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Disconnected Development? The Importance of Specific Human Capital in the Transition From Student Teaching to the Classroom

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We use a novel database of student teaching placements in Washington State to investigate teachers' transitions from student teaching classrooms to first job classrooms and the implications for student achievement. We find first-year teachers are more effective when they teach in the same or an adjacent grade, in the same school type, or in a classroom with student demographics similar to their student teaching classroom. We document that only 27% of first-year teachers are teaching the same grade they student taught, and that first-year teachers tend to begin their careers in higher poverty classrooms than their student teaching placements. This suggests that better aligning student teacher placements with first-year teacher hiring could be a policy lever for improving early-career teacher effectiveness.

Keywords: *student teaching, teacher education/development, policy, regression analyses, econometric analysis*

It is well documented that teacher quality is the most important school-based factor associated with improving student achievement, but research on policies designed to influence teacher quality has shown that it is difficult to change the productivity of inservice teachers at scale (e.g., Hill & Ball, 2004; Jacob & Lefgren, 2004; Springer et al., 2011). However, some research suggests that teacher quality may be quite malleable early in a teacher's career. Several studies, for instance, focus on the apprenticeships required of teachers before they enter the workforce (their "student teaching experiences") and find that the type and quality of student teaching placements are associated with future teacher effectiveness (Bastian et al., 2020; Boyd et al., 2009; Goldhaber, Krieg, & Theobald, 2017, 2020; Henry et al., 2013; Ronfeldt, 2012, 2015; Ronfeldt, Brockman, & Campbell, 2018; Ronfeldt et al., 2021). There is also evidence that the extent to which teachers improve with early-career teaching experience is associated with both their work environment (Papay & Kraft, 2015) and the specifics of their earlier teaching placements (Atteberry et al., 2017; Ost, 2014).

This study seeks to contribute to both lines of prior research by leveraging data on the student teaching experiences of teacher candidates that have been assembled as part of a research consortium, the Teacher Education Learning

Collaborative (TELC), that includes 15 teacher education programs (TEPs) in Washington State.[1] Graduates from these TEPs represent about 80% of the teachers hired in Washington who graduated from an in-state institution over the past decade. Since 2009–2010, individual TEP teacher candidates can be linked to the grade level and student demographics of both the classroom in which they completed their student teaching and, if they enter the state's public teaching workforce, the classroom(s) in which they begin their teaching careers. This allows us to explore the importance of specific human capital—that is, experiences that are specific to a candidate's future teaching positions—in the transition from student teaching to early-career teaching positions.

Specifically, we build on prior work that focused on the implications of the alignment between student teaching and early-career teaching positions (Boyd et al., 2009; Goldhaber et al., 2017; Henry et al., 2013) and investigate the alignment between candidates' student teaching and first-year *classroom* assignments, and the implications of this alignment for teacher effectiveness. We address three research questions (RQs):

Research Question 1 (RQ1): To what extent are teachers' student teaching and first job classrooms aligned in terms of grade, school type (elementary, middle, or high), school, district, and student demographics?

Research Question 2 (RQ2): Are first-year teachers who teach in the same grade, school type, school, or district in which they student taught more or less effective than teachers who did not?

Research Question 3 (RQ3): Are first-year teachers who teach in classrooms with student demographics similar to the classroom in which they student taught more or less effective than teachers who teach in very different classrooms than they experienced in student teaching?

Our investigation of RQ1 identifies several areas of misalignment between student teaching placements and first teaching positions in this sample of first-year teachers. While 16% of first-year teachers are hired into their student teaching school and 40% are hired into their student teaching district, only 27% are hired into the same grade in which they student taught. This misalignment is largely due to disproportionate student teacher placements in Grades 4 and 5 and Grades 9 to 12 relative to the number of teachers who are hired into these grades (and conversely, disproportionately fewer student teacher placements in Grades 6–8 relative to the number of new hires into these grades). In fact, less than half of first-year teachers in Grades 6 to 8 student taught in one of these grades. First-year teachers also tend to be teaching in considerably higher poverty classrooms than their student teaching classrooms, even after accounting for the poverty level of their student teaching and first teaching schools.

The primary finding from our analysis aligned with RQ2 is that first-year teachers are more effective in both mathematics and English language arts (ELA) when they teach in the same grade, in an adjacent grade, or in the same school type in which they student taught. The same-grade findings are consistent with prior evidence on the importance of specific human capital for inservice teachers (Atteberry et al., 2017; Ost, 2014), though we are cautious about interpreting these findings as causal due to concerns about the nonrandom sorting of candidates into and between student teaching and first teaching positions. Finally, when we investigate the alignment between student teaching and first teaching classroom demographics (RQ3), we find evidence that first-year teachers who are teaching in very high-poverty or low-poverty *classrooms* tend to be more effective when they student taught in a classroom with similar demographics. This is consistent with prior evidence on student disadvantage measured at the school level (Goldhaber et al., 2017). Put together, these findings are important because they illustrate that student teaching placements and first teaching positions could be substantially better aligned, potentially leading to better student outcomes.

Background

This study seeks to connect and build on two strands of literature. First, a growing body of literature highlights the importance of teacher candidates' student teaching experiences for their early-career effectiveness. For example, Ronfeldt (2012, 2015) finds that student teachers in schools with less teacher turnover, higher value added, and better teacher collaboration tend to be more effective once they enter the workforce. Bastian et al. (2020); Goldhaber, Krieg, and Theobald (2020); Matsko et al. (2020); Ronfeldt, Brockman, and Campbell (2018); and Ronfeldt et al. (2021) also connect the effectiveness of candidates' mentor teachers (i.e., the inservice teachers who supervise their student teaching placements) to the candidate's future feelings of preparedness (Matsko et al., 2020) and effectiveness; candidates who were mentored by teachers with higher evaluation scores (Bastian et al., 2020; Ronfeldt, Brockman, & Campbell, 2018; Ronfeldt et al., 2021) or higher value added (Bastian et al., 2020; Goldhaber, Krieg, & Theobald, 2020; Ronfeldt, Brockman, & Campbell, 2018) tend to be more effective according to these same measures once they enter the workforce. While all of these studies are subject to potential omitted-variable bias—for example, these findings could be explained by the nonrandom sorting of candidates to student teaching and first teaching positions—two recent experimental studies (Ronfeldt et al., 2020; Ronfeldt, Goldhaber, et al., 2018) provide preliminary evidence that candidates randomly assigned to "better" student teacher placements according to these measures report better self-perceived preparedness than candidates randomly assigned to "worse" placements.

The second line of literature that motivates this analysis focuses on the importance of specific human capital for *inservice* teachers or, put another way, the importance of the alignment between prior teaching experiences and current job assignments. Ost (2014) investigates whether teachers have greater returns to experience when they have prior experience in the same grade they are currently teaching. He finds significant returns to inservice grade-specific experience; in math, for example, the early-career returns to experience are about .01 standard deviations of student achievement higher for each additional year of grade-specific experience a teacher obtains. These findings are bolstered by quasi-experimental evidence showing that the "churn" of teachers between different grade and subject assignments has detrimental impacts on student achievement (Atteberry et al., 2017).

