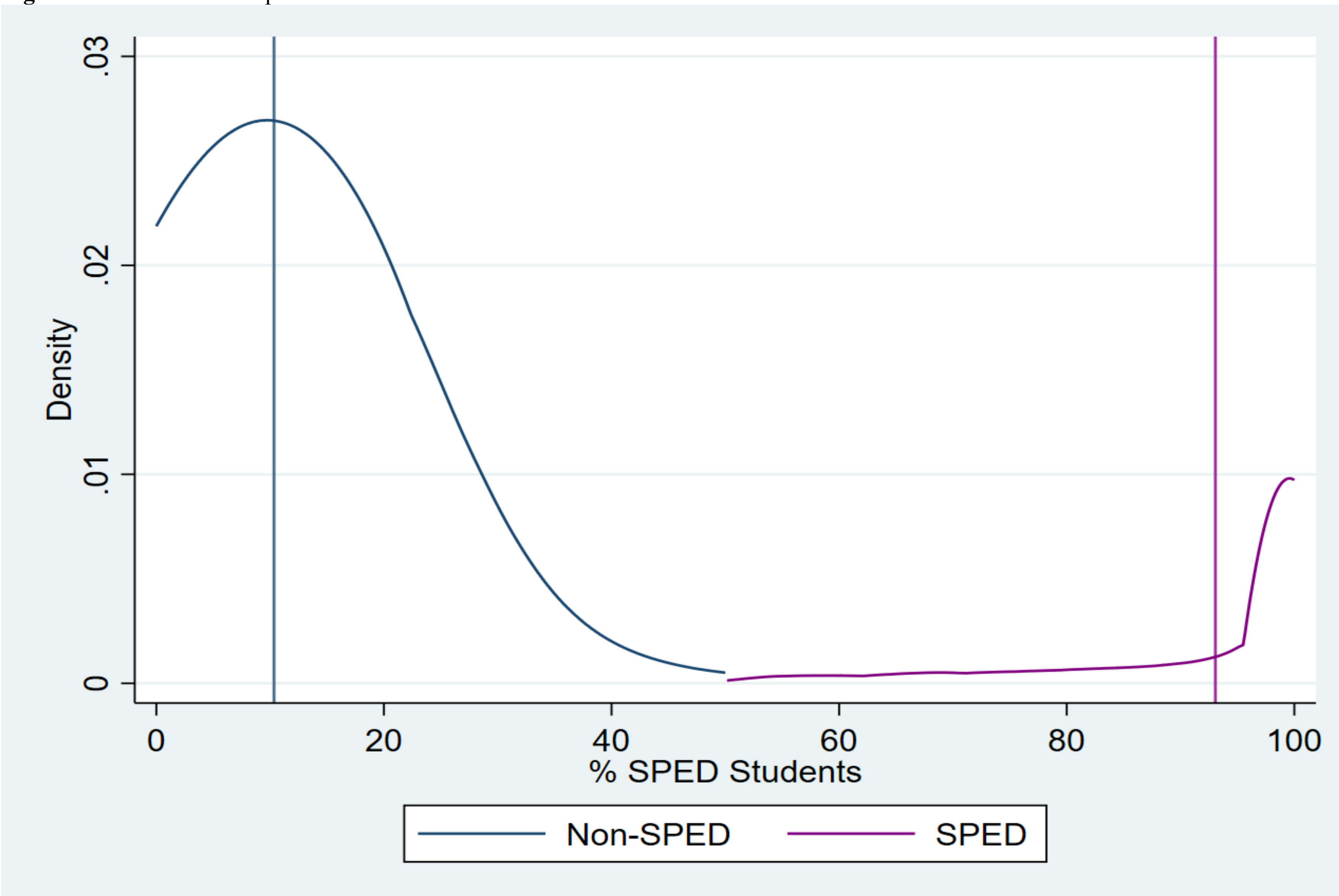
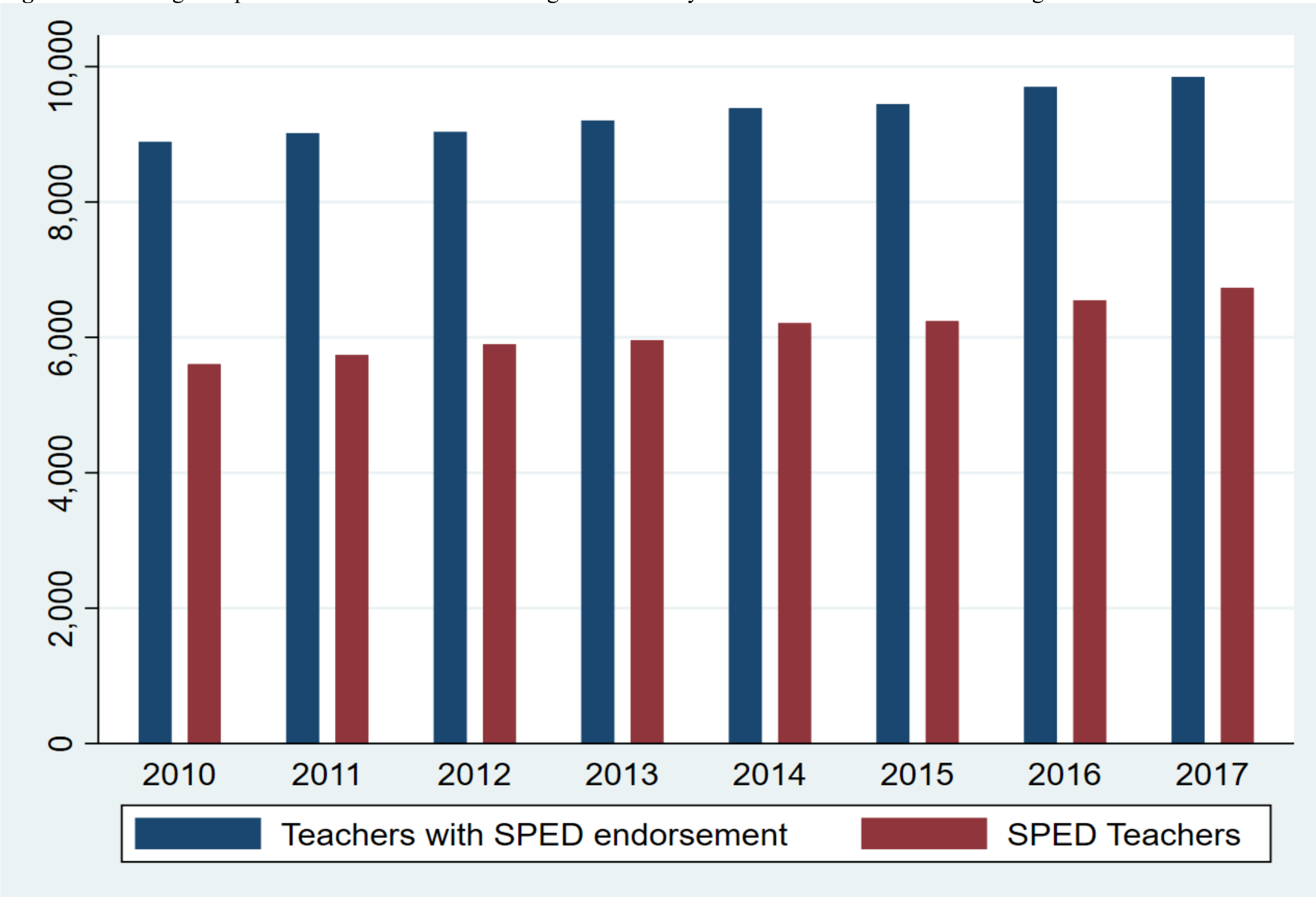
Figures and Tables

