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The Costs of Mentorship? Exploring Student Teaching Placements and Their Impact on Student Achievement

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Abstract

We use comprehensive data on student teaching placements from 14 teacher education programs (TEPs) in Washington State to explore the sorting of teacher candidates to the teachers who supervise their student teaching ("cooperating teachers" or CTs) and the schools in which student teaching occurs. All else equal, teachers with more experience and higher degree levels are more likely to host student teachers, as are schools with lower levels of historical teacher turnover but with more open positions the following year. Teacher candidates are also more likely to work with CTs of the same gender and race, and are more likely to be placed with CTs and in schools with administrators who graduated from the candidate's TEP. We then assess the impact of these placements on student achievement in the classrooms in which student teaching occurs, and find that a teacher's students perform only slightly worse in math and not significantly better or worse in English Language Arts, all else equal, in years in which the teacher hosts a student teacher than in other years. The negative effect in math is driven by CTs in the lowest quartile of value added, suggesting that more effective CTs can mitigate the impact of hosting a student teacher on student performance.

Keywords: Teacher Education, Student Teaching, Teacher Quality

1. Introduction

Student teaching is the capstone to a teacher candidate's preparation experience. These apprenticeships that candidates have with in-service teachers who supervise their student teaching (the "cooperating teachers," henceforth CTs) are hailed by teacher education programs, and student teachers themselves, as providing foundational preservice teacher education experiences. For instance, in a recent review of student teaching's contribution to teacher development, Anderson and Stillman (2013) note, "Policymakers and practitioners alike increasingly tout clinical experiences as a key component—even 'the most important' component of—pre-service teacher preparation." Ganser (2002) further states that the CTs "influence the career trajectory of beginning teachers for years to come" (p. 380).

Despite the perceived import of student teaching internships, there is relatively little systematic information about how matches are made between teacher candidates, internship schools, and CTs; or whether there are costs and benefits to schools of hosting student teachers. State-level policy makers can (and sometimes do) play a role in influencing student teaching assignments, as in some cases, state laws mandate aspects of field placements, such as the diversity of the school in which student teaching occurs or the qualifications of the cooperating teacher. But as is documented in Greenberg et al. (2011), few states have specific guidelines regulating the schools in which student teaching can occur or the teachers that are eligible to supervise student teaching. For example, as of 2011, only 20% of states required that a CT hold a minimum level of professional experience or demonstrate mentoring skills.

The one large-scale, published quantitative study that explores the factors predicting student teacher placements shows that placements tend to occur in schools that are close both to the student teacher's teacher education program (TEP) and to where the student teacher attended high school (Krieg et al., 2016). But a large body of research suggests that insufficient attention is paid to the specific schools and CTs that host student teachers, given the perceived centrality of student teaching to the teacher education experience. Clark et al. (2013), for instance, stress the importance of CTs for teacher candidate development, but also state that it is "widely acknowledged that the current practices for ensuring that CTs are professionally prepared for their work are inadequate and fail to address some of the most basic issues associated with their supervisory work" (p. 164).[1] This view is buttressed by a 2010 survey of school principals, in which 54% reported that they were unaware that the TEPs they worked with had criteria for the selection of CTs (Greenberg et al., 2011).

There is even less empirical evidence on whether and how hosting a student teacher tends to affect internship schools or CTs. The lack of information about the factors predicting placements or the influence of those placements on internship schools and classrooms represents a significant knowledge gap, given both the perceived import of student teaching for teacher candidate skill development and the potential that hosting a teacher candidate affects the culture or functioning of the internship classroom.

In this paper we use a unique database of student teachers from 14 of the 21 TEPs that place student teachers in Washington State public schools. In recent years, these TEPs have supplied about 80% of new teachers to the state and thus represent the lion's share of in-state teacher production. We connect student teaching data provided by these 14 institutions to administrative data on students and teachers in K–12 public schools in Washington to answer three specific questions:

1. What are the school- and teacher-level factors predicting where teacher candidate internships take place?
2. Does hosting a student teacher have an impact on student achievement?
3. Does the impact of hosting a student teacher vary for different CTs and student teachers?

[1] For more on the importance of student teaching and the perceived inadequacy of the process in many TEPs, see Anderson & Stillman (2013), Clark et al. (2013), Fives et al. (2016), Ganser (2002), and Zeichner (2010).

For research question #1, we find that, all else equal, teachers with more experience and higher degree levels are more likely to host student teachers, as are schools with lower levels of historical teacher turnover but with more open positions the following year.[2] We also find that teacher candidates are more likely to be placed with CTs of the same gender and race, and are more likely to work with CTs who graduated from the candidate's TEP and in schools with administrators who graduated from the candidate's TEP. These latter findings are strongly suggestive of the role of social networks in student teaching placements (Maier & Youngs, 2009), the importance of which is borne out in a companion qualitative analysis (St. John et al., in prep) that illustrates the importance of alumni networks in TEPs' recruitment of CTs and student teaching schools.[3]

For research question #2, we find that a teacher's students perform only slightly worse in math (by .015 standard deviations of student performance) and not significantly better or worse in English Language Arts (p = 0.201), on average, in years in which the teacher hosts a student teacher than in other years. These effects are modest in magnitude—the precision of our estimates means that we can rule out with 90% confidence effects larger than 0.03 standard deviations of student performance in either direction in either subject—but the statistically significant result in math does suggest that there is a small cost to student math achievement associated with hosting a student teacher.

Finally, we explore a number of potential sources of heterogeneity associated with research question #3. Of particular interest is whether hosting a student teacher has a differential impact on student achievement depending on the effectiveness of the CT. Our most rigorous models suggest that

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[2] These results are encouraging: As we discuss more extensively below, prior work has found that student teaching in a school with less teacher turnover is predictive of higher effectiveness in the workforce (Ronfeldt, 2012) and student teaching in a school with more openings the following year is predictive of the probability of workforce entry (Goldhaber et al., 2017).
[3] For example, one TEP student teaching placement coordinator reports, "I place a lot of people with our alumni, as well. Cause the alums, they know the program. They know the expectations. It's easier and then you know . . . the student teacher would feel more comfortable, because they're with a [Program] alumni" (St. John et al., in prep).

the negative effect on student achievement in math classrooms is driven by CTs in the *lowest* quartile of value added, which runs contrary to our hypothesis that there may be greater costs associated with replacing several weeks of an effective teacher's instruction with a completely novice teacher. Instead, this finding suggests that more effective CTs may be better able to mitigate the impact of hosting a student teacher on student performance, and further supports an emerging empirical research base (e.g., Ronfeldt et al., 2018) supporting the placement of student teachers with more effective CTs.

2. Background: The Importance of Student Teaching Apprenticeships

A growing literature suggests that characteristics of the schools in which student teaching occurs are predictive of the effectiveness and retention of student teachers who end up employed as teachers. Ronfeldt (2012), for instance, finds that teachers who student taught in schools with relatively low rates of nonretirement attrition (or a higher "stay ratio") are more effective and have higher retention rates. The stay ratio is also found to be correlated with other measures of workforce environment, so the interpretation is that teacher candidates benefit from student teaching in higher functioning school settings. In follow-up work, Ronfeldt (2015) collected more detailed data about internship schools and found that the level of teacher collaboration in these schools (and, to a lesser extent, the amount of teacher turnover in the school) is also predictive of later teacher effectiveness.

Our prior work with 6 TEPs in Washington—all of which are also part of the current study—finds that early-career teachers tend to be more effective when the student demographics of their student teaching schools are similar to the demographics of the schools in which they are employed (Goldhaber et al., 2017). This suggests that student teachers develop teaching skills specific to particular types of students (e.g., economically disadvantaged) that benefit them in their future classrooms. This work also replicated Ronfeldt's findings that student teaching in a low-turnover environment is predictive of lower rates of teacher attrition.

There is less evidence on the extent to which the skill set of CTs influences teacher candidates. However, it is no great leap to think that teacher candidates would benefit from working with more able CTs.[4] Numerous qualitative studies (Clarke et al., 2014; Ganser, 2002; Graham, 2006; Hoffman et al., 2015; Zeichner, 2009) document the myriad roles CTs play in the development of teacher candidates: they provide concrete examples of classroom preparation, instructional leadership, and student engagement, and help induct teacher candidates into school practices and processes. The only published study that we are aware of that links CT effectiveness to the future performance of the student teachers (Ronfeldt et al., 2018) finds that CTs with higher observational ratings have teacher candidates who also receive better observational performance ratings when they later become teachers. By contrast, Goldhaber et al. (2017) find little evidence of relationships between observable CT characteristics and the effectiveness or retention of the teacher candidates they supervise.[5] However, it is important to note that sample size limitations in this prior work did not allow the ruling out of educationally meaningful effects related to CT characteristics and in-service teacher outcomes.[6]

As noted earlier, the assignment of teacher candidates to field placement schools and CTs is determined by both state code and contractual arrangements between TEPs and school districts. In Washington State, the location of this study, there is little specific guidance built into state code (Greenberg et al., 2013). CTs are required to have a minimum of three years of full-time teaching experience, and state code also states, “Field experiences provide opportunity to work in communities with populations dissimilar to the background of the candidate,” which is often interpreted as a mandate to place interns in diverse internship schools (Goldhaber et al., 2014). Often, memoranda of

[4] Note that student teaching is jointly supervised by CTs and college- or university-based employees commonly referred to as field supervisors.
[5] With the notable exception that CTs with master’s degrees are less effective, a finding that may be related to sample selection.
[6] The match between CT and student teacher demographics was relatively large (about 4–5% of a standard deviation of student achievement) in some specifications, but imprecisely estimated.

understanding between TEPs and local school systems are ambiguous about the requirements of internship schools or CTs (Krieg et al., 2016).

