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Student Teaching and the Geography of Teacher Shortages

Dan Goldhaber
John Krieg
Natsumi Naito
Roddy Theobald

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Dan Goldhaber
American Institutes for Research/CALDER
University of Washington

John Krieg
Western Washington University

Natsumi Naito
University of Washington

Roddy Theobald
American Institutes for Research/CALDER

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CALDER • American Institutes for Research
1000 Thomas Jefferson Street NW, Washington, DC 20007
202-403-5796 • www.caldercenter.org

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Abstract

Prior research has shown that about 15% of teachers are hired into the same school in which they student taught, about 40% are hired into their student teaching district, and the location of teachers' student teaching placements is more predictive of where they are hired than where they went to high school or college. While this suggests that strategic student teaching placements are a potential policy lever for addressing regional teacher shortages, there is no prior empirical evidence of a relationship between student teaching placements and teacher shortages. In this paper, we describe research from Washington state that descriptively explores the relationship between student teaching placements and a proxy for teacher shortages, the proportion of new teacher hires in a school or district with emergency teaching credentials. We find that schools and districts that host fewer student teachers tend to hire significantly more new teachers with emergency credentials the following year, and that these relationships are robust to controlling for school and district urbanicity, distance to a teacher education program, and other observable school and district characteristics. This descriptive evidence suggests exploring efforts to place student teachers in schools and districts that struggle to staff their classrooms.

1. Introduction

There is little doubt that it has become more challenging in recent years to find qualified teachers to staff the nation's classrooms. This is reflected in newspaper headlines (e.g., Blume, 2016; Times Editorial Board, 2017) and numerous state reports detailing difficulties that schools face with teacher staffing.[1] There are varied explanations for what is commonly referred to as the *teacher shortage*, ranging from the long-term decline in relative teacher salaries and increases in school accountability to the general tightening of the labor market since the Great Recession.[2]

Importantly, however, teacher shortages are not uniformly geographically distributed. Certain types of schools and districts are far more likely to experience staffing challenges (Cowan, Goldhaber, Hayes, & Theobald, 2016; Pennington McVey & Trinidad, 2019).[3] And while some of this may be attributable to the working conditions in schools or the challenges of working with low-achieving student populations (Clark, McConnell, Constantine, & Chiang, 2013; Sutcher, Darling-Hammond, & Carver-Thomas, 2016), research suggests that the location of teacher education programs (TEPs) and where student teaching occurs are also likely to be important factors. In particular, there is significant evidence that teacher labor markets are quite localized: Teacher candidates tend to obtain their credentials close to where they grew up, and then find first jobs close to their home and TEP (Boyd, Lankford, Loeb, & Wyckoff, 2005; Reininger, 2012). Emerging evidence from Washington, the setting of this study, suggests that student-teaching placements may also contribute to these relationships (Krieg, Theobald, & Goldhaber, 2016; Krieg, Goldhaber, & Theobald, 2019). Specifically, teacher candidates tend to

[1] See Pennington McVey & Trinidad (2019) for an analysis of teacher shortage areas over time. For a full listing of shortage areas, see https://www2.ed.gov/about/offices/list/ope/pol/bteachershortageareasreport201718.pdf.
[2] See, for instance, Dee & Goldhaber (2017) and Kraft, Brunner, Dougherty, & Schwegman (2018).
[3] Staffing challenges also tend to be far more acute in certain subjects and grade levels, such as special education and high school mathematics and science courses (Cowan et al., 2016; Dee & Goldhaber, 2017).

student teach near their TEP and first job; in fact, about 15% of teachers are hired into the same school in which they student taught, about 40% are hired into their student teaching district, and the location of teachers' student teaching placements is more predictive of where they are hired than where they went to high school or college (Krieg et al., 2016).

While the localness of teacher labor markets has been widely studied, there is no large-scale quantitative research examining the extent to which this phenomenon is linked to the staffing challenges that some schools and districts face. We examine this issue using a unique dataset from Washington state that includes annual data on student teacher placements from the vast majority of TEPs in the state along with detailed school staffing information. These data enable us to investigate the extent to which schools and districts staff their open teaching positions with individuals who are teaching on an emergency credential (a measure of the degree of staffing challenge).

In this descriptive analysis, we find there is a strong inverse relationship between the proportion of teachers in a schools or districts that host a student teacher and the likelihood that those schools and districts rely on emergency credentialed teachers to staff classrooms. It is important to be cautious about overinterpreting these findings as causal, given, for instance, that student teachers may seek out placements in schools and districts in which they hope to work one day. That said, these findings hold up even when controlling for school and district urbanicity, distance to a TEP, and other observable school and district characteristics. Moreover, te findings are particularly strong when we consider the alignment between the subject areas in which schools and districts host student teachers and the subject areas in which schools and districts hire teachers the following year. This descriptive evidence suggests exploring efforts to place student teachers in schools and districts that struggle to staff their classrooms.

2. Student Teaching and Localized Nature of Teacher Labor Markets

Challenges that schools and districts face in staffing can arise from difficulties recruiting teachers, transfers within the teaching profession, or attrition of teachers from public schools. Evidence suggests that nearly all of these processes disproportionately contribute to staffing difficulties in disadvantaged schools. For instance, teacher applicants demonstrate a preference for advantaged schools in their initial job selection (Boyd et al., 2013; Engel, Jacob, & Curran, 2014), and teachers in disadvantaged schools are more likely to transfer to another school or leave the profession than teachers in advantaged schools (e.g., Goldhaber, Gross, & Player, 2011; Hanushek, Kain, & Rivkin, 2004; Scafidi, Sjoquist, & Stinebrickner, 2007).[4] Given the inequity in these processes, it is not surprising that there is also considerable evidence of teacher quality gaps between advantaged and disadvantaged schools (e.g., Clotfelter, Ladd, & Vigdor, 2005; Goldhaber, Lavery, & Theobald, 2015; Goldhaber, Quince, & Theobald, 2018; Isenberg et al., 2016; Lankford et al., 2002; Sass, Hannaway, Xu, Figlio, & Feng, 2012).

Newly minted teachers are an important source of teacher supply. About 50% of teachers newly hired into public schools are recent graduates from TEPs (the remaining 50% are individuals who are returning to the teacher labor market after 1 or more years when they were not teaching or teaching in private schools).[5] And most of these newly minted teachers were credentialed by traditional TEPs operated by institutions of higher education.[6]

[4] See Goldhaber, Quince, & Theobald (2018) for a comprehensive overview of inequity in these processes in the teacher labor market.

[5] See https://nces.ed.gov/surveys/sass/tables/sass0708_034_t1n.asp and Cowan et al. (2016).

[6] In the most recently available Title II report, more than 85% of individuals completing a credential program were from a traditional TEP. For the annual number of completers by credential program type, see https://title2.ed.gov/Public/TitleIIReport16.pdf. Importantly, however, there are no national definitions of alternative or traditional routes into teaching, as these definitions are determined by individual states (U.S. Department of Education, 2016). In Washington state, even fewer teacher candidates are trained to enter the teaching profession through alternative routes. While alternative certification pathways were recently approved in Washington, they were not yet available to new teachers during the years considered in this paper (2010–17).

A significant amount of empirical literature shows that many newly credentialed teacher candidates find employment close to the program from which they received their teaching credential and/or did their student teaching (also referred to as *clinical practice*); thus, the *potential* relationship between the geography of student teaching and staffing challenges. Boyd and colleagues (2005), for instance, find that nearly 85% of new teachers in New York find a job within 40 miles of where they went to high school; they call this phenomenon the *draw of home* in new teacher hiring. This same phenomenon has been observed nationally and is uniquely strong for teachers relative to those in other professions (Reininger, 2012).

These trends are true in Washington state as well: Krieg et al. (2016) find over half of first teaching jobs in the state are within 25 miles of the district in which the teacher attended high school and about two-thirds are within 50 miles. More closely related to our work here, Krieg et al. (2016) also find that student teaching placements are even more predictive of a first job location than the location of their TEP or high school. Specifically, they find about two-thirds of first jobs are within 25 miles of a student teaching internship and over 75% of first jobs are within 50 miles of an internship. Moreover, the odds that a teacher begins her career in the district in which she student taught relative to another district is about 10 times larger than the corresponding odds that she begins her career in her hometown district (Goldhaber, Krieg, & Theobald, 2014).[7]

The localized connections between teacher education and school system employment suggests that school systems that host few student teachers may face more limited hiring options

[7] It is difficult to know empirically the extent to which this *draw of home* phenomenon is a reflection of employer (i.e., school system) preferences or the preferences of teacher candidates themselves, but an important piece of related context is that the teaching profession (particularly in Washington) is overwhelmingly White and female; thus, these findings largely reflect this specific demographic.

and, thus, greater staffing challenges. Goldhaber et al. (2019) find that school districts in California that are geographically closer to TEPs have fewer staffing challenges (as measured by teacher vacancy rates) and suggest that "[g]iven that student teaching appears to be a key factor in influencing the location of a first job, it makes good sense for the state to encourage teacher candidate-student teaching internship matches be in districts with greater classroom staffing struggles" (p. 52). Yet despite the evidence pointing to the localness of teacher labor markets as a potential contributor to staffing challenges, it is unclear whether the patterns described above are driven by institutional relationships between TEPs and local schools or the preferences of teacher candidates themselves.

