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Abstract

We use data from Washington state to examine two distinct stages of the teacher pipeline: the placement of prospective teachers in student teaching assignments and the hiring of prospective teachers into their first teaching positions. We find that prospective teachers are likely to complete their student teaching near their colleges and hometowns but prospective teachers' student teaching positions are much more predictive of their first teaching positions than their hometowns. This suggests that the "draw of home" in new teacher hiring is driven by patterns in student teaching assignments. We also find that more qualified prospective teachers tend to student teach in more advantaged districts, suggesting that patterns in student teaching assignments may contribute to the inequitable distribution of teacher quality.

I. Introduction

In response to mounting evidence of substantial "teacher quality gaps" between advantaged and disadvantaged U.S. public schools, the federal government recently directed states to develop plans to reduce inequity in the distribution of teacher quality across schools (Rich, 2014).[1] Most of the interventions studied in the existing literature are designed to influence the distribution of teacher quality among *current teachers*, but empirical evidence suggests that policy makers should also be concerned about patterns in new teacher hiring.[2] Indeed, a growing literature shows that prospective teachers demonstrate a preference to teach in the disproportionately advantaged schools near where they grew up and went to college.[3] Recent work (Engel & Cannata, 2015) has explicitly noted that the localism of the teacher labor market may have important implications for the distribution of teacher quality.

One of the few aspects of the teacher hiring process that can easily be manipulated—and a part of the teacher pipeline that has received very little empirical attention—is the placement of prospective teachers in student teaching assignments. Student teaching is a nearly universal component of traditional teacher education (Anderson & Stillman, 2013) that takes place across 1,400 teacher education programs (TEPs) and involves nearly 200,000 student teacher placements each year (Greenberg et al., 2011). TEPs exercise great discretion over where prospective teachers complete their student teaching (Maier & Youngs, 2009), and recent evidence (Goldhaber et al., 2014) suggests a close relationship between where prospective teachers train and where they find their first teaching job; in fact, nearly 40% of prospective teachers who found a job were hired into the same district where they

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[1] For evidence on teacher qualification gaps (e.g., by experience and/or licensure status), see Clotfelter et al. (2005) and Lankford et al. (2002). For more recent work on teacher quality gaps (e.g., by value-added measures of teacher effectiveness), see Goldhaber et al. (2015) and Isenberg et al. (2013).

[2] Recent evidence on the difficulty and cost of convincing in-service teachers to transfer to disadvantaged schools (Glazerman et al., 2013) further motivates a focus on new teacher hiring.

[3] For research on preferences for school attributes, see, for instance, Bacolod (2007), Boyd et al. (2013), or Engel et al. (2014).

completed their student teaching. Other than this, the literature on teacher hiring has largely ignored the relationship between where a teacher student teaches and where she finds her first teaching job.

We address this gap in the literature by connecting data on prospective teachers and student teacher assignments from six Washington state TEPs to data on all public school teachers in Washington state. Using these data, we provide a comprehensive, descriptive analysis of the transition of prospective teachers from teacher education programs to student teaching placements and then into the teaching workforce. In doing so, we split this transition into two separate but related processes—the process that assigns prospective teachers to student teaching positions, and the process that moves these prospective teachers from student teaching to their first public teaching position—and investigate outcomes from each process separately. This investigation seeks to answer two basic questions:

What are the determinants of where prospective teachers complete their student teaching?

What role do student teaching placements play in determining where newly trained teachers find their first teaching jobs?

For the first question, we find a strong "draw of home" (Boyd et al., 2005) in student teaching assignments; that is, prospective teachers are likely to student teach near where they grew up and attended college. In addition, we find that more qualified prospective teachers (i.e., with higher licensure test scores and undergraduate GPAs) tend to student teach in more advantaged districts than other student teachers. To our knowledge, this is the first empirical evidence of inequities in student teaching placements, and—given the close connection between student teaching location and first job location discussed below—suggest that student teaching placements may contribute to the inequitable distribution of teacher talent across public schools.

For the second question, we demonstrate that the location of student teaching is more predictive of an individual's first teaching job than their hometown or college location. Specifically, when we consider college, hometown, and student teaching locations as joint predictors of where prospective teachers begin their teaching careers, student teaching location remains strongly predictive of first job location, while hometown and college location are much less predictive. Together, these findings suggest that the "draw of home" phenomenon in new teacher hiring (Boyd et al., 2005; Reininger, 2012; Killeen et al., in review) is driven by patterns in student teaching assignments.