Of course, the fact that the explicit requirements do not speak directly to the quality of internships is neither surprising (given the lack of historical evidence about what constitutes quality placements) nor necessarily indicative of placements being poorly conceived. Many TEPs seek feedback (formal or informal) from teacher candidates themselves about their experiences and use this information to seek out perceived high-quality internship placements. But in some cases, student teachers are left largely to their own devices to secure an internship, which does not necessarily imply a bad experience (Ludwig, 2017).

Prior work (e.g., Borko & Mayfield, 1995) also suggests that there is considerable variation in the roles that CTs play in the development of teacher candidates in terms of, for instance, the type or amount of formal feedback about practice teaching. In general, the case study literature on student teaching suggests that school placements, and particularly the role of CTs, do not receive enough attention (Anderson & Stillman, 2013; Clark et al., 2013; Fives et al., 2016; Ganser, 2002; Zeichner, 2010).[7] For instance, in a review of over 400 papers on the role of CTs, Clark et al. (2013) stress their centrality for teacher candidate development, but also state, it is "widely acknowledged that the current practices for ensuring that CTs are professionally prepared for their work are inadequate and fail to address some of the most basic issues associated with their supervisory work" (p. 164).

The quantitative work exploring the match between teacher candidates and placements suggests that geography plays an important role in their determination. Perhaps not surprisingly, in earlier work in Washington, Krieg et al. (2016) find that the majority of teacher candidate placements (roughly 60%) occur in school districts that are within 50 miles of the teacher education program (TEP) in

[7] The level of financial investment in the process is also seen as problematic. Fives et al. (2016), for instance, note that the average compensation that CTs receive per student teacher in 2012–13 is $232, far lower than the nearly $1,600 (adjusted for inflation) that was typical back in 1959.

which they are enrolled, while slightly more than half of student teaching placements are within 50 miles of the high school the candidate attended. This echoes earlier findings about the “draw of home” in the teacher labor market in general (Boyd et al., 2005; Reininger, 2012), as well as practical constraints on student teaching placements (e.g., the ability of TEPs to supervise student teaching placements).

CTs can play myriad roles as mentors, and while TEPs often provide guidelines on the length of internships and the hours teacher candidates are required to be in the classroom, little systemic information is known regarding the actual time breakdown of CT–teacher candidate interactions. It is generally understood that the hours CTs typically spend mentoring, the frequency teacher candidates observe the CT in instruction, and the time CTs observe instruction by the teacher candidate all vary both within and across TEPs (Greenberg et al., 2011). In some cases, having a teacher candidate intern may be highly interactive, with the CT–teacher candidate relationship akin to a coteaching environment (e.g., Heck & Bacharach, 2016), whereas in other scenarios, CTs may simply “hand off” the classroom and the corresponding responsibilities to the teacher candidate. One might imagine, then, that these divergent roles could have very different impacts on student learning in classrooms hosting student teachers: in one case, the classroom would be staffed for a period of time by an instructor who is a true novice (i.e., the student teacher), whereas in the other characterization the classroom is staffed by the regular teacher who has additional human resources to draw upon. But there is little empirical evidence on whether these different models for student teaching, or hosting a CT in general, has an impact on student achievement.[8]

[8] One exception is Bacharach et al. (2010), who find some evidence that students taught by a student teacher in a coteaching setting have greater learning gains than students taught by a student teacher in a traditional setting.

3. Data and Summary Statistics

The data set we utilize combines student teaching data about teacher candidates from institutions participating in the Teacher Education Learning Collaborative (TELC), with K–12 administrative data provided by Washington State's Office of the Superintendent of Public Instruction (OSPI). The TELC data include information from 14 of the state's 21 college and university-based TEPs, and provide information about when student teaching occurred, the schools in which teacher candidates completed their student teaching, and the CTs that supervised their internships.[9]

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 focus on student teaching data from 2009–10 to 2014–15 in this analysis for two reasons. First, nearly all TEPs provided complete data about their teacher candidates over this time period, though 2 TEPs provided data for only 3 of the 6 years. Figure 1 shows the number of student teacher observations, by year, for each TELC participant. In total the TELC data we utilize here includes information on 8,077 teacher candidates, though in some cases, not all these observations are utilized because of missing observations of needed variables.[10] Second, these years of data correspond with years in which student-level data from OSPI can be linked to teachers through the state's CEDARS data system, introduced in the 2009–10 school year.[11] By connecting the student

[9] The institutions participating in TELC and that provided data for this study are Central Washington University, City University, Evergreen State College, Gonzaga University, Northwest University, Pacific Lutheran 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. St. Martin's University is also participating in TELC but did not provide data in time to be included in this study. The six institutions that are not participating in TELC include 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.

[10] Note that not all of these teacher candidates are ultimately eligible to teach in Washington. Some may fail to pass subject area licensure tests, while others may opt to pursue a teaching license outside of Washington. We use linear interpolation to impute missing data when possible (e.g., for annual school data), but otherwise are forced to drop candidates with missing student teaching information.

[11] CEDARS data includes 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.

teaching data from TELC institutions to the student-level data from OSPI, we can create a dataset that links student teachers to the K–12 students they taught in their student teaching placements, the CTs who supervised their student teaching, and the public schools in which student teaching occurred.[12]

It is important to note that this data set can be further linked to a number of additional variables about these students, CTs, and schools. Specifically, the student-level data from OSPI includes annual standardized test scores and demographic/program participation data for all K–12 students in the state, the OSPI personnel data includes information on teachers' years of teaching experience, degree level (e.g., bachelor's or master's), grade taught, race, and gender. The school data include aggregated student demographics, geographic information, and school closure information.

We use the student-level data described above to estimate value-added models of teacher effectiveness for teachers in tested grades and subjects. Specifically, for math and reading teachers in grades 4–8 (i.e., grades in which current and prior standardized test scores are available), we estimate the following value-added model (VAM) estimated separately for both math and reading:

$$Y_{ijst} = \alpha_0 + \alpha_1 Y_{i(t-1)} + \alpha_2 S_{it} + \tau_{js} + \varepsilon_{ijst} \qquad (1)$$

In (1), Y_{ijst} is the state test score for each student *i* with teacher *j* in subject *s* (math or reading) and year *t,* normalized within grade and year; $Y_{i(t-1)}$ is a vector of the student's scores the previous year in both math and reading, also normalized within grade and year; S_{it} is a vector of student attributes in year *t* (gender, race, free/reduced lunch eligibility, English language learner status, gifted status, special education status, learning disability status); and τ_{js} is the VAM estimate that captures the contribution of teacher *j* to student test scores in subject *s*. We describe the variations of this model that we consider in our analysis in Section 4. Overall, the standard deviation of value added in our sample is about 0.23 in math and 0.17 in ELA, suggesting that a one standard deviation increase in teacher effectiveness is

[12] Note that, while many placements occurred in private schools and out-of-state schools, we do not consider these placements in this analysis because we do not have data about these schools or the students and teachers in these schools.

predictive of a 0.23 standard deviation increase in student achievement in math and a 0.17 standard deviation increase in student achievement in ELA.

We further supplement this data set with two additional school-level measures that have been shown to be important in prior work on student teaching. First, the personnel data allow us to observe teacher mobility between schools, districts, and out of the Washington public school workforce, so we use this information to calculate the stay ratio for each school in the state. As noted above, the stay ratio is a measure that has been found to be predictive of later teacher effectiveness and retention (Goldhaber et al., 2017; Ronfeldt, 2012, 2015), and has been shown to correlate with other measures of school culture (Ronfeldt, 2012). We calculate the school stay ratio as the proportion of non-retirement-age teachers who stay in the school the following year, averaged over the current year and four previous years.[13] Schools with higher stay ratios tend to have more teachers who stay in the school from year to year, which serves as a proxy for positive school culture.

