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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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Abstract

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 that first-year teachers are more effective when they are teaching in the same grade, in the same school level, or in a classroom with student demographics similar to their student teaching classroom. We also 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.

1. Introduction

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., 2019; Boyd et al., 2009; Goldhaber et al., 2017, 2020; Ronfeldt, 2012, 2015; Ronfeldt et al., 2018a). 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., 2016; 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 the Teacher Education Learning Collaborative (TELC), a partnership with 15 of the then 21 teacher education programs (TEPs) training teachers in Washington State. Graduates from these TEPs represent about 80% of the teachers hired in Washington who graduated from an in-state institution over the past decade. And since 2009-10, individual TEP teacher candidates can be linked to the grade level and student demographics of both the classroom in which they did 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—i.e., 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 has focused on the implications of the school-level alignment between student teaching and early-career teaching positions (Boyd et al., 2009; Goldhaber et al., 2017) 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):

RQ1. To what extent are teachers' student teaching and first job classrooms aligned in terms of grade, school-level, school, district, and student demographics?

RQ2. Are first-year teachers who teach in the same grade, school level, school, or district in which they student taught more or less effective than teachers who did not?

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 upper elementary (grades 4-5) and high school (grades 9-12) grades relative to the number of teachers who are hired into these grades (and conversely, disproportionately fewer student teacher placements in middle school grades 6-8 relative to the number of new hires into these grades). In fact, less than half of first-year middle school teachers (i.e., teaching in grades 6-8) 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 or school level 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., 2016; Ost, 2014), though we are cautious about interpreting these findings as causal due to concerns about the non-random 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 *school*-level measures of student disadvantage (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.

2. 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. (2019), Goldhaber et al. (2020), and Ronfeldt et al. (2018a) also connect the effectiveness of candidates' mentor teachers (i.e., the inservice teachers who supervise their student teaching placements) to future candidate effectiveness; candidates who were mentored by teachers with higher evaluation scores (Bastian et al., 2019; Ronfeldt et al., 2018a) or higher value added (Bastian et al., 2019; Goldhaber et al., 2020; Ronfeldt et al., 2018a) 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—e.g., these findings could be explained by the non-random sorting of candidates to student teaching and first teaching positions—two recent experimental studies (Ronfeldt et al., 2018b, 2019) 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., 2016).

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 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., 2019; Goldhaber et al., 2015; Kalogrides, Loeb, & Béteille, 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, but this is the first study to consider measures of alignment at the *classroom* level between student teaching and first job placements.

3. 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 Washington State's Office of the 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 dataset 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 2009-10 to 2017-18, since 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 2018-19).[1]

[1] The state's CEDARS data system, introduced in 2009-10, allows classroom teachers to be linked to their classrooms and students through unique course identifiers. CEDARS data include fields designed to link students to

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 non-teaching 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 all teachers who are reported to have at least 0.5 years of prior teaching experience the first year they are observed in the teaching workforce after their student teaching placement; these could be teachers who began their careers in another state, were hired after the personnel reporting date the previous year (October 31), or had experience in K-12 schools prior to student teaching. These restrictions leave a final sample of 5,552 first-year teachers with complete preservice student teaching and inservice teaching data.

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 all new 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-

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.

TELC institutions or who receive their credential through OSPI and are coming into Washington from out of state.

Overall, TELC institutions supplied about 65 percent of the new teachers in the state and about 80 percent of teachers from an in-state institution during this time period. But 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 free or reduced-price lunch) 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. And, in terms of labor markets, 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, free/reduced-price lunch, and special education), and aggregated student demographics. The student-level data 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 dataset we utilize and address RQ1 (i.e., the extent to which first-year teachers experience a 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 highlight an important trend in student teaching grades and first teaching grades: there are more individuals who student teach in grades 4-5 (913) and 9-12 (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 6-8 (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%.