Qualitative assessments of clinical practice (Meyer, 2016; St. John, Goldhaber, Krieg, & Theobald, 2018) suggest that placement processes are quite varied across districts and TEPs. Placements are governed by the contractual arrangements between TEPs and school systems and reflect a combination of desired TEP practices, school system needs, and the preferences of individual teacher candidates. As such it is not surprising that these field experiences have been identified as "the most ad hoc part of teacher education in many programs" (National Council for Accreditation of Teacher Education, 2010, p. 4). There is relatively little *quantitative* research on the factors that predict where student teaching occurs, but the two quantitative studies on this topic (Krieg et al., 2016, 2019) find that teachers with more experience, higher degree levels, and higher value added in math 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. And, to our knowledge, there is no quantitative evidence on the link between student teaching placements and school system staffing challenges.

3. Data and Analytic Approach

3.1 Data

For this study, we combine data from Washington state's Office of Superintendent of Public Instruction (OSPI) on public school teachers with data on student teaching provided by a group of 15 TEPs in Washington that are participating in the Teacher Education Learning Collaborative (TELC).[8]

The OSPI data include detailed information on annual school staffing placements from the state's S-275 personnel database and teacher credentials from the state's eCert system. Importantly for our purposes, we can link these two datasets to identify individuals who are teaching in regular classroom positions (as identified in the S-275) with an "emergency credential" (as identified in eCert).[9] Specifically, school systems that are having difficulties staffing classrooms with fully licensed teachers can apply to OSPI for the ability to staff those classrooms with individuals who are granted emergency credentials. In the application, school systems must stipulate to OSPI that they are unable to find fully credentialed candidates to fill specific teaching slots. Districts that are granted the ability to utilize emergency credentials for staffing can hire individuals who will have the ability to teach for 1 year on this emergency credential.[10] The use of emergency credentials is rare; as discussed below, only about 1% of all new hires in recent years have an emergency credential, and emergency credentials were even less common earlier in the decade.

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[8] The institutions participating in TELC and that provided data for this study include Central Washington University, City University, Evergreen State College, Gonzaga University, Northwest University, Pacific Lutheran University, St. Martin's University, Seattle Pacific University, Seattle University, University of Washington Bothell, University of Washington Seattle, University of Washington Tacoma, Washington State University, Western Governors University, and Western Washington University. The six institutions that are not participating in TELC include 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.

[9] *Emergency credentials* are defined as "emergency substitute–elementary and secondary" and "emergency substitute teacher."

[10] After a year, districts would need to regain permission from OSPI to staff a position with an individual who is less than fully licensed.

We use data on emergency credentials to create three different school-level and district-level measures that are meant to proxy for the staffing challenges faced by the school or district: the proportion of all classroom teachers with an emergency credential, the proportion of all new hires with an emergency credential, and the proportion of all teachers with no prior experience with an emergency credential. In our primary models, we consider the proportion of new hires with an emergency credential, as we believe it is the measure most plausibly connected to student teaching placements, but we present in the appendix results using the other measures as well.

Our student teacher placement data come from TEPs from the 15 institutions participating in TELC. TEPs participating in TELC have provided data on all of their student teaching placements going back in some cases to the late 1990s, but for the purposes of this analysis, we focus on the 2009–10 through 2016–17 school years because all 15 institutions provided student teaching data for these years. The TELC data include information on the schools and districts in which student teachers completed their clinical placements, as well as the specific in-service teacher who supervised the student teaching placements (called the "cooperating teacher" in Washington). Our measure of student teaching placements is the proportion of classroom teachers in a given district and year who hosted a student teacher from the TELC data; as shown in Krieg et al. (2019), about 3% of teachers in Washington host a student teacher in the TELC data every year, but this proportion varies considerably across the different schools and districts in the state.[11] As an alternative measure, we also compute the proportion of classroom teachers within a *school* and year who hosted a student teacher.

These school- and district-level measures are then connected to three additional groups of variables, which serve as control variables in the analysis. First, we measure school and district

[11] For example, in a typical year, nearly 15% of all teachers in Bellingham Public Schools—the closest district to Western Washington University, one of the largest TEPs in the state—host a student teacher.

urbanicity (city, suburb, town, or rural) using data from the Local Education Agency Universe Survey in the Common Core of Data. We then calculate the distance (in miles) from each school and district to the nearest TEP in the state (and take the log of one plus this distance—so that districts that have a TEP within the district borders have a value of zero—to minimize the influence of outliers), and then merge in additional district demographic information from the Washington District Report Card.[12] As discussed in the results section, these variables are all potential confounders in the relationship between student teaching placements and teacher shortages—e.g., rural districts, districts far from TEPs, and less advantaged districts may host fewer student teachers and have more difficulty hiring teachers for reasons that are unrelated to their hosting of student teachers; thus, we use these variables as control variables in the models described in the next section.

The TELC dataset includes most teacher candidates who completed their training in Washington state in these years, but it does not represent the universe of student teacher placements. We describe the limitations of our sample *of student teachers* in **Figure 1** and **Table 1**. Figure 1 shows the proportion of newly hired teachers trained in Washington in each district who received a teaching credential from a TELC program.[13] For the state as a whole, 82% of the new in-state teachers in the state graduated from a TELC program. But as is apparent from the figure, the vast majority (91%) of new in-state teachers west of the Cascade Mountains graduated from a TELC program, while a much lower percentage (55%) in the eastern half of the

[12] Distances are computed as linear distances between the centroids of districts in the state, with TEP campuses matched the the district in which they are located. We supplement the School Report Card Data with additional data provided by the state on the median taxable value of single-family houses in the district as a proxy for district wealth.
[13] Note that we are *not* concerned about our data on teachers with an emergency credential given that the data represent a census of all teachers in the state.

state graduated from one of these TEPs; this is not surprising given that the three largest TEPs not participating in the study are all in the eastern half of the state.

Table 1 provides sample statistics for the districts in which newly credentialed teachers (a novice—i.e., no teaching experience) in 2010–11 through 2017–18—the years of hiring data we use for this analysis—are employed. The first column presents the mean for all teachers in the state, column 2 shows the mean for teachers who graduated from a TELC program, column 3 shows the mean for teachers who are credentialed by non-TELC programs in the state, and column 4 presents the mean for teachers who were not trained in Washington. There are some dramatic differences between the districts in which teachers from TELC and non-TELC programs begin their careers. For example, teachers from TELC programs are more likely to teach in suburbs, less likely to teach in towns or rural areas, and tend to teach in larger schools with more Asian and Black students, but fewer Hispanic students, than teachers from non-TELC programs. The general conclusion from this investigation is that graduates of TELC programs are not representative of all new teachers in the state, not even of new teachers who were trained in Washington.

Because of this limitation—and because of the geographical trends noted in Figure 1—we focus our analysis in this paper on districts west of the Cascades Mountains. While we cannot know how many student teacher placements are made in these districts by non-TELC programs, the fact that these districts overwhelmingly *hire* teachers from TELC programs (and the fact that student teaching placements tend to be very close to TEP campuses, and most non-TELC programs are in the eastern half of the state) suggests that the student teaching placements in these districts in the TELC data likely comes close to a census of all student teaching placements in these districts.

After the restriction described above, the analytic dataset we use for the models described next includes data from all districts west of the Cascade Mountains between 2009–10 and 2016–17; these districts hired 38,948 teachers over the course of these years of data.[14] **Table 2** compares the new hires in these districts who were on an emergency credential relative to other new hires into these districts. Perhaps not surprisingly given the literature discussed in the previous section, new hires on emergency credentials are more likely than other new hires to be teaching in towns and rural areas that are further from a TEP and have lower housing values, in districts with more Hispanic students and students receiving free or reduced price lunch, and in special education classrooms. These trends motivate the control variables included in the models described below

3.2 Analytic Approach

We rely on descriptive methods to assess the relationship between the proportion of emergency credentialed teachers in each district-year-credentialing area cell and district characteristics in the prior year, including student teaching placement rates. Specifically, we estimate binomial regressions in which the outcome of interest, p_{it}, represents the probability that school or district *i* in year *t* fills an open teaching position with a teacher on an emergency credential[15]:

$$\log\left(\frac{p_{it}}{1-p_{it}}\right) = \alpha_0 + \alpha_1 X_{i(t-1)} + \tau_t + \varepsilon_{it} \qquad (1)$$

[14] Table A1 in the appendix also provides summary statistics for the analytic dataset, broken out into four time periods (each representing 2 years from the 8-year time panel) to highlight some time trends in the data. It is important to note that these trends are *not* relevant for this analysis, given that the models described in the next section estimate relationships within the same school year between these two variables.