We also use the personnel data to calculate the number of "openings" that a school will have *in the next year*, which we define as the number of new teachers (i.e., with no prior teaching experience) employed in the school year after student teaching occurs. In prior work in Washington (Goldhaber et al., 2017), we showed that student teachers were more likely to enter the workforce if they student-taught in a school with more openings the following year, so we consider this variable to investigate whether TEPs may be more likely to place student teachers in schools that will be hiring teachers the following year.[14]

[13] We also transform and standardize the stay ratio, following the procedure described in Ronfeldt (2012).
[14] This hypothesis is supported by qualitative evidence from the companion study (St. John et al., in prep). For example, one TEP student teacher placement coordinator reported that districts and schools will sometimes communicate anticipated staffing needs during the student teacher placement process. The placement coordinator further stated, "I will try to place people in that endorsement for student teachers in [their] building the year before those retirements happen" (St. John et al., in prep).

An important issue is that, while we observe the majority of student teaching placements in the state, we do not observe all of them because student teaching information from 7 of the 21 TEPs that place student teachers in Washington is not included in this data set. To explore this issue further, in Figure 2, we plot the percentage of new, in-state teachers in each district in Washington between 2010 and 2015 who graduated from one of the institutions included in this study. The dots in Figure 2 represent the 21 TEPs in the state—yellow dots represent TEPs that are participating in the study, while red dots represent TEPs that are not—and the sizes of the dots are scaled to reflect the average number of new teaching credentials issued by each TEP between 2010 and 2015.

Overall, the TELC data include programs that supplied 81.2% of the new teachers in Washington State between 2010 and 2015.[15] However, there are notable geographical gaps in terms of the new teacher supply by TELC institutions, largely driven by the fact that the three largest TEPs not participating in the study are all in the eastern half of the state. In particular, TELC institutions provide only about 55% of new teachers from in-state institutions in districts east of the Cascade Mountains (indicated by the pink line through Figure 2), and there are a number of generally rural districts in eastern Washington (noted by the lighter shading in Figure 2) where TELC institutions supply less than 10% of new teachers credentialed from in-state institutions.[16] The flip side, of course, is that, for the rest of the state, these institutions provide the vast majority of new teachers credentialed from in-state institutions; for instance, TELC institutions provide 91.3% of the new in-state credentialed teachers to districts located west of the Cascade Mountains, and provide at least half of the in-state credentialed new teachers to more than 80% of school districts in the state overall.

Because of the limitations described above, we limit the analysis in this paper to student teaching placements in districts west of the Cascade Mountains. Our primary motivation for this

[15] We can get this estimate because the OSPI data include information on the institutions from which teachers (not teacher candidates) receive their teaching credentials.
[16] About 22% of new teachers come in from out of state (and receive an OSPI credential) (Goldhaber et al., 2013).

restriction is that the analytic models described in the next section rely on the assumption that we have complete student teaching data for the CTs and schools considered in the models. Specifically, the models predicting whether CTs and schools host a student teacher assume that, if a CT or school did not host a student teacher in our data set, that school did not host a student teacher at all. Likewise, the models predicting student achievement assume that, in years in which their teacher did not host a student teacher in our data set, students were not taught by a student teacher at all. Since TELC programs provide more than 90% of new in-state teachers to districts west of the Cascades, we believe that our data set also includes the vast majority of student teaching placements in those districts during the years we consider (though this assumption is not testable without data from programs not participating in TELC).

Figure 3 plots the variation across districts in terms of the percentage of teachers who hosted a student teacher from a TELC institution between 2010 and 2015. While 3.1 percent of teachers hosted a TELC student teacher in those years, there were a number of districts (even west of the Cascades) that did not host any student teachers, while a few districts (highlighted in the legend of Figure 3) had at least 7% of their teacher workforce hosting a student teacher from a TELC institution in any given year. A comparison of Figure 3 with the geographic distribution of TEPs in the state (shown in Figure 2) further illustrates the importance of geography in student teaching placements, as the districts in which a large percentage of teachers host a student teacher tend to be the districts near large TEPs, while the districts that host no student teachers tend not to have any TEPs nearby.

Before describing our analytic models in the next section, we present summary statistics of the key variables of interest in Table 1. We make two restrictions to the data before calculating these summary statistics (or estimating the analytic models described in the next section). First, the State of Washington prohibits teachers with fewer than three years of experience from hosting a student teacher. We exclude these observations from the data reducing the number of potential CTs by

10.81%.[17] Second, as discussed above, we limit the sample of potential CTs to teachers in districts west of the Cascade Mountains.

Among potential CTs, teachers who actually served as CTs in data had less teaching experience, were less likely to be male, and were more likely to hold a master's degree than teachers who did not serve as a CT.[18] Among potential CTs with a value-added estimate, teachers who served as a CT had higher value added in math (by about .03 standard deviations of student performance) and ELA (by about .01 standard deviations of student performance) than teachers who did not serve as a CT. Figure 4 plots the distribution of teacher effectiveness by CTs and non-CTs and illustrates that, while there are small mean differences between the two groups in terms of average value added, there is considerable overlap between these distributions. Finally, when we consider the characteristics of the schools of teachers who did and did not serve as CTs, at the bottom of Table 1, we find that CTs tend to be in schools with more URM students, more FRL students, a lower stay ratio, and more openings in the following school year. The models described in the next section are designed to tease apart the factors that appear to be most predictive of student teacher placements.

4. Analytic Approach

Research Question #1: What are the school- and teacher-based factors predicting where teacher candidate internships take place?

To answer research question #1, we follow Boyd et al. (2005) and Krieg et al. (2016) and estimate a series of conditional logit models predicting which teachers (i.e., potential CTs) host student teachers in our data set. Let P_{ij} represent the probability that student teacher *i* student-taught under the supervision of CT *j*. We model this probability using variants of the conditional logit equation:

[17] In our data it turns out that 2.4% of our observed student teachers were supervised by a CT with fewer than three years of experience.

[18] The experience finding is only among teachers with three or more years of experience.

$$P_{ij} = \frac{e^{\beta X_{ij} + \delta Z_j}}{\sum_k e^{\beta X_{ik} + \delta Z_k}}. \qquad (2)$$

In Equation 2, the Z_j represents teacher *j*'s characteristics, including his or her years of teaching experience, gender, race, level of education (e.g., master's degree), and endorsement area. Z_j also includes characteristics of the teacher's building: the stay ratio, the percentage of students who are underrepresented minorities, the percentage of students receiving free or reduced-price lunch, the number of new teachers hired in the following year, and a binary identifying whether the building closed after this year. The last two of these measures, the number of new teachers and the building-closed identifier, are intended to measure strategic placement of student teachers into buildings that are likely to need new teachers the year after student teaching occurs.

A downside endemic of all conditional logit models is that we are unable to introduce student teacher–level measures as stand-alone components of X_{ij} because variables only associated with student teacher *i* will divide out of Equation 2. However, we can interact student teacher characteristics with components of Z_j, so there is a unique observation per student teacher–teacher pair. For instance, X_{ij} contains binary variables equal to one if student teachers share the same race, the same gender, and the same endorsement areas as potential CTs. We also include a binary variable if the potential CT attended the same TEP as the student teacher. In addition, we identify the TEP attended by the school's principal and include in X_{ij} a binary variable equal to one if the principal attended the same TEP as the student teacher. Since Krieg et. al. (2016) found that the distance between a TEP and potential student teaching location reduced the probability of training at that location, X_{ij} also includes the log of distance (and its square) between the geographic centers of the teacher's district and the district that houses the campus that the candidate attends in his or her TEP.[19]

[19] The TELC data includes the campus candidates attended if an institution has more than one campus.

Estimating Equation 1 involves calculating the probability that each student teacher is trained by each potential CT. In 2015, there were 54,080 certificated teachers in Washington State and 1,172 TELC student teachers, for a total of 63,381,760 potential matched pairs in that year.[20] The restrictions discussed in the previous section reduce these sample sizes substantially, and Panel A of Table 2 presents the resulting sample size after these restrictions are in place. Over the 6 years of TELC data, on average, there are 30,000 teachers on the west side of the state who supervise about 900 student teachers per year; an average rate of 3.1% of teachers serve as CTs for TELC student teachers in any given year. Over the 6 observed years, there have been 164 million student teacher–teacher pairs used in the conditional logit estimation. Because of these data restrictions, the appropriate interpretation of the conditional logit model is that it estimates the probability of a non-novice teacher on the west side of the state hosting a student teacher trained at any TELC TEP in the state.

A final data restriction occurs in the subset of models that utilize teacher value added as a regressor. Since our second two research questions are related to the impact of hosting a student teacher on student achievement, we are attentive to the fact that we do not want estimates of teacher value added to be influenced by whether a teacher has hosted a student teacher in the past. For the specifications reported in this paper, we estimate teacher value added from the 2009–10 and 2010–11 school years (see equation 1) and omit years in which a teacher hosted a TELC student teacher. We then use these value-added estimates to predict whether a teacher hosted a student teacher between 2011–12 and 2014–15.[21] As shown in Panels B and C of Table 2, the value added samples include about 16% as many potential CTs in 2011-12 through 2014-15, of whom about the same percentage host a student teacher (3.1%) as in the broader sample.