Figure 1. Distribution of Special Education Students Across Classrooms



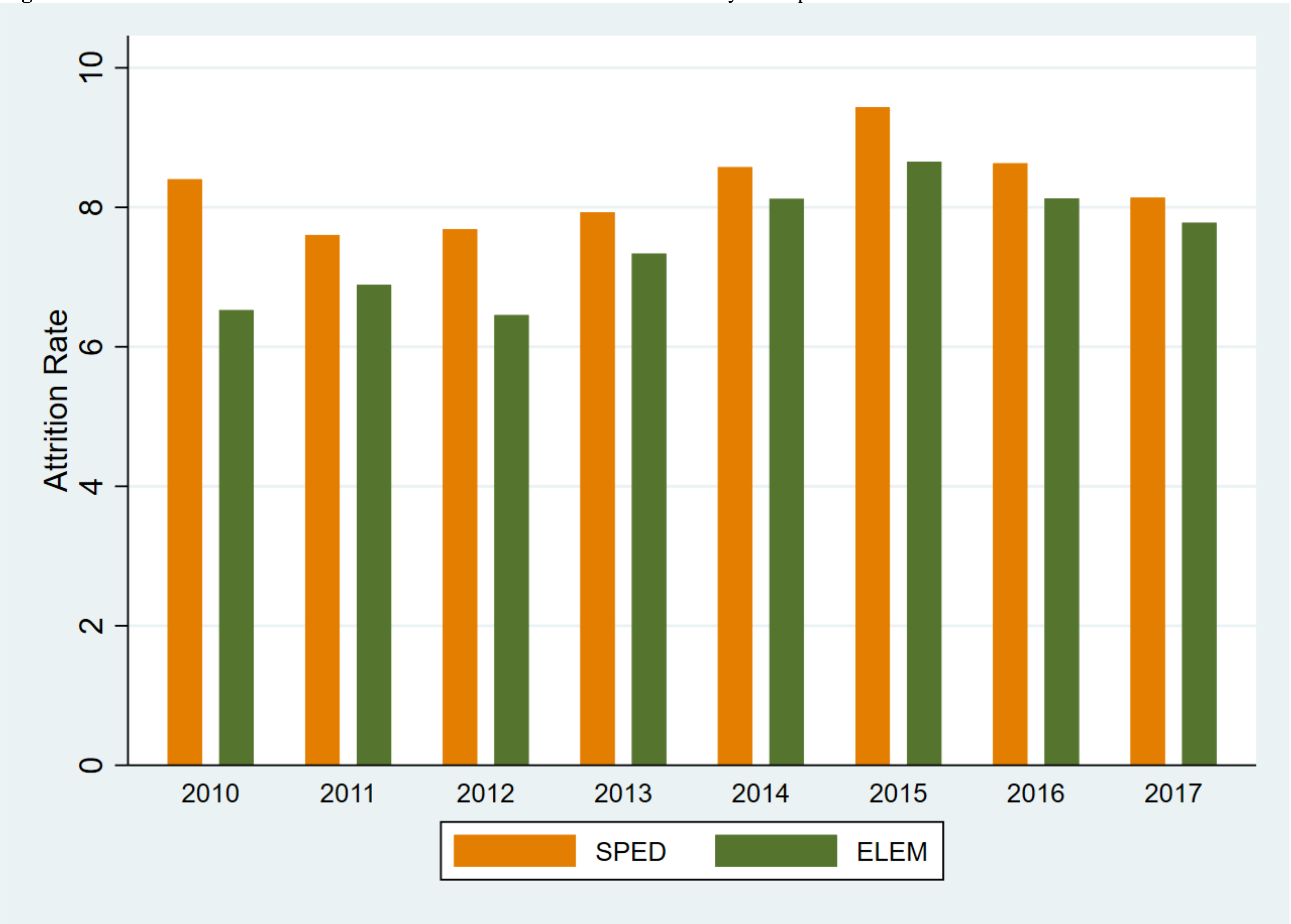
Note. SPED = special education classroom.

Figure 2. Washington Special Education Public Teaching Workforce by Endorsement and Classroom Assignment



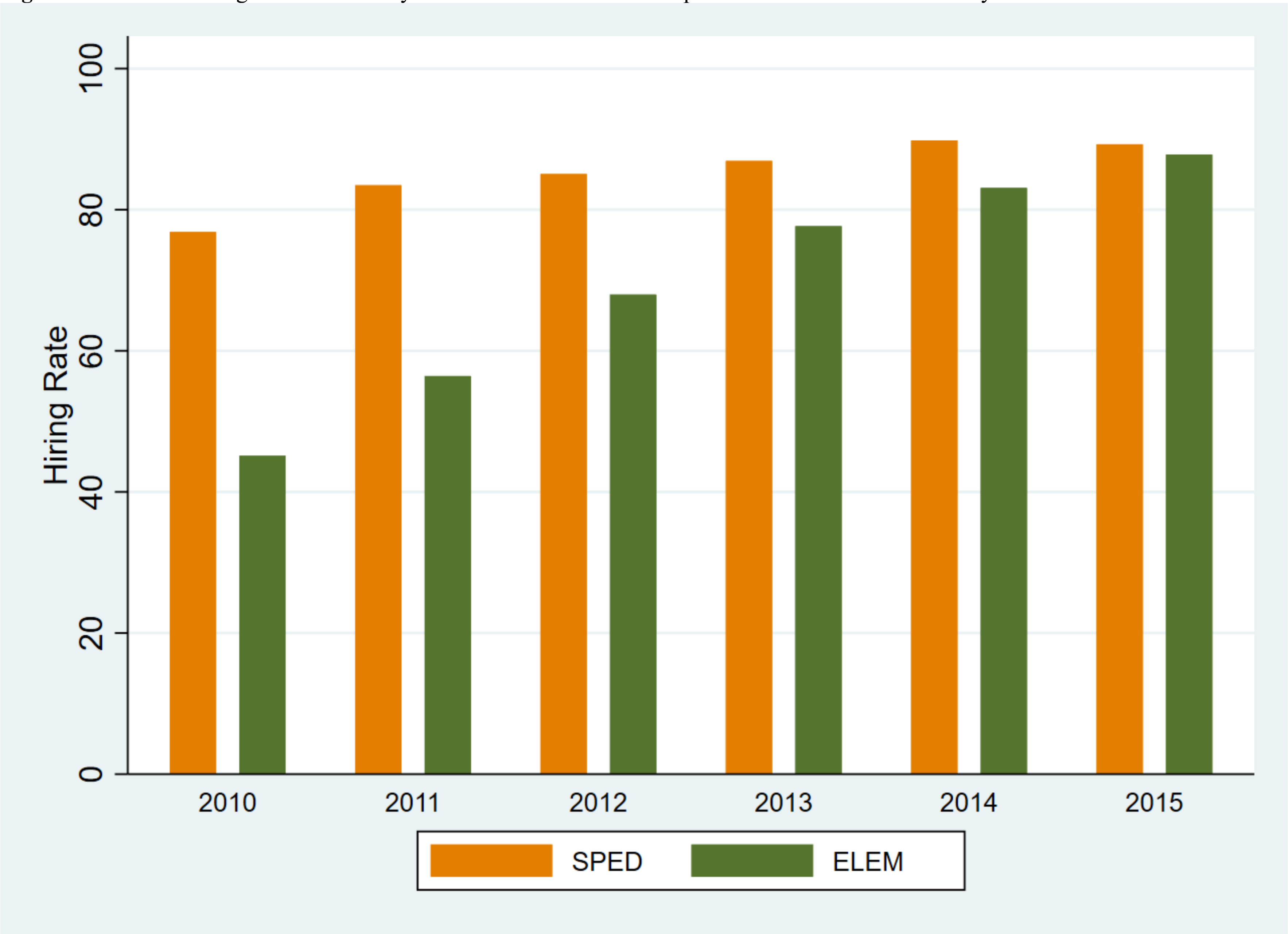
Note. SPED = special education.