[15] Binomial regressions predicting the number of new hires on an emergency credential out of the total number of new hires are equivalent to logistic regressions at the new-hire level predicting whether each new hire is on an emergency credential. We describe the models as binomial regressions for simplicity, but actually estimate the models as hire-level logistic regressions because this enables us to present marginal effects in the next section of the expected change in the probability of filling an open teaching position with a teacher on an emergency credential.

In the model in Equation (1), the vector $X_{i(t-1)}$ includes school or district characteristics *in the prior year*. We focus on the prior year because teachers who have preferences over the characteristics of their workplace (e.g., Boyd et al., 2013; Engel et al., 2014) will base employment decisions on the district characteristics in the year before they start working.[16] In all models, this vector includes the variable of interest, the proportion of teachers in the school or district that hosted a student teacher in year *t-1*. In subsequent specifications, we control for the urbanicity of school or district *i*, the distance from school or district *i* to the nearest TEP, and other observable student demographic characteristics of school or district *i* in year *t-1*. Importantly, all models include year effects to account for time trends in the proportion of new hires on an emergency credential; thus, all estimates represent *within-year* relationships between these variables and the proportion of new hires on an emergency credential. We also estimate some specifications of the school-level models with a district fixed effect to exploit variation across schools within the same district. Finally, we cluster standard errors at the school level in the school-by-year models and at the district level in the district-by-year models to account for correlations across observations from the same school or district over time.

The models described by Equation 1 are estimated across all subject areas, but prior work both nationally (e.g., Cowan et al., 2016) and in Washington (e.g., Goldhaber, Krieg, Theobald, & Brown, 2015) has shown that teacher shortages are much more common in some subject areas (e.g., special education) than others. Thus, there might be a particularly strong relationship between student teaching placements *in a given subject area* and staffing difficulties in that area. We explore this by estimating extensions of the model in Equation 1 in which the outcome, p_{ijt}, represents the probability that district *i* in year *t* fills an open teaching position in subject area *j*

[16] We also estimate models in which we do not lag the school and district variables, and the results are similar.

(elementary; science, technology, engineering, and mathematics (STEM); special education; or other) with a teacher on an emergency credential:

$$\log\left(\frac{p_{ijt}}{1-p_{ijt}}\right) = \beta_0 + \beta_1 X_{i(t-1)} + \tau_j + \tau_t + \varepsilon_{it} \qquad (2)$$

The control variables in the model in Equation (2) are the same as in Equation 1, with an additional fixed effect, τ_j, that captures the variation in new hires on an emergency credential by subject area *j*.

In our primary results, we calculate average marginal effects that represent the expected change in the probability that an average school or district hires a new teacher with an emergency credential associated with a one-unit change in each predictor variable. In the case of our variable of interest, this represents the expected change associated with a 1 percentage-point increase in the percentage of teachers in the school or district that hosted a student teacher (relative to a statewide average of about 3%). While some of our specifications control for observable differences between schools and districts in the sample, it is not appropriate to interpret these marginal effects as the causal effects of increasing the number of student teaching placements in a school or district on the school's or district's staffing difficulties. In particular, it is likely that schools and districts that host more student teachers may be more desirable places to work along dimensions that are not captured by the variables in our models; if this is the case, then the estimate of our coefficient of interest will be biased in a negative direction.

4. Results

Table 3 presents the results of our primary district-level regression analysis (outlined in Equation 1), in which the dependent variable is the proportion of new hires in the district that are on an emergency credential[17]; we have multiplied all coefficients and standard errors in Table 2 by 100 so they can be interpreted as the expected change in the *percentage* of new hires in the district that are on an emergency credential associated with a one-unit change in each predictor variable. The estimate in column 1, for example, suggests that a 1 percentage-point increase in the percentage of teachers in the district that host a student teacher is associated with a 0.22 percentage-point decrease in the percentage of new hires in the district that are on an emergency credential the next year. Given that the percent of new hires on an emergency credential in recent years has been about 1%, this marginal effect represents approximately a 20% decrease in the percentage of new hires on an emergency credential in these years.

This relationship is illustrated in **Figures 2** and **3**, in which the color of each bubble (one bubble per district in the state) represents the proportion of teachers in the district that host a student teacher from a TELC program in the average year of data, while the size of each bubble represents the proportion of the district's new hires who are on an emergency credential (again, in the average year of data).[18] Figure 2 presents results for the whole state, while Figure 3 is consistent with our analytic sample and focuses solely on districts in the western half of the state. The overall conclusion from these figures is that there are many small blue bubbles (i.e., districts that host many students teachers and hire few teachers on emergency credentials) and also many large red bubbles (i.e., districts that host few students teachers and hire relatively many teachers on emergency credentials), which indicates a negative correlation between these variables.

The correlations in column 1 and Figures 2 and 3 do not account for many potential confounders in the relationship between student teaching placements and district-hiring difficulties.

[17] Regressions predicting the overall number of teachers on an emergency credential (Appendix Table A2) and the number of teachers with no prior experience on an emergency credential (Appendix Table A3) show similar results.
[18] See Appendix Figures A1–A4 for analogous figures using the other two measures of emergency credentials.

For example, some recent work finds that small towns and rural areas are more likely to have teacher shortages (Pennington McVey & Trinidad, 2019) and are less likely to host student teachers (Krieg et al., 2019). Thus, we control for district urbanicity in the specification in column 2 of Table 3. As suggested by prior work, the marginal effects for the urbanicity indicators suggest that districts in towns and rural areas tend to hire more teachers on emergency credentials than suburban districts, and given that these districts also host fewer student teachers, the relationship between student teacher placements and staffing difficulties in column 2 attenuates somewhat relative to column 1. But this relationship is still negative and statistically significant, which means that even when comparing two districts within the same urbanicity category, districts that host more student teachers tend to hire fewer teachers on emergency credentials.

Another clear confounder is the distance from a district to the nearest TEP, given that teachers are both more likely to student teach and to get hired near their TEP (Krieg et al., 2016). We therefore control for the log distance of the district to the nearest TEP in the specification in columns 3 and 4 (by itself in column 3, and then also controlling for district urbanicity in column 4). In each case, the relationship between student teacher placements and staffing difficulties continues to attenuate toward zero and the pseudo R-squared of the model increases, suggesting that these confounders explain a meaningful portion of the relationship of interest. But even controlling for urbanicity and distance to the nearest TEP, this relationship is still negative and statistically significant, which means that even when comparing two districts within the same urbanicity category *and* the same distance from a TEP, districts that host more student teachers tend to hire fewer teachers on emergency credentials. This suggests that proximity to TEPs does not "explain away" the relationship between student teacher placements and staffing difficulties.

Finally, disadvantaged districts with more students of poverty, students of color, and students in other traditionally disadvantaged groups also tend to have greater staffing challenges (Cowan et al., 2016; Pennington McVey & Trinidad, 2019). We therefore control for all observable student demographics and other characteristics of the district (see the list in Table 1) in the final specification in column 5. As with all prior specifications, the addition of these variables continues to attenuate the relationship between student teaching placements and staffing difficulties toward zero. But yet again, the relationship of interest is negative and statistically significant—and specifically, a 1 percentage-point increase in the percentage of teachers in the district who host a student teacher is associated with a .093 percentage-point decrease in the percentage of new hires on an emergency credential in the district—which means that even when comparing two districts *with identical observable characteristics*, districts that host more student teachers tend to hire fewer teachers on emergency credentials.

Columns 1 through 5 of **Table 4** repeat the same specifications just described for columns 1 through 5 of Table 3, except from specifications estimated at the school-by-year level (and with all control variables measured at the school level). The relationships are relatively robust to the inclusion of additional control variables, and suggest that a 1 percentage-point increase in the percentage of teachers in the school that host a student teacher is associated with a .05 to .09 percentage-point decrease in the percentage of new hires on an emergency credential in the school. The district fixed-effects specification in column 6 of Table 4 highlights the importance of considering the school level, because *even when making comparisons between schools within the same district*, schools that host more student teachers tend to hire fewer new teachers on an emergency credential.

