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Special Education Teacher Preparation, Literacy Instructional Alignment, and Reading Achievement for Students with High-Incidence Disabilities

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Abstract

We used survey and administrative data from Washington State to assess the degree to which special education teacher preparation, district literacy instructional practices, and the alignment between preparation and practice were associated with the reading test score gains of students with high-incidence disabilities taught by early-career special education teachers in grades 4-8. These students tended to have larger reading gains when their district emphasized evidence-based literacy decoding practices (e.g., phonological awareness, phonics, and reading fluency) and when their special education teacher graduated from a teacher education program that also emphasized these practices. Students with high-incidence disabilities in districts that emphasized balanced literacy practices tended to have lower reading gains. Finally, students with high-incidence disabilities taught by early-career special education teachers tended to have larger reading gains when their teacher's student teaching placement was supervised by a more experienced cooperating teacher.

1. Introduction

A significant body of quantitative research demonstrates that teachers are the most important schooling factor in predicting a student's academic success (e.g., Rivkin et al., 2005). Notably, far fewer studies have investigated the influence of special education teachers on the outcomes of students with disabilities (e.g., Feng & Sass, 2013; Gilmour, 2019; Theobald, Goldhaber, Gratz, & Holden, 2021). Considerable prior research has emphasized the importance of special education teacher preparation (e.g., Brownell et al., 2005, 2010), particularly as it relates to subject expertise (e.g., Brownell et al., 2009), pedagogical skills (e.g., Leko et al., 2012), and high-leverage practices (e.g., Billingsley et al., 2019). However, several recent reviews have noted that no large-scale empirical evidence connects *specific features* of special education teachers' preparation to the achievement of students with disabilities in their classrooms (Brownell et al., 2020; Sindelar et al., 2010).

In response to this lack of empirical evidence, Brownell et al. (2020) recommended that future research on special education teacher preparation should "leverage preparation program and existing state data to better understand the characteristics of effective teacher education experiences," as measured by their "eventual performance once they transition to their first teaching jobs" (p. 39). The current study follows this recommendation by connecting literacy instructional practices taught in special education teacher education programs (TEPs) and/or emphasized by K–12 districts in special education instruction to the test achievement of students with high-incidence disabilities in English language arts (ELA).

Our analysis was made possible by a unique data set from Washington State that combines information about preservice teacher candidate experiences provided by 13 special education teacher education programs (TEPs) with data on K–12 teachers and their students provided by the Washington State Office of the Superintendent of Public Instruction (OSPI). We combined this data set with novel survey data on the literacy instructional practices taught in special education TEPs (as reported by teacher preparation faculty) and the instructional practices emphasized in special education instruction (as reported by district special education directors in the state). This data collection allowed us to create a longitudinal data set that tracks specific special education teacher candidates from their TEPs to their student teaching placements and into specific special education placements in the state's K–12 public schools.

We used this data set to contribute to three different lines of research. First, prior research has linked some broad measures of special educators' preservice experiences to outcomes for students with disabilities (Feng & Sass, 2013; Gilmour, 2019; Theobald, Goldhaber, Gratz, & Holden, 2021). For example, Feng and Sass (2013) found that teachers who were certified to teach special education, who majored in special education, and who took more special education coursework were more effective in terms of improving the achievement of students with disabilities in reading. A growing body of literature that is *not specific to special education* has also investigated the relationship between more specific measures of teacher preparation—such as the student teaching experiences of teacher candidates—and the achievement of their students once they enter the workforce (e.g., Boyd et al., 2009; Goldhaber et al., 2017, 2020; Ronfeldt, 2012, 2015; Ronfeldt et al., 2018). For example, Goldhaber et al. (2020) and Ronfeldt et al. (2018) found that candidates who were supervised by a more effective cooperating teacher during student teaching tended to be more effective once they entered the teaching workforce. However, we are not aware of prior research that has considered similarly specific measures of *special educators'* student teaching experiences as predictors of their later effectiveness. We therefore investigated whether the specific measures of preservice preparation in our data set (e.g., cooperating teacher characteristics) predicted ELA achievement for students with high-incidence disabilities taught by early-career special education teachers.

Second, debates about the best way to teach reading—dubbed the "reading wars" (Pearson, 2004)—have raged for decades. These debates have historically pitted proponents of phonics-based approaches (e.g., Chall, 1967) against those who advocate for language-based approaches (e.g., Goodman, 1967). To provide a more recent example, a special report on "Getting Reading Right" (Education Week, 2019) focused on the disconnect between the science and practice of reading instruction. The report concluded that the way in which reading is typically taught to early and struggling readers does not reflect "a settled body of research on how best to teach early reading" (Schwartz, 2019, p. 1). Recognizing this perceived disconnect between science and practice, we decided to investigate the extent to which the literacy instructional approaches emphasized by districts and TEPs predicted ELA achievement for students with high-incidence disabilities in Washington State.

Finally, a considerable body of theoretical and qualitative work has argued that the alignment or "coherence" between a teacher candidate's education experiences and inservice practice is important (e.g., Darling-Hammond, 2000; Darling-Hammond et al., 2005; Feiman-Nemser & Buchmann, 1983; Grossman et al., 2008; Powell, 2015). These studies are bolstered by a small body of quantitative literature that suggests that alignment between preparation and practice may have important implications for teacher and student outcomes (e.g., Boyd et al., 2009; Goldhaber et al., 2017; Krieg et al., in press), although none of these papers contain a specific focus on special education teachers. We are not aware of descriptive information about the alignment between what is taught to special educators in their TEPs and what is asked of them once they become special education teachers, and the quantitative literature does not address *why* the alignment between a candidate's student teaching experiences and early-career teaching experiences might matter for teacher and student outcomes. We therefore used the TEP and district survey data to investigate the extent to which the literacy instructional practices emphasized in special education TEPs and K–12 districts were aligned, and whether this alignment predicted the ELA achievement of students with high-incidence disabilities taught by special education teachers.

In summary, this study addressed four primary research questions (RQs), represented graphically in the conceptual framework in **Figure 1**:

1. To what extent do specific measures of preservice preparation (e.g., student teaching placements, credentials, and licensure test scores) predict ELA achievement for students with high-incidence disabilities taught by early-career special education teachers?
2. To what extent do the instructional approaches emphasized by districts and TEPs predict ELA achievement for students with high-incidence disabilities taught by early-career special education teachers?
3. To what extent is there alignment between the literacy instructional practices emphasized in special education teacher education programs and K–12 special education settings?
4. To what extent does this alignment predict ELA achievement of students with high-incidence disabilities taught by special education teachers?

2. Data and Methods

2.1 Data

We combined data from three sources for this study: data on teacher candidates collected from the TEPs participating in the Teacher Education Learning Collaborative (TELC),[1] data collected through surveys of special education TEP faculty and district special education directors in Washington State, and data on K–12 students and teachers provided by OSPI.

TELC Data

The broader TELC data set includes information from 15 of the state's 21 college- and university-based TEPs that were licensed to credential teachers during the years we studied, 13 of which had special education endorsement programs. The data provided by these programs included information about teacher candidates themselves (e.g., race and gender) as well as data about when student teaching occurred, the schools and districts in which teacher candidates completed their student teaching, and the cooperating teachers who supervised their internships. Though many of the institutions in TELC provided student teaching data going back to the mid-2000s (and in one case, to the late 1990s), we focused on student teaching data from 2009–10 to 2017–18 in this analysis because—as described in the section on OSPI data—we were able to link cooperating teacher information from these years to the students they taught, and use these as a proxy for the students candidates taught during their student teaching placement. Moreover, focusing on these more recent years of data made it more plausible that TEP faculty survey

[1] TELC is a consortium of 15 TEPs providing data on student teaching experiences. The institutions that are participating in TELC and 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 large (for Washington State) 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).

responses (described in the next section) would represent the instruction provided to all candidates in the sample. Following the work of Theobald, Goldhaber, Naito, and Stein (2021), this analysis focused on graduates of special education endorsement programs at these 13 institutions (defined as graduating from one of these institutions with a special education endorsement).

Survey Data

We designed and administered surveys to special education faculty from the 13 TELC institutions with special education endorsement programs, and we administered parallel surveys to special education directors of school districts in the state. The surveys were developed in collaboration with a team of special education TEP faculty and former special education district administrators. Questions were primarily derived from the Council for Exceptional Children's Initial Level Special Educator Preparation Standards, but we also consulted an advisory board of additional TEP and district personnel to determine instructional practices that are currently emphasized *for use with students with high-incidence disabilities* in TEP coursework and school districts.

The surveys were initially piloted with out-of-state contacts during the 2017–18 school year and were then administered during the 2018–19 school year. Faculty surveys were administered by e-mail to contacts within special education TEPs. Importantly, respondents could opt out of *any question* and could provide contact information for another faculty member better suited to answer a specific question. The final response rate across all questions in this survey and the 13 TEPs was 100%. District surveys were administered by project staff in person at meetings of special education district directors in the nine education service districts in the state. Unlike the faculty survey, directors were required to respond to all questions in the survey (though in many cases, they completed the survey in consultation with other district administrators who were attending the meeting). We received complete district responses for 82% of the candidates in the analytic sample.