Finally, prior research has suggested that there is some degree of misalignment when it comes to transitions between student teaching and first job schools and that this misalignment may have implications for student achievement. Goldhaber et al. (2017), for instance, find that there is a dichotomy between the relative advantage (as measured by the percentage of students receiving free or reduced-price lunch [FRL] or underrepresented minority students) of the schools in which student teaching occurs and teachers' first job schools. This reflects the broader teacher labor market trend that novice teachers tend to be assigned to more disadvantaged schools and classrooms than more experienced teachers (e.g., Bruno et al., 2020; Goldhaber et al., 2015; Kalogrides et al., 2013).

There is also evidence that the degree of self-reported (Boyd et al., 2009) and *school-level* (Goldhaber et al., 2017) alignment between student teaching and first jobs is predictive of future teacher effectiveness, as well as prior evidence from one TEP (Henry et al., 2013) that teaching in the same grade as student teaching is predictive of higher value added. Perhaps surprisingly, prior studies that consider matches between student teaching and first teaching positions in terms of school type (e.g., Ronfeldt, 2015) and the specific school (e.g., Goldhaber et al., 2017; Henry et al., 2013) have not found that these measures are predictive of teacher value added, though one recent study finds that same school hiring is predictive of higher teacher evaluation scores (Ronfeldt et al., 2020). To our knowledge, this is the first article to consider *all* of the measures of alignment discussed above, as well as measures of demographic alignment at the classroom level that have not been considered in prior analyses.

Data and Summary Statistics

Data

The data we use combine student teaching data, supplied by 15 (of 21 at the time of data collection) Washington TEPs participating in TELC, with K–12 administrative data provided by the Washington State Office of Superintendent of Public Instruction (OSPI). These TEPs provided information about when and where each teacher candidate's student teaching occurred, as well as the classroom teacher who supervised their internship. The full TELC data set includes over 20,000 teacher candidates who completed their student teaching (in some cases) as far back as the late 1990s. However, we focus on school years 2009–2010 to 2017–2018 because these are the years in which we can both match teachers to individual classrooms and students and follow these candidates into the state's teaching workforce (the most recent year of available data is 2018–2019).[2]

In this 9-year time span, we observe 12,514 teacher candidates who graduate from TELC institutions. Of these, 8,251 (66%) can be linked to both their student teaching and first teaching classrooms after student teaching; the majority of unmatched teachers (24% of all candidates in the sample) are never observed as employed in a Washington public school, another 3% of candidates are only observed in nonteaching positions (e.g., teacher's aide), while the remaining 7% of candidates are observed in teaching positions not joined to a specific classroom (e.g., special education resource teachers).

Finally, we focus only on each teacher's first teaching year to isolate the transition from student teaching to first job classrooms. To be conservative in identifying these first teaching positions, we drop the 2,699 teachers who are reported to have at least 0.5 years of certificated experience the first time they appear in the state's data systems; these could be teachers who began their careers in another state, were hired after the personnel reporting date the previous year (October 31), or were credited with certificated experience in K–12 schools prior or concurrent to student teaching that is not captured in the state's data systems (e.g., for substitute teaching experience).[3] These restrictions leave a final sample of 5,552 first-year teachers with complete preservice student teaching and inservice teaching data. In extensions to this model, we follow the lead of Boyd et al. (2009) by considering a smaller sample of teachers as they move through their second year of teaching.

A key feature of the data is that we only observe student teaching placements for teachers who graduate from one of the TEPs participating in TELC. This excludes in-state teachers from other TEPs and teachers trained out of state. Table 1 provides summary statistics for districts where new teachers are employed in the state of Washington for the same years in which we have TELC data, broken out by TELC institutions, non-TELC (but Washington-based TEPs), and teachers who are from outside of Washington ("out of state"). The *t* tests reported in the table indicate some significant differences between the TELC sample and teachers from non-TELC institutions or who receive their credential through OSPI and are coming into Washington from out of state.

Overall, TELC institutions supplied about 65% of the new teachers in the state and about 80% of teachers from an in-state institution during this time period. It is worth noting that there are some differences between the TELC teachers and teachers in the other categories. TELC-trained teachers are, for instance, less likely to be teaching in high-poverty districts (as measured by students eligible for FRL) than teachers trained in Washington non-TELC institutions, but more likely to be teaching in high-poverty districts than teachers who are trained outside of Washington. In terms of location, TELC teachers are far more likely to be employed in suburban districts and far less likely to be employed in rural districts and in districts east of the Cascades than non-TELC teachers.

These differences are not surprising, as is apparent from examining Figure 1, which shows the percentage of new in-state teachers in each Washington district that completed their preparation in a TELC institution. TELC includes institutions supplying an overwhelming share (over 90%) of teachers west of the Cascade mountains, but some larger institutions that serve many of the rural districts in the eastern half of the state chose not to participate in TELC. The bottom line is that these differences suggest we should be cautious in interpreting our findings outside of the TELC sample. With that said, we focus on the TELC sample for the remainder of our analysis because we only observe student teaching placements for this sample of teachers.

The OSPI data consist of three types of data: building-level information, student data, and teacher personnel records. The building data contain information used to replicate prior studies of teacher alignment (e.g., Goldhaber et al., 2017), including geographic information, aggregated program participation (e.g., gifted programs, FRL, and special education), and aggregated student demographics. The student-level data

TABLE 1

District Summary Statistics for New Teachers in State

Variable	Total	TELC	Non-TELC	Out of state
Proportion district in city	0.337	0.332	0.349	0.345
	(0.473)	(0.471)	(0.477)	(0.475)
Proportion district in suburb	0.427	0.457	0.334***	0.401***
	(0.495)	(0.498)	(0.472)	(0.490)
Proportion district in town	0.119	0.107	0.167***	0.120*
	(0.324)	(0.309)	(0.373)	(0.325)
Proportion district in rural	0.117	0.104	0.150***	0.134***
	(0.322)	(0.306)	(0.357)	(0.341)
Proportion district west of the Cascades	0.775	0.843	0.423***	0.825*
	(0.418)	(0.363)	(0.494)	(0.380)
Average district percent American Indian or Alaskan Native	1.658	1.557	2.371***	1.412
	(5.697)	(5.356)	(7.518)	(4.992)
Average district percent Asian Pacific Islander	10.07	11.25	5.886***	9.563***
	(10.70)	(11.14)	(7.994)	(10.24)
Average district percent Black	5.778	6.270	4.641***	5.081***
	(8.536)	(9.074)	(7.330)	(7.415)
Average district percent Hispanic	24.48	23.58	31.59**	21.73
	(22.52)	(21.19)	(29.21)	(19.21)
Average district percent female	48.31	48.28	48.51	48.24
	(3.360)	(3.231)	(3.408)	(3.715)
Average district percent migrant	2.099	1.882	4.046***	1.362***
	(5.397)	(5.171)	(7.029)	(4.307)
Average district percent transitional bilingual	13.22	13.18	15.68***	11.35***
	(15.42)	(14.92)	(18.70)	(13.73)
Average district percent SPED	13.21	13.12	13.39	13.33
	(6.860)	(6.489)	(5.982)	(8.507)
Average district percent FRL	48.96	47.54	58.44***	45.93**
	(25.32)	(25.37)	(24.61)	(23.93)
n	15,730	10,177	2,437	3,116

Note. Standard deviation in parenthesis. 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) between 2009–2010 and 2018–2019. The p values from two-sided t test relative to teachers who got teaching certificate from TELC institutions. TELC = Teacher Education Learning Collaborative; SPED = special education; FRL = free or reduced-price lunch.
*$p < .05$. **$p < .01$. ***$p < .001$.

include annual standardized test scores, demographic information, and program participation for all K–12 students in the state. The student-level data provide enough information to observe the members of all students' classrooms as well as to identify their teacher. We define a teacher's grade level as the most common grade across students taught by a teacher (either the cooperating teacher for the student teacher placement or the teacher for the first teaching placement). Finally, the OSPI personnel data include administrative and employment histories for each teacher in the state. We merge these three data sets with the TELC data using the classroom teacher's name and building information to identify the students in the classrooms where student teachers served as well as in their classrooms after being hired into their first teaching jobs.