Finally, **Table 5** summarizes results of the district-level regressions that consider the subject area of both new hires and student teachers (i.e., Equation 2 in Section 3.2). Consistent with prior evidence (e.g., Cowan et al., 2016) and the summary statistics in Table 2, districts are more likely to face staffing difficulties in special education than other subjects; the point estimate in Table 5 suggests that new hires in special education are about 0.6 percentage points more likely to be on an emergency credential than new hires in other subject areas. But controlling for this variation, we observe strong, negative, and statistically significant relationships between the percentage of teachers *in a given subject area* who host a student teacher and the percentage of new hires in that subject area on an emergency credential. Specifically, the most conservative specification (column 5) suggests that a 1 percentage-point increase in the percentage of teachers in a given subject area and district who host a student teacher is associated with about a .07 percentage-point decrease in the percentage of new hires in that subject area on an emergency credential in the district.

5. Conclusions and Policy Implications

As outlined in the introduction, it is clear from prior research on student teacher placements and teacher hiring that there *may* be a relationship between student teacher placements and district staffing difficulties. This analysis adds the next brick to the empirical wall that could eventually support a focus on student teaching placements as a policy lever for addressing regional teacher shortages, as the correlations reported in this paper establish that—at least in a descriptive sense—districts that tend to host more student teachers also tend to hire fewer teachers on emergency credentials. Given that these relationships cannot be explained away by the observable characteristics of these districts, we view these results as suggestive of a relationship that could inform policy decisions.

A natural implication from this analysis is that TEPs and states could consider policies that seek to broaden the set of schools and districts that host student teachers in the state. States are beginning to consider these policies; for instance, the Washington state legislature recently passed legislation (E2SHB 1139) that funds a report on policy recommendations to "encourage or require" TEPs in the state to "develop relationships with, and provide supervisory support for field placements of student teachers in, school districts that are not in the general geographic area of an approved teacher preparation program."[19] More ambitious policies could seek to incentivize student teacher placements in specific schools and districts that experience staffing difficulties as an explicit means of addressing teacher shortages in these districts.[20]

That said, it is also important to acknowledge that more geographically-dispersed student teaching placements place a burden on TEPs, as TEPs are responsible for facilitating these placements and supervising student teachers. This burden could be alleviated somewhat by technology—for instance, the same legislation described above also funds "the necessary audiovisual technology and equipment for university faculty to remotely supervise teachers in ten schools"—but it is still important to know whether the relationships documented in this paper are, in fact, causal. Given that the effects of student teacher placement policies are difficult to assess through observational research, there is an opportunity for states to consider an implementation design from the outset that could yield *causal* evidence about these relationships and provide further evidence about whether student teaching placements are a potential a policy lever for addressing teacher shortages.

[19] See http://lawfilesext.leg.wa.gov/biennium/2019-20/Pdf/Bills/Session%20Laws/House/1139-S2.SL.pdf, Section 204.

[20] These types of policies are further motivated by prior evidence (Goldhaber et al., 2017) that teachers tend to student teach in more advantaged schools and districts than those in which they are hired, but tend to be more effective when the student demographics of their current school are similar to the student demographics of their student teaching school.

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Tables and Figures

Table 1. District Summary Statistics for New Teachers in State

	Total	TELC	Non-TELC	Out of State
Average Percent Emergency Sub Teachers	0.832 (2.933)	0.628 (2.374)	1.421*** (4.055)	0.910*** (3.146)
Average Percent Teachers Hosting a ST	2.747 (2.208)	3.071 (2.299)	2.040*** (1.838)	2.434*** (2.046)
Proportion City	0.386 (0.487)	0.370 (0.483)	0.36 (0.479)	0.455*** (0.498)
Proportion Suburb	0.418 (0.493)	0.463 (0.499)	0.354*** (0.478)	0.346*** (0.476)
Proportion Town	0.124 (0.330)	0.106 (0.308)	0.183*** (0.387)	0.124* (0.330)
Proportion Rural	0.0720 (0.258)	0.0606 (0.239)	0.106*** (0.308)	0.0749* (0.263)
Average Log Distance to Nearest TEP	1.534 (1.437)	1.381 (1.397)	2.011*** (1.432)	1.559*** (1.461)
Proportion West Cascades	0.792 (0.406)	0.859 (0.348)	0.503*** (0.500)	0.85 (0.359)
Average Percent American Indian or Alaskan Native	1.516 (4.698)	1.462 (4.409)	1.989*** (6.286)	1.27 (3.812)
Average Percent Asian Pacific Islander	10.47 (8.760)	11.80 (8.839)	6.435*** (7.101)	10.14*** (8.734)
Average Percent Black	5.937 (6.187)	6.447 (6.360)	4.706*** (5.760)	5.545*** (5.864)
Average Percent Hispanic	23.13 (19.89)	22.03 (18.34)	28.86*** (25.62)	21.39 (17.57)
Average Percent Females	48.40 (1.094)	48.39 (0.867)	48.42 (1.603)	48.41 (1.133)
Average Percent Migrant	1.839 (4.807)	1.545 (4.430)	3.366*** (6.220)	1.374 (4.165)
Average Percent Transitional Bilingual	11.88 (9.902)	11.80 (9.370)	12.94*** (11.98)	11.19* (9.341)
Average Percent Special Education	13.34 (2.147)	13.29 (2.107)	13.64*** (2.371)	13.26 (2.035)
Average Percent FRL	46.35 (19.81)	44.59 (20.02)	53.94*** (18.72)	44.88 (18.59)
Average Percent Section 504	2.524 (1.595)	2.607 (1.611)	2.177*** (1.526)	2.585 (1.567)
Average Median Housing Value (taxable value)	281,611.0 (148,735.8)	305,062.2 (152,491.0)	205,807.4*** (112,161.2)	279,743.9*** (143,608.8)
Proportion Teaching Elementary Courses	0.388 (0.487)	0.415 (0.493)	0.386* (0.487)	0.315*** (0.465)
Proportion Teaching SPED Courses	0.136 (0.343)	0.141 (0.348)	0.118* (0.323)	0.138 (0.345)
Proportion Teaching STEM Courses	0.166 (0.372)	0.164 (0.370)	0.196** (0.397)	0.145 (0.353)
N	9293	5606	1685	2002

Note: FRL = Free or Reduced Lunch. SPED = Special Education. ST = Student Teaching. STEM = Science, Technology, Engineering, and Mathematics. TELC = Teacher Education Learning Collaborative. TEP = Teacher Education Program. N = Total number of novice teachers: in the state (column 1); credentialed from TELC institutions (column 2); credentialed from Non-TELC institutions (column 3); credentialed from out-of-state institutions (column 4). Log distance to nearest TEP is calculated by log(distance + 1). *P*-values from two-sided *t*-test relative to teachers who got teaching certificate from TELC institutions: **p* < 0.05; ***p* < 0.01; ****p* < 0.001.

Table 2. District Summary Statistics from Analytic Sample for New Hires on Emergency Credential and Other New Hires

	New Hires on Emergency Credential	Other New Hires
Average Percent Emergency Sub Teachers	1.640 (3.505)	0.365*** (1.181)
Average Percent Teachers Hosting a ST	2.016 (1.577)	3.241*** (2.480)
Proportion City	0.270 (0.445)	0.401*** (0.490)
Proportion Suburb	0.480 (0.500)	0.485 (0.500)
Proportion Town	0.186 (0.390)	0.083*** (0.277)
Proportion Rural	0.063 (0.243)	0.031*** (0.173)
Average Log Distance to Nearest TEP	2.053 (1.228)	1.425*** (1.309)
Proportion West Cascades	1 (0)	1 (0)
Average Percent American Indian or Alaskan Native	1.404 (2.531)	1.175* (1.861)
Average Percent Asian Pacific Islander	7.676 (6.912)	11.620*** (7.998)
Average Percent Black	5.048 (5.123)	6.523*** (6.250)
Average Percent Hispanic	18.004 (8.507)	16.280*** (8.294)
Average Percent Females	48.411 (1.187)	48.415 (0.758)
Average Percent Migrant	0.512 (1.633)	0.329** (1.210)
Average Percent Transitional Bilingual	7.793 (6.496)	8.873** (6.195)
Average Percent Special Education	13.882 (2.235)	13.258*** (1.918)
Average Percent FRL	45.742 (16.322)	40.457*** (16.631)
Average Percent Section 504	2.758 (1.444)	2.688 (1.547)
Average Median Housing Value (taxable value)	238138.6 (96436.3)	314147.0*** (138983.1)
Proportion Teaching Elementary Courses	0.375 (0.485)	0.323* (0.468)
Proportion Teaching SPED Courses	0.201 (0.402)	0.129*** (0.335)
Proportion Teaching STEM Courses	0.105 (0.307)	0.114 (0.317)
N	333	38616

Note: FRL = Free or Reduced Lunch. SPED = Special Education. ST = Student Teaching. STEM = Science, Technology, Engineering, and Mathematics. TEP = Teacher Education Program. N = Total number new hires by year. Log distance to nearest TEP is calculated by log(distance + 1). P-values from two-sided t-test relative to emergency sub teachers: *$p<0.05$; **$p<0.01$; ***$p<0.001$.