Table 3 provides additional summary statistics about the teachers in Table 2 (column 1) and then the teachers in the various analytic samples described previously (columns 3-5, all compared to teachers not in any analytic sample in column 2). The means in column 1 provide some important statistics about RQ1; for example, consistent with Goldhaber et al. (2014), 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 level (elementary, middle, or high school) as their student teaching school. But this overall figure masks some heterogeneity by school level (over 90% for teachers who teach both math and ELA—i.e., mostly elementary teachers—while closer to 50% for subject specialists who tend to teach in middle school).

Table 3 also presents information on the alignment with respect to the percentage of students eligible for free/reduced-price lunch (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) levels. Both measures provide evidence that student teaching tends to occur in more advantaged settings than first job teaching, but the dichotomy 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 46 percent of teachers who aren't hired into the same school find a first teaching position in a more disadvantaged school; 16 percent 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 percent of teachers who aren't 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 percent, 16 percent, and 34 percent.

4. Analytic Models

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

$$\mathrm{Y}_{\mathrm{isjt}} = \beta_0 + \beta_1 \mathrm{Y}_{\mathrm{ist-1}} + \beta_2 \mathrm{Y}_{\mathrm{is't-1}} + \beta \mathbf{X}_{\mathrm{it}} + \rho \mathbf{Z}_{jt} + \mathbf{I}_j + \varepsilon_{\mathrm{ijst}} \quad (1)$$

where Y_{isjt} represents the test score of student i, in subject s (math or ELA), in teacher j's classroom, during year t; **X** represents a matrix of student-level controls (gender, race/ethnicity, free/reduced-price lunch status, grade, and learning disability), **Z** represents a matrix of classroom controls (class size; percentage of class by student demographics; average math and ELA scores), and $\mathbf{I}_j$ is a series indicators indicating the teacher's TEP).[2]

RQ2 focuses on the roles that alignment between student teaching and first-job grades, school level, school, or district play 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 level, or district) with those who didn't match. These match variables are introduced individually and jointly.

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 free/reduced-price lunch 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 $\mathrm{FRL}_{jt'}$ be the percent FRL of that teacher's student teaching classroom/school. We construct flexible, polynomial models of the difference between C_{jt} and I_j:

$$\gamma_1 \mathrm{FRL}_{\mathrm{jt}} + \sum_{\mathrm{k}=1}^{3} \gamma_{\mathrm{k}+1} \left(\mathrm{FRL}_{\mathrm{jt}} - \mathrm{FRL}_{\mathrm{jt}'}\right)^{\mathrm{k}} + \mathrm{FRL}_{\mathrm{jt}} \sum_{\mathrm{k}=1}^{3} \gamma_{\mathrm{k}+4} \left(\mathrm{FRL}_{\mathrm{jt}} - \mathrm{FRL}_{\mathrm{jt}'}\right)^{\mathrm{k}} \qquad (2)$$

The first term in equation (2) is the main effect of the FRL on 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

[2] There are good arguments for assessing whether measures of alignment are also associated with teacher observational performance measures (e.g., Ronfeldt et al., 2018). Unfortunately, this is not currently possible statewide in Washington as the state does not collect teacher performance ratings at the individual teacher level.

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 measure (2) at both the school level and classroom level, and include each, sometimes separately and sometimes together, as additional independent variables in equation (2).

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 levels, 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-level, 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.[3]

[3] Student teachers can use alternatives to the WEST-B to satisfy program entry requirements, so the WEST-B sample is smaller than the sample used in our full models.

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 2 are statistically significant—about what would be expected by random chance. This provides some evidence that there is not non-random sorting to first-job alignment along observed student dimensions, but of course does not rule out sorting along unobserved dimensions, which may impact our results.

5. Results

5.1 Grade, School, and District Alignment Findings (RQ2)

Table 5 presents coefficients on each of the binary variables indicating a match at the grade, school level, 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.[4] Columns 1-5 show the association between various measures of alignment between student teaching and first jobs for student achievement in math and columns 6-10 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, while matches in terms of overall school level (elementary or middle school) are only significantly predictive in math. The magnitudes of the same-grade coefficients are somewhat larger in math than in ELA

[4] High school teachers are not included because there are not clearly aligned grade-to-grade math and ELA tests in high school grades in Washington State.

