FEATURE ARTICLES

Student Teaching and the Geography of Teacher Shortages

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We use a unique dataset of student teaching placements in the State of Washington and a proxy for teacher shortages, the proportion of new teacher hires in a school or district with emergency teaching credentials, to provide the first empirical evidence of a relationship between student teaching placements and teacher shortages. We find that schools and districts that host fewer student teachers or are nearby to districts that host fewer student teachers tend to hire significantly more new teachers with emergency credentials the following year. These relationships are robust to district fixed-effects specifications that make comparisons across schools within the same district. This descriptive evidence suggests exploring efforts to place student teachers in schools and districts that struggle to staff their classrooms.

Keywords: economics of education; educational policy; regression analyses; student teaching

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 (e.g., Pennington McVey & Trinidad, 2019). 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 (e.g., Dee & Goldhaber, 2017; Kraft et al., 2018).

Importantly, however, teacher shortages are not uniformly geographically distributed. Certain types of schools and districts are far more likely to experience staffing challenges (Cowan et al., 2016; Pennington McVey & Trinidad, 2019). And although some of this may be attributable to the working conditions in schools or the challenges of working with low-achieving student populations (Clark et al., 2013; Sutcher et al., 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 they find first jobs close to their home and TEP (Boyd et al., 2005; Reininger, 2012). Emerging evidence from the State of Washington, the setting of this study, suggests that student-teaching placements may also contribute to these relationships (Krieg et al., 2016, 2020). Specifically, teacher candidates tend to 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).

Although 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 schools or

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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. This descriptive evidence suggests exploring efforts to place student teachers in schools and districts that struggle to staff their classrooms.

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, which is typically proxied by the percentage of students of poverty or students of color in the school (Goldhaber et al., 2018). For instance, teacher applicants demonstrate a preference for advantaged schools in their initial job selection (Boyd et al., 2013; Engel et al., 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 et al., 2011; Hanushek et al., 2004; Scafidi et al., 2007). 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 et al., 2005; Goldhaber, Lavery, et al., 2015; Goldhaber et al., 2018; Isenberg et al., 2016; Lankford et al., 2002; Sass et al., 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).[1] And most of these newly minted teachers were credentialed by traditional TEPs operated by institutions of higher education.[2]

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 teachers begin their career in the district in which they student taught relative to another district is about 10 times larger than the corresponding odds that they begin their career in their hometown district (Goldhaber, Krieg, et al., 2014).

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 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

> given 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 et al., 2018) suggest that placement processes are quite varied across districts and TEPs. One of these prior studies, based on interviews with the individuals responsible for student teaching placements in the same Washington TEPs participating in this study (St. John et al., 2018), suggests that placements in Washington are often driven by personal relationships, for example, between TEPs and their alumni, with teachers/schools in the same district as the TEP, or with teachers/schools in a candidate's hometown. That said, placements in Washington are also governed by the contractual arrangements between TEPs and districts and reflect a combination of desired TEP practices, school system needs, and the preferences of individual teacher candidates. This is broadly consistent with anecdotal evidence nationally that field placements are often "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, 2020) 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.

Data and Analytic Approach

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).[3]

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).[4] 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 this 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. 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.

We use data on emergency credentials to create annual school-level and district-level measures of the proportion of all new hires with an emergency credential. These measures are meant to proxy for the staffing challenges faced by the school or district. Although there are other possible proxies for staffing challenges, including annual attrition rates, we prefer the emergency credentials measure to the annual attrition measure because it reflects staffing challenges that arise because of both supply and demand for teachers in schools and districts (as opposed to just demand, as is the case of annual attrition).

Our student teacher placement data come from TEPs participating in TELC. These TEPs include 15 of the state's 21 TEPs that were approved to credential teachers in the state during the years of data we use. There are important differences between the institutions participating and not participating in TELC; specifically, the average TELC institution is about three times larger, has average SAT scores about 50 points higher, and enrolls about 10 percentage points more students of color than the average nonparticipating institution.[5] Another important feature of the Washington setting is that alternative certification routes have been approved only recently in the state—in fact, only 6% of all new teacher credentials in the state were through alternative pathways during the years of data we consider (Title II, 2018)—so alternative routes to teacher certification play little role in this analysis.