Figure 3. Annual Public Workforce Attrition Rates for Teachers in Elementary and Special Education Classrooms



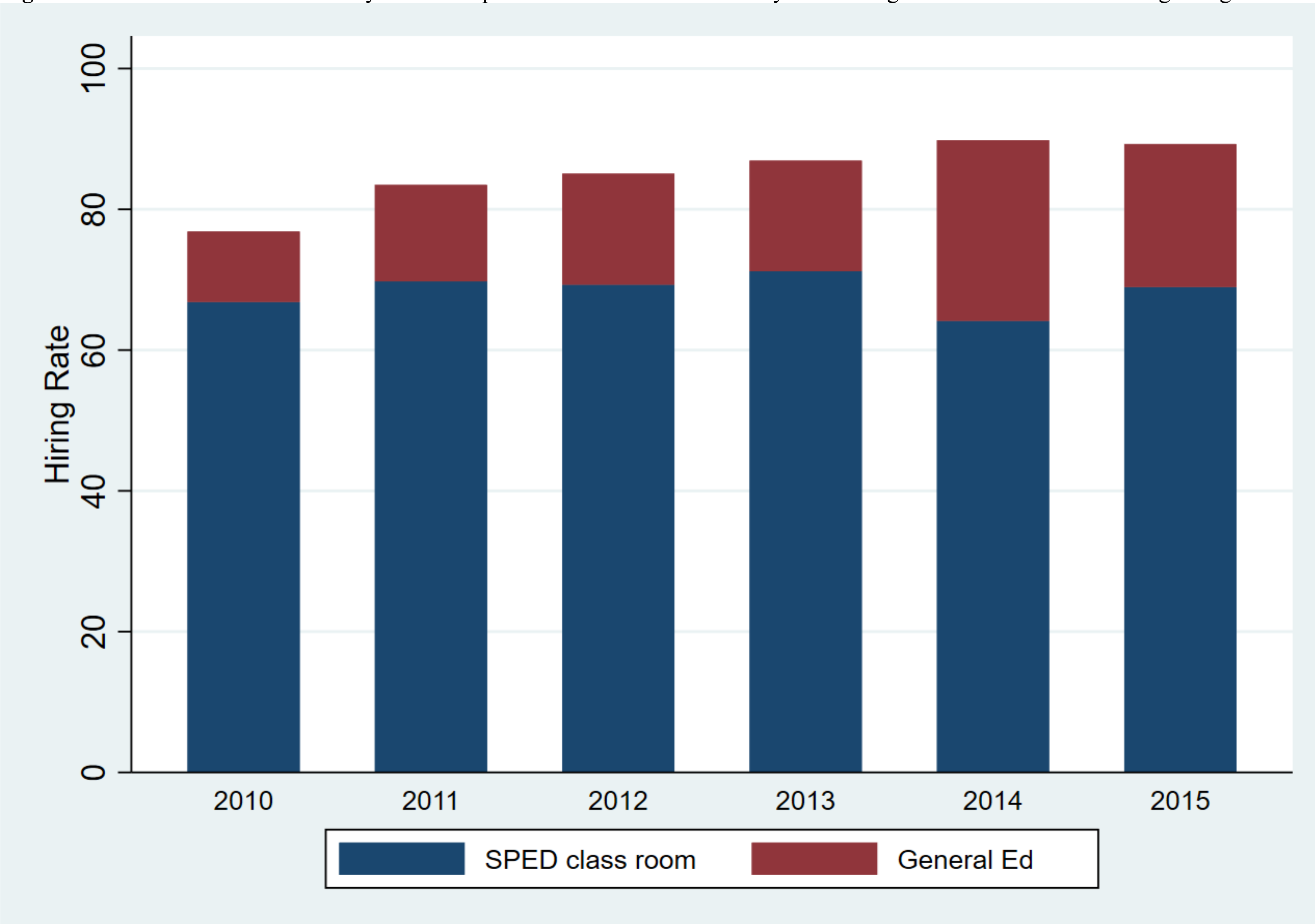
Note. ELEM = elementary classroom; SPED = special education classroom.

Figure 4. Public Teaching Workforce Entry Rates for Candidates With Special Education and Elementary Endorsements From TELC Data



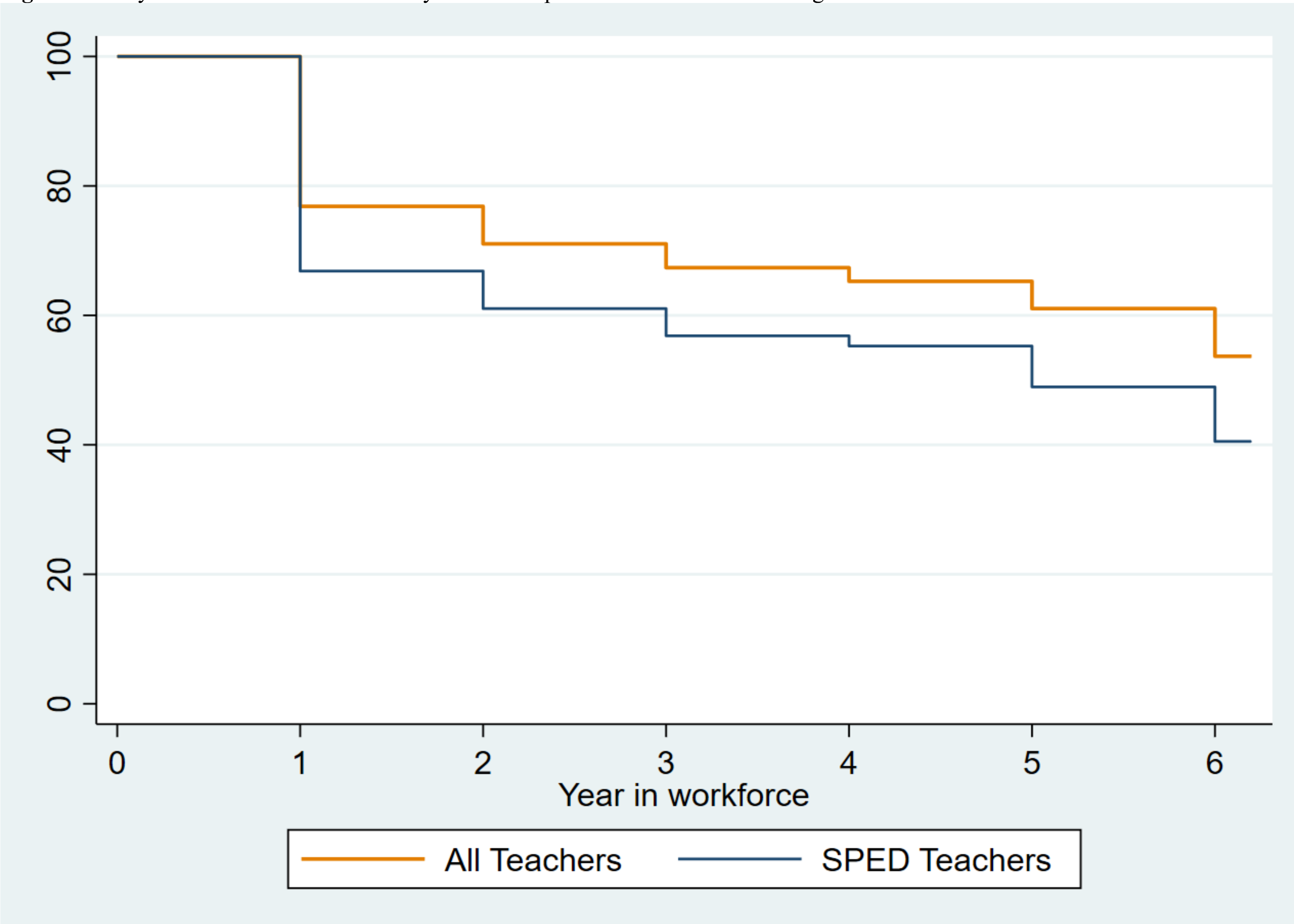
Note. ELEM = elementary endorsement; SPED = special education endorsement.