A final set of findings reveals strong similarities between student teaching and first job districts. Even ignoring the 15% of newly hired teachers who are hired into the same school in which they student taught, student teachers who trained in advantaged districts are much more likely to receive first jobs in advantaged districts. Although we cannot distinguish whether these patterns are driven by the preferences of student teachers, TEPs, or school districts, they do suggest that purposeful student teaching placements could be an important policy lever to influence the distribution of teacher quality across districts.[4]

The paper proceeds as follows. In Section II, we give some background information and review prior work in this area and then in Section III, we describe our data and present summary statistics. In Section IV, we outline our analytic models and in Section V, we present the estimates from these models. Finally, in Section VI, we discuss policy implications, the limitations of our current analysis, and directions for future research.

II. Background and Prior Work

Our analysis examines outcomes from two different processes: the process that assigns prospective teachers to student teaching schools (research question #1) and the process that moves these prospective teachers from their student teaching schools to their first public teaching position

[4] As we discuss in the conclusion, we also cannot know how the relationship between student teaching location and first job location might change if patterns in student teaching assignments change substantially.

(research question #2). We provide some background and review existing empirical literature about each process before proceeding to our analyses.

Placement into student teaching positions

In Washington state (the setting for our study), the assignment of prospective teachers to student teaching positions is governed both by state code and contractual arrangements between TEPs and school districts. Washington is one of a few states that provide guidance to TEPs about the nature of student teaching placements (NCATE, 2010), but even these guidelines are extremely vague, stating that "field experiences provide opportunity to work in communities with populations dissimilar to the background of the candidate." This is interpreted by TEPs as a mandate to place student teachers in racially diverse schools.[5] Field placement agreements, on the other hand, generally state that the TEP and district will make "cooperative arrangements" to determine student teaching assignments, and—at least among the contracts we reviewed—contain no further restrictions on the process of assigning individuals to student teaching schools.

To our knowledge there is no large-scale empirical evidence about the factors predicting the assignment of prospective teachers to student teaching positions, but Maier and Youngs (2009) provide an important case study. They describe the matching of teaching candidates at Michigan State University to student teaching assignments as a two-stage process: candidates are allowed to choose the region in the state where they want to do their student teaching, and then university coordinators work with local schools and districts to assign candidates to student teaching schools and cooperating teachers. They find teaching candidates at Michigan State tend to do their student teaching at schools that are more affluent than the average school in the state and speculate that the "social networks"

[5] The state code is from WAC 181-78A-264(3)(b)(ii), while the interpretation is from Jennifer McCleery of Western Washington University (personal communication, February 2014).

created from these student teaching assignments may have implications for these candidates' subsequent job searches.

Placement into first teaching positions

Although Maier and Youngs (2009) provide the only existing empirical evidence concerning placement in student teaching assignments, there is more quantitative evidence about the hiring of new teachers into initial teaching jobs. However, we stress that only Goldhaber et al. (2014) consider student teaching experiences as a factor in this process. Boyd et al. (2005) find that teachers are very likely to begin their teaching careers near where they grew up and/or went to college, Reininger (2012) shows that this draw of home is much stronger for teachers than individuals in other professions, and Killeen et al. (in review) use application data to demonstrate that candidates who grew up near a school are both more likely to apply to that school and more likely to receive a job offer if they apply, all else being equal. Because teachers disproportionately grow up and attend college in advantaged areas, Engel and Cannata (2015) note that the draw of home phenomenon handicaps disadvantaged schools in the hiring process.

Killeen et al. (in review) build on prior work focusing on the broader preferences of either prospective teachers or school districts in teacher hiring; for example, Bacolod (2007), Cannata (2010), and Engel et al. (2014) provide evidence that prospective teachers prefer to teach in more advantaged schools, while Hinrichs (2013) focuses on the demand side of the equation and shows that schools demonstrate a strong aversion to out-of-state applicants. Recently, Boyd et al. (2013) disentangle teacher and hiring school preferences using a two-sided matching model of new teacher hiring and confirm the findings that teachers prefer advantaged schools while districts prefer teachers with stronger qualifications.