Though tangential to the primary analysis, we highlight one question from these surveys that provides additional motivation for this study (**Figure 2**). Specifically, the TEP surveys asked faculty about their perceptions of the extent to which their TEP graduates were prepared, on average, to perform a number of tasks required of special education teachers (e.g., supervise paraeducators and address challenging behaviors), while the district surveys asked directors the same question about their incoming special education teachers. As shown in Figure 2, special education TEP faculty members' perceptions of the preparedness of their graduates were dramatically higher than directors' perceptions of the preparedness of incoming special education teachers. While perhaps not surprising, this finding provides some additional motivation for our focus on alignment in this analysis, given that one possible explanation for these divergent perceptions is that early-career special education teachers are being asked to do something different from what they were taught in their TEPs.

Although the survey contained additional questions addressing necessary knowledge and skills—such as classroom management and preparing individualized education programs—for the purposes of this analysis, we primarily focused on one question that asked faculty and directors to select all *literacy* instructional practices for students with high-incidence disabilities that were emphasized or used in their TEP or district. Because this question included a relatively large number of potential responses, we performed a factor analysis across TEP and district survey responses to identify combinations of practices that tended to "go together," and to reduce the dimensionality of the data. **Table 1** summarizes the results of this analysis, which identified three principal components with an eigenvalue of at least 1.0 (i.e., that explain more variation than the average principal component).[2] We labeled the three principal components "Phonics, Fluency, and Comprehension," "Guided and Close Reading," 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). Interestingly, the five practices that load onto the first factor—text comprehension, phonemic awareness, vocabulary, fluency, and phonics—are the five literacy instructional areas identified as evidence based by the National Reading Panel (2000) and in follow-up research (e.g., Castles et al., 2018). We used the factor loadings in Table 1 to create measures of the extent to which each *individual special education teacher's* district and TEP emphasized the practices within each factor.

OSPI Data

We merged the TELC and survey data with several sources of data on K–12 students and teachers maintained by OSPI. First, the state's S-275 database provides annual employment information for all public school employees in the state. We used this data set to identify individuals in public school teaching positions, teachers who had a master's degree or higher, and teachers who were hired into the same district in which they student taught. Second, the S-275 database 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), teaching endorsements (i.e., the subject areas teachers are endorsed to teach), and licensure test scores in the state. We used this database to identify whether candidates and their cooperating teachers held an endorsement in special education, another subject, or both; and to measure candidates' performance on the state's Washington Educator Skills Test – Basic (WEST-B) in mathematics, reading, and writing.

[2] The scree plot in Appendix Figure A1 also suggests that there is a "kink" in these eigenvalues after the third eigenvector, which suggests keeping three principal components in each subject.

Finally, for 2009–10 through 2018–19 (the most recent year of available data), these databases can be connected to the state's Comprehensive Education Data and Research System (CEDARS), which allowed us to connect candidates both to the students they taught in their student teaching (i.e., in their cooperating teacher's classrooms) and to the students they taught once they entered the workforce.[3] The CEDARS database also allowed us to identify special education teachers, which (following Theobald, Goldhaber, Naito, & Stein, 2021) we defined as teachers in classroom assignments in which at least 50% of students were receiving special education services. The 50% cutoff is relatively arbitrary, but as the density distribution in **Figure 3** shows, the classification of special education teachers was not terribly sensitive to the chosen cutoff as students with disabilities account for less than 40% or more than 90% of students in the majority of classrooms in the state.

The CEDARS database also allowed us to connect these special education teachers to the test performance of students they taught. Students in Washington State take standardized tests each year in mathematics and ELA for Grades 3–8; we standardized these scores across all students in the state by grade and year and only considered ELA test scores for students who took a test aligned with their current grade level. Because our analytic approach (described later) required both current and prior student test scores, our sample of teachers included special education teachers who provided ELA instruction to students with high-incidence disabilities in Grades 4–8. The data also included student demographic information such as gender, race/ethnicity, and program participation. Most importantly for this analysis, the data allowed us

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

to focus on students with high-incidence disabilities, which we defined as students with an emotional/behavioral disorder, health impairment, or specific learning disability.[4]

2.2 Samples, Measures, and Summary Statistics

Table 2 provides summary statistics for all variables of interest across both of the samples considered in this analysis. We observed 285 special education teachers (accounting for 600 teacher-year observations) who appeared in the TELC data and provided ELA instruction to students with high-incidence disabilities. Of these, 243 teachers (and 506 teacher-year observations) were linked to survey responses from their TEP and district about the literacy instructional practices emphasized in each. Column 1 of Table 2 summarizes the 10 variables of interest that were observed for all of these teachers. About two thirds of teachers in this sample had a dual endorsement in special education and another subject, while slightly less than half had at least a master's degree. Teachers in this sample tended to score slightly higher on the WEST-B mathematics test than the reading and writing tests.

Turning to the student teaching variables, about 40% of the special education teachers were teaching in the same district in which they student taught; this is comparable to estimates for all teachers in Washington State reported in Krieg et al. (in press). About 60% of special education teachers in each sample did their culminating student teaching placement in special education, while about 70% student taught with a teacher who had a special education endorsement. Finally, when we considered the characteristics of candidates' cooperating teachers, we found that about 75% were supervised by a cooperating teacher with a master's degree, and that candidates' cooperating teachers had 13 years of teaching experience on average. We then calculated summary statistics for these same measures and the principal

[4] Summary statistics of these variables are provided in Appendix Table A1.

component analyses (PCAs) derived from the TEP and district survey data for the subset of candidates who were linked to these survey data (column 2 of Table 2).

2.3 Analytic Approach

Our research questions connect the variables of interest in Table 2, measured for special education teachers in these samples, to the ELA achievement of students with high-incidence disabilities taught by these teachers. We performed these analyses in two steps. First, we estimated first-stage "value-added" models (VAMs) *across the full sample of special education teachers who provided ELA instruction to students with high-incidence disabilities in the state*. These models attributed student test score gains to specific teachers. We then used the resulting value-added estimates as the outcome variable in second-stage models that used the variables of interest described above to predict value added *only within the samples in which we observed these variables.* One advantage of this approach is that we used the largest sample possible to remove variation due to student characteristics and prior test scores, classroom composition, and teacher experience that could confound our estimates.

First-Stage Value-Added Models

To investigate the performance of students with high-incidence disabilities in ELA, we estimated VAMs that have been shown to produce unbiased estimates of the contributions of individual teachers to student test performance (e.g., Chetty et al., 2014) but are only rarely applied to special education teachers (e.g., Feng & Sass, 2013). One challenge unique to the special education context is that about 40% of students with high-incidence disabilities who receive ELA instruction from special education teachers also receive ELA instruction from a general education teacher. We therefore followed Chetty et al. (2014) and calculated the ELA value added of all general education teachers in the state (omitting the year each student in the sample was in these teachers' classrooms) and included the general education teacher's value added as an additional predictor of the performance of students with high-incidence disabilities taught by special education teachers.[5]

In addition to the general education teacher value added, the first-stage models controlled for lagged student achievement, other student and classroom covariates that are correlated with student ELA test performance, and a teacher fixed effect that captures a teacher's contributions to student test score gains:

$$Y_{ijkt} = \alpha_0 + \alpha_1 Y_{i(t-1)} + \alpha_2 X_{it} + \alpha_3 \bar{X}_{kt} + \alpha_4 T_{jt} + \alpha_5 \hat{\tau}_{(-t)} + \tau_{jt} + \varepsilon_{ijkt} \quad (1)$$

In (1), Y_{ijkst} is the ELA state test score for each student *i* with teacher *j* in classroom k and year *t,* normalized within grade and year; while $Y_{i(t-1)}$ is a cubic of the student's scores the previous year in both mathematics and ELA, also normalized within grade and year and interacted by grade level. Student covariates in year *t,* X_{it}, include student attributes typically included in VAMs (gender, race, eligibility for free or reduced-price lunch, English learner status); student disability type; and indicators for whether the student only received ELA instruction from a special education teacher, the level of inclusion in special education as captured by the student's least restrictive environment designations, and whether the student was taught mathematics by the same teacher. These variables have all been shown to be important in prior work on outcomes for students with disabilities (Buzick & Jones, 2015; Feng & Sass, 2013; Lai et al., 2020; Theobald et al., 2019). We also controlled for classroom means of these variables, $\bar{X}_{kt}$, and teacher experience in year *t,* T_{js}, which we categorized using the same experience ranges used in Feng and Sass (2013). $\hat{\tau}_{(-t)}$ is the value added of the student's general education teacher in ELA,

[5] We also included an indicator for whether each student had a general education teacher in the model. This served as a *de facto* missing value dummy for general education teacher value added. See Backes et al. (2018) for details on this value-added model.

calculated from all years other than year *t.* Finally, the fixed effect τ_{jt} is the value added of special education teacher *j* in year *t,* which can be interpreted as the expected difference between the average ELA achievement of students taught by a given special education teacher and how those students were *predicted* to score based on other variables in the model.