Summary Statistics (RQ1)

The summary statistics describe the analytic data set we utilize and address RQ1 (i.e., the extent to which first-year teachers experience a

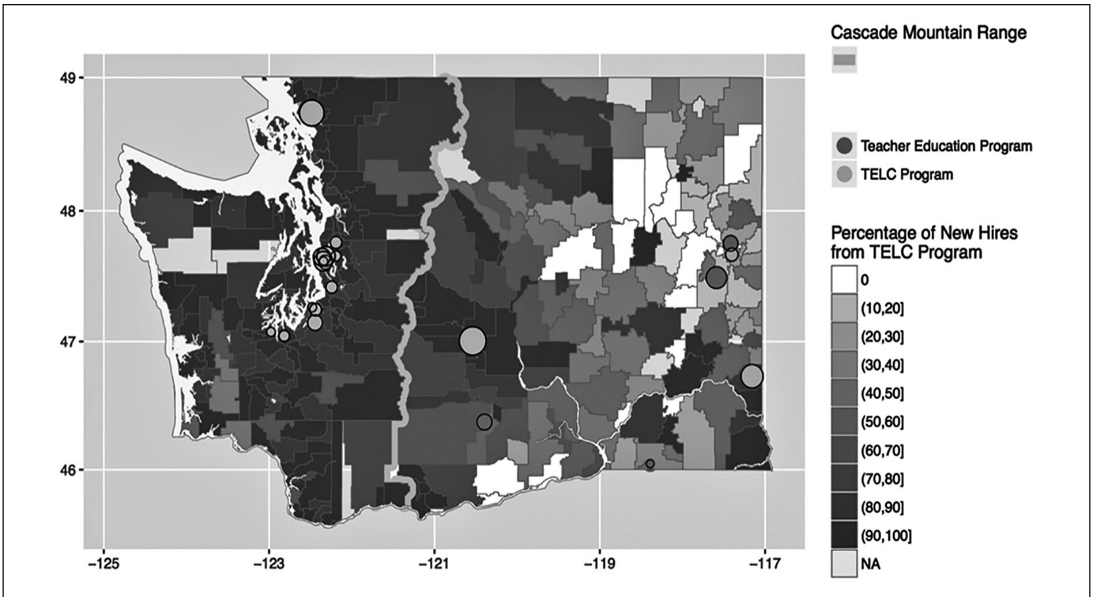

FIGURE 1. *Percentage of new, in-state teachers from TELC programs, by district.*
Note. Size of bubble corresponds to the number of graduates from each TEP. TELC = Teacher Education Learning Collaborative; TEP = teacher education program.

match between their student teaching placements and first job placements). We begin by investigating the alignment between student teaching grades and first teaching grades in Table 2. Each of the 5,552 first-year teachers in the sample is placed into one of the cells of Table 2, in which the rows represent student teaching grades and the columns represent first teaching grades. The bolded counts along the diagonal represent teachers who experience an exact alignment between their student teaching grade and first teaching grade. As shown in Column 1 of Table 3, this represents slightly more than 25% of all teachers in the sample. One takeaway from Table 2 is that while only about one in four new teachers student taught in their current grade, it is rare to observe grade placements that are dramatically different from the student teaching experience.

The bottom row and far-right column of Table 2 highlights an important trend in student teaching grades and first teaching grades: There are more individuals who student teach in Grades 4 and 5 (913) and Grades 9 to 12 (1,553) than are initially hired into these grades (850 and 1,342, respectively). Conversely, it is far more common for teachers to begin their careers in Grades 6 to 8 (1,260) than to student teach in these grades (972). In other words, teachers are disproportionately likely to student teach in upper elementary and high school grades but are disproportionately likely to be hired into middle school grades. In fact, fewer than half of teachers who begin their careers in a middle school grade (6–8) student taught in one of these grades, while the comparable rate for teachers who begin their careers in elementary grades (K–5) is over 90%.

A potential explanation for these trends—and an important factor to consider in terms of the generalizability of these trends to other states—is related to the state's teacher licensure system. Each of Washington's teaching endorsements falls into one of four categories that certify teachers to teach in different grades: Early Childhood (Grades P–3), Elementary (Grades K–8), Middle Level (Grades 4–9), and Subject Areas (Grades K–12). When we consider patterns of student teaching grades and first teaching grades for each of these endorsement categories (see Supplementary Tables A1–A4 in the online version of the journal), it appears that the trends described above are driven by teachers with subject endorsements (e.g., "Math," "English," "Special Education") or an elementary education endorsement. In particular, many teacher candidates with a subject area

TABLE 2

Student Teaching Grade and First Job Grade

		First teaching grade														
		K	1	2	3	4	5	6	7	8	9	10	11	12	Row Totals	
Student teaching grade	K	**212**	86	34	32	13	11	5	7	5	2	2	1	0	410	2,114
	1	172	**169**	97	61	36	24	10	8	6	3	2	0	1	589	
	2	109	132	**124**	82	53	41	15	4	5	1	3	0	2	571	
	3	55	66	75	**148**	83	68	24	10	6	3	2	2	2	544	
	4	35	32	51	75	**119**	89	31	10	12	3	5	0	1	463	913
	5	29	29	21	51	96	**124**	46	22	14	8	5	2	3	450	
	6	15	3	10	12	19	16	**79**	56	39	25	13	10	6	303	972
	7	8	3	1	7	6	13	60	**74**	50	39	19	6	8	294	
	8	3	5	3	7	5	12	72	88	**82**	52	21	16	9	375	
	9	4	1	1	6	7	2	40	50	55	**163**	111	39	30	509	1,553
	10	5	5	1	4	3	2	32	48	47	137	**114**	41	23	462	
	11	3	0	0	5	1	3	19	27	28	88	80	**38**	18	310	
	12	4	3	3	1	0	4	20	18	36	69	54	30	**30**	272	
	Column totals	654	534	421	491	441	409	453	422	385	593	431	185	133	5,552	
			2,100			850			1,260			1,342				

Note. The bolded numbers along the diagonal represent teachers who experience an exact alignment between their student teaching grade and first teaching grade.

endorsement student teach in high school and are subsequently hired into middle school, while many candidates with an elementary education endorsement student teach in elementary school and are subsequently hired into middle school. We are cautious not to overinterpret these trends given that these categories are not mutually exclusive and, moreover, credentials may be endogenous to grade placements (e.g., if a teacher completes requirements for a given credential once they have an offer to teach a given grade level). But it does suggest that these findings may be most generalizable to other states that certify teachers for wide grade ranges that allow for the types of discrepancies between student teaching grades and first teaching grades that we observe in Washington.