What is not clear from the existing literature, however, is what policy makers can do to make new teacher hiring more equitable across schools and districts. Surprisingly, despite empirical evidence that student teaching experiences may influence teacher attrition and effectiveness in the workforce (Boyd et al., 2009; Ronfeldt, 2012, 2015), no paper in the existing literature considers the characteristics or location of the prospective teacher's student teaching assignment as a factor in determining *where* prospective teachers begin their teaching careers. In fact, the only paper to consider the role of student teaching placements in teacher hiring is Goldhaber et al. (2014), who find that more qualified prospective teachers (i.e., those with higher credential test scores) are more likely to be hired into the school in which they student taught. In the next section, we describe the data that will allow us to build on this prior work

III. Data and Summary Statistics

Our data set combines detailed information about prospective teachers and their student teaching experiences from six Washington state teacher education programs (TEPs) that primarily serve the western half of the state (see **Figure 1**)—Central Washington University (CWU), Pacific Lutheran University (PLU), University of Washington Bothell (UWB), University of Washington-Seattle (UWS), University of Washington-Tacoma (UWT), and Western Washington University (WWU)[6]—with K–12 data provided by Washington state's Office of the Superintendent of Public Instruction (OSPI). The earliest individuals considered in this study completed their student teaching in 1998, while the most recent did their student teaching in 2010. **Figure 2** shows the frequency of observations by student teaching year as well as the years each TEP provided data for their student teachers. The TEPs in our sample graduate roughly one-third of the teachers who enter the Washington state teaching workforce each year, and

[6] Four of these institutions offer bachelor's degree programs, five offer certificate-only programs, and all six offer master's degree programs. The individuals in our sample come from all three types of programs.

include three of the four largest teacher training institutions in the state (as measured by the average number of workforce entrants from each program).[7]

Our full analytic data set consists of 8,527 individuals, each of whom completed student teaching in a Washington state public school and received a teaching credential and endorsements to teach in Washington K–12 public schools.[8] However, several variables of interest are only available for a subset of the full sample. Two of these variables—undergraduate GPA and high school attended—were provided by only a subset of TEPs, while a third variable—the teacher credentialing exam score, or WEST-B—was required for applicants to TEPs in Washington state starting in 2002 (and are thus missing for many individuals in the earlier years of data).[9] Finally, we can only investigate teacher hiring for the subset of 6,023 individuals who were actually hired into a teaching position by our last year of observation (the 2013–2014 school year).[10]

Because of these limitations, we can estimate analytic models that consider these variables only for subsets of our full sample. **Table 1** provides the sample size (both overall and by participating institution) of each sample that we use in our analysis. Table 1 divides these samples into four collections of samples (that correspond to the samples used to estimate the models reported in Tables 5–8): we use the "full sample" to investigate placement into student teaching (research question #1); we use the "full high school sample" when we incorporate information about each individual's hometown

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[7] There are a total of 21 TEPs in Washington (see Goldhaber et al. [2013] for a full list.) Approximately 15% of the state's public school teachers were trained outside the state. See http://program.pesb.wa.gov/reports/reporting_progress/clinicallocation for detailed maps on where Washington teachers tend to do their student teaching.

[8] 616 interns (all from Western Washington, UW Bothell, or UW-Tacoma) completed more than one internship. Representatives from these universities report that an intern's first internship is often for observational purposes, while the second is where he or she does student teaching. So for these interns, we include the intern's second internship experience in our final data set. A very small number of interns from Western Washington University completed two student teaching internships. For these interns, we randomly select one internship experience to include in our analytic data set.

[9] The WEST-B credentialing test consists of three subtests: reading, writing, and mathematics. Students may take each subtest as many times as necessary to get a passing score. Our WEST-B measure averages the math, reading, and writing scores from the first time each prospective teacher took the test.

[10] See Goldhaber et al. (2014) for predictors of which student teachers enter the public teaching workforce.

as a predictor of student teaching placement; we use the “hired sample” to investigate placement into first teaching job (research question #2); and we use the “full high school sample” when we incorporate information about each individual’s hometown as a predictor of first job placement. We must consider a subset of each of these samples when we consider either WEST-B scores or GPAs as additional predictors of these outcomes.

The sample sizes by institution in Table 1 illustrate how the composition of our sample varies depending on the variables we consider. Although a little over half of our full sample comes from Western Washington University, for example, these individuals comprise more than 95% of the sample for whom we observe undergraduate GPAs. Perhaps more importantly, the high school samples—which we use in our analysis to investigate the “draw of home” in student teaching and first job placements—disproportionately consist of individuals from institutions outside the Seattle/Tacoma metro area. We address this limitation of our analysis in the conclusion, but are also careful to estimate all models (not just models that include distances to home) on the high school samples to check the robustness of our findings.