Table 3. District Percentage of Emergency Substitute Teachers in Year *t* Versus District Characteristics in Year *t*-1

	(1)	(2)	(3)	(4)	(5)
Percent of Teachers Hosting a ST	-0.222***	-0.181**	-0.142**	-0.137**	-0.093*
	(0.058)	(0.058)	(0.053)	(0.051)	(0.038)
City (ref. Suburb)		0.003		0.183	0.077
		(0.181)		(0.228)	(0.198)
Town (ref. Suburb)		0.645*		0.417+	0.231
		(0.259)		(0.236)	(0.229)
Rural (ref. Suburb)		0.588		0.305	-0.152
		(0.358)		(0.277)	(0.220)
Log distance to nearest TEP			0.239**	0.217*	0.145*
			(0.079)	(0.085)	(0.068)
Additional District Controls					X
Number of District-Year Observations	1,097	1,097	1,097	1,097	1,097
R-squared	0.116	0.123	0.126	0.129	0.152

Note: FRL = Free or Reduced Lunch. ST = Student Teaching. TEP = Teacher Education Program. All models include year effects and are limited to districts west of the Cascades. "Additional District Controls" include all additional variables listed in Table 1. Regressions are weighted by district total enrollment of students and include year effects. Standard errors are clustered by district. Log distance to nearest TEP is calculated by log(distance + 1). *P*-values from two-sided *t*-test: +$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 4. School Percentage of Emergency Substitute Teachers in Year *t* Versus School Characteristics in Year *t*-1

	(1)	(2)	(3)	(4)	(5)	(6)
Percent of Teachers Hosting a ST	-0.077*** (0.018)	-0.067*** (0.017)	-0.060*** (0.017)	-0.058*** (0.017)	-0.045** (0.016)	-0.049*** (0.015)
City (ref. Suburb)		-0.118 (0.082)		0.060 (0.102)	-0.002 (0.099)	
Town (ref. Suburb)		0.653*** (0.192)		0.323* (0.161)	0.185 (0.158)	
Rural (ref. Suburb)		0.566** (0.175)		0.225+ (0.133)	0.103 (0.141)	
Log distance to nearest TEP			0.269*** (0.040)	0.235*** (0.00045)	0.137** (0.046)	
Additional School Controls					X	
District Fixed Effect						X
Number of School-Year Observations	10,702	10,702	10,702	10,702	10,666	9,388
R-squared	0.086	0.096	0.104	0.106	0.134	0.167

Note: FRL = Free or Reduced Lunch. ST = Student Teaching. TEP = Teacher Education Program. All models include year effects and are limited to districts west of the Cascades. "Additional School Controls" include all additional variables listed in Table 1 measured at the school level. Regressions are weighted by school total enrollment of students and include year effects. Standard errors are clustered by school. Log distance to nearest TEP is calculated by log(distance + 1). *P*-values from two-sided *t*-test: $+p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Table 5. District-by-Subject Percentage of Emergency Substitute Teachers in Year *t* Versus District Characteristics in Year *t*-1

	(1)	(2)	(3)	(4)	(5)
Percent of Teachers Hosting a ST	-0.159**	-0.134**	-0.101*	-0.099*	-0.067*
	(0.052)	(0.049)	(0.041)	(0.041)	(0.032)
Elementary (ref. Other)	0.165	0.133	0.087	0.085	0.078
	(0.142)	(0.142)	(0.132)	(0.131)	(0.120)
STEM (ref. Other)	0.170	0.178	0.156	0.163	0.194
	(0.142)	(0.146)	(0.141)	(0.144)	(0.139)
SPED (ref. Other)	0.604**	0.652**	0.641**	0.652**	0.726***
	(0.212)	(0.212)	(0.211)	(0.211)	(0.216)
City (ref. Suburb)		-0.120		0.067	-0.033
		(0.209)		(0.236)	(0.198)
Town (ref. Suburb)		0.621*		0.353	0.206
		(0.298)		(0.276)	(0.253)
Rural (ref. Suburb)		0.259		0.024	-0.107
		(0.457)		(0.329)	(0.321)
Log distance to nearest TEP			0.256**	0.239**	0.104
			(0.081)	(0.091)	(0.068)
Additional District Controls					X
Number of District-Subject-Year Observations	2,561	2,561	2,561	2,561	2,561
R-squared	0.092	0.097	0.104	0.105	0.128

Note: FRL = Free or Reduced Lunch. SPED = Special Education. ST = Student Teaching. STEM = Science, Technology, Engineering, and Mathematics. TEP = Teacher Education Program. All models include year effects and are limited to districts west of the Cascades. "Additional District Controls" include all additional variables listed in Table 1. Regressions are weighted by district total enrollment of students and include year effects. Standard errors are clustered by district. Log distance to nearest TEP is calculated by log(distance + 1). *P*-values from two-sided *t*-test: $+p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Figure 1. Percentage of New, in-State Teachers From TELC Programs, by District

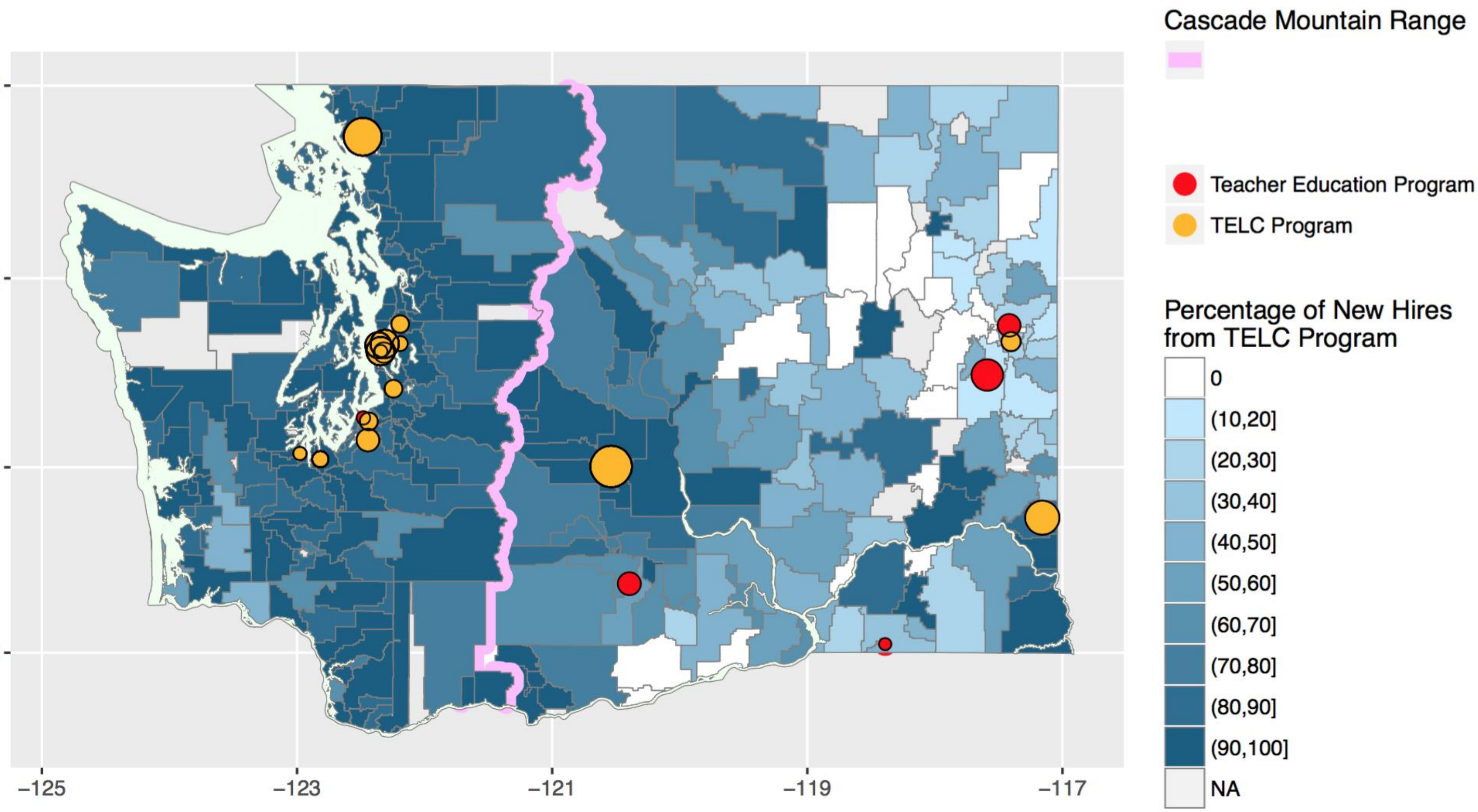


Figure 2. Proportion of Emergency Substitute Teachers and Proportion of Teachers Hosting Student Teachers, by District