(columns 1 and 6), but both suggest that students assigned to first-year teachers who experience this type of match score about 2-4 percent of a standard deviation better than students assigned to other first-year teachers.

There is less evidence that it matters for the average teacher in the sample whether they are hired into the same school district (columns 3 and 8) or school (columns 4 and 9) 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 5 and 10), the grade match is statistically significant for ELA and both the grade and the school-level match is significant for math, suggesting that both types of matches are important in math even accounting for the other.

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. One important source of heterogeneity in the findings is in columns 3-4 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.

5.2 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** presents coefficients on FRL differences at the classroom-level (C_{tj} – Ij) 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." 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 column 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 impacts 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. 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 with large differences in their current classroom relative to their training 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 matching the student teaching experience with that of the first job 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 the negative impact of FRL differences between current and student teaching differences are 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 Panel A of **Figure 3**.

Panel A of Figure 3 shows students tend to have higher test scores when taught by a teacher with small differences—that is similar FRL experiences—between their student teaching experience and their first time on the job. These are especially strong at the upper right and lower left of the figure, which means that teachers who had rather extreme FRL experiences (either classrooms with very few or very many FRL students) 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, as represented by the negative signs in the bluer portion of the graph, were those whose teacher trained in a low-FRL classroom but were employed into classrooms with higher levels of FRL and, to a lesser extent, vice versa.

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 employs the teacher leads to higher student test score gains. Student teaching in a low-FRL school leads to lower student test score gains, especially when the current school is high FRL.

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 this 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.

6. Conclusions

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 level, or student demographics) as the classroom in which the teacher student taught. The policy implications of this conclusion, however, are complicated by two issues. The first is whether these descriptive relationships capture any causal mechanisms that could be used to improve student achievement. This distinction does not matter for all stakeholders; for example, if parents are 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, they should choose the teacher with a match *regardless* of whether our findings are descriptive or causal. 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 complication is 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 since grade and school-level 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.

The stronger findings for grade and school-level 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 levels (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. 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.

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.

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Tables and Figures

Table 1. District Summary Statistics for New Teachers in State

	Total	TELC	Non-TELC	Out of State
Proportion District in City	0.337 (0.473)	0.332 (0.471)	0.349 (0.477)	0.345 (0.475)
Proportion District in Suburb	0.427 (0.495)	0.457 (0.498)	0.334*** (0.472)	0.401*** (0.490)
Proportion District in Town	0.119 (0.324)	0.107 (0.309)	0.167*** (0.373)	0.120* (0.325)
Proportion District in Rural	0.117 (0.322)	0.104 (0.306)	0.150*** (0.357)	0.134*** (0.341)
Proportion District West of Cascades	0.775 (0.418)	0.843 (0.363)	0.423*** (0.494)	0.825* (0.380)
Average District Percent American Indian or Alaskan Native	1.658 (5.697)	1.557 (5.356)	2.371*** (7.518)	1.412 (4.992)
Average District Percent Asian Pacific Islander	10.07 (10.70)	11.25 (11.14)	5.886*** (7.994)	9.563*** (10.24)
Average District Percent Black	5.778 (8.536)	6.270 (9.074)	4.641*** (7.330)	5.081*** (7.415)
Average District Percent Hispanic	24.48 (22.52)	23.58 (21.19)	31.59** (29.21)	21.73 (19.21)
Average District Percent Female	48.31 (3.360)	48.28 (3.231)	48.51 (3.408)	48.24 (3.715)
Average District Percent Migrant	2.099 (5.397)	1.882 (5.171)	4.046*** (7.029)	1.362*** (4.307)
Average District Percent Transitional Bilingual	13.22 (15.42)	13.18 (14.92)	15.68*** (18.70)	11.35*** (13.73)
Average District Percent SPED	13.21 (6.860)	13.12 (6.489)	13.39 (5.982)	13.33 (8.507)
Average District Percent FRL	48.96 (25.32)	47.54 (25.37)	58.44*** (24.61)	45.93** (23.93)
N	15,730	10,177	2437	3116