Figure 5. Three-Year Workforce Entry Rates of Special Education Candidates by Graduating Cohort and Initial Teaching Assignment



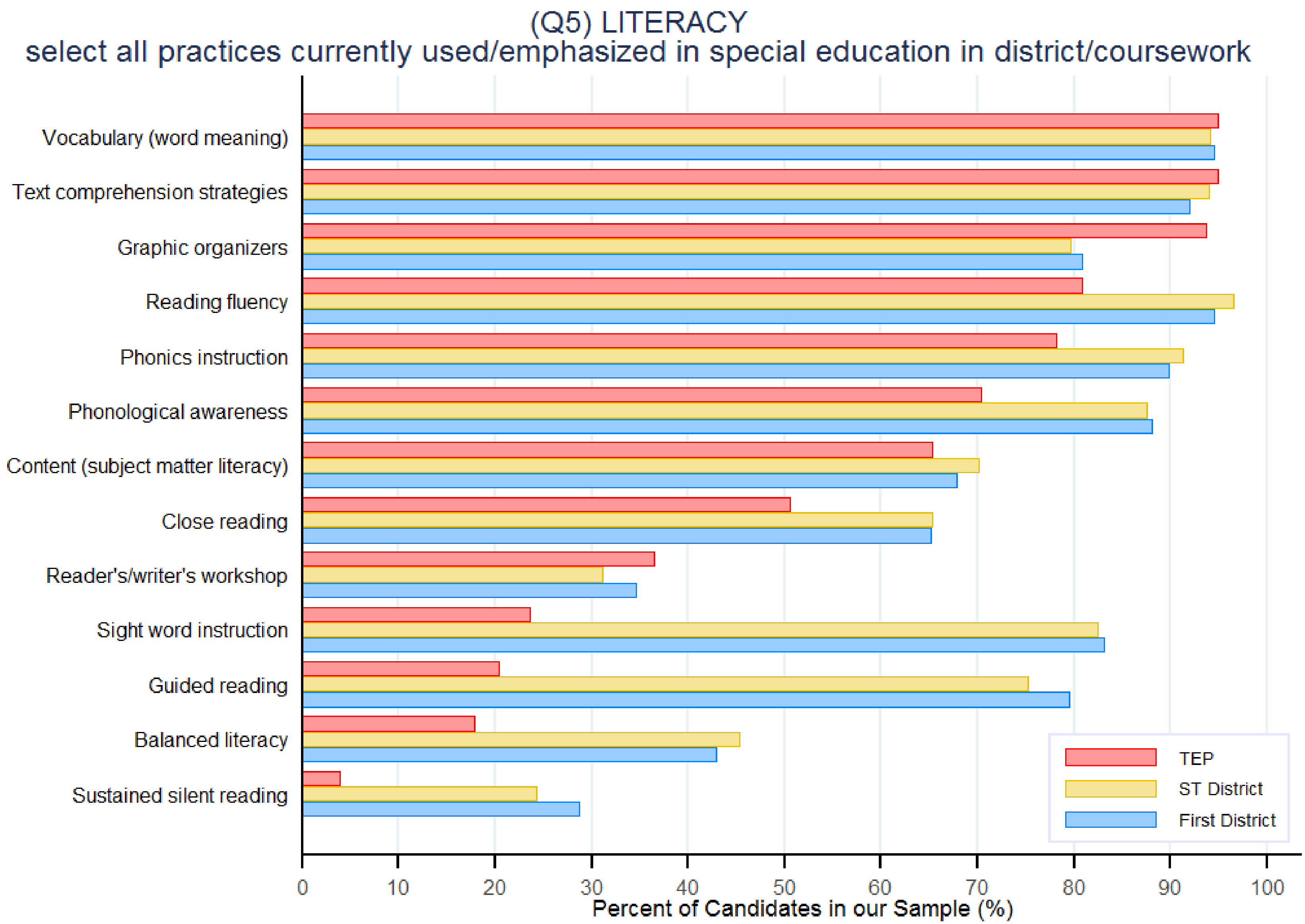
Note. General Ed = general education classroom; SPED = special education classroom.

Figure 6. Entry Rates and Retention Rates by Year of Experience for 2010 Graduating Cohort in TELC Data



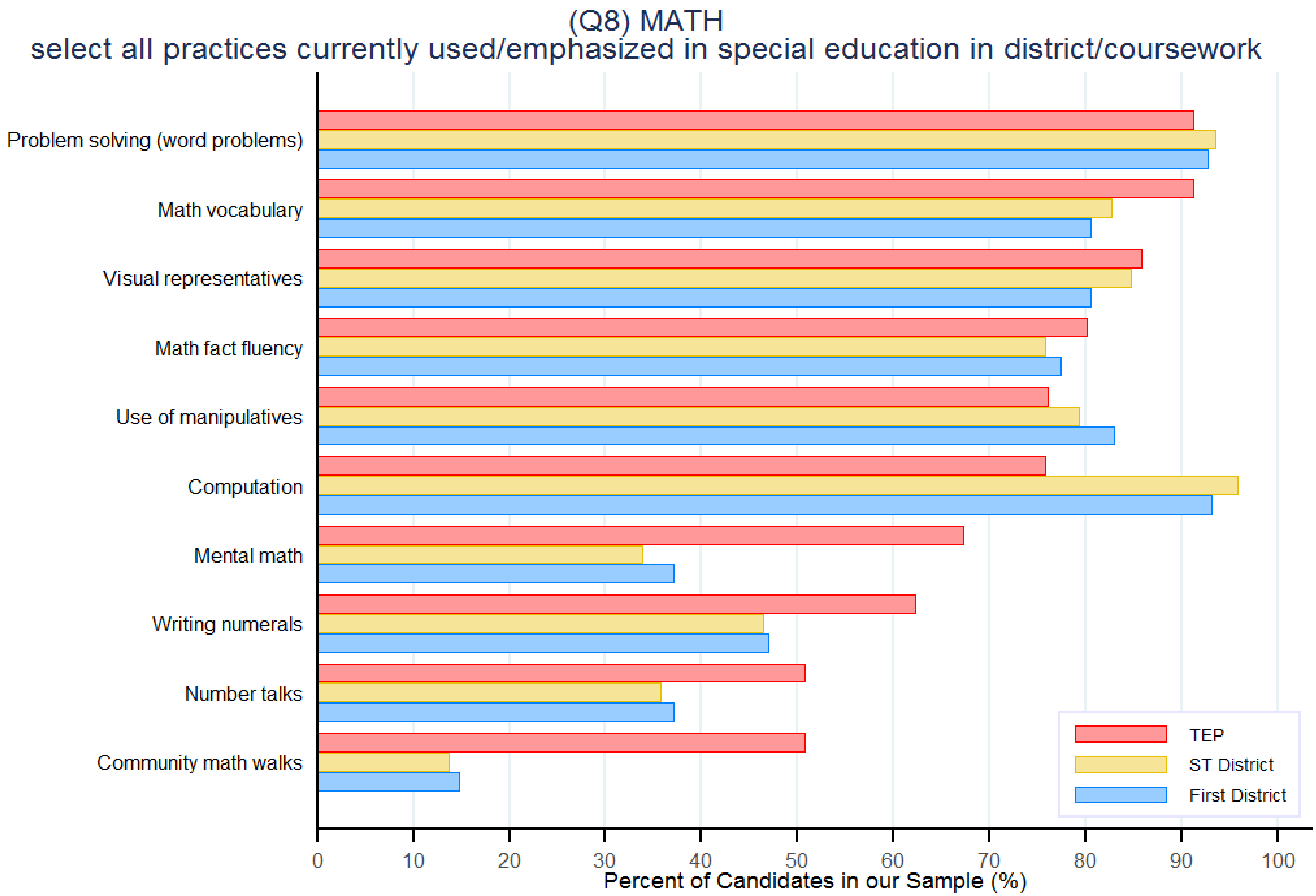
Note. SPED = special education classroom.