[20] http://www.k12.wa.us/DataAdmin/pubdocs/personnel/2015-2016_RaceEthnicity.pdf

[21] We divide the sample in this specific way because it ensures the highest sample of teachers who both have prior value-added estimates and host a student teacher in a later year.

Research Question #2: Does hosting a student teacher have an impact on student achievement?

To investigate research question #2, we estimate variants of the value added model described in Section 3 (equation 1), which includes indicators for whether a teacher hosted a student teacher in each year *t:*

$$Y_{ijst} = \gamma_0 + \gamma_1 Y_{i(t-1)} + \gamma_2 S_{it} + \gamma_3 ST_{jt} + \gamma_4 Exp_{jt} + \tau_{js} + \varepsilon_{ijst} \qquad (3)$$

Unlike the value-added model described in equation 1, in which the parameter of interest is the teacher fixed effect τ_{js}, the parameter of interest in equation 3 is γ_3, which is the coefficient of the indicator for whether teacher *j* hosted a student teacher in year *t*, ST_{jt}. This coefficient can be interpreted in the average difference in student performance, all else equal, between years in which a teacher hosted a student teacher and years in which the *same* teacher did not host a student teacher. We control for returns to experience directly by including a number of teacher experience indicators Exp_{jt}, and cluster all standard errors at the teacher level.

Research Question #3: Does the impact of hosting a student teacher vary for different CTs and student teachers?

We explore a number of potential sources of heterogeneity associated with this question, but given our particular interest in whether hosting a student teacher has a differential impact on student achievement depending on the effectiveness of the CT, we describe our models for this source of heterogeneity and note that this methodology can be extended to explore heterogeneity in any CT or student teacher characteristic. To explore heterogeneity by CT effectiveness, we estimate extensions of the model described in equation 3, which include interactions between the term of interest, ST_{jt}, and teacher value added, VA_j:

$$Y_{ijst} = \gamma_0 + \gamma_1 Y_{i(t-1)} + \gamma_2 S_{it} + \gamma_3 ST_{jt} + \gamma_4 ST_{jt} * VA_j + \gamma_5 Exp_{jt} + \tau_{js} + \varepsilon_{ijst} \qquad (4)$$

A considerable portion of our preliminary analysis, described in the next section, concerns the correct specification of value added that is included in this model.

5. Results

Research Question #1: What are the school- and teacher-based factors predicting where teacher candidate internships take place?

Table 3 presents estimates from five different specifications of the model in Equation 2. All estimates in Table 3 represent marginal effects evaluated at the mean of the independent variables. Positive coefficients signify an increase in the likelihood that a teacher will supervise a student teacher, all else equal. While not reported in

Table 3, all models control for a polynomial of the logged distance between the candidate's TEP and the teacher's district, teacher endorsement areas, and an indicator for whether the teacher holds the same endorsement that the candidate will receive. The distance measures and endorsement match variables are, not surprisingly, highly predictive of student teaching matches, so all results should be interpreted as holding these important variables constant. In particular, an endorsement match between a teacher and student teacher increases the probability that the teacher will host the student teacher by 29 percentage points, and consistent with the existing literature (Krieg et al., 2016), the probability that a teacher will host a student teacher decreases substantially as the distance between the teacher's district and the student teacher's TEP increases. For instance, a teacher that is 20 miles away from the student's TEP is about 9 percentage points less likely to supervise that student than a teacher who is 10 miles away from the TEP.

To aid in interpretation of the variables in Table 3, consider the variable *Teacher Experience*, which measures the years of teaching experience held by cooperating teachers. If all else is constant, each additional year of teacher experience is expected to increase the probability of hosting a student teacher by 0.10 percentage points. To put this in perspective, over the period of our observations, 3.1%, on average, of potential CTs have supervised student teachers. Thus, a 0.10 percentage point increase represents a 3.2% (= 0.11/3.1) increase in the probability of supervising a student teacher.

An overall summary of the first column of Table 3 is that shared characteristics between potential CTs and student teachers are quite predictive of placement in a CT's classroom. For instance, student teachers are much more likely to be placed in a CT's classroom when they share the same gender (a 4.54 percentage point increase), when they share the same race (2.70 percentage point increase), and when they have attended the same TEP (4.94 percentage point increase). These represent very large relationships in percentage terms, as shared gender is associated with a 146% increase in the probability of a CT placement, attending the same TEP is associated with a 87% increase in the probability of a CT placement, and shared race is associated with a 159% increase in the probability of a CT placement. Indeed, these findings are large enough to make the other teacher-level results seem small in comparison: teachers with master's degrees are about 2 percentage points (or 70%) more likely to host a student teacher than teachers with bachelor's degrees, and among student teachers who are not placed with CTs of the same gender, female student teachers are more likely to be hosted by male CTs than vice versa.[22]

The specification in column 1 of Table 3 also contains some characteristics of the potential CTs' schools, and here we observe similarly strong network effects. Specifically, teachers in schools in which the principal attended the same TEP as a student teacher are 2 percentage points more likely to host that student teacher. Teachers at schools that are stable with respect to their teaching labor force (as measured by Stay Ratio) are also more likely to host student teachers, which is encouraging, given the evidence in Ronfeldt (2012) linking the stay ratio of the internship school to future teaching effectiveness. Schools that have more job openings in the year after a student teacher placement

[22] This interpretation comes from the estimate *CT Male* in column 1 of Table 3, and reflects the fact that the gender match variable is also in the model.

(Openings) are also more likely to host student teachers. This suggests that placements may be strategic in the sense that they occur in schools in which there will be future job availability, perhaps a sign that principals who are aware of likely hiring needs may use student teaching as a recruitment or screening process for potential future employees. Interestingly, there are equal and opposite signed coefficients on building free or reduced-price lunch and building percentage of under-represented minority students. Buildings with more underrepresented minorities are less likely to host student teachers, while those with higher levels of free or reduced-price lunch are more likely to train student teachers.[23]

The final four columns of Table 3 present models that include teacher measures of math and ELA value added. Because these models are estimated only for a subset of both potential CTs and student teachers, we reproduce all coefficients from the first column, using the more restricted value-added sample. Overall, the most notable difference between the full sample and the value-added samples is that, among student teachers who do not experience a gender match with their CT, male student teachers are more likely to be hosted by a female CT than vice versa (while the opposite is true in the broader sample). This difference almost certainly occurs because value-added grades, grades 3 through 8, are overwhelming taught by female teachers. Other than this, the coefficients on the remaining variables are of similar magnitudes and signs as those in the full sample.

Because value added is measured for only a subset of teachers and relatively few student teachers actually student-taught with one of these teachers, our interpretation of these results is conditional upon a student teacher's being hosted by a CT with a valid value-added measure. With that said, columns 2 and 4 illustrate that neither math nor reading value added is a statistically significant predictor of hosting a student teacher, all else equal. In columns 3 and 5 of Table 3, we consider the same relationships but replace the linear measures of value added with binary variables representing

[23] When we estimate a model that includes only school %URM, this coefficient is no longer statistically significant, which suggests that placements are not in fact less likely in higher %URM schools overall, but rather that—conditional on school %FRL—schools with more minority students are less likely to host a student teacher.

the CT’s quartile of value added. Again, there is no evidence that student teacher placements occur with respect to either math or reading value added.

Research Question #2: Does hosting a student teacher have an impact on student achievement?

Column 1 of Table 3 presents estimates from equation 3 for math classrooms. The conclusion from this model is that hosting a student teacher has a modest, negative, and statistically significant average impact on student performance; specifically, a teacher’s students score .015 standard deviations lower on the state math test, all else equal, in years in which the teacher hosts a student teacher than in other years. On the other hand, Column 1 of Table 4 reports the equivalent estimate for ELA classrooms, and it is not statistically significant. That is, there is not sufficient evidence to conclude that teachers’ students perform any better or worse on ELA tests in years in which they host a student teacher than in years they do not.

It is important to note that these estimates are quite precisely estimated—that is, the standard error of each estimate is less than 0.01 standard deviations of student performance—meaning that we can rule out large average impacts in both subjects. For example, the 90% confidence intervals in each subject imply that we can rule out with 90% confidence average impacts larger than 0.03 student standard deviations or smaller than -0.03 in both subjects. Therefore, while the estimate in math is statistically significant and generally supports the hypothesis that there may be costs to student teacher placements in terms of student achievement in the student teaching classroom, we would characterize this effect as very modest.

Research Question #3: Does the impact of hosting a student teacher vary for different CTs and student teachers?

The remaining columns of Tables 4 and 5 explore heterogeneity in these effects by the value added of the CTs, estimated from years in which these teachers do not host a student teacher (i.e., equation 4 in Section 4). Since in many models of student teaching, hosting a student teacher essentially involves replacing several weeks or months of a teacher's instruction with instruction from a completely novice student teacher, one might expect students in the classrooms of effective teachers to have their test scores impacted more negatively than students in other classrooms. On the other hand, since other models of student teaching involve a close partnership between the student teacher and CT, it may be the case that students in the classrooms of ineffective teachers are disproportionately impacted when their teacher hosts a student teacher.