Note: FRL = Free or reduced-price lunch. SPED = Special education. TELC = Teacher Education Learning Collaborative. 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 2009-10 and 2018-19. *P*-values from two-sided *t*-test relative to teachers who got teaching certificate from TELC institutions: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 2. 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					

Table 3. Summary Statistics

	All Teachers	Not Analytic Sample	Both ELA and Math Samples	Math Sample Only	ELA Sample Only
Same Grade	0.266	0.268	0.287	0.222*	0.217*
Same School Level	0.786	0.799	0.914***	0.552***	0.508***
Same School	0.163	0.163	0.171	0.141	0.164
Same District	0.398	0.391	0.453***	0.370	0.391
Classroom % FRL Difference	6.169 (30.214)	6.049 (30.058)	3.822* (32.381)	10.613** (28.474)	9.507* (27.935)
School % FRL Difference	2.945 (25.288)	2.835 (25.157)	1.965 (26.684)	5.936** (25.280)	4.173 (23.533)
Observations	5552	4265	718	270	299
Classroom % FRL Difference (Same School Hiring)	2.891 (16.033)	2.888 (16.369)	0.077* (16.444)	7.505* (9.307)	6.424* (12.780)
Observations	904	694	123	38	49

Note. P-values calculated from t-tests relative to column 2. *p<0.05; **p<0.01; ***p<0.001.

Table 4. Summary Statistics by Match Category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Same Grade	Not Same Grade	Same School Level	Not Same School Level	Same School	Not Same School	Same District	Not Same District
Panel A: Math Sample								
ST Classroom % FRL	50.13 (29.14)	47.64 (26.74)	48.86 (28.12)	45.86 (23.98)	50.28 (29.76)	47.92 (26.94)	48.30 (28.81)	48.32 (26.34)
ST School % FRL	45.64 (24.95)	45.09 (22.72)	45.99 (23.78)	41.92* (20.93)	45.64 (25.12)	45.16 (22.98)	45.17 (24.27)	45.28 (22.61)
Observations	266	722	805	183	161	827	425	563
Average WEST-B Score	274.61 (14.56)	274.15 (12.35)	274.32 (13.18)	274.10 (12.20)	274.60 (13.28)	274.23 (12.96)	275.13 (12.90)	273.72 (13.05)
Observations	125	323	365	83	67	381	179	269
Panel B: ELA Sample								
ST Classroom % FRL	50.10 (28.39)	47.75 (27.32)	49.02 (28.31)	45.86 (24.65)	47.81 (29.67)	48.49 (27.20)	47.23 (28.50)	49.25 (26.91)
ST School % FRL	45.98 (24.56)	45.08 (23.29)	46.20 (24.25)	41.91* (20.76)	44.13 (25.59)	45.57 (23.21)	44.92 (24.54)	45.63 (22.92)
Observations	271	746	808	209	172	845	442	575
Average WEST-B Score	274.76 (14.16)	274.21 (12.26)	274.56 (13.09)	273.71 (11.81)	274.13 (12.72)	274.41 (12.84)	274.17 (13.27)	274.50 (12.48)
Observations	130	332	358	104	69	393	194	268

Note. ELA = English language arts; FRL = free/reduced price lunch; ST = student teaching; WEST-B = Washington Educator Skills Test – Basic. P-values calculated from t-tests relative to corresponding odd column. *$p<0.05$; **$p<0.01$.