Because this is one of the first studies to estimate teacher value added just for special education teachers, we present a subset of the estimates from model 1 in **Table 3** and plot the distribution of estimated teacher value added from these models in **Figure 4.** The coefficients on the student variables in Table 3 are generally consistent with student growth models estimated for general education teachers in Washington State (e.g., Goldhaber et al., 2020). Of the variables unique to this study, we found that students receiving ELA instruction only from special education teachers scored about 3% of a standard deviation lower (all else equal) than students who also received ELA instruction from a general education teacher. Students with health impairments and with a specific learning disability scored considerably lower than students with an emotional/behavioral disorder, all else equal. We also found that students experiencing higher levels of inclusion in general education classrooms tended to have considerably greater ELA test score gains than students in the 0%–40% inclusion designation.

Importantly, and consistent with considerable prior research on general education teachers (e.g., Rice, 2013), we found significant returns to teacher experience in special education. For example, the test score gains of students with high-incidence disabilities were about 0.04–0.05 standard deviations higher for students who were taught by a special education teacher with 1–2 years of experience, compared with those who were taught by a special education teacher with no prior teaching experience. These returns to special education teacher experience are slightly larger than the comparable estimates reported from Florida by Feng and

Sass (2013), but it is important to note that they pale in comparison to the overall variation in value added (Figure 4). Finally, and not surprisingly, we found strong, positive relationships between the value added of students' general education teachers and their test score gains in each subject. Subsequent estimates of special education teacher value added should therefore be interpreted as *controlling for* the contributions that general education teachers make to their students' test score gains.

Second-Stage Models

We then estimated a series of second-stage models that predicted the value-added estimates from equation 1, now denoted $\hat{\tau}_{jlmt}$ to represent the estimated value added of special education teacher *j* who graduated from TEP *l* and was teaching in district *m* and year *t*. To investigate RQ1 (connecting measures of teacher preparation to teacher effectiveness), we estimated variants of the following second-stage model:

$$\hat{\tau}_{jlmt} = \beta_0 + \beta_1 P_{jl}(+\beta_l)(+\beta_m) + \varepsilon_{jlmt} \qquad (2)$$

In (2), the vector P_{jl} includes the preservice measures of interest (e.g., credentials, student teaching placements, and licensure test scores) for teacher *j* from TEP *l*, discussed previously. The coefficients of interest in β_1 can be interpreted as the expected increase in special education teacher value added associated with a one-unit increase in each of these variables, all else equal. We estimated these models with and without TEP (β_l) and district (β_m) effects that make comparisons between special education teachers who graduated from the TEP and taught in the same district, respectively.[6] We weighted these models by the number of students with high-incidence disabilities taught by teacher *j* in year t, and used two-way clustering (Cameron et al.,

[6] Because there are often few special education teachers in a specific district, we adjust for district using a grouped fixed-effects method (Bonhomme & Manresa, 2015).

2012) to cluster our standard errors at both the teacher and district levels to account for dependence between multiple observations from the same teacher and district, respectively.

The models used to investigate RQ2 (connecting instructional practices emphasized by districts and TEPs to teacher effectiveness) were similar to model 2:

$$\hat{\tau}_{jlmt} = \gamma_0 + \gamma_1 D_m + \gamma_2 I_l (+\delta_l)(+\delta_m) + \varepsilon_{jlmt} \qquad (3)$$

In (3), D_m includes the PCA measures of instructional practices for district *m* discussed previously, while I_l includes the PCA measures of instructional practices emphasized by TEP *l*. The coefficients of interest in γ_1 and γ_2 can be interpreted as the expected increase in special education teacher value added associated with a one-unit increase in each of these PCA measures, all else equal. We were able to include fixed effects for districts and TEPs in some specifications, but we could not include district effects in specifications that considered district practices, or TEP effects in specifications that considered TEP practices, because these terms are collinear.

Our investigation of RQ3 (the alignment of preparation and practice) is purely descriptive, but to investigate RQ4 (connecting the alignment between TEP and district practice to teacher effectiveness), we estimated variants of the following model:

$$\hat{\tau}_{jlmt} = \delta_0 + \delta_1 P_{jl} + \delta_2 D_m + \delta_3 I_l + \delta_4 D_m * I_l (+\delta_l)(+\delta_m) + \varepsilon_{jlmt} \qquad (4)$$

The only new term in this model is the interaction between the vectors D_m and I_l from equation 3. The coefficients of interest are in δ_4, which capture the relationships between the *interactions* between district and TEP instructional practices and special education teacher effectiveness. For example, if these coefficients are positive, this implies that teachers are more effective when both their TEP *and* their district emphasize a given set of instructional practices.

There were several potential threats to the validity of estimates from the above models. The first was nonrandom selection into the sample, due either to nonrandom entry into or attrition from the special education teacher workforce. We were not very concerned about nonrandom entry due to the high rates (greater than 90%) of hiring of special education candidates into special education teaching positions in Washington State documented by Theobald, Goldhaber, Naito, and Stein (2021); in other words, there was little scope for this source of bias. We were more concerned about nonrandom attrition, given that, as documented in Theobald, Goldhaber, Naito, and Stein (2021), many early-career special education teachers in Washington State with dual endorsements leave special education positions for general education positions in their first few years in the profession. We explored this potential source of bias in two ways: by estimating models that focused only on first-year teachers (i.e., where attrition bias was not an issue) and by exploring patterns of attrition from the sample as a function of variables of interest in equations 2–4. We found that estimates based on first-year teachers were qualitatively similar to the estimates presented in the Results section, and found little evidence that special education teachers were more or less likely to leave the sample as a function of the variables of interest.

Perhaps the most likely threat to validity in these models was the nonrandom sorting of candidates with specific preparation experiences into districts that emphasized specific instructional approaches. For example, if stronger special education candidates from TEPs that emphasized a given instructional practice tended to be hired into districts that also emphasized this practice, we might have misattributed this nonrandom sorting to "alignment" between the instructional approaches emphasized by the candidate's TEP and district. The models in equations 2–4 attempted to control for this omitted variable bias by controlling for candidates' licensure test scores (i.e., a preservice measure of candidate subject knowledge). Moreover, since one mechanism for this nonrandom sorting might be that stronger candidates tended to do their student teaching in the same districts that ultimately hired them, we also controlled for an indicator for whether the teacher was teaching in their student teaching district. Together, these controls accounted for two plausible sources of omitted variable bias. That said, it is still possible that estimates from the models in equations 2–4 are biased by nonrandom sorting along *unobserved* dimensions, which is one reason for discussing our results in descriptive terms.

3. Results

RQ1. To what extent do specific measures of preservice preparation (e.g., student teaching placements, credentials, and licensure test scores) predict ELA achievement for students with high-incidence disabilities taught by early-career special education teachers?

Table 4 presents estimates from the model in equation 2. Column 1 presents estimates from a specification with no fixed effects (i.e., making comparisons across all special education teachers in the sample), column 2 presents estimates from a specification with district group fixed effects (i.e., making comparisons across special education teachers in similar districts), and column 3 presents estimates from a specification with TEP fixed effects (i.e., making comparisons across special education teachers who graduated from the same TEP). The one consistently statistically significant relationship was between the experience of a special education teacher's cooperating teacher and ELA test score gains in their classroom: A 1-year increase in the experience of a special education teacher's cooperating teacher was predictive of about a 0.004 standard deviation increase in the ELA test scores of the teacher's students. Otherwise, there was little evidence that the specific measures we considered of early-career special education teachers' degree level, credentials, and student teaching placements were significantly predictive of the test score gains of students with high-incidence disabilities they taught.

RQ2. To what extent do the instructional approaches emphasized by districts and TEPs predict ELA achievement for students with high-incidence disabilities taught by special education teachers?

In columns 1–3 of **Table 5**, we connect the TEP and district survey responses about literacy instructional practices to test score gains by students with high-incidence disabilities taught by special education teachers. Column 1 considers the practices emphasized by special education teachers' TEP, column 2 considers the practices emphasized by their district, and column 3 considers both within the same model specification. We found that students with high-incidence disabilities in districts that emphasized Balanced Literacy practices (i.e., one standard deviation more than the average district) tended to have considerably lower reading gains by over 0.05 standard deviation. This relationship was robust to specifications that included fixed effects that made comparisons between teachers who graduated from the same TEP (column 7).

RQ3. To what extent is there alignment between the literacy instructional practices emphasized in special education teacher education programs and K–12 special education settings?