Figure 7. Literacy Practices Used/Emphasized by TEPs and Districts



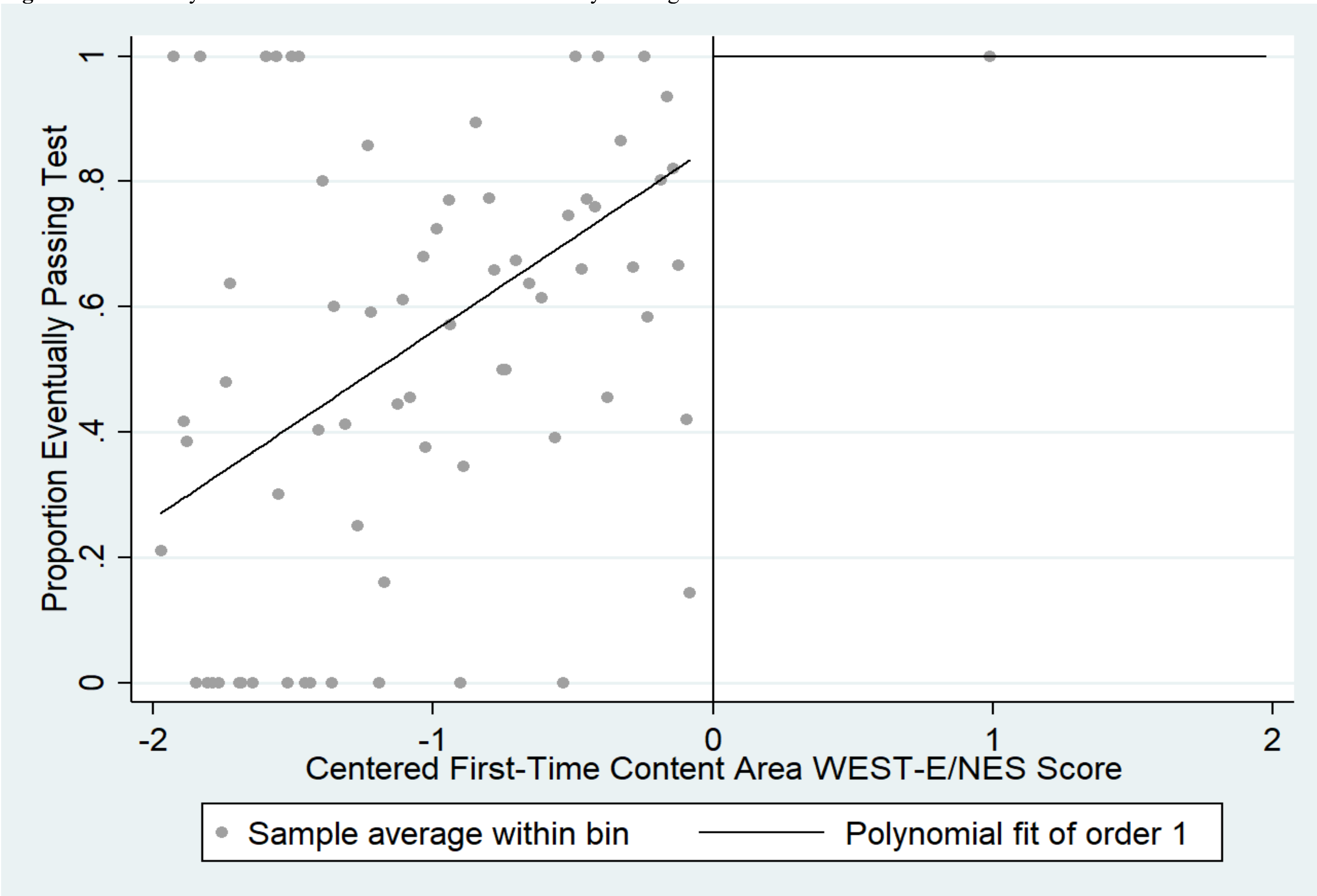
Note. ST = student teaching; TEP = teacher education program.

Figure 8. Math Practices Used/Emphasized by TEPs and Districts



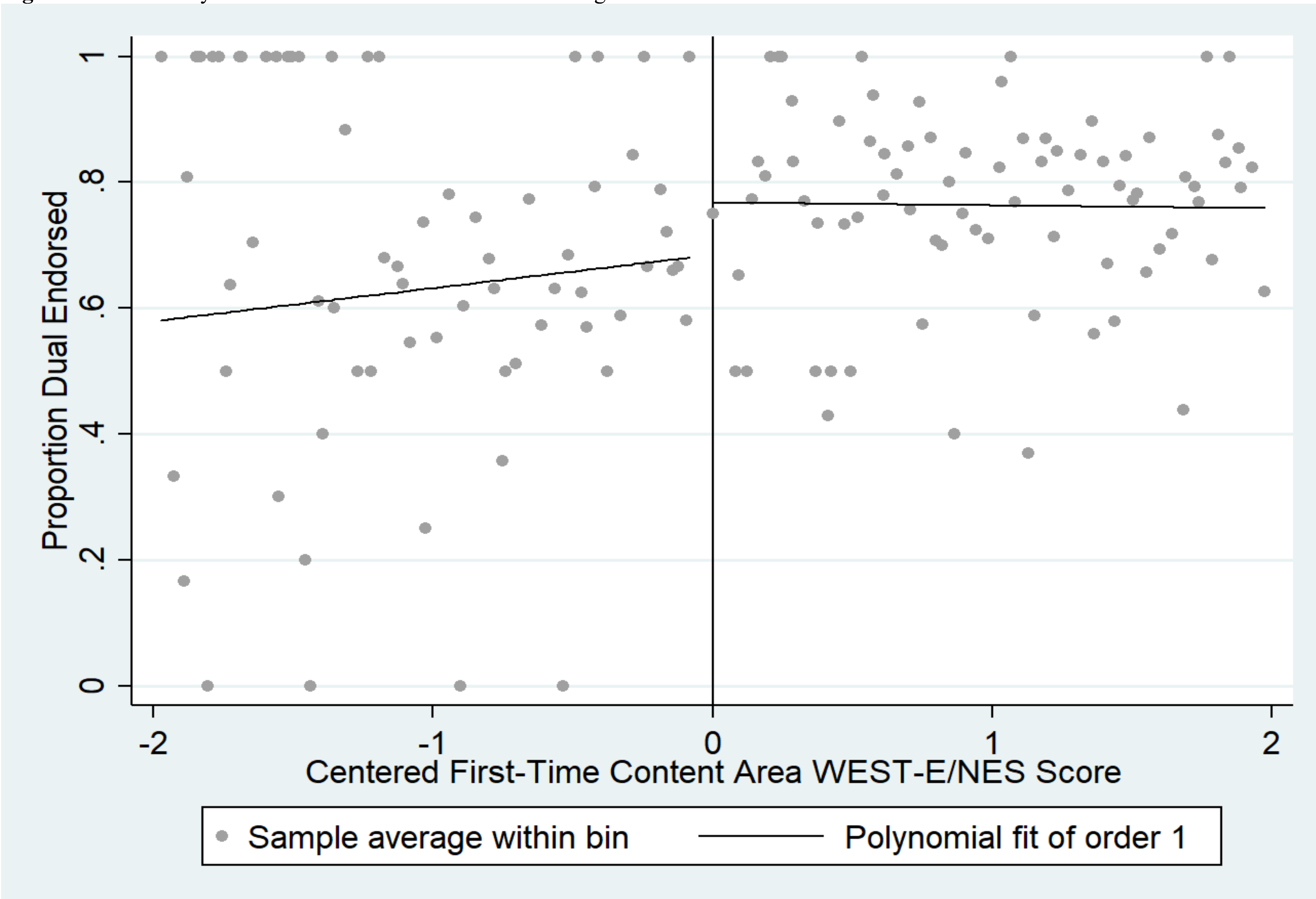
Note. ST = student teaching; TEP = teacher education program.