Table 5. Binary Match Measures as Predictors of Student Achievement in Teachers' First Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Outcome:	Student Achievement in Math					Student Achievement in ELA				
Panel A. All Teachers										
Same Grade as Student Teaching	0.041** (0.017)				0.030* (0.017)	0.026* (0.014)				0.027* (0.015)
Same School Level as Student Teaching		0.055*** (0.021)			0.046** (0.021)		0.003 (0.016)			-0.006 (0.017)
Same District as Student Teaching			0.024 (0.017)		0.018 (0.018)			0.019 (0.014)		0.022 (0.014)
Same School as Student Teaching				0.029 (0.025)	-0.001 (0.027)				0.009 (0.019)	-0.009 (0.021)
Student Observations	29,252	29,252	29,252	29,252	29,252	28,872	28,872	28,872	28,872	28,872
Panel B. Elementary Teachers										
Same Grade as Student Teaching	0.031 (0.020)				0.023 (0.020)	0.026 (0.018)				0.024 (0.018)
Same School Level as Student Teaching		0.045 (0.041)			0.039 (0.040)		0.007 (0.033)			0.003 (0.033)
Same District as Student Teaching			0.054*** (0.019)		0.033 (0.020)			0.027 (0.017)		0.030 (0.019)
Same School as Student Teaching				0.060*** (0.023)	0.035 (0.026)				0.008 (0.023)	-0.013 (0.025)
Student Observations	15,312	15,312	15,312	15,312	15,490	15,152	15,152	15,152	15,152	1,5152
Panel C. Middle School Teachers										
Same Grade as Student Teaching	0.062** (0.029)				0.063** (0.029)	0.026 (0.024)				0.033 (0.025)
Same School Level as Student Teaching		0.041* (0.025)			0.040 (0.026)		-0.005 (0.019)			-0.021 (0.020)
Same District as Student Teaching			-0.012 (0.027)		0.001 (0.026)			0.007 (0.021)		0.005 (0.021)
Same School as Student Teaching				-0.041 (0.044)	-0.079* (0.046)				0.013 (0.033)	0.013 (0.037)
Student Observations	13,940	13,940	13,940	13,940	13,940	13,720	13,720	13,720	13,720	13,720

Note: ELA = English language arts. 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. *P*-values from two-sided *t*-test: $*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

Table 6. Continuous Match Measures as Predictors of First-Year Teacher Value Added

		(1)	(2)	(3)	(4)	(5)	(6)
	Outcome:	Student Achievement in Math			Student Achievement in ELA		
Classroom Match	Current Classroom % FRL	-0.1888311*** (0.0471603)		-0.2460214** (0.0966524)	-0.2097670*** (0.0384743)		-0.2989267*** (0.0776808)
	(Current Classroom % FRL - Student Teaching Classroom % FRL)	-0.2077767** (0.0970554)		-0.1374866 (0.1377864)	-0.0765417 (0.0770550)		-0.0910052 (0.1030660)
	(Current Classroom % FRL - Student Teaching Classroom % FRL)^2	-0.0023431 (0.0021314)		-0.0006612 (0.0027534)	0.0014731 (0.0020535)		0.0019034 (0.0024139)
	(Current Classroom % FRL - Student Teaching Classroom % FRL)^3	0.0000133 (0.0000274)		0.0000368 (0.0000330)	0.0000279 (0.0000248)		0.0000432 (0.0000281)
	Current Classroom % FRL*(Current Classroom % FRL - Student Teaching Classroom % FRL)	0.0030372* (0.0016901)		0.0012629 (0.0021181)	0.0004568 (0.0014150)		0.0003688 (0.0017100)
	Current Classroom % FRL*(Current Classroom % FRL - Student Teaching Classroom % FRL)^2	-0.0000004 (0.0000372)		-0.0000145 (0.0000461)	-0.0000441 (0.0000360)		-0.0000392 (0.0000420)
	Current Classroom % FRL*(Current Classroom % FRL - Student Teaching Classroom % FRL)^3	0.0000002 (0.0000004)		0.0000001 (0.0000004)	0.0000003 (0.0000003)		0.0000001 (0.0000003)
School Match	Current School % FRL		-0.1723854*** (0.0558612)	0.0482936 (0.1124630)		-0.1771364*** (0.0439374)	0.0961249 (0.0856987)
	(Current School % FRL - Student Teaching School % FRL)		-0.1793642 (0.1285558)	-0.0682485 (0.1655340)		-0.0096453 (0.1031469)	0.0870236 (0.1294492)
	(Current School % FRL - Student Teaching School % FRL)^2		-0.0063856** (0.0029000)	-0.0056685 (0.0036873)		-0.0024234 (0.0030025)	-0.0036143 (0.0037691)
	(Current School % FRL - Student Teaching School % FRL)^3		-0.0000703 (0.0000440)	-0.0000966** (0.0000464)		-0.0000634 (0.0000412)	-0.0000960** (0.0000444)
	Current School % FRL*(Current School % FRL - Student Teaching School % FRL)		0.0041311* (0.0023755)	0.0023904 (0.0027977)		0.0010649 (0.0018363)	-0.0003842 (0.0022479)
	Current School % FRL*(Current School % FRL - Student Teaching School % FRL)^2		0.0000664 (0.0000618)	0.0000815 (0.0000723)		0.0000186 (0.0000534)	0.0000487 (0.0000655)
	Current School % FRL*(Current School % FRL - Student Teaching School % FRL)^3		0.0000006 (0.0000005)	0.0000006 (0.0000005)		0.0000009** (0.0000004)	0.0000009* (0.0000004)
	Student Observations	29829	28919	28919	29477	28645	28645