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 2009–2010 through 2016–2017 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. (2020), 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. 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 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),[6] and then merge in additional district demographic information from the Washington District Report Card.[7] As discussed in the Results section, these variables are all potential confounders in the relationship between student teaching placements and teacher shortages—for example, 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.[8] Figure 1 shows the proportion of newly hired in-state teachers in each district who received a teaching credential from a TELC program. 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 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.

Because of this limitation, we focus our analysis in this article on districts west of the Cascade Mountains. Although 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 include most 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 2009–2010 and 2016–2017; these districts hired 38,948 teachers over the course of these years of data.[9] Table A3 of the online appendix, available on the journal website, compares the new hires in these districts

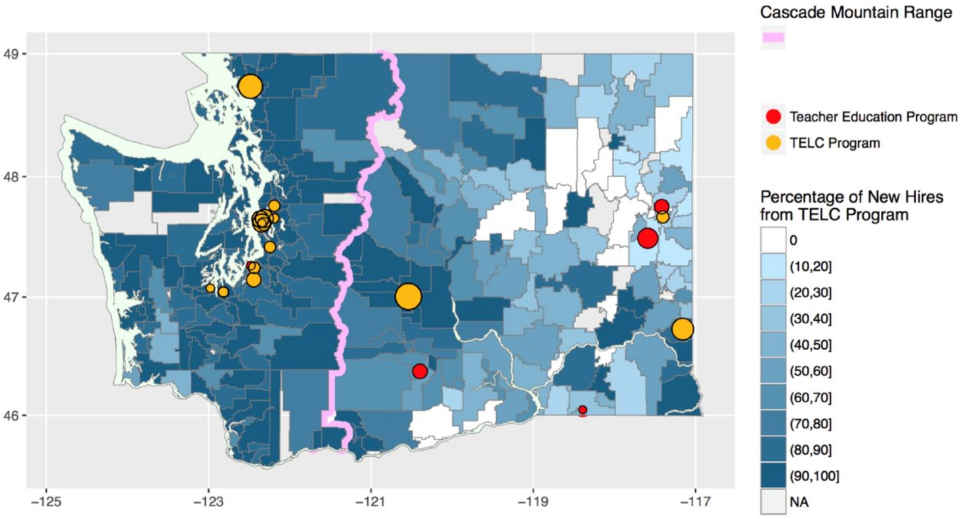

FIGURE 1. *Percentage of new, in-state teachers from TELC programs, by district.*

who were on an emergency credential relative to other new hires into these districts. 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.

Analytic Approach

We rely on descriptive methods to assess the relationship between the proportion of emergency credentialed teachers hired in a given district/year and student teaching placement rates in the district in the prior year. Specifically, define p_{it} as the probability that district i in year t fills an open teaching position with a teacher on an emergency credential. We are interested in modeling the relationship between this probability and the proportion of teachers in the district that hosted a student teacher in the previous year, $S_{i(t-1)}$. We begin with a district-level analysis because student teacher agreements are made between districts and teacher education program and districts are responsible for applying for emergency certification, although we discuss additional school-level models below that are potentially more relevant to other settings where placements are made through schools or even specific teachers. Specifically, we estimate a naïve district-year binomial regression that relates these two variables and includes 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.[10]

$$\log\left(\frac{p_{it}}{1-p_{it}}\right)=\alpha_0+\alpha_1 S_{i(t-1)}+\tau_t. \quad (1)$$

There are, however, several reasons we would be cautious about interpreting the coefficient of interest, α_1, from this naïve model as the causal effect of student teacher placements on subsequent emergency substitute hiring. The first is the possibility of "spillover effects" between nearby districts; that is, districts located near another district with a high concentration of student teacher placements may benefit in their teacher hiring regardless of how many student teachers they host themselves. This type of spillover would tend to create a spatial relationship between districts and attenuate estimates of the benefits of hosting student teachers.[11]