Table 3 provides additional summary statistics about the teachers in Table 2 (Column 1), then separated by federally defined school types (Columns 2–4), and finally by the various analytic samples described in the next section (Columns 6–8, all compared with teachers not in any analytic sample in Column 5). The means in Column 1 provide some important statistics about RQ1; for example, consistent with Goldhaber et al. (2017), a large proportion of student teachers get their first jobs in the same school (16%) or district (40%) in which they student taught. In terms of other measures of alignment, nearly 80% of teachers are hired into the same school type (elementary, middle, or high school) as their student teaching school. But this overall figure masks some heterogeneity by school type, shown in Columns 2 to 4; for example, 90% for elementary school teachers experience a school-type match, while less than 50% of middle school teachers student taught in a middle school. More generally, middle school teachers are less likely to experience a match along *any* of our measures of alignment than elementary or high school teachers.

Table 3 also presents information on the alignment with respect to the percentage of students eligible for FRL in teachers' first teaching and student teaching classroom and schools (calculated as the percentage at the current classroom/school minus the corresponding percentage at the student teaching classroom/school). On average, student teachers are hired into classrooms and schools with higher FRL percentages than their student teaching experiences. We highlight this in Figure 2 by plotting the percentage of FRL students in each teacher's classroom during their student teaching (x-axis) and first job (y-axis) at the classroom (Panel A) and school (Panel B) types. Both measures provide evidence that student teaching tends to occur in more advantaged settings than first job teaching, but the dichotomy

TABLE 3

Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All teachers	Elementary teachers	Middle school teachers	High school teachers	Not analytic sample	Both ELA and math samples	Math sample only	ELA sample only
Same grade	0.266	0.299	0.188***	0.262**	0.268	0.287	0.222*	0.217*
Adjacent grade	0.329	0.341	0.288***	0.344	0.329	0.348	0.309	0.304
Same school type	0.786	0.928	0.480***	0.781***	0.799	0.914***	0.552***	0.508***
Same school	0.163	0.170	0.122***	0.191*	0.163	0.171	0.141	0.164
Same district	0.398	0.443	0.386***	0.318***	0.391	0.453***	0.370	0.391
Classroom % FRL difference	6.169 (30.214)	5.552 (32.121)	8.624*** (28.702)	5.802 (26.591)	6.049 (30.058)	3.822* (32.381)	10.613** (28.474)	9.507* (27.935)
School % FRL difference	2.945 (25.288)	3.621 (26.619)	4.977 (24.902)	–0.044*** (21.847)	2.835 (25.157)	1.965 (26.684)	5.936** (25.280)	4.173 (23.533)
Observations	5,552	3039	1088	1288	4,265	718	270	299
Classroom % FRL difference (same school hiring)	2.891 (16.033)	1.370 (17.295)	5.973*** (12.125)	4.523*** (14.983)	2.888 (16.369)	0.077* (16.444)	7.505* (9.307)	6.424* (12.780)
Observations	904	516	133	246	694	123	38	49

Note. The p values calculated from t tests relative to Column 2 (Columns 3 and 4) and Column 5 (Columns 6–8). Standard deviations in parenthesis. ELA = English language arts; FRL = free or reduced-price lunch.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

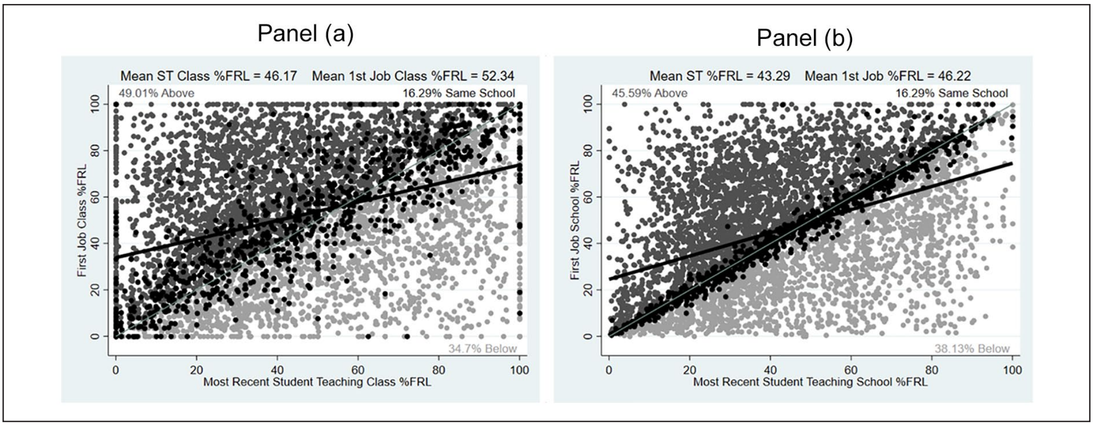

FIGURE 2. *Scatterplots of % FRL in student teaching and first job placements: Panel A: Classroom-level FRL and Panel B: School-level FRL.*
Note. FRL = free or reduced-price lunch; ST = student teaching.

between the two is clearly greater when we focus on the classroom level (indicating sorting of new teachers into higher poverty classrooms within schools). At the school level (Panel B), we find that among teachers not hired into their student teaching school, 46% were hired into a more disadvantaged school than where they student taught, 16% are in the same school (though the FRL can differ from year to year so that these teachers may not be on the 45-degree line), and 38% of teachers who are not hired into the same school find a first teaching position in a more advantaged school. When we instead focus on the classroom level, the corresponding figures are 50%, 16%, and 34%.

Analytic Models

To address RQ2 and RQ3, which examine the effectiveness of teachers who experienced an alignment between student teaching and first job (whether same grade, adjacent grade, school type, school, district, or demographic), we estimate variants of the following model:

$$Y_{isjt} = \dagger_0 + \dagger_1 Y_{ist-1} + \dagger_2 Y_{is't-1} + \dagger \mathbf{X}_{it} + ` \mathbf{Z}_{jt} + \mathbf{I}_j + {}_{ijst}, \quad (1)$$

where Y_{isjt} represents the test score of student i, in subject s (math or ELA), in teacher j's classroom, during year t; $\mathbf{X}$ represents a matrix of student-level controls (gender, race/ethnicity, FRL status, grade, and learning disability); and $\mathbf{Z}$ represents a matrix of classroom controls (class size, percentage of class by student demographics, and average math and ELA scores). There are likely differences in student outcomes based upon the TEP that assigns student teachers to that student. For instance, different types of students are likely to be served by different TEPs throughout the state. Moreover, TEPs are likely to send student teachers to different sets of schools. For both reasons, we include $\mathbf{I}_j$, which are binary indicators for the student teacher's TEP. The resulting estimates can be thought of as a within-TEP comparison of student test score gains. Finally, because the student testing regime in Washington is administered in consecutive years only for Grades 4 through 8, Equation 1 excludes grades outside this range. Thus, RQ2 and RQ3 focus on middle-level grades and exclude high school and early grades.

RQ2 focuses on the roles that alignment between student teaching and first job grades, school type, school, or district plays in predicting teacher effectiveness. We approach this by adding to Equation 1 binary variables equal to one if a match occurs between a teacher's student teaching experience and first job. This amounts to comparing student learning gains among teachers with a match (at the grade level, school, school type, or district) with those who did not match. These match variables are introduced first individually and then jointly to the model in Equation 1. The joint models are our preferred specification because they indicate which types of matches are most predictive of student test score gains, controlling for the others. But the individual specifications can also be important in some settings; for example, if a principal knows that a teacher will experience a school-level match but does not know the teacher's student teaching grade, the coefficient on school-level match in the individual specification gives the expected increase in student test scores unconditional on the unobserved information.