Note: ELA = English language arts. 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. P-values from two-sided t-test: *p < 0.10; **p < 0.05; ***p < 0.01.

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

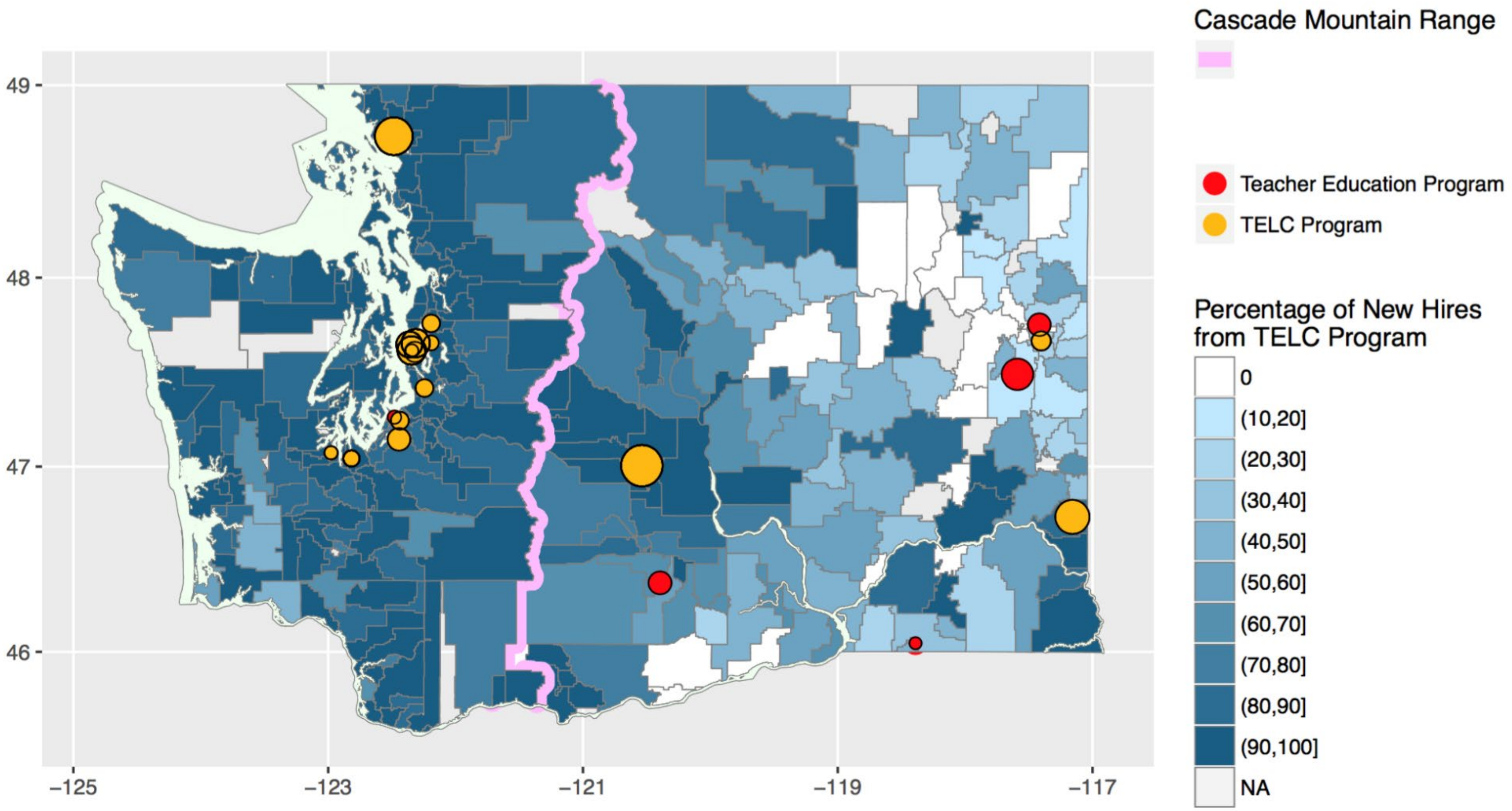