The estimates from our first specification of equation 4, presented in column 2 of Tables 4 and 5, appear to confirm the first hypothesis. In this specification, VA_j in equation 4 is estimated from all years in which the CT did not host a student teacher between 2009-10 and 2014-15 (i.e., a "leave-one-out" specification of value added). When we interact quartiles of CT value added according to this specification with the indicator for hosting a student teacher, we see large differences in the impacts of hosting a student teacher by teacher effectiveness; for example, students in effective teachers' classrooms do considerably worse in years when the teacher hosts a student teacher than in other years.

However, the estimates in column 2 of Tables 4 and 5 may be biased if there is regression to the mean in teacher effectiveness. Specifically, the years of data we are using to estimate teacher value added are the same years of data that are being used as the "reference years" for estimating the impact of hosting a student teacher. Suppose, for example, that a teacher has an unusually bad year in year t and then hosts a student teacher in year $t + 1$. This bad year both makes it more likely that the teacher is identified as an ineffective teacher and makes the year that the teacher hosted a student teacher look better in comparison (assuming the teacher's performance regresses to the mean). To verify that these issues do result in biased estimates, we create a random placebo student teacher in 3% of teacher observations and use this placebo in place of the true student teaching placements ST_{jt} in equation 4. As shown in Column 3 of Tables 4 and 5, these placebo placements lead to the similar estimates (though smaller in magnitude) as those found in models using true placements, which suggests that the estimates in Column 2 are biased.

We therefore make two modifications to the model from Column 2 to account for regression to the mean. First, to ensure that teacher value added is truly an "out-of-sample" estimate that is not estimated from the same years that are being used to estimate the impact of hosting a student teacher, we employ a similar approach to that of the conditional logit models: We first estimate teacher value added from the 2009–10 and 2010–11 school years (see equation 1) and omit years in which a teacher hosted a TELC student teacher; then we use these value-added estimates to explore heterogeneity in the impacts of hosting a student teacher between 2011–12 and 2014–15. Second, as shown by Atteberry et al. (2015)—and as reproduced in Column 4 of Tables 4 and 5—teachers who are less effective in 2010–2011 tend to be more effective in later years (and teachers who are more effective in 2010–2011 tend to be less effective in later years) for reasons that have nothing to do with hosting a student teacher. We therefore include interactions between these later school years and quartiles of teacher value added to directly account for this regression to the mean.

The estimates from this modified specification, reported in Column 5 of Tables 4 and 5, tell a very different story from that of the estimates in Column 2. In math (Table 4), the result actually flips direction—that is, the students of ineffective teachers actually perform considerably *worse* (by 0.065 standard deviations of student performance) in years when these teachers host a student teacher than in years when they do not. The interactions between hosting a student teacher and the other three quartiles of value added imply that the effect of hosting a student teacher is close to zero for teachers not in the bottom quartile of value added, which suggests that the modest negative effect in math from column 1 of Table 4 is driven by CTs in the lowest quartile of value added. This in turn supports the second hypothesis, described above, that more effective CTs can mitigate the impact of hosting a student teacher on student performance.

In ELA (Table 5), the estimates in Column 5 are directionally consistent with the earlier results but are not statistically significant, which suggests that there is not significant heterogeneity in the impacts of hosting a student teacher by ELA CT effectiveness. The estimates in Column 6 of Tables 4 and 5, which again use the placebo placements instead of the true placements, verifies that the estimates in Column 5 are no longer biased by regression to the mean. Finally, Tables 6 and 7 replace quartiles of teacher value added with continuous value added and show that the interaction between teacher value added and hosting a student teacher is not statistically significant in either math or ELA in our preferred specification (column 5).

We conclude this section by discussing a number of additional tests for heterogeneity in the effects of hosting a student teacher, none of which produce more statistically significant interactions than we would expect by random chance. Since the nature of student teaching may be very different depending on the grade in which student teacher occurs, we explore heterogeneity by the student teaching grade and do not find consistent patterns by grade level. We also explore heterogeneity by the TEP from which the student graduated, and do not find significant heterogeneity across different TEPs.[24] We also hypothesized that the impact of hosting student teachers may vary depending on how many prior student teachers a CT has hosted, but we do not find significant interactions between the number of previously observed student teachers (in the TELC data) and the impact of hosting a student teacher.

[24] This is perhaps not surprising, since prior work in Washington finds that only about 1% of the variation in teacher value added in the state can be explained by the TEPs from which teachers graduated (Goldhaber et al., 2013).

6. Conclusions

This paper provides the first empirical evidence of the factors that determine which teachers and schools host student teachers, and the extent to which these placements may affect student achievement. We find that teacher candidates are more likely to student-teach in schools with more openings the following year and with lower rates of teacher turnover across years. We would characterize these results as encouraging, given the empirical evidence connecting school openings (Goldhaber et al., 2017) and school stay ratios (Ronfeldt, 2012) to future workforce entry, effectiveness, and retention.

It is important to note, however, the fact that student teaching is occurring in schools and with teachers that are associated with positive future outcomes certainly does not imply that student teacher placements are optimized. For as we illustrated in Figure 4, there is a large number of promising classrooms where student teachers are not hosted, and there tend to be geographic holes (Figure 2) in parts of Washington that are not close to TEPs. These holes may have important teacher equity implications, given the locality of teacher labor markets (Boyd et al., 2005; Krieg et al., 2016; Reininger, 2012).

We also find some evidence that hosting a student teacher is associated with lower math achievement in the classroom in which student teaching occurs. That said, the average impact of hosting a student teacher on student math performance is quite modest (less than .02 standard deviations of student performance) and the average impact on student ELA performance is not significantly different from zero, so we do not view this as evidence that schools and districts should generally reconsider hosting student teachers. But since the negative effect in math is driven by CTs in the lowest quartile of value added, we do believe that this paper further strengthens an emerging empirical research base (e.g., Ronfeldt et al., 2018) supporting the placement of student teachers with more effective CTs.[25]

To fully contextualize the findings in this paper, though, we need to know much more about the specific characteristics of CTs that are predictive of future candidate success. While the emerging quantitative research in this area (e.g., Ronfeldt et al., 2018) is starting to back up the long-standing claims of the importance of CTs discussed in Section 2, TEPs and districts could benefit from much more nuanced information about what kinds of placements appear to benefit student teacher development. Without this additional information, it is difficult to conclude whether the patterns described in this paper are in the best interest of candidate development and, ultimately, the success of these candidates' future students.

[25] This is particularly true since the impact on student math performance in these classrooms is relatively large (more than .06 standard deviations of student performance), particularly considering that students in these classrooms already have an ineffective teacher