A second concern is whether the *characteristics* of prospective teachers in each of these samples are consistent. We explore this by providing summary statistics for five of these samples in **Table 2**. The first column displays summary statistics for the full sample; note that about 65% of our sample is endorsed in elementary education, and underrepresented minority (URM) student teachers comprise less than 5% of our sample. The other columns display summary statistics for subsamples of these data. As we discuss earlier in this paper, there are dramatic differences between the *institutional* compositions of each of these samples but far smaller differences in terms of the demographics and endorsements of individuals in each sample.

A key component of our analysis incorporates measures of the distance between each of the state's 296 public school districts and between each TEP and these districts.[11] We calculate the distance between two districts as the linear distance between the geographic center of each district, while the distance between TEP A and school district B is the linear distance between the center of the school district that includes TEP A and the center of school district B. We use these distances to construct the following distance measures, not all of which apply to each student teacher: (a) the distance from the student teacher's TEP to their student teaching district (all individuals); (b) the distance from the student teacher's high school district to student teaching district (all individuals with high school data); (c) the distance from the student teacher's TEP to first job district (all hired individuals); (d) the distance from the student teaching district to first job district (all hired individuals); and (e) the distance from the student teacher's high school district ("home") to first job district (all hired individuals with high school data). In each case, we also create an indicator for whether the districts are the same (i.e., whether the individual's first job district is the same as their student teaching district).

Table 3 presents summary statistics for these distance measures. Panel A focuses on student teaching placement. For the 8,527 observations in our data, 51.4% students teach within 25 miles of their TEP and, for individuals with high school data, nearly 50% train within 25 miles of their hometown. But there are significant differences between TEPs in terms of the proximity of student teaching assignments. The four TEPs located within the Seattle/Tacoma urban area place nearly all of their student teachers within 25 miles of themselves. The non-Seattle/Tacoma TEPs place fewer students nearby, likely because they are outside of the highly concentrated urban areas that contain more potential student teaching schools. This is important because student teachers from the non-Seattle/Tacoma TEPs constitute the majority of our high school sample. As shown in the last row of

[11] Washington state is somewhat unique in having such a large number of small, relatively homogenous districts. This is one rationale for considering districts as the level of analysis.

Panel A, student teachers from our high school sample are less likely to be placed within 25 or 50 miles of their TEP than the average student teacher in our full sample.

Panel B of Table 3 presents similar summary statistics for the first job location of hired individuals. Consistent with the "draw of home" findings of Boyd et al. (2005), Reininger (2012), and Killeen et al. (in review), a high proportion of individuals find their first teaching job near home; over half of first jobs are within 25 miles of home and about two-thirds are within 50 miles. Moreover, nearly one in four first jobs are in the same district from which the student teacher graduated high school. But Panel B also suggests that the relationship between first job location and student teaching location is even stronger than the draw of home phenomenon. We focus on the "High School Sample" row of Panel B, because the summary statistics for "distance from home district" and "distance from student teaching district" are based on the same sample of hired student teachers. In this row, we see that almost 40% of hired student teachers begin their teaching career in the same district where they did their student teaching (compared to less than 25% who returned to their high school district). Hired students are also considerably more likely to teach within 25 or 50 miles of their student teaching district than their home district. Importantly, this is true even when we ignore the 15% of students who are hired into the same building where they did their student teaching (in the last row on Panel B).[12] We will explore these relationships further in the analytic models described in the next section.

A second component of our analysis focuses on the level of "disadvantage" in each individual's student teaching district and (for hired students) first job district. We quantify this with four different variables: the percent of underrepresented minority (URM) students (defined as Black, Hispanic, or American Indian); the percent of students eligible for free/reduced price lunch (FRL); the percent of students who passed the state math exam; and the percent of students who passed the state reading

[12] Goldhaber et al. (2014) explore the determinants of which student teachers are hired into the same building in which they trained. Minority student teachers, especially at schools with more minority students, as well as those with high WEST-B scores were found to be more likely to be hired into the buildings in which they trained.

exam.[13] Because there is considerable variation in these variables across years (particularly in state exam passing rates), we standardize each of these variables within school years. Thus in our regression results, a one unit change in each of these variables represents a one standard deviation change (relative to other districts within the same year).

We present means of these variables for both student teaching districts and first job districts in **Table 4** (we focus solely on hired student teachers in this table so the same student teachers inform both sets of means). Two patterns emerge from Table 4. First, because these variables are standardized (so the average district in the state has a value of zero), the signs reveal that individuals tend to student teach and get their first job in districts that have fewer FRL students, more URM students, and more students passing state tests than the average district in the state. This is primarily because the TEPs who supplied our data disproportionately serve the western half of the state (see Figure 1), where there are more minority students, fewer students of poverty, and higher achievement rates. Second, student teachers tend to train in higher-performing districts than the districts where they get their first job, perhaps suggesting that patterns in student teaching placements do not reflect current patterns in initial teacher hiring.