Another type of match can occur between the characteristics of student teaching classroom or school and the first job classroom or school. RQ3 focuses on the role of the match with respect to student characteristics. Following Goldhaber et al. (2017), we focus on the percentage of students receiving FRL in a teacher's classroom or schools and include flexible polynomials for the differences between the first classroom and their student teaching experience. Specifically, let FRL_{jt} be the percent FRL of teacher *j*'s current classroom/school and let FRL_{jt} be the percent FRL of that teacher's student teaching classroom/school. We construct flexible, polynomial models of the difference between the FRL status in the teacher's first year and the FRL status when they served as a student teacher[4]:

$$\ddagger_1 \mathrm{FRL}_{jt} + \sum_{k=1}^{3} \ddagger_{k+1} \left(\mathrm{FRL}_{jt} - \mathrm{FRL}_{jt'} \right)^k + \mathrm{FRL}_{jt} \sum_{k=1}^{3} \ddagger_{k+4} \left(\mathrm{FRL}_{jt} - \mathrm{FRL}_{jt'} \right)^k . \tag{2}$$

The first term in Equation 2 is the main effect of the FRL on contemporaneous student test scores, the second term is a polynomial of the match between current and internship experiences, while the third term interacts this polynomial with the main effect of the current characteristics. Goldhaber et al. (2017) measured these characteristics at the school level and showed that students of teachers who interned in schools similar to those of their first job performed better on standardized tests. However, it is an open question whether it is the characteristics of the school that matter or the characteristics of the classroom. We thus use the FRL measured at both the school level and classroom level in Equation 2, and include each, sometimes separately and sometimes together, as additional independent variables in Equation 1.

One threat to interpreting the coefficients of interest in the models above is that student teachers and teachers are not randomly assigned student teaching or first job classrooms (i.e., grades, school types, schools, districts, or specific types of students). For instance, if student teachers who are more likely to become effective teachers regardless of student teaching assignment tend to be hired into the same grade as they student taught—either because they sought out a student teaching placement in a grade they knew they wanted to teach, or perhaps because principals are more likely to place more effective first-year teachers in the same grade they student taught—then their future students would perform better not because of a grade match but because they are taught by a more effective teacher. In a similar vein, one might expect more effective student teachers to be placed in more advantaged (lower FRL) schools for training and then subsequently receive jobs in schools with similar levels of FRL. Again, their future students would benefit not because of having a teacher with experiences similar to their current classroom but simply because of the (unobserved) attributes of their teacher.

We explore these possibilities in Table 4, which provides summary statistics for teachers based upon their grade, school type, school, and district-match status. Table 4 introduces the Washington Education Skills Test–Basic (WEST-B) test score, which is the average of scores in math, reading, and writing tests that many candidates take prior to entering a TEP.[5] Importantly, there is little evidence that teachers who experience alignment between their student teaching and first job classrooms differ in their WEST-B scores or in the poverty levels of their student teaching schools relative to those who are less well aligned. Indeed, across the 24 statistical comparisons in Table 4, only two are statistically significant—about what would be expected by random chance. This provides some evidence that there is not nonrandom sorting to first job alignment along observed student dimensions, which is perhaps not surprising given prior evidence on the decentralized and informal process through which student teacher placements are made in Washington (St. John et al., 2018). But this of course does not rule out sorting along unobserved dimensions—including teacher evaluation scores, which have been considered in prior work (e.g., Bastian et al., 2020; Matsko et al., 2020) but are not available statewide in Washington—which may affect our results.

TABLE 4

Summary Statistics by Match Category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Same grade	Not same grade	Same school type	Not same school type	Same school	Not same school	Same district	Not same district
Panel A: Math sample								
ST classroom % FRL	50.13	47.64	48.86	45.86	50.28	47.92	48.30	48.32
	(29.14)	(26.74)	(28.12)	(23.98)	(29.76)	(26.94)	(28.81)	(26.34)
ST school % FRL	45.64	45.09	45.99	41.92*	45.64	45.16	45.17	45.28
	(24.95)	(22.72)	(23.78)	(20.93)	(25.12)	(22.98)	(24.27)	(22.61)
Observations	266	722	805	183	161	827	425	563
Average WEST-B score	275.12	274.17	274.22	275.38	274.69	274.39	275.41	273.78
	(12.67)	(11.69)	(12.04)	(11.62)	(11.30)	(12.09)	(11.56)	(12.20)
Observations	125	324	366	83	67	382	180	269
Panel B: ELA sample								
ST classroom % FRL	50.10	47.75	49.02	45.86	47.81	48.49	47.23	49.25
	(28.39)	(27.32)	(28.31)	(24.65)	(29.67)	(27.20)	(28.50)	(26.91)
ST school % FRL	45.98	45.08	46.20	41.91*	44.13	45.57	44.92	45.63
	(24.56)	(23.29)	(24.25)	(20.76)	(25.59)	(23.21)	(24.54)	(22.92)
Observations	271	746	808	209	172	845	442	575
Average WEST-B score	274.85	273.71	274.24	273.32	274.37	273.97	274.28	273.85
	(12.60)	(12.14)	(12.45)	(11.66)	(11.71)	(12.38)	(12.29)	(12.28)
Observations	130	333	359	104	69	394	195	268

Note. The p values calculated from t tests relative to corresponding odd column. ST = student teaching; FRL = free or reduced-price lunch; WEST-B = Washington Educator Skills Test–Basic; ELA = English language arts.

*$p < .05$.

Results

Grade, School, and District Alignment Findings (RQ2)

Table 5 presents coefficients on each of the binary variables indicating a match at the grade, an adjacent grade, school type, school, and district. Panel A presents results for all teachers in the analytic samples, Panel B is estimated just for elementary teachers, while Panel C includes just middle school teachers.[6] Columns 1 to 5 show the association between various measures of alignment between student teaching and first jobs for student achievement in math, and Columns 6 to 10 for ELA. Student achievement in each subject is standardized so the coefficient estimates report the association between a match (e.g., same grade-level assignment in first job as in student teaching) on student test scores in standard deviation units.

When models are estimated across all teachers (Panel A), the results provide consistent evidence that having a grade match between first job and student teaching classrooms is associated with higher student test achievement in both math and ELA. Interestingly, the relationships are even stronger when we account for both same grade and adjacent grade matches at the same time; in other words, students have considerably higher learning gains (~.07 *SD* in math, ~.04 *SD* in ELA) when their teacher is teaching in the same or adjacent grade to their student teaching grade, compared with students whose teacher is teaching in neither the same nor an adjacent grade to student teaching. Matches in terms of overall school type (elementary or middle school) are only significantly predictive in math.

There is less evidence that it matters for the average teacher in the sample whether they are hired into the same school district (Columns 4 and 10) or school (Columns 5 and 11) in which student teaching occurred. The coefficients on the match variables are positive but smaller than the grade match variables and not statistically significant. Finally, when we include all the match variables simultaneously (Columns 6 and 12), the grade matches are statistically significant in both math and ELA even controlling for the other measures, suggesting that they are matches in terms of grade placements that are driving these results.

The above findings are largely consistent for both elementary (Panel B) and middle school (Panel C) teachers in the sample, though not consistently statistically significant due to smaller sample sizes that occur when the sample is split. One important source of heterogeneity in the findings is in Columns 4 and 5 of Panel B, which show that first-year elementary teachers (as opposed to middle school teachers) are significantly more effective when they teach in their student teaching school or district than first-year elementary teachers who do not. Likewise, middle school *math* teachers seem to particularly benefit from teaching in the same grade as their student teaching.