To account for the potential of this spatial relationship because of spillover effects, we create spatial weighting matrices $\boldsymbol{W}$ (Anselin, 2013) in which the $(i,j)^{\text{th}}$ entry is a measure of the proximity between districts i and j. In our primary results we use the reciprocal of the distance between districts i and j (following Goldhaber, Lavery, et al., 2014), but also consider a simpler weighting matrix that just includes indicators for whether each pair of districts is within 50 miles of each other (in both cases, the entries along the diagonal are zero). These weighting matrices are row-standardized to sum to one, and then multiplied by the vector of student teaching proportions $\boldsymbol{S}_{(t-1)}$ to create a spatial-lag term:

$$\overline{\boldsymbol{S}}_{(t-1)}=\boldsymbol{W}\boldsymbol{S}_{(t-1)}. \quad (2)$$

In our primary specifications, the i^{th} entry of $\overline{\boldsymbol{S}}_{(t-1)}$, $\overline{S}_{i(t-1)}$, can be interpreted as the proportion of teachers in districts close to district i who host student teachers in the previous year, weighted by the proximity of those districts to district i. In the simpler specification in which W has indicators for whether each pair of districts is within 50 miles of each other, $\overline{S}_{i(t-1)}$ is simply the proportion of teachers outside of district i but within 50 miles of district i who host a student teacher the previous year. We can then include this spatial-lag term as an additional predictor in the model predicting emergency substitute hiring:

$$\log\left(\frac{p_{it}}{1-p_{it}}\right)=\beta_0+\beta_1 S_{i(t-1)}+\beta_2\overline{S}_{i(t-1)}+\tau_t. \quad (3)$$

We interpret the coefficient β_2 as the spillover effect of *nearby* student teaching placements on emergency substitute hiring in the district. The coefficient β_1, then, can be interpreted as the relationship between the concentration of student teaching placements and the use of emergency credentials in the district after accounting for these spillovers.

A second concern with interpreting this coefficient is the potential presence of omitted variables that influence both the hosting of student teachers and teacher staffing challenges; for example, both teacher candidates and teachers might care about unobserved community attributes or school working conditions in ways that influence student teaching placements and teacher shortages. This potential omitted variable problem would also lead to spatial relationships between districts, but in this case the estimate of the coefficient of interest would likely be upwardly biased.[12] We hope that unobserved district attributes are not a significant issue given that we include a rich set of variables in the some specifications, such as the urbanicity of district i, the distance from district i to the nearest TEP, and other observable student demographic characteristics of district i in year $t-1$. All of these variables are potential confounders in the relationship between student teaching placements and teacher shortages, and 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.

But to more fully account for unobservable variation across districts, we also estimate additional models at the *school* level and include a district fixed effect to exploit variation across schools within the same district and account for all time-invariant differences between different districts in the state (e.g., desirability of location, etc.). We believe that estimates from these district fixed-effect specifications are the most convincing estimates of a causal relationship, although we acknowledge that time-*varying* district confounders or school-level confounders or could still lead to biased estimates. Hence, although the findings from these models support the overall conclusion that hosting student teachers does affect the degree of district staffing challenges (as we describe below), our findings should be interpreted as descriptive.

A final concern with the model outlined above is that causality could actually be reversed. Specifically, if schools and districts face difficulties in staffing their classrooms, they may subsequently be less likely to train student teachers (perhaps because of TEPs avoiding these schools or districts in making student teacher placements). In that case, one would expect a negative regression coefficient on the student teacher variable even if student teacher placements do not lead to fewer emergency teacher hires. We therefore pursue a falsification test in which we estimate a variation of the model in Equation (3) that also controls for the number of student teachers hosted in future years.

$$\log\left(\frac{p_{it}}{1-p_{it}}\right) = \gamma_0 + \gamma_1 S_{i(t-1)} + \gamma_2 S_{i(t+1)} + \tau_t . \tag{4}$$

If hiring more emergency certified teachers today causes a reduction in training student teachers in the future, we would expect γ_2 to be negative. A limitation of this falsification test is that we must exclude the final years of our sample because we do not know the number of future student teachers outside of the sample.

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 one-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%). 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.