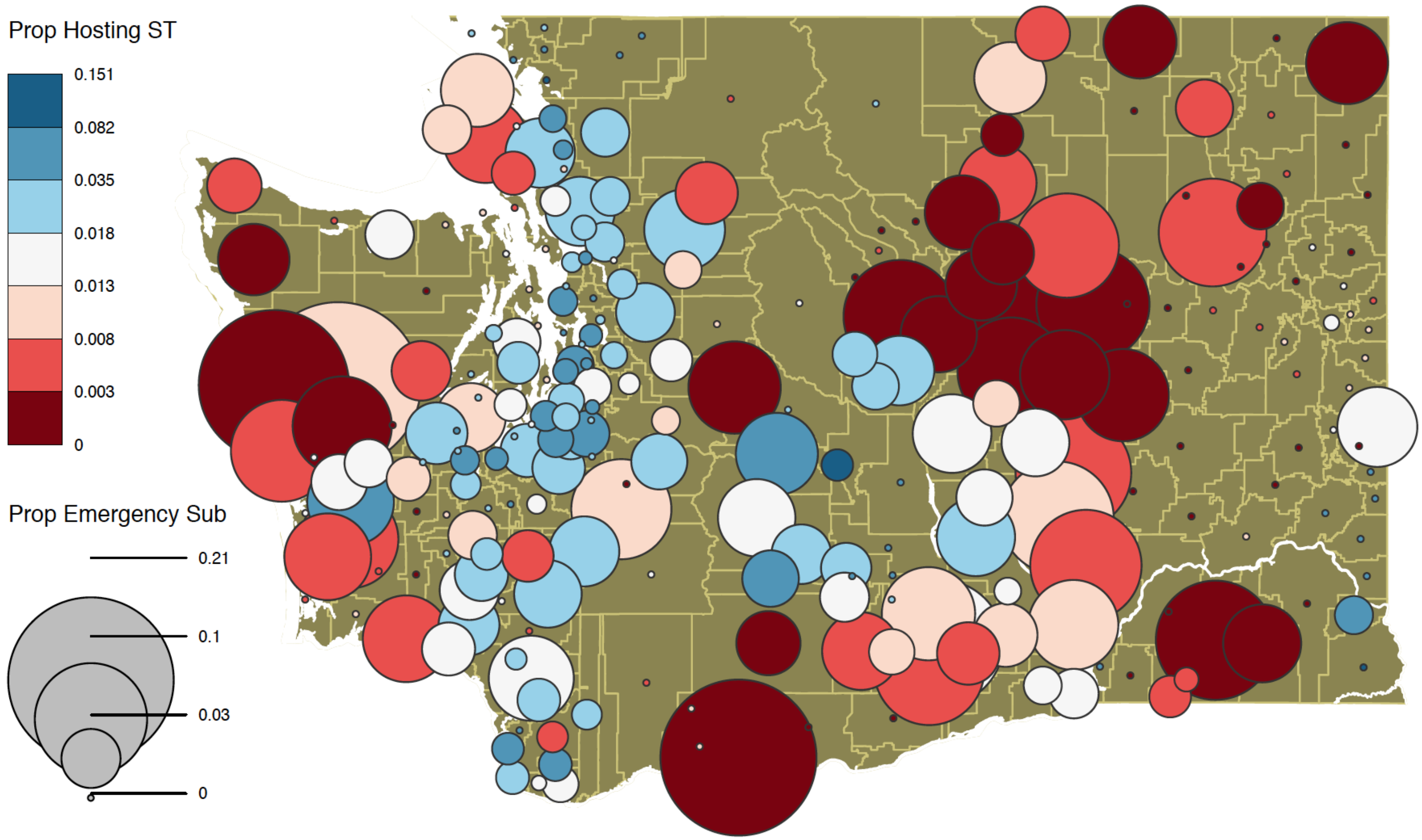
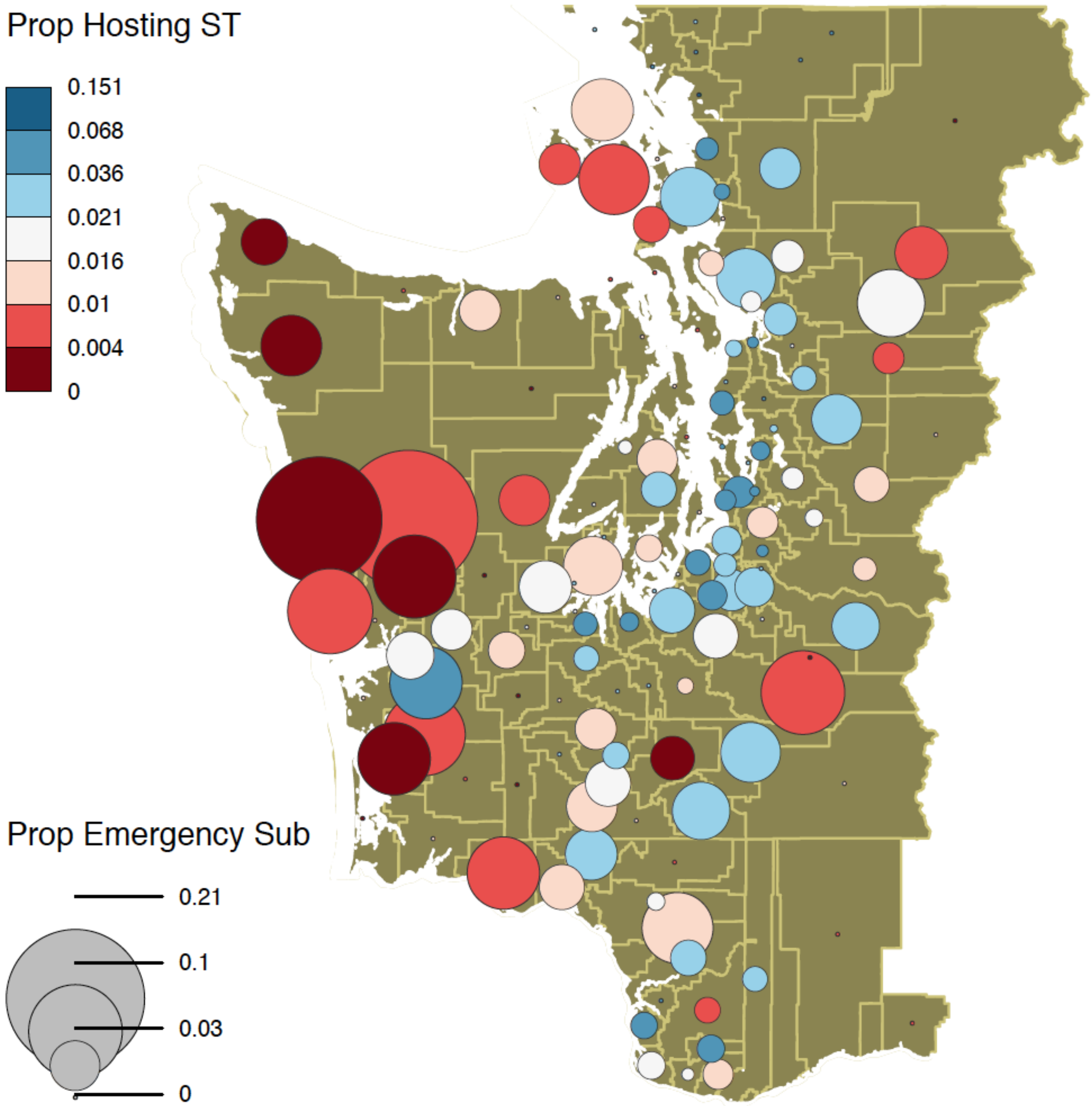


Figure 3. Proportion of Emergency Substitute Teachers and Proportion of Teachers Hosting Student Teachers, by District