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Figures

Figure 1. Distribution of Student Teaching Placements, by Year and TEP

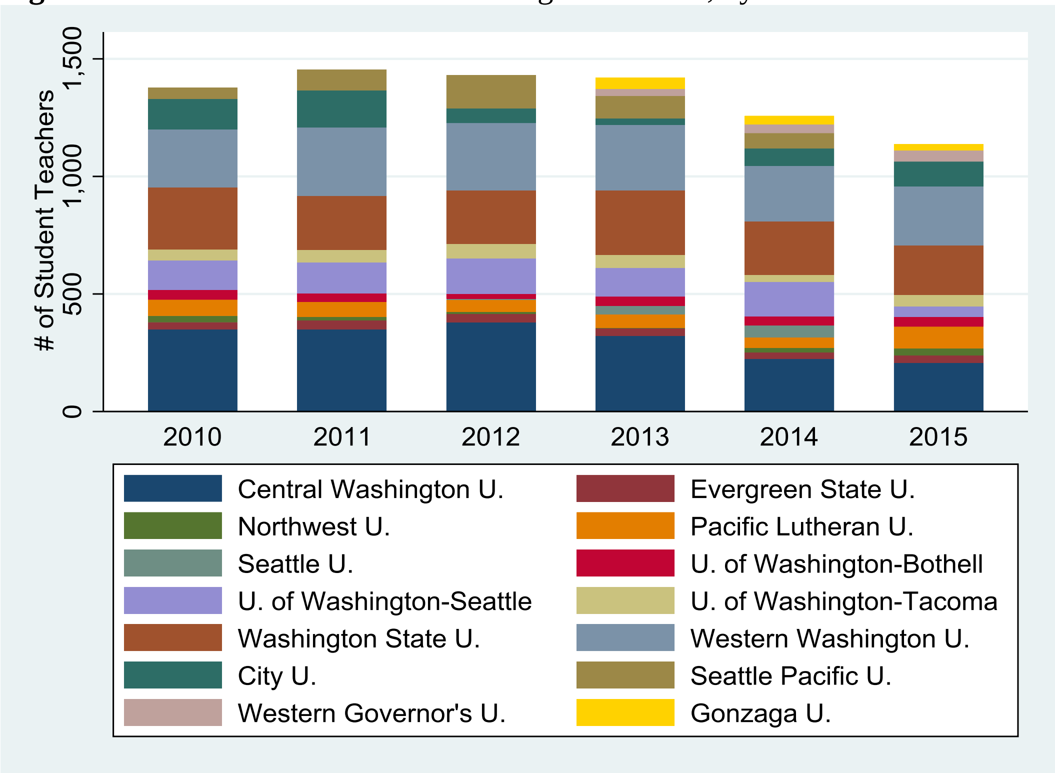
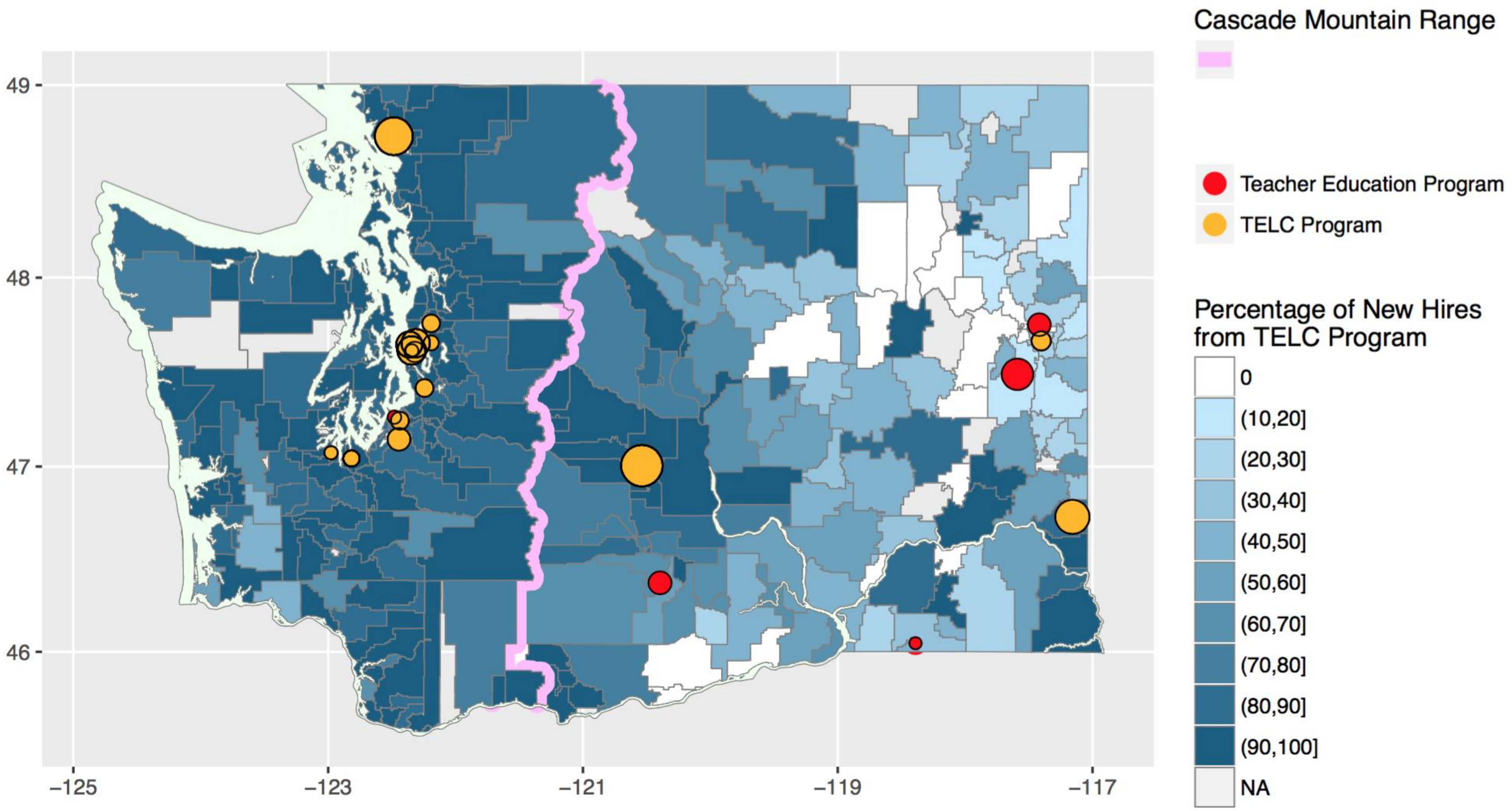


Figure 2. Percentage of Newly Hired, In-State Teachers From Participating TEPs, 2010–2015



Note. The size of the dot for each TEP represents the number of newly credentialed teachers from that program between 2010 and 2015.

Figure 3. Percentage of Teachers Hosting a Student Teacher From a Participating TEP, 2010–2015

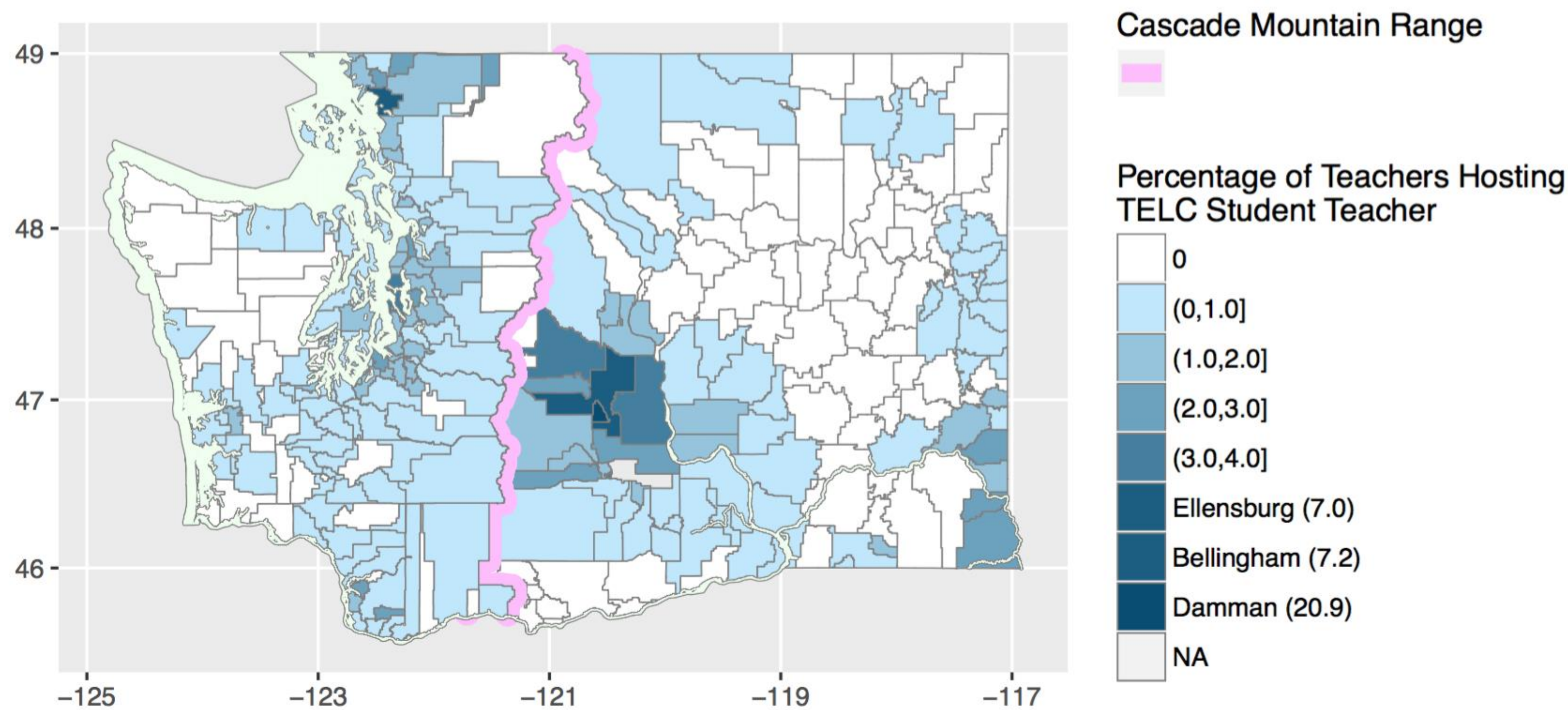
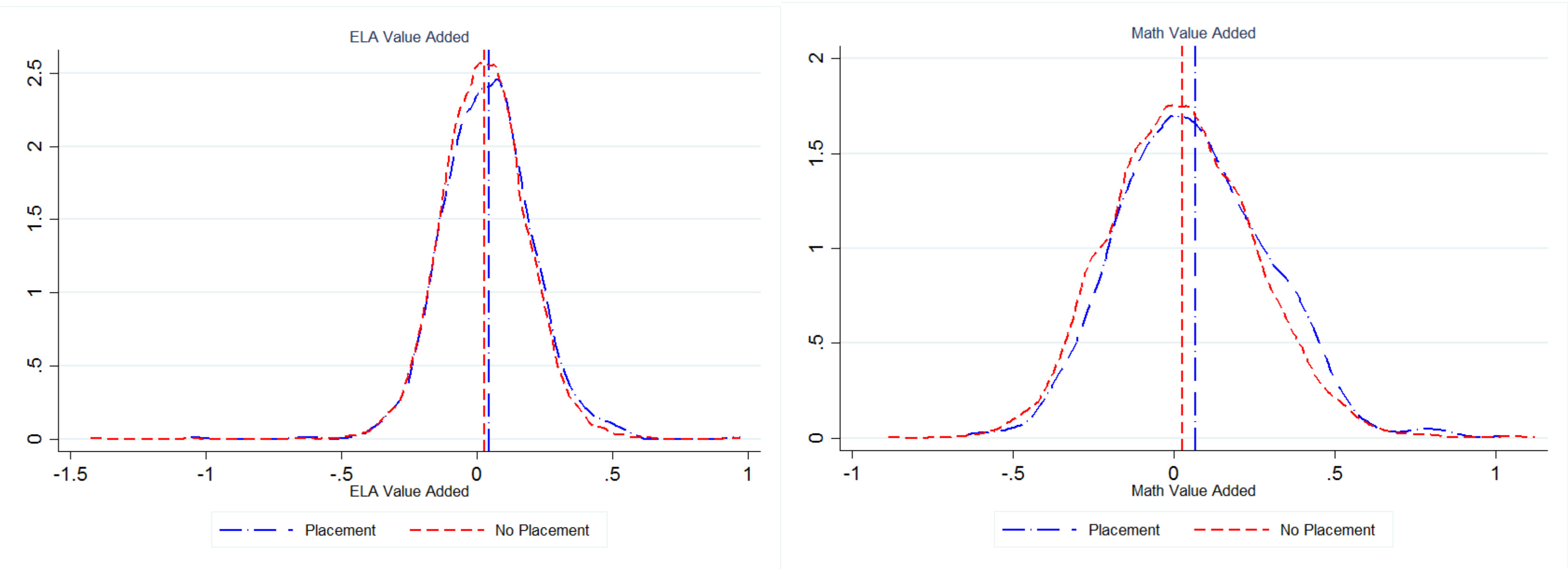