As shown in additional tables in the supplementary appendix of online version of the journal, these results are similar (but somewhat weaker) when we explore several alternative assumptions, including expanding our sample to teachers in their first 2 years of teaching (see Supplementary Table A5), relaxing our definition of a grade "match" to include any grade in which teachers taught at least 10 students in student teaching (see Supplementary Table A6), and controlling for basic-skills licensure test scores on the WEST-B for the subset of teachers who have these scores (see Supplementary Table A7). The results are notably weaker when we pool across teachers' first 2 years in the workforce (see Supplementary Table A5), but it is unclear whether this reflects a "fade out" in these relationships or if it is due to the fact that we observe different samples of teachers in their first and second years. We explore this further in Supplementary Tables A8 to A10, first by limiting the sample to the exact same group of teachers for whom we estimate models in Table 5, and then focusing only on second-year teachers in these two samples. The relationships for second-year teachers in Supplementary Tables A9 and A10 are not generally statistically significant, indicating that the relationships documented in Table 5 are considerably stronger for first-year teachers than second-year teachers.

Student Demographic Match Alignment Findings (RQ3)

Table 6 presents coefficients from Equation 2 for FRL differences on math (Columns 1–3) and ELA (Columns 4–6). The top panel of Table 6

TABLE 5

Binary Match Measures as Predictors of Student Achievement in Teachers' First Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Outcome	Student achievement in math						Student achievement in ELA					
Panel A: All teachers												
Same grade as student teaching	0.041*	0.074**				0.064**	0.026+	0.039*				0.044**
	(0.017)	(0.019)				(0.021)	(0.014)	(0.016)				(0.017)
Adjacent grade to student teaching		0.070**				0.064**		0.026+				0.030*
		(0.017)				(0.019)		(0.014)				(0.015)
Same school type as student teaching			0.055**			0.020			0.003			–0.018
			(0.021)			(0.023)			(0.016)			(0.017)
Same district as student teaching				0.024		0.018				0.019		0.019
				(0.017)		(0.017)				(0.014)		(0.014)
Same school as student teaching					0.029	0.003					0.009	–0.006
					(0.025)	(0.026)					(0.019)	(0.021)
Student observations	29,252	29,252	29,252	29,252	29,252	29,252	28,872	28,872	28,872	28,872	28,872	28,872
Panel B: Elementary teachers												
Same grade as student teaching	0.031	0.068**				0.059*	0.026	0.041*				0.038+
	(0.020)	(0.023)				(0.024)	(0.018)	(0.020)				(0.021)
Adjacent grade to student teaching		0.071**				0.065**		0.029				0.026
		(0.021)				(0.022)		(0.019)				(0.019)
Same school type as student teaching			0.045			0.013			0.007			–0.003
			(0.041)			(0.041)			(0.033)			(0.034)

(continued)

TABLE 5 (CONTINUED)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Outcome	Student achievement in math						Student achievement in ELA					
Same district as student teaching				0.054**		0.029				0.027		0.026
				(0.019)		(0.022)				(0.017)		(0.019)
Same school as student teaching					0.060**	0.037					0.008	–0.010
					(0.023)	(0.027)					(0.023)	(0.025)
Student observations	15,312	15,312	15,312	15,312	15,312	15,312	15,152	15,152	15,152	15,152	15,152	15,152
Panel C: Middle school teachers												
Same grade as student teaching	0.062*	0.089**				0.097**	0.026	0.030				0.051+
	(0.029)	(0.030)				(0.033)	(0.024)	(0.025)				(0.027)
Adjacent grade to student teaching		0.063*				0.061*		0.009				0.027
		(0.027)				(0.029)		(0.020)				(0.022)
Same school type as student teaching			0.041+			0.011			–0.005			–0.036
			(0.025)			(0.029)			(0.019)			(0.022)
Same district as student teaching				–0.012		0.010				0.007		0.005
				(0.027)		(0.026)				(0.021)		(0.021)
Same school as student teaching					–0.041	–0.076+					0.013	0.014
					(0.044)	(0.045)					(0.033)	(0.037)
Student observations	13,940	13,940	13,940	13,940	13,940	13,940	13,720	13,720	13,720	13,720	13,720	13,720

Note. All models are limited to a teacher's first year in the workforce and also control for institution indicators and the following student- and classroom-level control variables: prior performance in math and reading, gender, race/ethnicity, receipt of free or reduced-price lunch, special education status and disability type, limited English proficiency indicator, migrant indicator, and homeless indicator. Standard errors clustered at the teacher level are in parentheses. The p values are calculated from two-sided t test. ELA = English language arts.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

TABLE 6

Continuous Match Measures as Predictors of First-Year Teacher Value Added

	Outcome	(1)	(2)	(3)	(4)	(5)	(6)
		Student achievement in math			Student achievement in ELA		
Classroom match	Current classroom % FRL	–0.1888311***		–0.2460214**	–0.2097670***		–0.2989267***
		(0.0471603)		(0.0966524)	(0.0384743)		(0.0776808)
	(Current classroom % FRL – Student teaching classroom % FRL)	–0.2077767*		–0.1374866	–0.0765417		–0.0910052
		(0.0970554)		(0.1377864)	(0.0770550)		(0.1030660)
	(Current classroom % FRL – Student teaching classroom % FRL)^2	–0.0023431		–0.0006612	0.0014731		0.0019034
		(0.0021314)		(0.0027534)	(0.0020535)		(0.0024139)
	(Current classroom % FRL – Student teaching classroom % FRL)^3	0.0000133		0.0000368	0.0000279		0.0000432
		(0.0000274)		(0.0000330)	(0.0000248)		(0.0000281)
	Current classroom % FRL × (Current classroom % FRL – Student teaching classroom % FRL)	0.0030372		0.0012629	0.0004568		0.0003688
		(0.0016901)		(0.0021181)	(0.0014150)		(0.0017100)
	Current classroom % FRL × (Current classroom % FRL – Student teaching classroom % FRL)^2	–0.0000004		–0.0000145	–0.0000441		–0.0000392
		(0.0000372)		(0.0000461)	(0.0000360)		(0.0000420)
	Current classroom % FRL × (Current classroom % FRL – Student teaching classroom % FRL)^3	0.0000002		0.0000001	0.0000003		0.0000001
		(0.0000004)		(0.0000004)	(0.0000003)		(0.0000003)
School match	Current school % FRL		–0.1723854**	0.0482936		–0.1771364***	0.0961249
			(0.0558612)	(0.1124630)		(0.0439374)	(0.0856987)
	(Current school % FRL – Student teaching school % FRL)		–0.1793642	–0.0682485		–0.0096453	0.0870236
			(0.1285558)	(0.1655340)		(0.1031469)	(0.1294492)
	(Current school % FRL – Student teaching school % FRL)^2		–0.0063856*	–0.0056685		–0.0024234	–0.0036143
			(0.0029000)	(0.0036873)		(0.0030025)	(0.0037691)
	(Current school % FRL – Student teaching school % FRL)^3		–0.0000703	–0.0000966*		–0.0000634	–0.0000960*
			(0.0000440)	(0.0000464)		(0.0000412)	(0.0000444)
	Current school % FRL × (Current school % FRL – Student teaching school % FRL)		0.0041311	0.0023904		0.0010649	–0.0003842
			(0.0023755)	(0.0027977)		(0.0018363)	(0.0022479)
	Current school % FRL × (Current school % FRL – Student teaching school % FRL)^2		0.0000664	0.0000815		0.0000186	0.0000487
			(0.0000618)	(0.0000723)		(0.0000534)	(0.0000655)
	Current school % FRL × (Current school % FRL – Student teaching school % FRL)^3		0.0000006	0.0000006		0.0000009*	0.0000009*
			(0.0000005)	(0.0000005)		(0.0000004)	(0.0000004)
	Student observations	29,829	28,919	28,919	29,477	28,645	28,645

Note. All estimates are multiplied by 100. Models are limited to a teacher's first year in the workforce and control for the same student variables as Tables 3 and 4. Standard errors clustered at the teacher level are in parentheses. The p values are calculated from two-sided t test. ELA = English language arts; FRL = free or reduced-price lunch.