Figure 2. Scatterplots of % FRL in Student Teaching and First Job Placements

Panel A: Classroom-Level FRL | Panel B: School-Level FRL

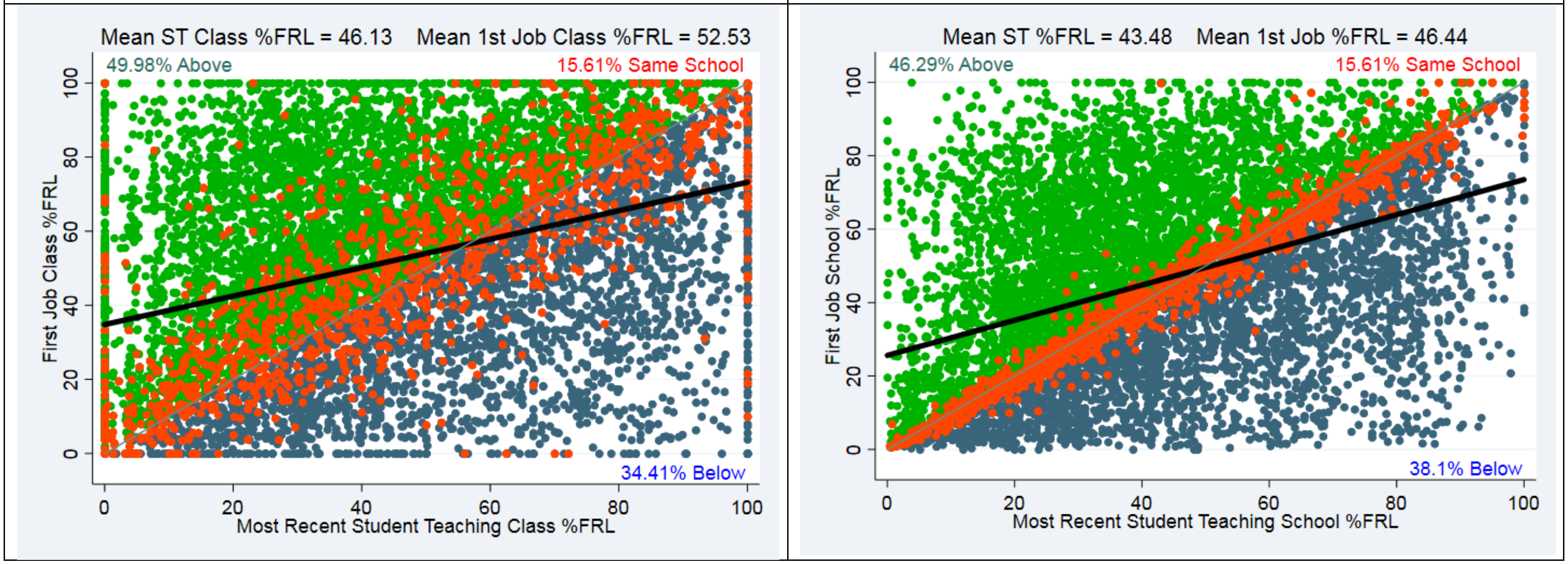
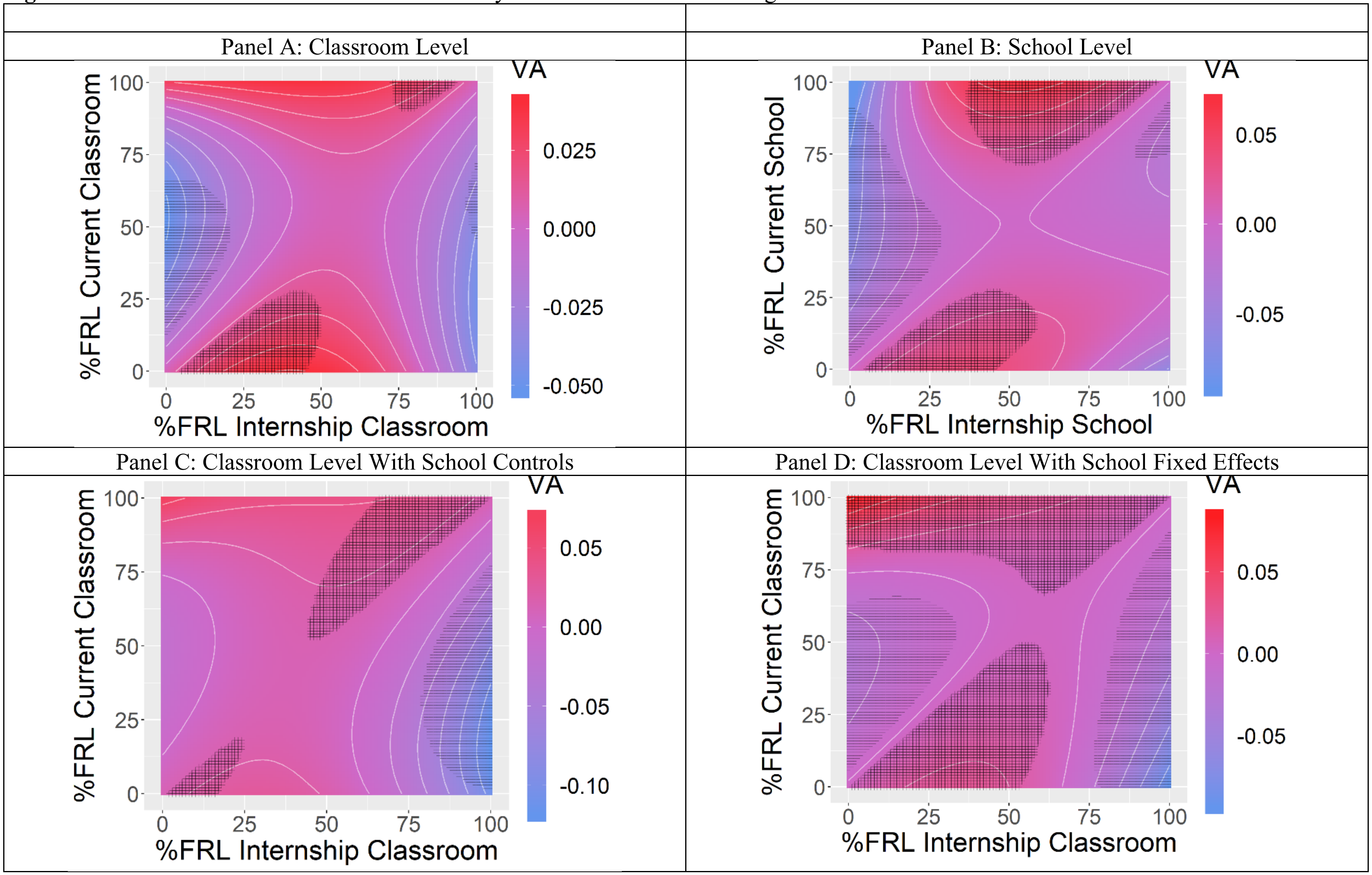


Figure 3. Predicted Student Achievement in Math by % FRL in Student Teaching and First Job Placements



Notes: + Indicates regions statistically significantly greater than zero, - indicates regions statistically significantly less than zero.