Before interpreting the interaction specifications in Table 5 (i.e., columns 4, 6, and 8), we present figures contrasting the survey responses of TEPs and districts. **Figure 5** presents survey responses by TEPs (blue bars) and districts (red bars) to the following survey question: "Select all practices currently used/emphasized in special education in your coursework/district." The most notable trend in Figure 5 is that several literacy instructional methods were more commonly emphasized by districts than TEPs; for example, while about 80% of teachers' districts reported that they emphasized sight word instruction and guided reading, these practices were emphasized by less than 30% of teachers' TEPs. These are prime examples of potential misalignment between candidates' teacher education and early-career experiences. Interestingly, the literacy practices generally recognized as evidence based (e.g., phonological awareness and phonics) were more likely to be emphasized by districts than TEPs.

However, Figure 5 does not tell the full story, as it matters *which candidates* fall into each of these specific categories. To investigate this further, we explored each pair of responses and summarized the percentage of teachers for whom a given practice was emphasized by just their TEP, just their district, both, or neither (**Figure 6**). For example, *over 50% of special education teachers* in the ELA sample taught in a district that emphasized sight word instruction and guided reading yet graduated from a TEP that did not emphasize these practices. While we found better alignment for the literacy practices that are generally recognized as evidence based (discussed previously), almost 40% of special education teachers taught in a district that emphasized phonological awareness but graduated from a TEP that did not.

RQ4. To what extent does this alignment predict ELA achievement of students with high-incidence disabilities taught by special education teachers?

We now return to the interaction models in Table 5 (i.e., the models in equation 4) that investigate the importance of alignment between teacher preparation and inservice practices for ELA test score gains. We found consistently positive and statistically significant interactions between the TEP and district PCA associated with phonics, fluency, and comprehension. Because these interactions varied both within TEPs (i.e., for graduates from the same TEP who taught in different districts) and within districts (i.e., for special education teachers in the same district who graduated from different TEPs), we were able to explore the robustness of these findings to various comparison groups and found that this interaction was positive and statistically significant in a model with district group effects (column 6) and TEP effects (column 8). Moreover, the specification with TEP effects (column 8) suggests that, when comparing graduates from the same TEP, special education teachers in districts that emphasized phonics, fluency, and comprehension tended to have students with higher reading gains. This relationship was even stronger for special education teachers who graduated from a TEP that also emphasized these literacy practices.

To help visualize this result, we used the coefficients from the model in column 4 of Table 5 to create a contour plot of predicted ELA test score gains for students with high-incidence disabilities taught by special education teachers (**Figure 7**). The colors in the contour plot represent the predicted ELA test score gains for students with high-incidence disabilities (with red being positive and blue being negative) in a given classroom. The x-axis represents the extent to which the teacher's TEP emphasized phonics, fluency, and comprehension; the y-axis represents the analogous measure for the district. The "+" signs indicate regions of the figure that are statistically significant and positive. (No regions of the figure are significant and negative.) Figure 7 illustrates that ELA test score gains by students with high-incidence disabilities taught by special education teachers were highest when both their district *and their special education teacher's preparation program* emphasized phonemic awareness, phonics, fluency, vocabulary, and text comprehension (i.e., the top-right corner of Figure 7).

4. Discussion

This study provides the first empirical evidence—to our knowledge—supporting the importance of alignment between teacher preparation and K–12 literacy instructional practices for the reading achievement of students with high-incidence disabilities. Specifically, our findings suggest that these students experience greater learning gains when both their district and their special education teachers' preparation program are aligned in their emphasis on evidence-based literacy practices (e.g., Castles et al., 2018). Our findings also suggest that Balanced Literacy practices in districts are associated with negative test score gains in ELA. While this study has a number of limitations, it also has some important policy implications. Both limitations and policy implications are discussed in the sections that follow.

4.1 Limitations

One important limitation is that the specific measures of special education teachers' preparation considered in this analysis were broad, each capturing a wide range of specific preparation experiences. It is possible that many of the the null relationships between these measures of teacher preparation and student test score gains reflect these broad categorizations. Future research could consider more nuanced measures (e.g., more specific measures of student teaching classroom settings) or additional program factors (e.g., the structure of a candidate's dual endorsement program) as additional predictors of student test score gains.

The survey measures considered in this study were also broad, in that they represent the perspectives of a single individual replying on behalf of a TEP (i.e., a faculty member in the program) or a district (i.e., the special education director). We used these surveys to quantify the instructional methods emphasized by candidates' TEPs and districts, but there is likely considerable variation both within districts and TEPs in terms of the literacy instructional practices emphasized in different classrooms and courses. These surveys were intended to collect broad measures of district and TEP practices, but future research could leverage teacher-level survey responses to generate more granular measures of instructional practices.

There are also general concerns about attributing the test score gains of students with disabilities to special education teachers. We have followed best practices outlined by prior research (Buzick & Jones, 2015; Feng & Sass, 2013) and extended this prior literature by controlling for general education teachers' value added (Chetty et al., 2014). However, it is still the case that student test score gains can reflect unobserved factors outside the special education teacher's control. We would only be concerned about this if these unobserved factors were correlated with our variables of interest—for example, if special education teachers who experienced alignment between the literacy practices emphasized by their TEP and district were also more effective for other reasons, even controlling for licensure test scores and other observed variables in these models.

4.2 Policy Implications

Despite the limitations outlined above, we believe that this work has several potential implications for both practice and policy. For example, the finding that alignment between TEPs and district literacy practices contributes to student learning provides additional support for increasing efforts to develop more substantive partnerships between TEPs and school districts. Critical to improving these partnerships may be a focus on implementing evidence-based practices. While university–school district collaborations are not new to teacher preparation, the partnerships that currently exist often do not address curriculum alignment directly (e.g., Maheady et al., 2016). More frequently, the partnerships involve student teaching placements only, with minimal interactions between cooperating teachers and university supervisors. One approach to the improvement of TEP–school district partnerships, outlined by Stein et al. (2018), would be to ensure that teacher candidates observe exemplary practices, that district priorities are aligned with university goals related to implementing evidence-based instruction, that administrative and teacher support exists for tight collaboration between university faculty and teachers on matters of curriculum and instruction, and that staffing models—jointly supported by the university and school district—allow teacher candidates to receive frequent support from expert field supervisors in addition to their formal classroom mentors.

Another implication of this work relates to the disconnect between what science suggests is evidence-based literacy practice and the literacy instructional practices emphasized in public schools. The results from the surveys of special education directors indicate that about half of the special education teachers in Washington State teach in a district that emphasizes Balanced Literacy practices, and that almost 80% are in districts that emphasize guided reading, despite the fact that these practices are not supported by research. This analysis connects emphases on these practices with negative ELA test score gains for students with high-incidence disabilities taught by special education teachers.

Given that curriculum selection is the primary *policy* mechanism for influencing the literacy instructional strategies used to teach reading, addressing the policies used by school districts to select their instructional materials seems critical. In more than half of the states in the country (including Washington State), curriculum selection *in general education* occurs at the district level; that is, districts can select curricula that best meet the needs of their local communities. Regarding *special education*, anecdotal evidence indicates substantial heterogeneity in the processes through which curricula are selected for students with high-incidence disabilities across different districts.

The question remains: Why are many school districts in Washington State *not* using evidence-based literacy programs in special education? One hypothesis is that special education directors may be unfamiliar with the evidence base on the science of reading. Another is that special education directors may not have a “seat at the table” for program selection at the district level (as opposed to the special education program level). Given that the alignment between preparation and practice in evidence-based instruction appears to have a significant effect on the outcomes of students with high-incidence disabilities, implementing policies that encourage such alignment would seem critical.

As mentioned earlier, to our knowledge, this is the first large-scale study linking literacy instructional practices taught in special education TEPs and/or emphasized in special education settings to the achievement of students with high-incidence disabilities in ELA. As such, this study generates many more questions and opportunities for further investigation regarding the relationship between teacher preparation and school district instructional practices and their impact on student outcomes. Given that no group of students is more vulnerable to the implementation of questionable instructional practices than those with disabilities, this line of research takes on greater urgency.