Results

Table 1 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; we have multiplied all coefficients and standard errors in Table 1 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 Figure 2, in which the color of each bubble (one bubble per district in the western half of 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, whereas 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). This figure illustrates the connection between student teaching and staffing challenges, measured by districts hiring teachers with emergency credentials. In particular, there are both many small blue bubbles (i.e., districts that host many students teachers and hire few teachers on emergency credentials) and 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.

Figure 2 also illustrates the spatial relationships we discuss in the Analytic Approach section, above, as both the size and color of the bubbles tend to be similar for geographically proximate districts. This motivates the spatial regressions outlined in Equation (3) and reported in column 2 of Table 1. The coefficient on the percentage of teachers near the district hosting a student teacher, or the district "spillover effect," indicates that a

Table 1
District Percentage of Emergency Substitute Teachers in Year *t* Versus District Characteristics in Year *t* – 1

	(1)	(2)	(3)	(4)	(5)	(6)
Percentage of teachers in district hosting an ST	−.222***	−.175**	−.150**	−.105+	−.105*	−.075+
	(.058)	(.054)	(.055)	(.054)	(.052)	(.039)
Percentage of teachers near the district hosting an ST (weighted by inverse distance)		−.454***	−.354**	−.385**	−.343**	−.227*
		(.136)	(.124)	(.121)	(.114)	(.096)
City (ref. suburb)			−.011		.158	.093
			(.176)		(.209)	(.197)
Town (ref. suburb)			.531*		.368+	.183
			(.240)		(.208)	(.217)
Rural (ref. suburb)			.459		.206	−.203
			(.319)		(.248)	(.214)
Log distance to nearest TEP				0.224**	.212**	.153*
				(0.077)	(0.078)	(.067)
Additional district controls						X
Number of district-year observations	1,097	1,097	1,097	1,097	1,097	1,097
R-squared	.116	.124	.128	.133	.135	.158

Note. 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 percentage American Indian or Alaskan Native students, percentage Asian Pacific Islander students, percentage Black students, percentage Hispanic students, percentage female students, percentage migrant students, percentage transitional bilingual students, percentage students with disabilities, percentage students receiving free or reduced-priced lunch, percentage students in Section 504 housing, and district median housing value (taxable value). 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: $+p < .1$. $*p < .05$. $**p < .01$. $***p < .001$.

1-percentage-point increase in the percentage of teachers near the district who host a student teacher is associated with a 0.45-percentage-point decrease in the percentage of emergency hires in the district. Notably, the coefficient on student teaching placements in the district itself is somewhat attenuated towards zero once we account for these spatial relationships. This provides evidence that student teaching placements both within *and* nearby a district are predictive of staffing challenges in the district, which has important implications for policy (discussed in the Conclusion).[13]

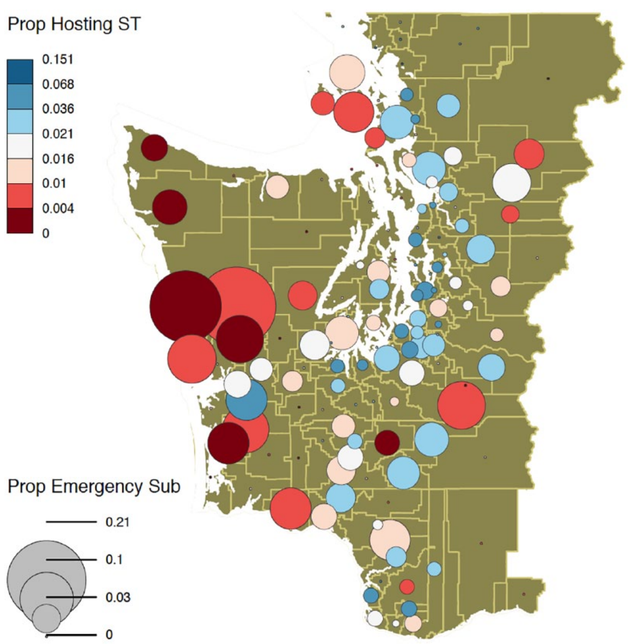

FIGURE 2. *Proportion of emergency substitute teachers and proportion of teachers hosting student teachers, by district.*