Figure 4. Distribution of Value Added for Cooperating Teachers and Other Teachers



Tables

Table 1: Summary Statistics of Student Teaching Placements and Nonstudent Teaching Placements

	Placement	No Placement
Teacher Experience	14.951***	15.462
	(8.379)	(8.963)
Teacher Male	0.227***	0.284
Teacher Race Asian	0.030	0.034
Teacher Race Black	0.017	0.015
Teacher Race American Indian	0.007	0.007
Teacher Race Hispanic	0.020	0.020
Teacher Master's Degree	0.729***	0.697
Teacher PhD	0.007	0.007
Teacher Math Value Added	0.062***	0.027
	(0.232)	(0.228)
Teacher ELA Value Added	0.039**	0.0267
	(0.167)	(0.158)
School % URM Students	25.417***	23.030
	(16.286)	(14.481)
School % FRL Students	42.199***	41.090
	(22.496)	(21.888)
School Five-Year Stay Ratio	-0.047***	0.037
	(0.758)	(0.815)
School Openings Next Year	4.423***	4.296
	(3.270)	(3.209)
School Closure Next Year	0.003	0.004

Note. CT = cooperating teacher; ELA = English Language Arts; FRL = free or reduced-priced lunch; TEP = teacher education program; URM = under-represented minority. P-values from two-sided *t*-test relative to column 2: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Number of Observations in Conditional Logit Models

	Panel A: West Side Sample			
Year	# of Student Teachers	# of Supervising Teachers	Total Observations	% of Teachers Hosting Student Teacher
2010	954	29,610	28,247,940	3.2%
2011	1,026	30,500	31,293,000	3.3%
2012	937	30,410	28,494,170	3.1%
2013	962	29,942	28,804,204	3.2%
2014	832	29,744	24,747,008	2.8%
2015	788	29,587	23,314,556	2.7%
Total	**5,499**	**179,793**	**164,900,878**	**3.1%**
	Panel B: ELA Value-Added Sample			
Year	# of Student Teachers	# of Supervising Teachers	Total Observations	% of Teachers Hosting Student Teacher
2012	176	5,615	988,244	3.1%
2013	169	5,435	918,511	3.1%
2014	154	5,197	800,339	3.0%
2015	140	4,804	672,556	3.0%
Total	**639**	**21,051**	**3,379,650**	**3.0%**
	Panel C: Math Value-Added Sample			
Year	# of Student Teachers	# of Supervising Teachers	Total Observations	% of Teachers Hosting Student Teacher
2012	172	5,323	915,561	3.2%
2013	147	5,151	757,189	2.9%
2014	138	4,953	683,516	2.8%
2015	137	4,592	629,104	3.0%
Total	**594**	**20,019**	**2,985,370**	**3.0%**

Table 3: Conditional Logit Marginal Effects Estimates of Hosting a Student Teacher

	(1)	(2)	(3)	(4)	(5)
Teacher Experience	0.0010*** (0.0002)	0.0008 (0.0005)	0.0008 (0.0005)	0.0008 (0.0005)	0.0008 (0.0005)
Teacher Male	0.0117*** (0.0037)	-0.0112 (0.0098)	-0.0112 (0.0098)	-0.0108 (0.0076)	0.0009 (0.0091)
Teacher Race Asian	0.0094 (0.0091)	0.0032 (0.0237)	0.0035 (0.0242)	0.0032 (0.0237)	0.0243 (0.0215)
Teacher Race Black	-0.0057 (0.0117)	-0.0575 (0.0367)	-0.0588 (0.0375)	-0.0575 (0.0367)	-0.0721 (0.0353)
Teacher Race American Indian	0.0366** (0.0173)	0.0148 (0.0542)	0.0152 (0.0552)	0.0148 (0.0542)	0.0374 (0.0439)
Teacher Race Hispanic	0.0090 (0.0110)	-0.0339 (0.0319)	-0.0339 (0.0325)	-0.0339 (0.0319)	-0.0148 (0.0276)
Teacher Master's Degree	0.0218*** (0.0032)	0.0163* (0.0089)	0.0166* (0.0091)	0.0163* (0.0089)	0.0169** (0.0081)
Teacher PhD	0.0202 (0.0167)	0.0470 (0.0456)	0.0498 (0.0464)	0.0470 (0.0456)	0.0470 (0.0477)
Teacher Math Value Added		0.0247 (0.0167)			
Teacher Math Value Added Q2			0.0126 (0.0126)		
Teacher Math Value Added Q3			0.0066 (0.0123)		
Teacher Math Value Added Q4			0.0140 (0.0123)		
Teacher ELA Value Added				0.0129 (0.0217)	
Teacher ELA Value Added Q2					-0.0127 (0.0098)
Teacher ELA Value Added Q3					-0.0148 (0.0098)
Teacher ELA Value Added Q4					-0.0005 (0.0093)
School % URM Students	-0.0009*** (0.0002)	-0.0024*** (0.0004)	-0.0025*** (0.0005)	-0.0024*** (0.0005)	-0.0015*** (0.0004)
School % FRL Students	0.0008*** (0.0001)	0.0016*** (0.0004)	0.0016*** (0.0004)	0.0016*** (0.0004)	0.0012*** (0.0003)
School 5-Year Stay Ratio	0.0057*** (0.0019)	0.0000 (0.0050)	0.0001 (0.0051)	0.0000 (0.0050)	0.0000 (0.0050)
School Openings Next Year	0.0026*** (0.0005)	-0.0001 (0.0012)	-0.0001 (0.0012)	-0.0001 (0.0015)	-0.0004 (0.0012)
School Closure Next Year	-0.0360 (0.0434)	0.0656 (0.0645)	0.0668 (0.0657)	0.0656 (0.0645)	0.0409 (0.0058)
Teacher Same Race	0.0270*** (0.0080)	-0.0080 (0.0201)	-0.0084 (0.0205)	-0.0080 (0.0201)	0.0107 (0.0184)
Teacher Same Gender	0.0454*** (0.0039)	0.0325*** (0.0104)	0.0331*** (0.0105)	0.0325*** (0.0104)	0.0327*** (0.0103)
Teacher Same TEP	0.0494*** (0.0041)	0.0437*** (0.0111)	0.0445*** (0.0113)	0.0437*** (0.0111)	0.0344*** (0.0100)
School Administrator Same TEP	0.0200*** (0.0045)	0.0095 (0.0118)	0.0097 (0.0120)	0.0095 (0.0118)	0.0171* (0.0101)
Observations	153,319,499	2,975,271	2,975,271	3,368,597	3,368,597

Notes. ELA = English Language Arts; FRL = free or reduced priced lunch; TEP = teacher education program; URM = underrepresented minority. P-values from two-sided *t*-test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models control for a polynomial of the linear distance between candidate's teacher education program and the CT's school, CT endorsement areas, and an indicator for whether the CT holds the same endorsement that the candidate will receive.