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Table 1. PCA Factors and Factor Loadings

All literacy practices currently used/emphasized in special education in district/coursework:			
	PCA 1 (*Phonics, Fluency, & Comprehension*)	PCA 2 (*Guided & Close Reading*)	PCA 3 (*Balanced Literacy*)
Text comprehension strategies	**0.475**	-0.350	0.184
Phonological awareness	**0.460**	0.057	-0.153
Vocabulary (word meaning)	**0.412**	-0.049	0.088
Reading fluency	**0.338**	0.199	-0.233
Phonics instruction	**0.309**	0.202	-0.234
Guided reading	-0.034	**0.587**	0.109
Close reading	-0.008	**0.545**	-0.003
Reader's/writer's workshop	0.072	-0.043	**0.563**
Balanced literacy	-0.131	0.183	**0.496**
Sustained silent reading	0.078	0.081	**0.420**
Graphic organizers	0.248	0.163	0.133
Content (subject matter literacy)	0.246	-0.060	0.240
Sight word instruction	0.179	0.281	0.004

Note. This table displays factor loadings from principal components analysis (PCA), 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. Summary Statistics of Predictor Variables

	(1)	(2)
Dual endorsement	0.695	0.698
Master's or higher	0.465	0.470
WEST-B mathematics score	276.125	276.480
	(17.418)	(17.683)
WEST-B reading score	271.010	271.767
	(14.960)	(14.557)
WEST-B writing score	264.067	264.713
	(17.582)	(17.968)
Same district as ST district	0.393	0.427
CT SPED setting	0.608	0.595
CT SPED endorsement	0.702	0.696
CT master's or higher	0.767	0.753
CT experience	12.970	12.866
	(8.243)	(8.191)
PCAs for districts		
Phonics, Fluency, and Comp		0.026
		(0.964)
Guided and Close Reading		-0.871
		(0.972)
Balanced Literacy		0.213
		(1.241)
PCAs for TEPs		
Phonics, Fluency, and Comp		0.388
		(0.576)
Guided and Close Reading		0.225
		(0.806)
Balanced Literacy		0.114
		(0.921)
Survey data		X
Unique teachers	285	243
Teacher-year observations	600	506

Note. CT = cooperating teacher; PCA = principal components analysis; TELC = Teacher Education Learning Collaborative; TEP = teacher education program. Standard errors of continuous variables shown in parentheses.

Table 3. Predictors of ELA Test Gains for Students with High-Incidence Disabilities Taught by Special Education Teachers

	(1)
Student in only special education courses	-0.032***
	(0.006)
80%–100% inclusion (ref. 0–40%)	0.174***
	(0.009)
40%–80% inclusion (ref. 0–40%)	0.095***
	(0.008)
Different mathematics and ELA teacher	0.012*
	(0.005)
Health impairment (ref. EBD)	-0.095***
	(0.010)
Specific learning disability (ref. EBD)	-0.083***
	(0.010)
Female	0.096***
	(0.005)
American Indian (ref. White)	-0.028*
	(0.011)
Asian (ref. White)	0.031**
	(0.012)
Black (ref. White)	-0.041***
	(0.008)
Hispanic (ref. White)	-0.017**
	(0.006)
Native Hawaiian or Pacific Islander (ref. White)	-0.045*
	(0.020)
Participate in LEP	-0.037***
	(0.008)
Eligible for FRL	-0.043***
	(0.005)
Teacher experience: 1–2 (ref. 0–1)	0.050***
	(0.012)
Teacher experience: 3–4 (ref. 0–1)	0.042***
	(0.013)
Teacher experience: 5–9 (ref. 0–1)	0.044***
	(0.012)
Teacher experience: 10–14 (ref. 0–1)	0.053***
	(0.012)
Teacher experience: 15–24 (ref. 0-1)	0.032**
	(0.011)
Teacher experience: 25+ (ref. 0-1)	0.036**
	(0.012)
General education teacher VA	0.643***
	(0.043)
Unique students	56,344
Student-year observations	86,631

Note. EBD = emotional behavioral disorder; ELA = English language arts; FRL = free or reduced-price lunch; HI = high incidence; LEP = limited English proficiency; VA = value added. All models control for cubic in prior test scores interacted by grade and missing dummy for general education teacher VA. Standard errors are clustered at the district and teacher level. *$p < .05$. **$p < .01$. ***$p < .001$. Probability values are from a two-sided t test.

Table 4. Special Education Teacher Preparation Experiences as Predictors of ELA Test Scores of Students with High-Incidence Disabilities

	(1)	(2)	(3)
Dual endorsement	0.022	0.018	0.011
	(0.028)	(0.023)	(0.026)
Master's or higher	0.004	0.016	-0.002
	(0.026)	(0.025)	(0.031)
WEST-B mathematics score	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
WEST-B reading score	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
WEST-B writing score	0.001	-0.000	0.001
	(0.001)	(0.001)	(0.001)
Same ST district	-0.044	-0.054	-0.025
	(0.034)	(0.029)	(0.036)
CT special education teacher	-0.020	-0.030	0.013
	(0.030)	(0.030)	(0.038)
CT special education endorsement	0.010	0.007	0.009
	(0.032)	(0.032)	(0.043)
CT master's or higher	-0.004	-0.023	-0.001
	(0.026)	(0.026)	(0.028)
CT experience	0.004*	0.004*	0.004*
	(0.001)	(0.001)	(0.001)
District group FE		X	
TEP FE			X
N	600	600	600

Note. CT = cooperating teacher; ELA = English language arts; FE = fixed effect; ST = student teaching; TEP = teacher education program. First-stage value-added models control for the following student and classroom-level control variables: prior performance in mathematics and reading, gender, race/ethnicity, receipt of free or reduced-price lunch, special education status and disability type, limited English proficiency indicator, and teacher experience categories summarized in Table 3. Standard errors are clustered at the district and teacher level. *$p < .05$. **$p < .01$. ***$p < .001$. Probability values are from a two-sided t test.

Table 5. District and TEP Practices as Predictors of ELA Test Scores of Students with High-Incidence Disabilities Taught by Early-Career Special Education Teachers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PCA 1: Phonics, Fluency, and Comp								
TEP	0.003		0.002	-0.003	0.019	0.012		
	(0.021)		(0.020)	(0.018)	(0.022)	(0.024)		
District		0.028	0.037	0.056			0.055	0.078*
		(0.036)	(0.037)	(0.036)			(0.039)	(0.037)
TEPxDistrict				0.041*		0.025**		0.046*
				(0.017)		(0.009)		(0.019)
PCA 2: Guided and Close Reading								
TEP	-0.012		-0.019	-0.029	-0.019	-0.044		
	(0.026)		(0.026)	(0.023)	(0.020)	(0.025)		
District		0.004	0.005	-0.024			-0.000	-0.031
		(0.021)	(0.024)	(0.043)			(0.024)	(0.046)
TEPxDistrict				-0.029		0.001		-0.031
				(0.029)		(0.013)		(0.032)
PCA 3: Balanced Literacy								
TEP	0.000		-0.007	-0.003	-0.019	-0.028		
	(0.016)		(0.017)	(0.018)	(0.014)	(0.019)		
District		-0.051*	-0.054*	-0.055*			-0.055*	-0.057*
		(0.020)	(0.023)	(0.025)			(0.022)	(0.024)
TEPxDistrict				-0.024		-0.017		-0.024
				(0.018)		(0.017)		(0.017)
District group FE					X	X		
TEP FE							X	X
N	595	511	506	506	595	506	511	506

Note. ELA = English language arts; FE = fixed effect; PCA = principal components analysis; ST = student teaching; TEP = teacher education program. First-stage value-added models control for the following student and classroom-level control variables: prior performance in mathematics and reading, gender, race/ethnicity, receipt of free or reduced-price lunch, special education status and disability type, limited English proficiency indicator, and teacher experience categories summarized in Table 3. Second-stage models control for additional individual and teacher preparation variables shown in Table 4. Standard errors are clustered at the district and teacher level. *$p < .05$. **$p < .01$. ***$p < .001$Probability values are from a two-sided t test.