The correlations in columns 1 and 2 of Table 1 and depicted in Figure 2 do not account for many potential confounders in the relationship between student teaching placements and district-hiring difficulties. 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., 2020). Thus, we control for district urbanicity in the specification in column 3 of Table 1. 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 relationships between student teacher placements and staffing difficulties in column 3 attenuate somewhat relative to column 2. But these relationships are still negative and statistically significant, which means that even when comparing two districts within the same urbanicity category, districts that host more student teachers or are nearby to 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 4 and 5 (by itself in column 4, and then also controlling for district urbanicity in column 5). In the model in column 5, the relationships between student teacher placements and staffing difficulties continue to attenuate

Table 2
School Percentage of Emergency Substitute Teachers in Year *t* Versus School Characteristics in Year *t* – 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Percentage of teachers in school hosting an ST	−.077***	−.067***	−.061***	−.053**	−.053**	−.042**	−.048**
	(.018)	(.017)	(.017)	(.017)	(.017)	(.016)	(.015)
Percentage of teachers near the district hosting an ST (weighted by inverse distance)		−.493***	−.374***	−.362***	−.335***	−.172**	−.067
		(.090)	(.082)	(.080)	(.075)	(.065)	(.111)
City (ref. suburb)			−.122		.046	−.005	
			(.082)		(.101)	(.100)	
Town (ref. suburb)			.490**		.276+	.159	
			(.183)		(.150)	(.158)	
Rural (ref. suburb)			.466**		.183	.094	
			(.164)		(.128)	(.142)	
Log distance to nearest TEP				.245***	.220***	.142**	
				(.040)	(.043)	(.045)	
Additional school controls						X	
District fixed effect							X
Number of school-year observations	10,702	10,702	10,702	10,702	10,702	10,666	9,388
R-squared	.086	.091	.100	.109	.111	.137	.167

Note. 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 percentage American Indian or Alaskan Native students, percentage Asian Pacific Islander students, percentage Black students, percentage Hispanic students, percentage female students, percentage migrant students, percentage transitional bilingual students, percentage students with disabilities, percentage students receiving free or reduced-priced lunch, percentage students in Section 504 housing, and district median housing value (taxable value). 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: $+p < .1$. $*p < .05$. $**p < .01$. $***p < .001$.

toward zero and the *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, these relationships are 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 or are nearby to 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 the footnote of Table 1) in the final specification in column 6. As with all prior specifications, the addition of these variables continues to attenuate the relationships between student teaching placements and staffing difficulties toward zero. But yet again, the relationships of interest are negative and statistically significant, which means that even when comparing two districts *with identical observable characteristics*, districts that host more student teachers or are nearby to districts that host more student teachers tend to hire fewer teachers on emergency credentials.

Columns 1 through 6 of Table 2 repeat the same specifications just described for columns 1 through 6 of Table 1, 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 0.05- to 0.08-percentage-point decrease in the percentage of new hires on an emergency credential in the school, with similarly robust geographical spillover effects as in the district models. The district fixed-effects specification in column 7 of Table 2 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.

A concern with Tables 1 and 2 is that one would expect a negative coefficient on the student teacher variables if districts experiencing hiring difficulties were subsequently less likely to host student teachers. We test for this with the falsification test outlined in Equation (4), in which we add *future* student teachers as an additional explanatory variable. If the presence of emergency certified teachers discourages the training of student teachers, we would expect the coefficient on future student teacher hosting to be negative. Results from this falsification test are presented in Table 3. Because Table 3 restricts the sample to only years where we observe both current and future student teaching placements, column 1 of Table 3 presents baseline results. The remaining columns of Table 3 correspond to all columns in Tables 1 and 2.