Figure 9. Probability of SPED-Endorsed Candidates Eventually Passing Content Area WEST-E/NES Test as Function of First Score



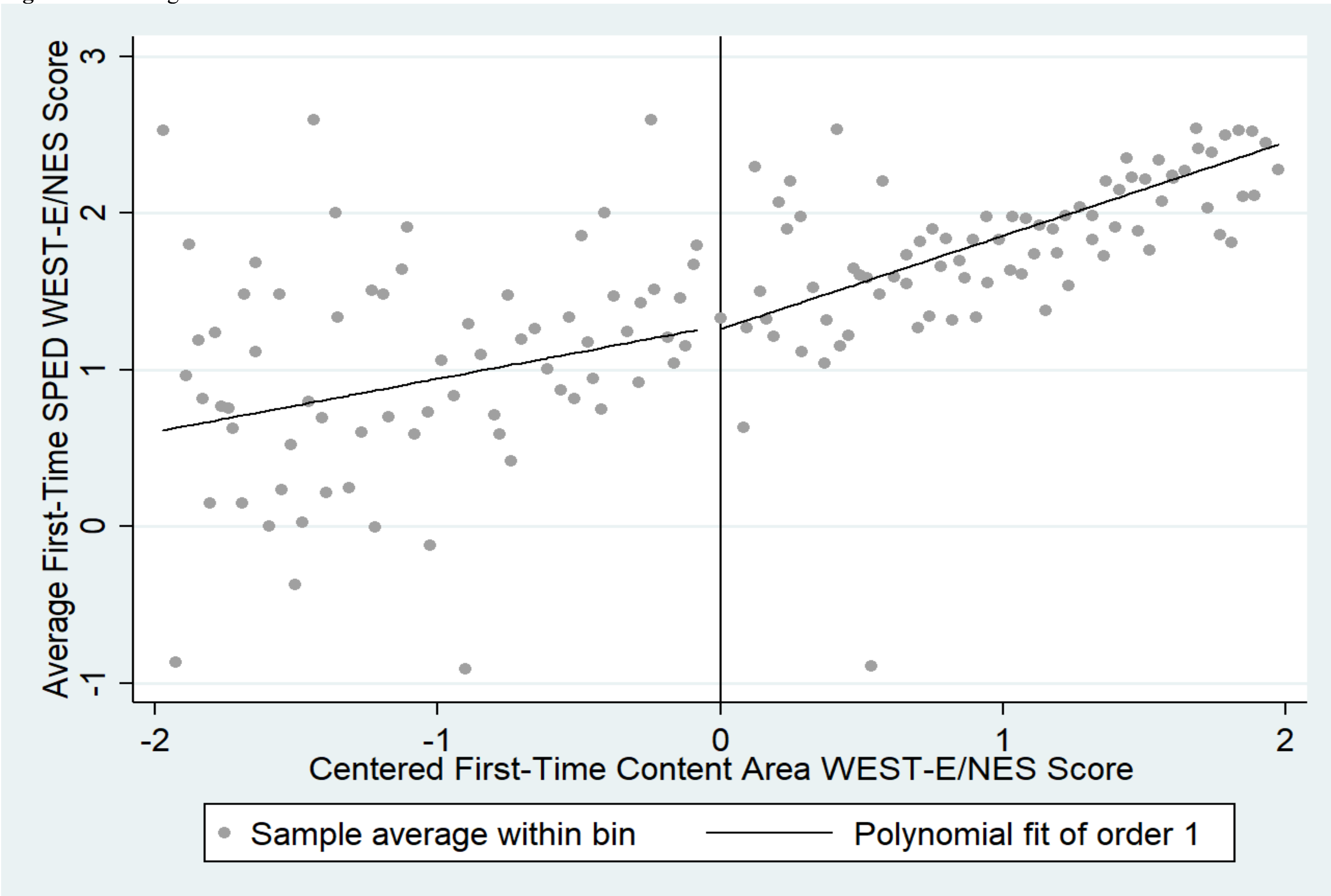
Note. NES = National Evaluation Series; SPED = special education; WEST-E = Washington Educator Skills Test – Endorsement. The passing score for each exam set to zero.

Figure 10. Probability of SPED-Endorsed Candidates Receiving Dual Endorsement as Function of First Content Area WEST-E/NES Score