Figure 1. Conceptual Figure

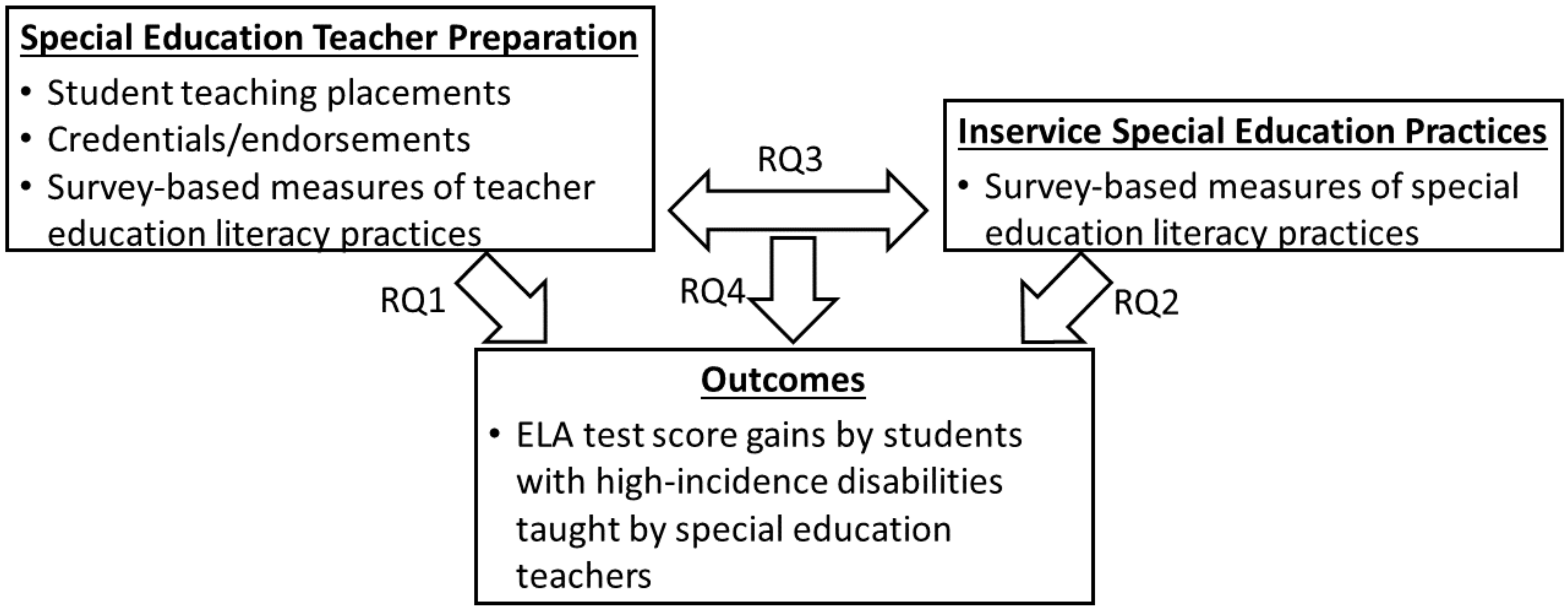


Figure 2. Special Education TEP Faculty and Special Education Director Perceptions of Incoming Teacher Preparation