Appendix

Table A1. District Summary Statistics for Analytic Sample by Year

	2010–11	2012–13	2014–15	2016–17
Average Percent Emergency Sub Teachers	0.0152 (0.224)	0.155 (0.701)	0.125 (0.520)	1.017 (1.950)
Average Percent Teachers Hosting a ST	4.004 (2.810)	3.333 (2.476)	3.321 (2.459)	2.566 (2.056)
Proportion City	0.425 (0.494)	0.420 (0.494)	0.394 (0.489)	0.373 (0.484)
Proportion Suburb	0.461 (0.498)	0.470 (0.499)	0.488 (0.500)	0.509 (0.500)
Proportion Town	0.0812 (0.273)	0.0781 (0.268)	0.0887 (0.284)	0.0868 (0.282)
Proportion Rural	0.0330 (0.179)	0.0321 (0.176)	0.0299 (0.170)	0.0309 (0.173)
Average Log Distance to Nearest TEP	1.407 (1.310)	1.381 (1.322)	1.435 (1.314)	1.477 (1.296)
Proportion West Cascades	1 (0)	1 (0)	1 (0)	1 (0)
Average Percent American Indian or Alaskan Native	1.749 (2.532)	1.182 (1.651)	1.075 (1.688)	0.902 (1.575)
Average Percent Asian Pacific Islander	12.05 (7.594)	11.67 (7.790)	11.33 (7.999)	11.48 (8.378)
Average Percent Black	7.702 (7.205)	6.809 (6.469)	6.121 (5.874)	5.902 (5.601)
Average Percent Hispanic	13.01 (7.623)	15.77 (7.784)	17.02 (8.224)	18.10 (8.489)
Average Percent Females	48.44 (0.861)	48.41 (0.773)	48.42 (0.737)	48.40 (0.710)
Average Percent Migrant	0.231 (1.213)	0.270 (1.076)	0.378 (1.205)	0.393 (1.311)
Average Percent Transitional Bilingual	7.782 (5.689)	7.877 (5.543)	9.081 (6.362)	10.07 (6.556)
Average Percent Special Education	12.93 (1.825)	13.30 (1.776)	13.18 (2.017)	13.53 (1.950)
Average Percent FRL	39.34 (15.70)	42.22 (16.40)	41.29 (16.87)	39.23 (17.00)
Average Percent Section 504	1.582 (1.020)	2.461 (1.424)	2.859 (1.428)	3.407 (1.581)
Average Median Housing Value (taxable value)	315471.6 (140350.8)	316858.7 (139873.1)	311549.3 (138420.4)	311681.4 (137491.6)
Proportion Teaching Elementary Courses	0.234 (0.424)	0.295 (0.456)	0.352 (0.478)	0.374 (0.484)
Proportion Teaching SPED Courses	0.139 (0.346)	0.131 (0.338)	0.122 (0.327)	0.131 (0.337)
Proportion Teaching STEM Courses	0.127 (0.334)	0.118 (0.322)	0.112 (0.315)	0.103 (0.305)
N	7523	8443	11,402	11,581

Note: FRL = Free or Reduced Lunch. SPED = Special Education. ST = Student Teaching. STEM = Science, Technology, Engineering, and Mathematics. TEP = Teacher Education Program. N = Total number new hires by year. Log distance to nearest TEP is calculated by log(distance + 1).

Table A2. Percentage of Emergency Substitute Teachers in Year *t* + 1 Versus District Characteristics in Year *t* (All Emergency Substitute Teachers)

	(1)	(2)	(3)	(4)	(5)
Percent of Teachers Hosting a ST	-0.043***	-0.034***	-0.029**	-0.028**	-0.019**
	(0.011)	(0.010)	(0.010)	(0.009)	(0.007)
City (ref. Suburb)		0.000		0.026	0.005
		(0.031)		(0.041)	(0.033)
Town (ref. Suburb)		0.124**		0.090*	0.067
		(0.048)		(0.043)	(0.046)
Rural (ref. Suburb)		0.123+		0.076	-0.017
		(0.073)		(0.058)	(0.040)
Log distance to nearest TEP			0.039**	0.032*	0.025*
			(0.014)	(0.015)	(0.012)
Additional District Controls					X
Number of District-Year Observations	2,056	2,056	2,056	2,056	2,056
R-squared	0.106	0.113	0.114	0.118	0.139

Note: FRL = Free or Reduced Lunch. ST = Student Teaching. TEP = Teacher Education Program. All models include year effects and are limited to districts west of the Cascades. "Additional District Controls" include all additional variables listed in Table 1. Regressions are weighted by district total enrollment of students and include year effects. Standard errors are clustered by district. Log distance to nearest TEP is calculated by log(distance + 1). *P*-values from two-sided *t*-test: +p <0.1; *p < 0.05; **p < 0.01; ***p < 0.001.

Table A3. Percentage of Emergency Substitute Teachers in Year *t* Versus District Characteristics in Year *t* - 1 (Zero Experience Emergency Substitute Teachers)

	(1)	(2)	(3)	(4)	(5)
Percent of Teachers Hosting an ST	-0.645***	-0.512***	-0.371**	-0.357**	-0.259*
	(0.171)	(0.150)	(0.134)	(0.121)	(0.102)
City (ref. Suburb)		-0.034		0.518	0.146
		(0.445)		(0.487)	(0.436)
Town (ref. Suburb)		1.264*		0.510	0.226
		(0.621)		(0.487)	(0.542)
Rural (ref. Suburb)		2.757*		1.377	-0.110
		(1.303)		(0.892)	(0.623)
Log distance to nearest TEP			0.782***	0.728***	0.503**
			(0.184)	(0.183)	(0.170)
Additional District Controls					X
Number of District-Year Observations	1,547	1,547	1,547	1,547	1,547
R-squared	0.128	0.140	0.151	0.155	0.176

Note: FRL = Free or Reduced Lunch. ST = Student Teaching. TEP = Teacher Education Program. All models include year effects and are limited to districts west of the Cascades. “Additional District Controls” include all additional variables listed in Table 1. Regressions are weighted by district total enrollment of students and include year effects. Standard errors are clustered by district. Log distance to nearest TEP is calculated by log(distance + 1). *P*-values from two-sided *t*-test: +$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Figure A1. Proportion of Emergency Substitute Teachers (All Teachers) and Proportion of Teachers Hosting Student Teachers, by District

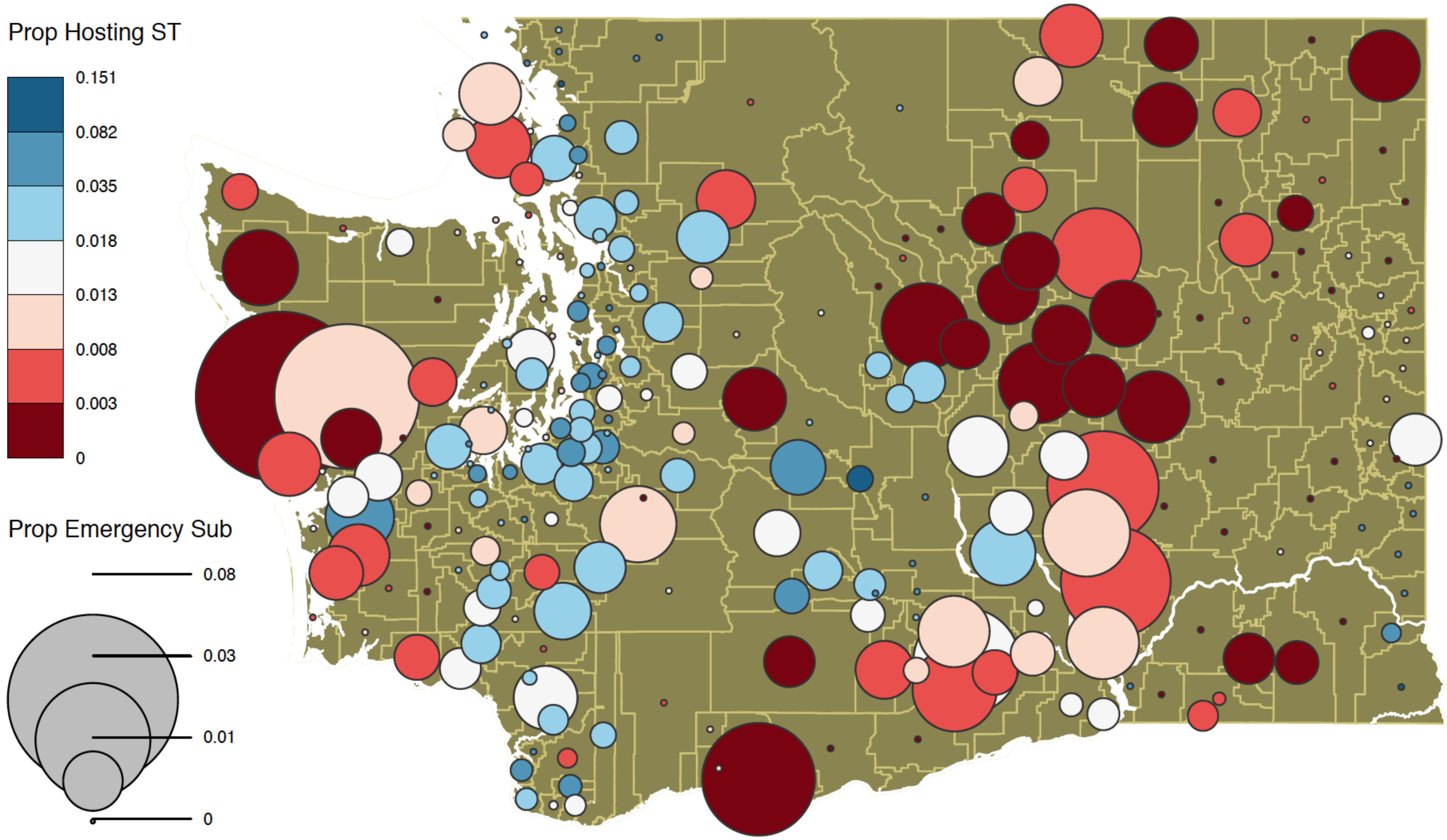


Figure A2. Proportion of Emergency Substitute Teachers (All Teachers) and Proportion of Teachers Hosting Student Teachers, by District