Table 4. Effects of Hosting a Student Teacher in Math, by Quartile of Math Value Added

	1	2	3	4	5	6
Hosted Student Teacher	-0.015* (0.008)	0.015 (0.015)	0.052*** (0.016)		-0.065** (0.032)	0.018 (0.024)
Hosted Student Teacher * Q2 Math Value Added		0.011 (0.022)	-0.054** (0.023)		0.073* (0.038)	0.006 (0.034)
Hosted Student Teacher * Q3 Math Value Added		-0.039* (0.022)	-0.056** (0.022)		0.075* (0.043)	-0.022 (0.031)
Hosted Student Teacher * Q4 Math Value Added		-0.085*** (0.022)	-0.105*** (0.025)		0.043 (0.039)	-0.025 (0.036)
2013				0.013* (0.008)	0.013* (0.008)	0.013 (0.008)
2014				0.059*** (0.010)	0.058*** (0.010)	0.059*** (0.010)
2015				0.063*** (0.012)	0.064*** (0.012)	0.063*** (0.012)
Q2 Math Value Added * 2013				-0.003 (0.011)	-0.003 (0.011)	-0.003 (0.011)
Q2 Math Value Added * 2014				-0.037*** (0.014)	-0.037*** (0.014)	-0.038*** (0.014)
Q2 Math Value Added * 2015				-0.007 (0.016)	-0.007 (0.016)	-0.007 (0.016)
Q3 Math Value Added * 2013				-0.013 (0.011)	-0.013 (0.011)	-0.012 (0.011)
Q3 Math Value Added * 2014				-0.062*** (0.014)	-0.062*** (0.014)	-0.062*** (0.014)
Q3 Math Value Added * 2015				-0.038** (0.016)	-0.039** (0.016)	-0.038** (0.016)
Q4 Math Value Added * 2013				-0.030*** (0.011)	-0.030*** (0.011)	-0.030*** (0.011)
Q4 Math Value Added * 2014				-0.077*** (0.014)	-0.077*** (0.014)	-0.077*** (0.014)
Q4 Math Value Added * 2015				-0.088*** (0.016)	-0.088*** (0.017)	-0.087*** (0.016)
Student Teaching	Real	Real	Placebo	n/a	Real	Placebo
Sample Years	2010–2015	2010–2015	2010–2015	2012–2015	2012–2015	2012–2015
VAM Years	n/a	Leave-one-out	Leave-one-out	2010–2011	2010–2011	2010–2011

Note. P-values from two-sided *t*-test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models include a teacher fixed effect, control for teacher experience, and control for the following student control variables interacted by grade: prior performance in math and reading, gender, race, receipt of free or reduced-priced lunch, special education status and disability type, Limited English Proficiency indicator, migrant indicator, and homeless indicator. Standard errors are clustered at the teacher level.

Table 5. Effects of Hosting a Student Teacher in ELA, by Quartile of ELA Value Added

	1	2	3	4	5	6
Hosted Student Teacher	0.009 (0.007)	0.069*** (0.016)	0.045** (0.017)		0.036 (0.026)	-0.011 (0.027)
Hosted Student Teacher * Q2 ELA Value Added		-0.029 (0.020)	-0.003 (0.023)		-0.021 (0.033)	0.020 (0.038)
Hosted Student Teacher * Q3 ELA Value Added		-0.064*** (0.020)	-0.061** (0.023)		-0.024 (0.033)	-0.010 (0.035)
Hosted Student Teacher * Q4 ELA Value Added		-0.124*** (0.021)	-0.099*** (0.022)		-0.036 (0.034)	0.008 (0.036)
2013				0.023*** (0.009)	0.023*** (0.009)	0.023*** (0.009)
2014				0.041*** (0.011)	0.042*** (0.011)	0.041*** (0.011)
2015				0.098*** (0.014)	0.099*** (0.014)	0.098*** (0.014)
Q2 ELA Value Added * 2013				0.002 (0.011)	0.002 (0.011)	0.002 (0.011)
Q2 ELA Value Added * 2014				0.004 (0.015)	0.003 (0.015)	0.004 (0.015)
Q2 ELA Value Added * 2015				-0.024 (0.019)	-0.024 (0.019)	-0.024 (0.019)
Q3 ELA Value Added * 2013				-0.019* (0.011)	-0.019* (0.011)	-0.019* (0.011)
Q3 ELA Value Added * 2014				-0.034** (0.014)	-0.035** (0.014)	-0.034** (0.014)
Q3 ELA Value Added * 2015				-0.038** (0.018)	-0.038** (0.018)	-0.038** (0.018)
Q4 ELA Value Added * 2013				-0.040*** (0.011)	-0.040*** (0.011)	-0.040*** (0.011)
Q4 ELA Value Added * 2014				-0.047*** (0.014)	-0.047*** (0.014)	-0.047** * (0.014)
Q4 ELA Value Added * 2015				-0.061*** (0.018)	-0.062*** (0.018)	-0.061*** (0.018)
Student Teaching	Real	Real	Placebo	n/a	Real	Placebo
Sample Years	2010–2015	2010–2015	2010–2015	2012–2015	2012–2015	2012–2015
VAM Years	n/a	Leave-one-out	Leave-one-out	2010–2011	2010–2011	2010–2011

Note. ELA = English Language Arts. P-values from two-sided *t*-test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models include a teacher fixed effect, control for teacher experience, and control for the following student control variables interacted by grade: prior performance in math and reading, gender, race, receipt of free or reduced-priced lunch, special education status and disability type, Limited English Proficiency indicator, migrant indicator, and homeless indicator. Standard errors are clustered at the teacher level.

Table 6. Effects of Hosting a Student Teacher in Math, by Continuous Math Value Added

	1	2	3	4	5	6
Hosted Student Teacher	-0.015* (0.008)	-0.011 (0.009)	-0.002 (0.009)		-0.013 (0.013)	0.007 (0.012)
Hosted Student Teacher * Math Value Added		-0.227*** (0.055)	-0.243*** (0.054)		0.071 (0.067)	-0.057 (0.053)
2013				0.002 (0.004)	0.002 (0.004)	0.002 (0.004)
2014				0.013** (0.005)	0.013** (0.005)	0.013* (0.005)
2015				0.030*** (0.006)	0.030*** (0.006)	0.030*** (0.006)
Value Added * 2013				-0.052** (0.018)	-0.052*** (0.017)	-0.052*** (0.018)
Value Added * 2014				-0.138*** (0.022)	-0.138*** (0.022)	-0.138*** (0.022)
Value Added * 2015				-0.173*** (0.025)	-0.173*** (0.025)	-0.173*** (0.025)
Student Teaching	Real	Real	Placebo	n/a	Real	Placebo
Sample Years	2010–2015	2010–2015	2010–2015	2012–2015	2012–2015	2012–2015
Value Added Years	n/a	Leave-one-out	Leave-one-out	2010–2011	2010–2011	2010–2011

Note. P-values from two-sided *t*-test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models include a teacher fixed effect, control for teacher experience, and control for the following student control variables interacted by grade: prior performance in math and reading, gender, race, receipt of free or reduced-priced lunch, special education status and disability type, Limited English Proficiency indicator, migrant indicator, and homeless indicator. Standard errors are clustered at the teacher level.

Table 7. Effects of Hosting a Student Teacher in ELA, by Continuous ELA Value Added

	1	2	3	4	5	6
Hosted Student Teacher	0.009 (0.007)	0.016** (0.007)	0.004 (0.008)		0.017 (0.011)	-0.011 (0.013)
Hosted Student Teacher * ELA Value Added		-0.485*** (0.066)	-0.363*** (0.073)		-0.070 (0.060)	0.046 (0.081)
2013				0.010*** (0.004)	0.010*** (0.004)	0.010*** (0.004)
2014				0.024*** (0.005)	0.024*** (0.005)	0.024*** (0.005)
2015				0.069*** (0.007)	0.069*** (0.007)	0.069*** (0.007)
Value Added * 2013				-0.104*** (0.024)	-0.105*** (0.024)	-0.105*** (0.024)
Value Added * 2014				-0.145*** (0.030)	-0.148*** (0.031)	-0.145*** (0.030)
Value Added * 2015				-0.163*** (0.037)	-0.166*** (0.037)	-0.163*** (0.037)
Student Teaching	Real	Real	Placebo	n/a	Real	Placebo
Sample Years	2010–2015	2010–2015	2010–2015	2012–2015	2012–2015	2012–2015
Value Added Years	n/a	Leave-one-out	Leave-one-out	2010–2011	2010–2011	2010–2011

Note. ELA = English Language Arts. P-values from two-sided *t*-test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models include a teacher fixed effect, control for teacher experience, and control for the following student control variables interacted by grade: prior performance in math and reading, gender, race, receipt of free or reduced-priced lunch, special education status and disability type, Limited English Proficiency indicator, migrant indicator, and homeless indicator. Standard errors are clustered at the teacher level.