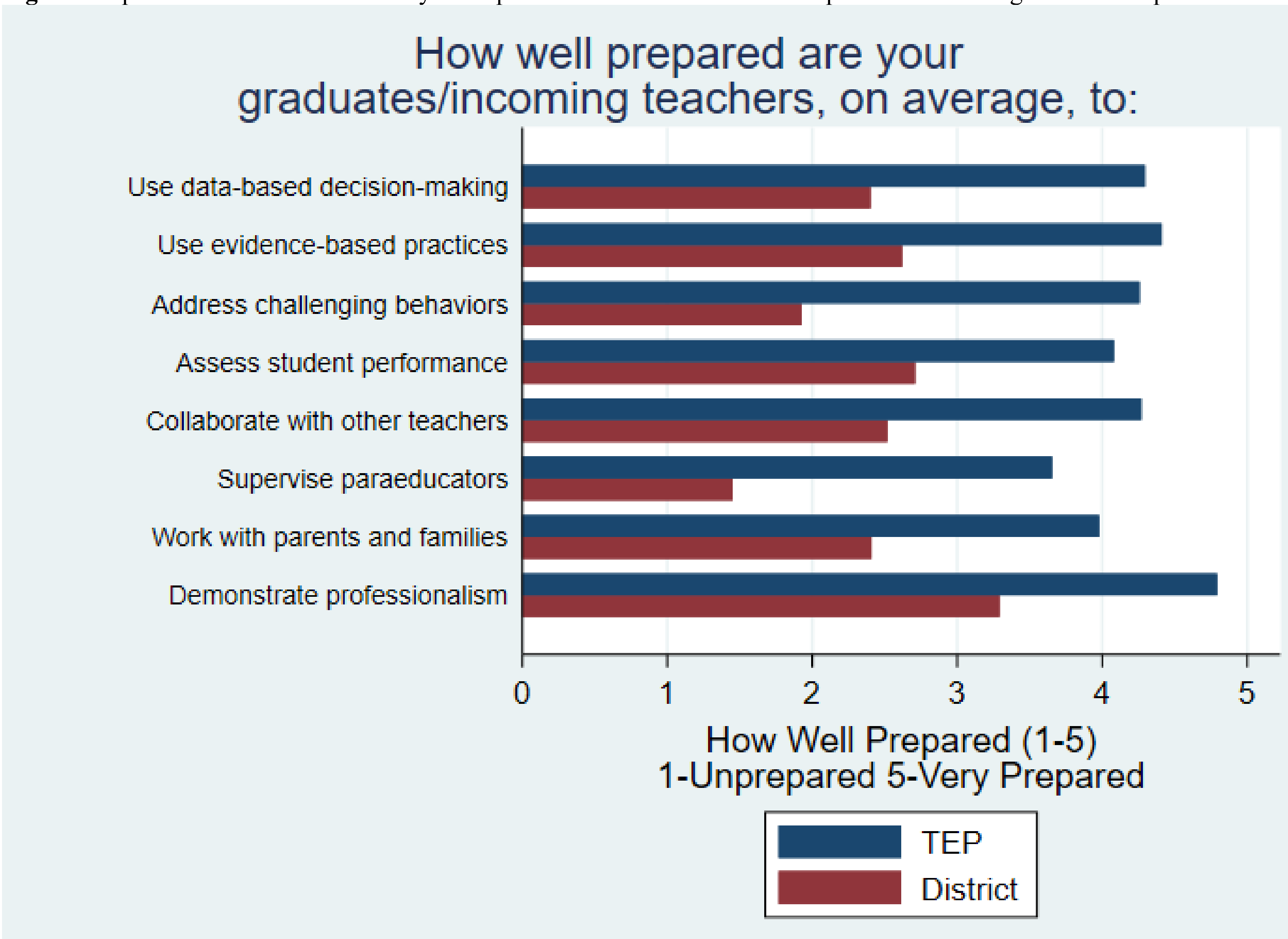


Figure 3. Distribution of Special Education Students Across Settings

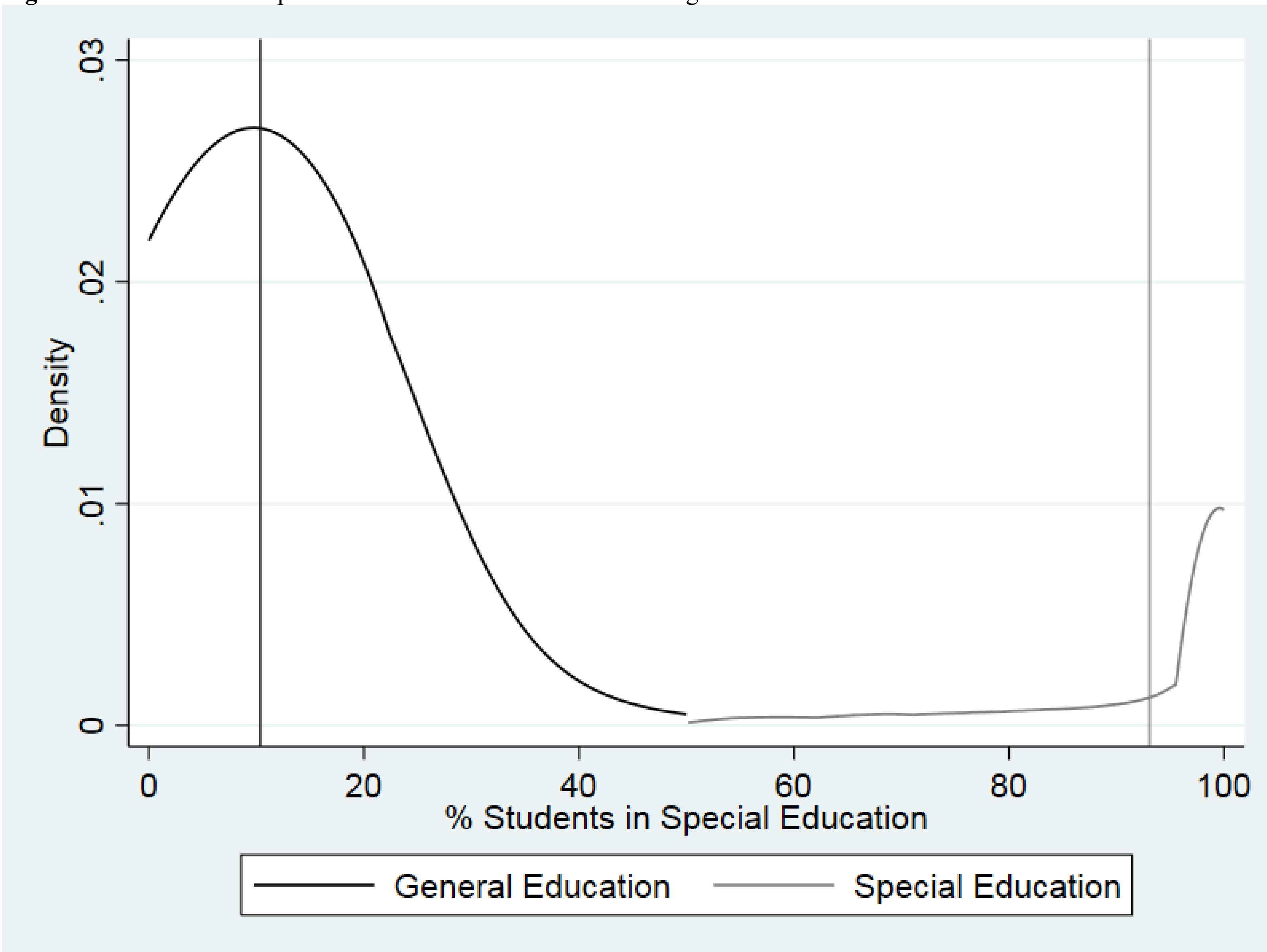


Figure 4. Distribution of Special Education Teacher Value Added in ELA

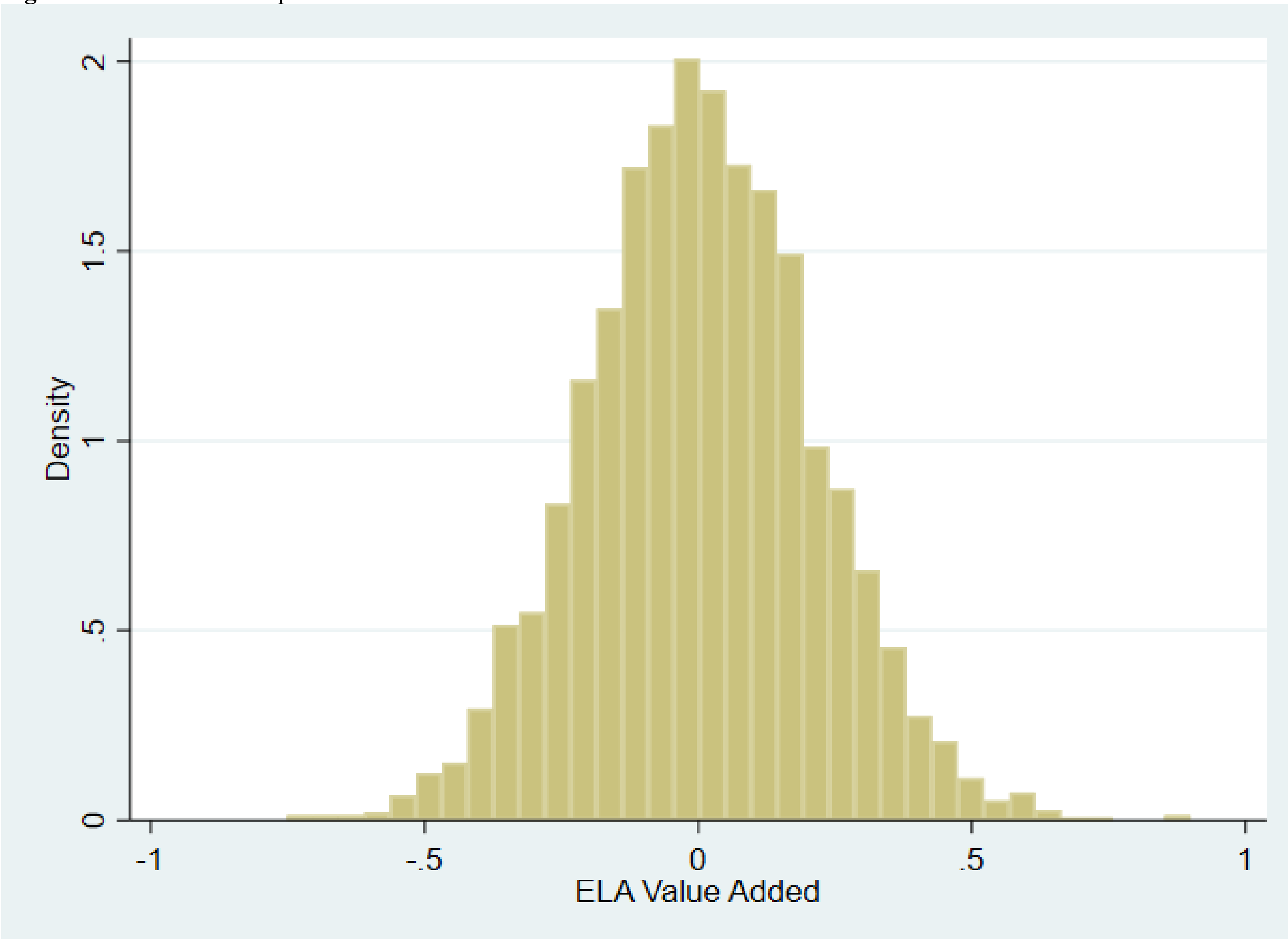


Figure 5. Literacy Practices Used/Emphasized by TEPs and Districts

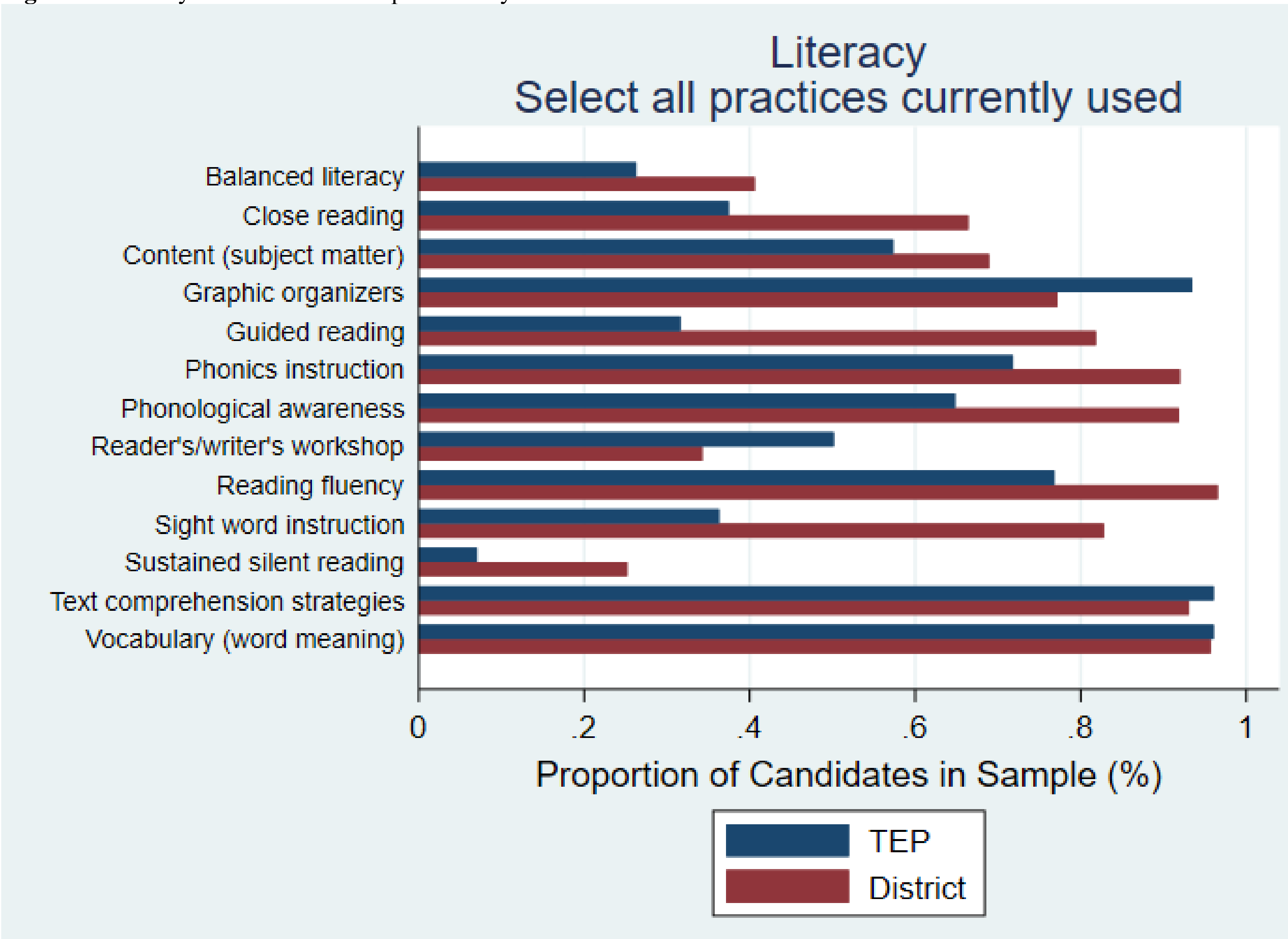


Figure 6. Literacy Practices TEP/First District Alignment

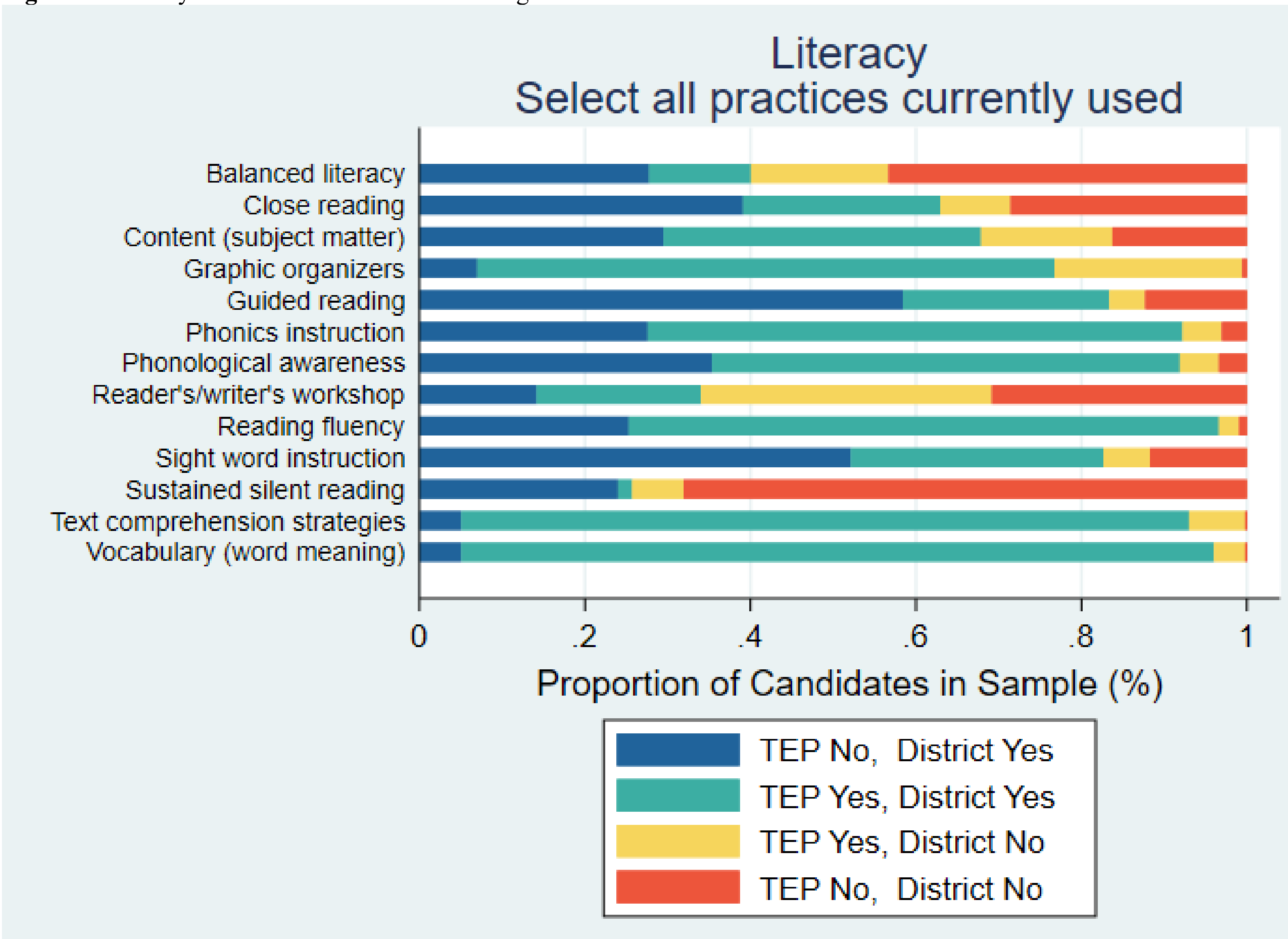
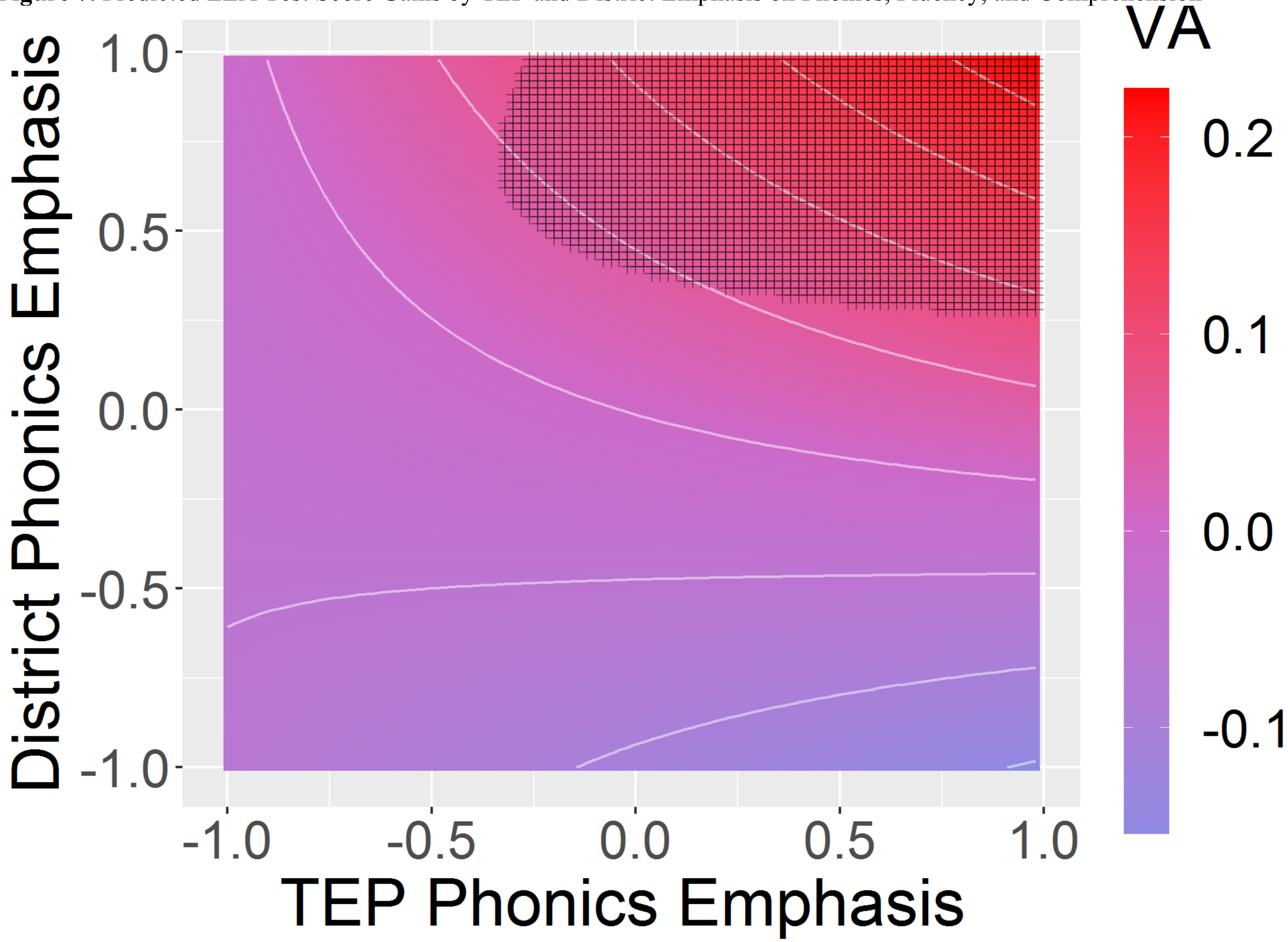


Figure 7. Predicted ELA Test Score Gains by TEP and District Emphasis on Phonics, Fluency, and Comprehension



Appendix Table A1. Student and Teacher Summary Statistics

	(1)	(2)	(3)
	All	Special Education & Other	Special Education Only
Prior mathematics score (std.)	-1.277	-1.184	-1.337
	(0.753)	(0.751)	(0.749)
Prior ELA score (std.)	-1.373	-1.258	-1.446
	(0.788)	(0.773)	(0.789)
80%–100% inclusion	0.343	0.484	0.253
40%–80% inclusion	0.573	0.493	0.624
0%–40% inclusion	0.080	0.022	0.117
Different mathematics and ELA teacher	0.296	0.248	0.327
Emotional/behavioral disorder	0.054	0.039	0.063
Health impairment	0.286	0.264	0.299
Specific learning disability	0.661	0.697	0.637
Female	0.346	0.368	0.332
American Indian	0.049	0.048	0.050
Asian	0.037	0.037	0.037
Black	0.095	0.097	0.094
Hispanic	0.276	0.291	0.266
Native Hawaiian or Pacific Islander	0.012	0.013	0.011
Participate in LEP	0.163	0.187	0.148
FRL	0.700	0.703	0.698
Special education teacher experience	13.070	12.850	13.220
	(9.617)	(9.614)	(9.616)
General education teacher value added	-0.002	-0.002	.
	(0.097)	(0.097)	(.)
Student-year observations	86,631	33,924	52,707

Note. EBD = emotional behavioral disorder; ELA = English language arts; FRL = free or reduced-price lunch; LEP = limited English proficiency; VA = value added.

Appendix Figure A1. Scree Plot for Principal Components Analysis