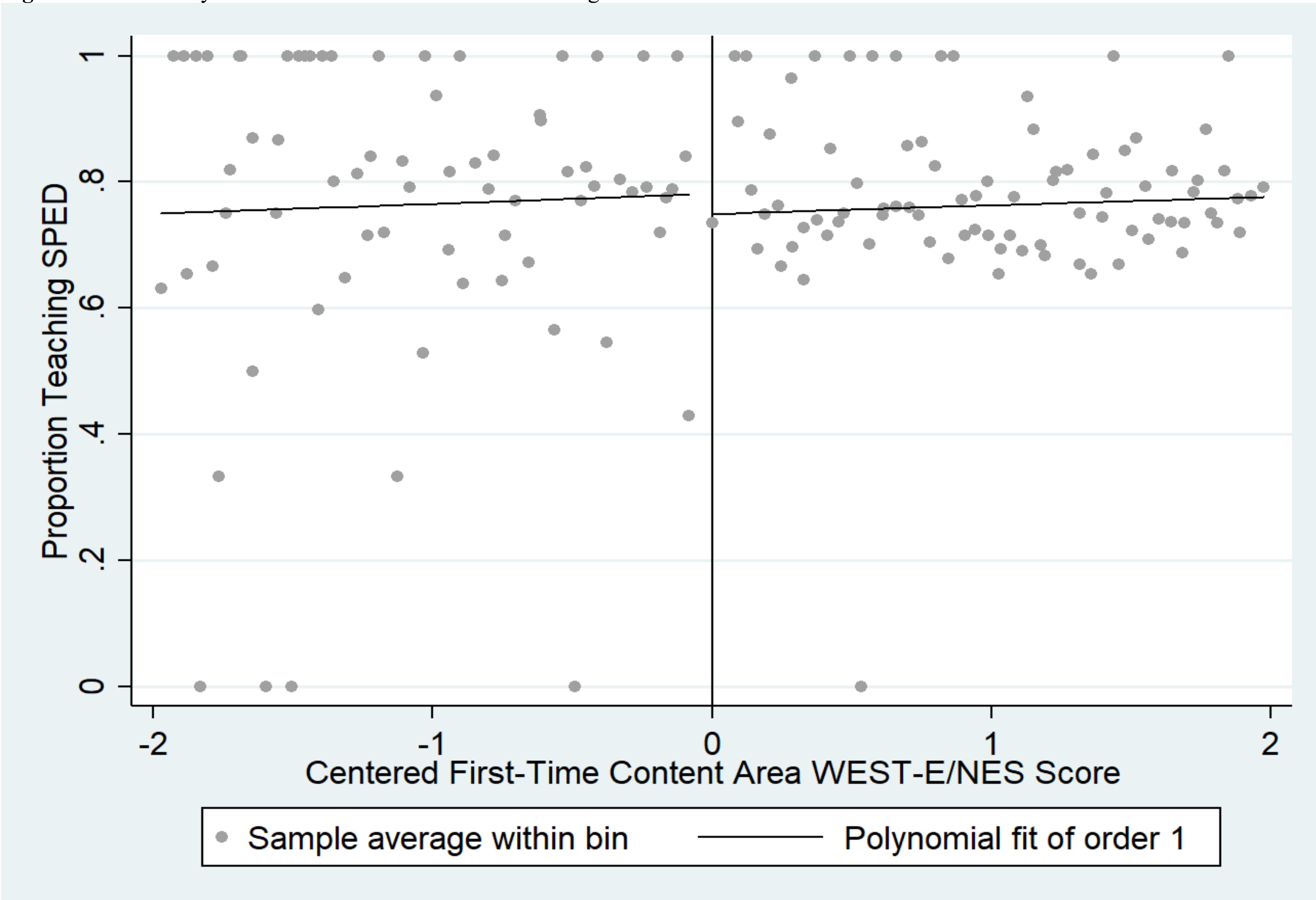
Note. NES = National Evaluation Series; SPED = special education; WEST-E = Washington Educator Skills Test—Endorsement. The passing score for each exam set to zero.

Figure 11. Average SPED WEST-E/NES Score as Function of First Content Area WEST-E/NES Score



Note. NES = National Evaluation Series; SPED = special education; WEST-E = Washington Educator Skills Test—Endorsement. The passing score for each exam set to zero.

Figure 12. Probability of SPED-Endorsed Candidates Teaching in a SPED Classroom as Function of First Content Area WEST-E/NES Score



Note. NES = National Evaluation Series; SPED = special education; WEST-E = Washington Educator Skills Test—Endorsement. The passing score for each exam set to zero.

Table 1. PCA Factors and Factor Loadings

Panel A. Literacy: All practices currently used/emphasized in special education in district/coursework				
	PCA 1 (*Guided and Close Reading*)	PCA 2 (*Fluency and Phonics*)	PCA 3 (*Reading and Writing*)	PCA 4 (*Balanced Literacy*)
Vocabulary (word meaning)	–0.064	**0.540**	0.015	0.072
Text comprehension strategies	0.026	**0.370**	0.185	–0.110
Graphic organizers	**0.468**	–0.065	0.162	0.048
Reading fluency	0.103	**0.491**	–0.026	–0.059
Phonics instruction	–0.090	**0.468**	–0.135	0.123
Phonological awareness	**0.393**	0.281	–0.071	–0.082
Content (subject matter literacy)	–0.076	0.044	0.107	**0.600**
Close reading	**0.405**	–0.144	–0.280	**0.331**
Reader's/writer's workshop	0.069	–0.058	**0.693**	–0.082
Sight word instruction	**0.465**	–0.015	0.119	0.054
Guided reading	**0.452**	0.024	–0.008	–0.215
Balanced literacy	0.061	0.016	–0.048	**0.616**
Sustained silent reading	–0.064	0.049	**0.574**	0.222
Panel B. Math: All practices currently used/emphasized in special education in district/coursework				
	PCA 1 (*Manipulatives and Fact Fluency*)	PCA 2 (*Vocabulary and Visualization*)	PCA 3 (*Number Talks and Walks*)	PCA 4 (*Problem Solving*)
Problem solving (word problems)	0.0331	–0.1183	–0.0266	**0.7777**
Math vocabulary	–0.096	**0.6899**	–0.1401	–0.1325
Visual representatives	–0.0698	**0.4079**	0.2988	0.2925
Math fact fluency	**0.5625**	–0.0338	0.0569	0.0381
Use of manipulatives	**0.6317**	–0.1187	–0.0252	0.0029
Computation	–0.0622	**0.3089**	–0.0278	**0.4499**
Mental math	0.2659	**0.3056**	–0.0798	–0.2007
Writing numerals	**0.3168**	0.1524	**–0.5804**	0.1763
Number talks	0.2593	**0.3394**	**0.3376**	–0.107
Community math walks	0.1649	–0.0345	**0.6547**	0.0727

Note. This table displays factor loadings from Principal Components Analysis (PCA) on questions summarized in Figures 5 and 6, limited to factors with an eigenvalue of at least 1.0. All factors with an absolute value of at least 0.3 are bolded.

Table 2. Teacher Candidate Summary Statistics

	All Candidates	Not Hired	Hired		
			All	General Education Classroom	SPED Classroom
Panel A: Outcome Variables					
Enter workforce	0.890	0.000	1.000	1.000	1.000
Enter SPED classroom	0.708	0.000	0.795	0.000	1.000
Stay in workforce after Year 1			0.931	0.947	0.927
Stay in SPED classroom after Year 1					0.877
Panel B: Variables of Interest					
Master's degree			0.291	0.134	0.332
Dual endorsed	0.717	0.676	0.722	0.927	0.669
ST SPED classroom	0.677	0.709	0.673	0.567	0.701
CT SPED endorsement	0.631	0.682	0.625	0.474	0.664
CT master's degree	0.720	0.730	0.719	0.733	0.715
CT experience	13.673 (8.603)	14.505 (8.695)	13.570 (8.589)	13.407 (8.280)	13.612 (8.672)
Panel C: Survey-Based Alignment Measures					
TEP-job overall alignment			0.000 (1.000)	0.217 (0.928)	–0.054 (1.010)
TEP-ST overall alignment	0.000 (1.000)	0.179 (0.952)	–0.022 (1.004)	0.241 (0.892)	–0.086 (1.020)
ST-job overall alignment			0.000 (1.000)	–0.023 (1.026)	0.006 (0.994)
Observations	1,351	148	1,203	247	956

Note. CT = cooperating teacher; SPED = special education; ST = student teaching; TEP = teacher education program; VA = value added.

Table 3. Workforce Entry Models (marginal effects from logit models)

	(1)	(2)	(3)	(4)
Dual endorsed	0.020 (0.020)	0.023 (0.021)	0.015 (0.022)	0.009 (0.023)
ST SPED classroom	0.001 (0.027)	0.001 (0.028)	–0.005 (0.028)	–0.002 (0.029)
CT SPED endorsement	–0.012 (0.026)	–0.013 (0.027)	0.004 (0.027)	0.004 (0.028)
CT master's degree	–0.003 (0.019)	–0.002 (0.021)	–0.002 (0.019)	0.002 (0.021)
CT experience	–0.001 (0.001)	–0.002 (0.001)	–0.001 (0.001)	–0.002 (0.001)
TEP-ST overall alignment		–0.013 (0.010)		0.002 (0.016)
Institution FE			X	X
Sample	Full	Survey	Full	Survey
Observations	1,284	1,104	1,282	1,102

Note. CT = cooperating teacher; FE = fixed effect; ST = student teaching; TEP = teacher education program. All models control for internship year and internship school characteristics.
**p* < .05. ***p* < .01. ****p* < .001. Probability values are from a two-sided *t* test.