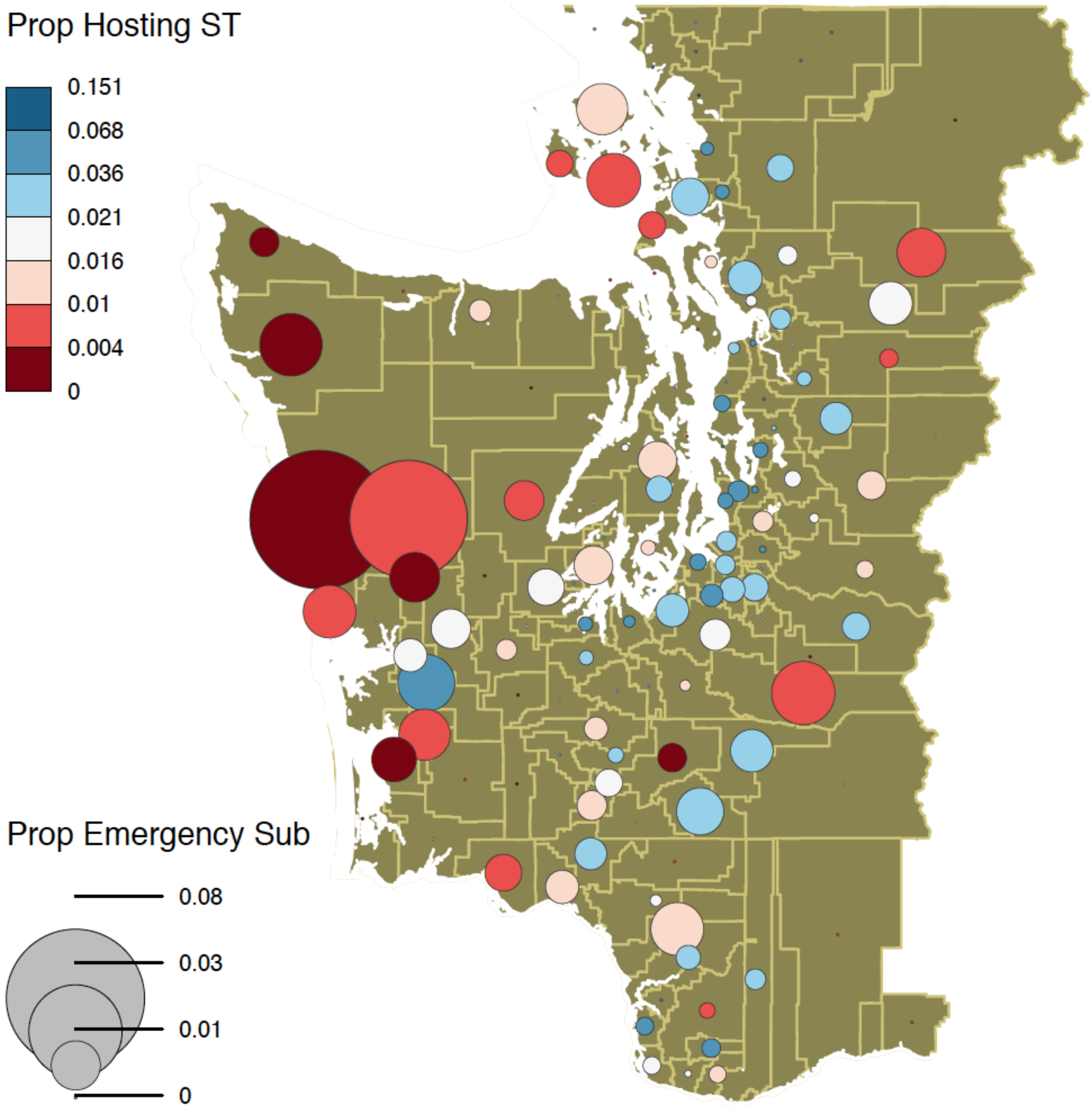


Figure A3. Proportion of Emergency Substitute Teachers (Zero Experience) and Proportion of Teachers Hosting Student Teachers, by District

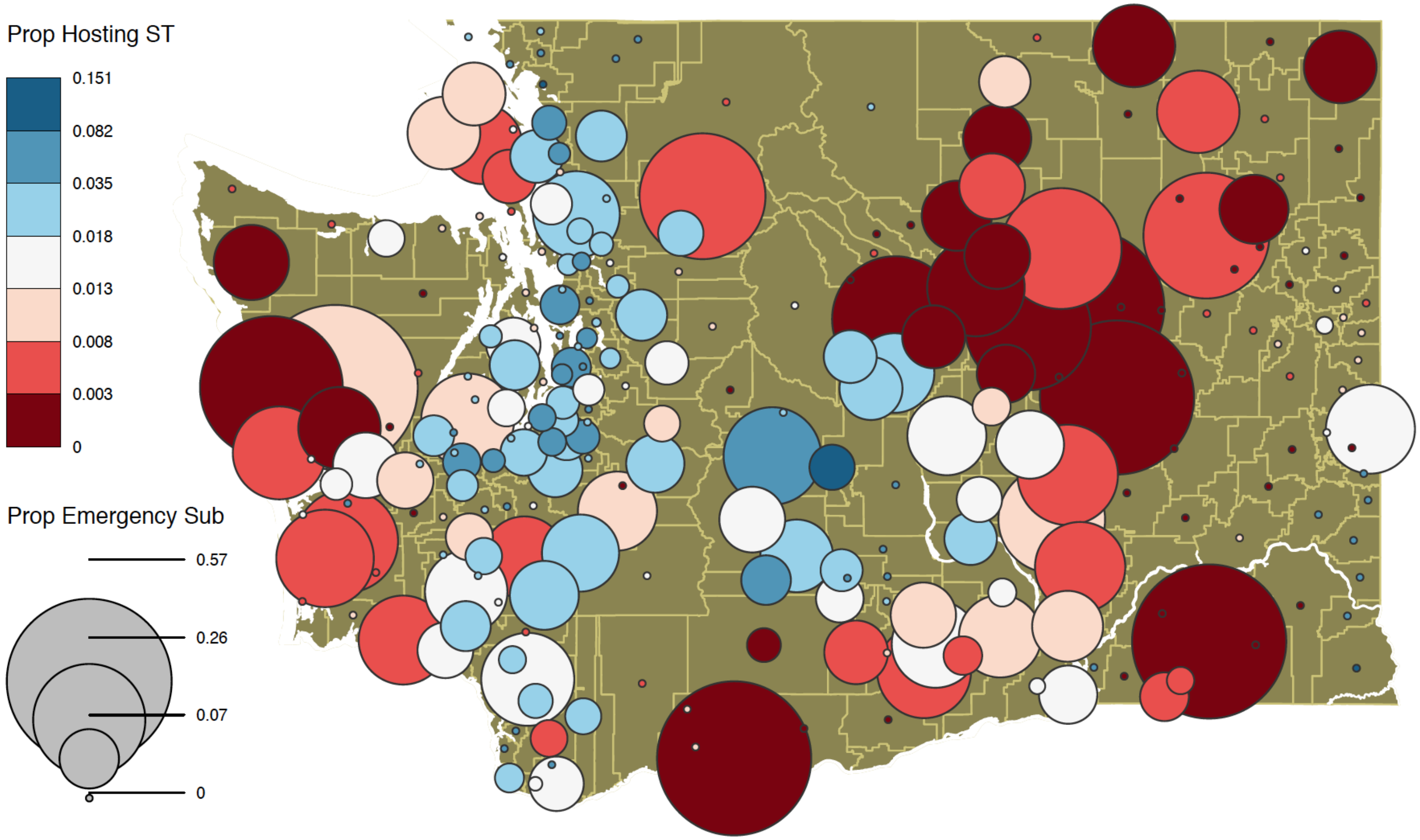


Figure A4. Proportion of Emergency Substitute Teachers (Zero Experience) and Proportion of Teachers Hosting Student Teachers, by District