The most important conclusion from Table 3 is that past student teacher placements still predict staffing difficulties conditional on future student teaching placements, whereas future student teaching placements do not predict staffing difficulties

Table 3
School Percentage of Emergency Substitute Teachers in Year *t*, Falsification Test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Percentage of teachers hosting an ST in year *t* – 1	–.031**	–.026*	–.022*	–.019*	–.019*	–.019+	–.016
	(.010)	(.010)	(.010)	(.010)	(.009)	(.010)	(.013)
Percentage of teachers hosting an ST in year t + 1		–.016+	–.014	–.012	–.012	–.007	–.000
		(.010)	(.009)	(.009)	(.009)	(.009)	(.013)
City (ref. suburb)			–.021		.065	.055	
			(.062)		(.079)	(.077)	
Town (ref. suburb)			.396**		.234+	.160	
			(.154)		(.126)	(.128)	
Rural (ref. suburb)			.364**		.188+	.076	
			(.139)		(.109)	(.102)	
Log distance to nearest TEP			.130***		.109**	.078*	
			(.030)		(.033)	(.036)	
Additional school controls						X	
District fixed effect							X
Number of school-year observations	8,863	8,863	8,863	8,863	8,863	8,844	6,416
R-squared	.097	.098	.108	.111	.114	.133	.180

Note. 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 percentage American Indian or Alaskan Native students, percentage Asian Pacific Islander students, percentage Black students, percentage Hispanic students, percentage female students, percentage migrant students, percentage transitional bilingual students, percentage students with disabilities, percentage students receiving free or reduced-priced lunch, percentage students in Section 504 housing, and district median housing value (taxable value). Standard errors are clustered by school. Log distance to nearest TEP is calculated by log(distance + 1).
P-values from two-sided *t*-test: $+p < .1$. $*p < .05$. $**p < .01$. $***p < .001$.

conditional on past student teaching placements. In other words, not employing student teachers seems appears to be predictive of the use of emergency certification and not vice versa. This provides some evidence supporting the directionality of the models outlined in the Analytic Approach section, above, and discussed above, but it certainly does not address all endogeneity concerns in this analysis, which is one reason why we are still careful to discuss our results in this section in descriptive terms.

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 article establish that—at least in a descriptive sense—districts that tend to host more student teachers or are nearby to districts that 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 and are robust to a district fixed-effects specification and a falsification test of the directionality of the relationship, we view these results as suggestive of a directional relationship between student teaching placements and teacher shortages. 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 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" (E2SHB 1139, 2019). 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, or develop regional collaborations between districts to form joint relationships with teacher education programs. The spillover effects between districts are particularly important for policies like these, as they suggest that student teacher placements in one specific district are predictive of fewer staffing difficulties beyond just that single district.

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 article are, in fact, causal. Moreover, it is possible that incentivizing student teaching placements in hard-to-staff districts and schools could have unintended consequences for candidate career paths and effectiveness, particularly given prior evidence linking student teaching placements in schools with lower teacher turnover to higher effectiveness and rates of teacher retention (Ronfeldt, 2012). Given that the effects of student teacher placement policies on staffing and candidate outcomes 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.

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NOTES

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

[2]See https://title2.ed.gov/Public/TitleIIReport16.pdf.

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

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

[5]The difference in average SAT scores understates the difference in competitiveness between participating and nonparticipating institutions because 2 of the 6 non-participating institutions have open-enrollment policies and do not require SAT scores, compared to just 1 of the 15 participating institutions.

[6]We experimented with polynomials in distance and the square root in distance and found quantitatively similar results.

[7]Distances are computed as linear distances between the centroids of districts in the state, with TEP campuses matched 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.

[8]We also present summary statistics in Appendix Table A1, available on the journal website, showing that new teachers from TELC programs are not particularly representative of all new teachers in the state.

[9]Table A2 in the online 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.

[10]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.

[11]Benefits will be attenuated because the spillover reduces the contrasts between geographically proximate districts. Imagine, for instance, that District A hosts a large number of student teachers and neighboring District B hosts none. Assuming that student teachers are more likely to apply to districts in communities they are familiar with, then District B will have more applicants than they would have in the absence of District A's hosting of student teachers; hence a lower probability of staffing challenges despite having not hosted any student teachers.

[12]The presumption here is that there are unobserved attributes of communities that make them both desirable places to be as a student teacher and for permanent employment. Bias could, however, be in the opposite direction. Student teachers, for instance, might be less likely to apply for jobs in districts with undesirable attributes, attributes that they are only aware of having student taught in those districts.

[13]Tables A4 and A5 in the online appendix present results using the alternative spatial weighting matrix in which proximity is measures by a binary indicator of whether two districts are within 50 miles of each other. Results are qualitatively similar.

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