Table 4. SPED Classroom Entry Models (marginal effects from logit models, conditional on entry)

	(1)	(2)	(3)	(4)
Master's degree	0.091** (0.031)	0.070* (0.033)	0.029 (0.035)	0.005 (0.037)
Dual endorsed	-0.219*** (0.039)	-0.221*** (0.042)	-0.177*** (0.039)	-0.182*** (0.042)
ST SPED classroom	-0.047 (0.033)	-0.065 (0.034)	-0.025 (0.032)	-0.040 (0.034)
CT SPED endorsement	0.125*** (0.031)	0.147*** (0.033)	0.102** (0.032)	0.126*** (0.034)
CT master's degree	-0.020 (0.025)	-0.042 (0.028)	-0.031 (0.025)	-0.051 (0.027)
CT experience	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
TEP-ST overall alignment		-0.028* (0.013)		0.006 (0.022)
Institution FE			X	X
Sample	Full	Survey	Full	Survey
Observations	1,154	992	1,152	990

Note. CT = cooperating teacher; FE = fixed effect; ST = student teaching; TEP = teacher education program. All models control for internship year and internship school characteristics.
*$p < .05$. **$p < .01$. ***$p < .001$. Probability values are from a two-sided t test.

Table 5. Workforce Retention Models (marginal effects from discrete-time logit models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Master's degree	–0.001 (0.010)	–0.005 (0.011)	0.014 (0.011)	0.009 (0.013)	–0.001 (0.012)	–0.003 (0.013)	0.016 (0.013)	0.013 (0.015)
Dual endorsed	0.014 (0.010)	0.020 (0.012)	0.005 (0.012)	0.016 (0.014)	0.010 (0.012)	0.017 (0.014)	0.006 (0.014)	0.020 (0.016)
ST SPED classroom	–0.002 (0.013)	–0.001 (0.015)	–0.003 (0.013)	–0.001 (0.015)	–0.013 (0.016)	–0.016 (0.019)	–0.014 (0.017)	–0.017 (0.020)
CT SPED endorsement	0.002 (0.013)	0.004 (0.015)	–0.002 (0.013)	–0.002 (0.015)	0.006 (0.016)	0.011 (0.019)	0.004 (0.016)	0.011 (0.019)
CT master's degree	0.008 (0.010)	0.009 (0.011)	0.008 (0.010)	0.009 (0.012)	0.013 (0.011)	0.015 (0.013)	0.015 (0.012)	0.017 (0.013)
CT experience	0.000 (0.000)	0.001 (0.001)	0.000 (0.000)	0.001 (0.001)	0.001* (0.001)	0.001* (0.001)	0.001* (0.001)	0.001* (0.001)
TEP-job overall alignment		0.004 (0.010)		0.006 (0.011)		–0.007 (0.013)		–0.009 (0.022)
TEP-ST overall alignment		0.002 (0.009)		0.002 (0.014)		0.011 (0.012)		0.006 (0.015)
ST-job overall alignment		0.004 (0.005)		0.004 (0.005)		0.008 (0.007)		0.009 (0.007)
Institution FE			X	X			X	X
District FE					X	X	X	X
Sample	Full	Survey	Full	Survey	Full	Survey	Full	Survey
Observations	3,758	2,921	3,748	2,911	3,353	2,673	3,343	2,663

Note. CT = cooperating teacher; FE = fixed effect; ST = student teaching; TEP = teacher education program. All models control for internship year, internship school characteristics, experience indicators, current school characteristics, and special education classroom placement. Standard errors are clustered at the teacher level.

**p* < .05. ***p* < .01. ****p* < .001. Probability values are from a two-sided *t* test.

Table 6. SPED Classroom Retention Models (marginal effects from discrete-time logit models, conditional on staying in the workforce)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Master's degree	0.003 (0.010)	–0.001 (0.012)	0.003 (0.013)	0.003 (0.015)	0.003 (0.011)	–0.003 (0.013)	–0.001 (0.013)	–0.001 (0.014)
Dual endorsed	–0.051** (0.014)	–0.061** (0.017)	–0.054** (0.015)	–0.068** (0.018)	–0.043** (0.011)	–0.048** (0.013)	–0.047** (0.012)	–0.058** (0.014)
ST SPED classroom	0.019 (0.013)	0.018 (0.014)	0.021 (0.013)	0.020 (0.014)	0.030 (0.017)	0.030 (0.019)	0.035† (0.017)	0.035 (0.019)
CT SPED endorsement	–0.006 (0.013)	0.000 (0.014)	–0.006 (0.013)	–0.001 (0.015)	–0.013 (0.016)	–0.007 (0.018)	–0.010 (0.016)	–0.005 (0.018)
CT master's degree	–0.005 (0.009)	–0.007 (0.011)	–0.005 (0.009)	–0.006 (0.011)	–0.009 (0.010)	–0.013 (0.012)	–0.009 (0.010)	–0.013 (0.012)
CT experience	0.000 (0.000)	–0.001 (0.001)	0.000 (0.000)	–0.001 (0.001)	–0.001 (0.001)	–0.001* (0.001)	–0.001 (0.001)	–0.002* (0.001)
TEP-job overall alignment		0.006 (0.012)		0.009 (0.013)		–0.004 (0.013)		0.002 (0.016)
TEP-ST overall alignment		–0.015 (0.013)		–0.009 (0.015)		–0.006 (0.013)		–0.009 (0.015)
ST-job overall alignment		0.000 (0.006)		–0.002 (0.007)		–0.003 (0.007)		–0.005 (0.007)
Institution FE			X	X			X	X
District FE					X	X	X	X
Sample	Full	Survey	Full	Survey	Full	Survey	Full	Survey
Observations	2,747	2,127	2,721	2,117	2,747	2,127	2,747	2,127

Note. CT = cooperating teacher; FE = fixed effect; ST = student teaching; TEP = teacher education program. All models control for internship year, internship school characteristics, experience indicators, current school characteristics, and special education classroom placement. Standard errors are clustered at the teacher level.
**p* < .05. ***p* < .01. ****p* < .001. Probability values are from a two-sided *t* test.

Table 7. Relationships Between Dual Endorsement and SPED Classroom Assignment by Sample and Model (marginal effects from Probit models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dual endorsed	–0.390*** (0.010)	–0.334*** (0.023	–0.267*** (0.017)	–0.269*** (0.038)	–0.255*** (0.019)		–0.435* (0.209)
WEST-E/NES passing score						.080** (0.030)	
Sample	All SPED	TELC	WEST-E	WEST-E and TELC	WEST-E	WEST-E	
WEST-E/NES controls	No	No	No	No	Yes	Yes	
Model	Probit	Probit	Probit	Probit	Probit	IV Probit	
Stage	n/a	n/a	n/a	n/a	n/a	First	Second
Unique teachers	12,413	2,393	2,904	1,390	2,904	2,904	2,904

Note. IV = instrumental variable; NES = National Evaluation Series; SPED = special education; TELC = Teacher Education Learning Collaborative; WEST-E = Washington Educator Skills Test—Endorsement. All models control for candidate degree level, gender, test type, test year, and school year. WEST-E/NES controls include a centered WEST-E/NES score interacted with a WEST-E/NES passing score. Standard errors are clustered at the teacher level.

**p* < .05. ***p* < .01. ****p* < .001. Probability values are from a two-sided *t* test.