*$p < .05$. **$p < .01$. ***$p < .001$.

presents coefficients on FRL differences at the classroom measuring the difference in the current classroom's FRL and the FRL of the student teaching classroom. For ease of discussion, we refer to this simply as the "difference"; note that this is *not* the absolute difference but rather is largest for teachers who are teaching in much higher poverty classrooms than their student teaching placement and lowest for teachers who are teaching in much lower poverty classrooms than their student teaching placement. The bottom portion of Table 6 follows the approach of Goldhaber et al. (2017) by presenting coefficients on the FRL differences measured at the school level, rather than the classroom level. Our approach in presenting these results is to highlight the role of the student teaching classroom on current students' test results (the first and fourth columns of Table 6). We then reproduce the Goldhaber et al. (2017) results by focusing on the school difference (Columns 2 and 5). Finally, we include both the classroom- and school-level differences simultaneously in hopes of identifying which part of the student teaching environment affects student learning in the first year after student teaching.

We highlight three of the coefficients, in particular, in the first and fourth columns of Table 6 as they represent the importance of FRL classroom alignment, though note that these coefficients are difficult to interpret given the presence of cubic terms and the interactions. First, as expected, the role of classroom-level FRL suggests that the higher the percentage of FRL students within a classroom, the lower math and ELA scores of any individual student in that classroom. Second, the larger the FRL classroom difference, the lower math and ELA scores of a student, suggesting that teachers in considerably higher poverty classrooms than their student teaching classroom are not as effective. Interestingly, for math, this coefficient (–.209) is about 10% larger than the direct impact of FRL on student learning (–.188), suggesting that this relationship can be quite important. The third is the positive coefficient on the interaction of the current classroom FRL with the difference between current and student teaching FRL. The positive coefficient suggests that this negative relationship is smaller for classrooms that have high levels of FRL.

The goal of the models reported in Table 6 is to evaluate the impact of the match between current teaching environment and the student teaching environment. However, as the preceding discussion highlights, this match is a function of the difference and an interaction of the difference and current teaching environment. Because we have estimated both of these with polynomials, it is difficult to evaluate the match solely by focusing on regression coefficients. As an alternative, we use the coefficients from Column 1 of Table 6 to calculate the average predicted student-level test score across combinations of internship school FRL and current school FRL. We plot these estimates in the contour plot in Panel A of Figure 3. The light gray regions of this figure show areas where teachers tend to be more effective, while teachers in the darker regions tend to be less effective.

We focus particularly on the regions in these heat maps in which the predicted test score gains are statistically significantly different than the mean, as denoted by the "+" (significantly positive) and "–" (significantly negative) symbols. The significantly positive regions of Panel A of Figure 3 are in the upper right and lower left of the figure, which means that teachers who student taught in very high-poverty or very low-poverty classrooms and then had similar first-classroom experiences tended to have students with greater learning gains. The students who had significantly below average test score gains were those whose teacher student taught in a low-FRL classroom but were employed into classrooms with higher levels of FRL. The overall trend supports the conclusion that better matches in terms of student teaching and classroom FRL are predictive of higher value added for teachers in very high-poverty or very low-poverty settings.

We further explore the match between the student teaching and first job by looking at the differences in FRL measured at the school level, following Goldhaber et al. (2017). Columns 2 and 5 of Table 6 present the regression results regarding the differences, while Panel B of Figure 3 summarizes these results in a contour plot. The results are very similar to those found in the earlier literature: Student teaching in a school with similar FRL to that which ultimately

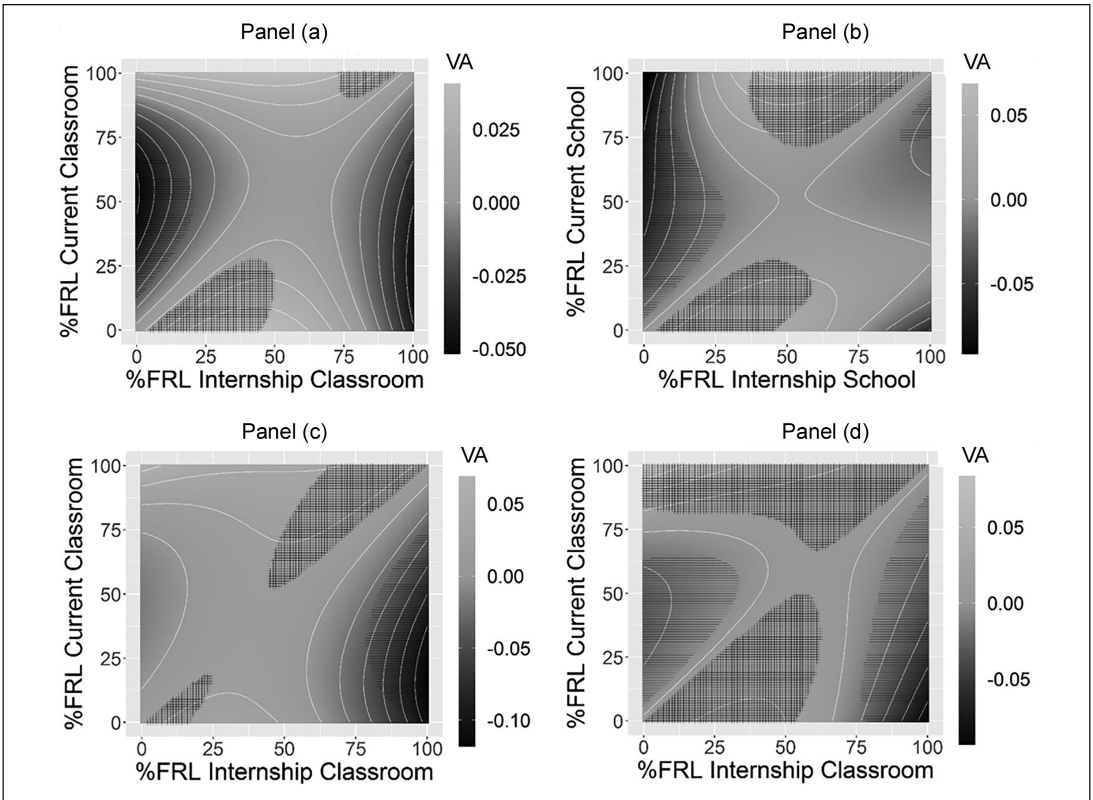

FIGURE 3. *Predicted student achievement in math by % FRL in student teaching and first job placements: Panel A: Classroom level, Panel B: School level, Panel C: Classroom level with school controls, and Panel D: Classroom level with school fixed effects.*
Note. + Indicates regions statistically significantly greater than zero, – indicates regions statistically significantly less than zero. FRL = free or reduced-price lunch, VA = value added.

employs the teacher leads to higher student test score gains, particularly for teachers in high-poverty or low-poverty settings.

The third and sixth columns of Table 6 simultaneously include classroom-level and school-level differences. Not surprisingly, school- and classroom-level measures of FRL are highly correlated: .87 at the elementary level and .88 at the middle school level. But we are interested in what appears to drive the student alignment findings, so that we can assess, for instance, whether it makes a difference whether a teacher is assigned to a high- or low-poverty classroom within a given school. By including both school- and classroom-level differences simultaneously, we estimate the impact of changing the classroom (school) characteristics while holding the school (classroom) characteristics constant. One can see the importance of this by simply examining the FRL coefficients for both the classroom- and school-level results in Columns 3 and 6. For both math and ELA, classroom-level FRL is strongly and negatively significant, while the school-level FRL is neither, and from the contour plot in Panel C of Figure 3. Both suggest that the classroom context is what matters most for teacher preparation, rather than the school-level measures that are most frequently used and discussed. Finally, we can also explore this same concept by estimating the model in Column 1 with a school fixed effect; the predicted values from these models are plotted in Panel D of Figure 3 and illustrate that the conclusions from Panel A of Figure 3 are robust to making comparisons only between candidates who are hired into the same school.

Conclusion

The primary conclusions from this analysis are relatively straightforward: Students of first-year teachers tend to perform better in both math and ELA when the teacher is teaching in a similar classroom (according to grade level, school type, or student demographics) as the classroom in which the teacher student taught. This effect shrinks to statistical insignificance in the second year of teaching perhaps because of the importance of skills learned on-the-job relative to those gained during student teaching. The policy implications of these findings, however, are complicated by three limitations of this study. The first limitation is that, as an observational study, the descriptive relationships outlined in this analysis may not capture causal mechanisms that could be used to improve student achievement. This distinction does not matter for all stakeholders; for example, parents faced with the choice of getting their child into the classroom of a first-year teacher who is teaching the same grade as their student teaching placement and another first-year teacher who is not should choose the teacher with a match *regardless* of whether our findings are descriptive or causal. Likewise, a principal may consider a new hire's prior student teaching experience when placing that teacher in their first classroom. But any policy that seeks to increase student achievement by improving the alignment between teachers' student teaching and first teaching positions would rely on these relationships being at least partly causal to achieve any impact.

A second limitation is that the results in this article are based on data collected from a single state (Washington), and thus the results may not generalize to other states. In particular, Washington is somewhat unique in that many of the state's subject area teaching credentials certify teachers to teach in any Grade K–12, while some other states have licenses that cover a narrower range of grades. As a result, the large differences in student teaching grades and first job grades documented in this study may be more likely in Washington than in other states.

A final limitation is that these results provide little guidance about how policymakers should go about better aligning student teaching placements with early-career teaching positions. Given that policy likely influences student teaching placements more than open teaching positions, a good starting place would be to better align the grades in which student teachers are placed with the grades into which they tend to be hired. The results in this study suggest that this would involve placing fewer student teachers in upper elementary and high school grades, and more in middle school grades, particularly because grade and school-type matches appear to be particularly important for middle school teachers. While this would not guarantee better alignment for *individual teachers*, it would likely improve the alignment in the aggregate and could be supplemented with efforts to place student teachers into schools and grades in which teachers are leaving or retiring (as reported in St. John et al., 2018) to leverage the specific human capital that candidates have accumulated in their student teaching placement. A second consideration would be for hiring committees to consider a candidate's student teaching experience and, to the extent there is a causal relationship, provide preference to applicants with experiences similar to those in their schools. Another promising avenue for policy response to these findings is through partnerships between TEPs and districts in which these partners work together to align student teaching placements with district hiring needs; these partnerships also address the "information asymmetry" in student teaching placements identified by St. John et al. (2018) as districts have the best information about their classrooms and hiring needs while TEPs have the best information about their candidates' strengths and interests.

The stronger findings for grade and school-type matching relative to matching into specific student teaching schools and districts also speak to the *type* of specific human capital that seems to matter most for teacher candidate development. These findings suggest that human capital specific to grades and school types (e.g., curriculum and subject matter) may be more important for teacher candidate development than human capital specific to individual schools and districts (e.g., school/district culture and colleagues). But these conclusions are not universal, as for elementary math teachers, it appears that human capital specific to individual schools and districts is more important, which echoes findings on teacher evaluation ratings from Ronfeldt et al. (2020). These findings have potentially important implications for the broader field of teacher preparation, though future research will need to disentangle the specific mechanisms that explain these relationships.

It is also important to place these results in the context of the broader literature on student teaching placements and future teaching effectiveness, discussed in the "Background" section. On one hand, the effect sizes in this study—for example, a predicted increase of .07 standard deviations of math performance associated with teaching in the same grade or an adjacent grade as student teaching relative to teaching in another grade—are larger than any prior effect size we are aware of in this literature (summarized in Goldhaber, Krieg, Naito, & Theobald, 2020). This suggests that TEPs and districts should prioritize alignment between student teaching placements and first job placements. On the other hand, other factors like the effectiveness of the cooperating teacher and the stability of the teaching staff at the student teaching school have also been shown to be predictive of future teacher effectiveness. This potentially sets up trade-offs between placing student teachers in the grades and schools that will be best aligned with their future teaching positions and placing them with the types of cooperating teachers and schools that have been shown to predict a candidate's future effectiveness. That said, our perspective is that it is very likely that *both* of these objectives are possible—that is, better aligning student teaching placements and first job placements *and* placing student teachers with high-performing cooperating teachers in high-functioning schools—given that only about 3% of teachers host a student teacher in a given year (Krieg et al., 2020). In other words, there is considerable "scope for change" in student teaching assignments.

Finally, the fact that the classroom-level measures of alignment predict future student performance better than the school-level match variables suggests that researchers should pay closer attention to the harder-to-measure classroom experiences of student teachers. If student teaching classroom experience is significantly more important in a teacher's early career, this opens the possibility that student teachers may develop different human capital than suggested by the building-level measures commonly observed on a resume. For instance, a student teacher in a high-FRL classroom but a low-FRL building likely has a different impact on future FRL students than a student from a low-FRL classroom in that same building. This adds nuance to understanding the role of teacher training by those who hire these teachers.

Authors' Note

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Notes

1. At the time of the data used for this research, Teacher Education Learning Collaborative (TELC) represented 15 of 21 teacher education programs (TEPs) in Washington State. For more information on TELC, see www.TELC.us.

2. The state's CEDARS (Comprehensive Education Data and Research System) data system, introduced in 2009–2010, allows classroom teachers to be linked to their classrooms and students through unique course identifiers. CEDARS data include fields designed to link students to their individual teachers, based on reported schedules. However, limitations of reporting standards and practices across the state may result in ambiguities or inaccuracies around these links.

3. We are able to indirectly test for differences between teachers who do and do not appear as a "new teacher" by comparing class assignments for these two groups of teachers in their second year. Teachers observed in their first year tend to teach fewer free or reduced-price lunch (FRL) students and more students of color in their second year than teachers who are not observed in their first year.

4. We also experiment with nonparametric local linear models and find results that are qualitatively similar.

5. Student teachers can use alternatives to the WEST-B (Washington Education Skills Test–Basic) to satisfy program entry requirements, so the WEST-B sample is smaller than the sample used in our full models.

6. High school teachers are not included because there are not clearly aligned grade-to-grade math and English language arts (ELA) tests in high school grades in Washington State.

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