IV. Analytic Models

We now explicitly model outcomes from each of the processes (student teaching assignments and first job placements) discussed in sections II and III. Our analytic models build directly on prior work by Boyd et al. (2005), who model the probability that teachers begin their careers in one of 17 regions in

[13] We compile these data from three sources to ensure that these district-level variables are available for the student teaching district of all 8,527 individuals in our sample. First, the Washington State Report Card from the Washington State Office of the Superintendent of Public Instruction includes district-level student demographics (race and FRL percentages) going back to 2001 and district-level passing rates on the state tests going back to 1998. We get district-level race information for 1998–2000 by aggregating the Public School Universe Survey from the Common Core of Data to the district level, while we compile district-level FRL data for 1998–2000 from the USDA Child Nutrition website (http://www.fns.usda.gov/pd/child-nutrition-tables).

New York state as a function of the proximity of those regions to the teacher's hometown and college. We extend these models in three ways. First, we estimate a similar model to Boyd et al. (2005), except predicting the location of each individual's student teaching rather than first job. Second, when we predict the location of each first teaching job, we consider the location of student teaching as an additional set of predictors. Finally, in each set of analyses, we use school districts as the unit of analysis rather than regions; that is, we predict whether student teaching or first teaching job occur in each school district in Washington. This allows us to directly control for different school district characteristics that may make it more attractive for student teaching or employment.

In what follows, we describe our models in terms of individual preferences, but we stress that outcomes from the process that assigns student teaching positions reflect individual, TEP, and district preferences, and outcomes from the teacher hiring process similarly reflect the preferences of both the student teachers and hiring districts. Let $U_{ij} = \beta X_{ij} + \lambda Z_j + \varepsilon_{ij}$ be the i^{th} student teacher's utility for being trained in district j (research question #1) or receiving their first job in district j (research question #2). The X_{ij} represent the characteristics of individual i relative to district j (so there is one observation per individual and district), including a cubic of the log distance of district j to student teacher i's TEP program and, for those observations with data, a cubic of log distance from district j to student i's hometown. In the case where we examine first job placement, X_{ij} also contains distances between the first job district and those of the TEP, student teaching location, and hometown. The Z_j represent district j's characteristics, including enrollment and its annual growth rate, the percentage of free/reduced price lunch students, the percentage of bilingual students, the percentage of under-represented minorities, and binary variables indicating the type of community the school district serves (urban, rural, township with suburban as the omitted category). Following Boyd et al. (2005), we assume the error term is Gumbel distributed and estimate variants of the following conditional logit model:

$$(1) \qquad P_{ij} = \frac{e^{\beta X_{ij} + \lambda Z_j}}{\sum_k e^{\beta X_{ik} + \lambda Z_k}}$$

In (1), P_{ij} represents the probability that individual i did their student teaching in district j (in the first set of results) or received their first teaching job in district j (in the second set of results).[14] All standard errors produced from (1) are corrected for clustering at the individual level.

A drawback of (1) is that we are unable to introduce individual level measures as stand-alone components of X_{ij} because variables associated with teacher i will divide out of (1). However, we can interact individual characteristics with either the distance measures in X_{ij} or the district controls in Z_j and investigate whether different types of student teachers are more or less likely to train or teach close to their TEP or in a district with a particular characteristic. The individual level measures we consider in this way are the gender, minority status, and (for subsamples) collegiate GPA and average WEST-B credentialing test score. For models investigating first job placement, we can also consider the individual's age (at time of first hire) and the length of time between their student teaching and first job, as these variables are only available for hired teachers.

Prior to turning to the estimates from various parameterizations of model (1), it is important to emphasize that we cannot interpret the estimates from these models as causal. For example, as we will demonstrate, individuals in our sample are likely to do their student teaching near their TEPs, but this could be because individuals prefer to remain near their TEPs, the TEPs themselves assign student teachers nearby for supervisory reasons, or districts near the TEPs prefer student teachers from that TEP. Nonetheless, the estimates from model (1) provide useful, descriptive information about patterns in the placement of individuals in student teaching positions and their transition from student teaching to their first teaching jobs.

[14] Washington state has several extremely small school districts that do not report district passing rates because of small sample sizes. Because we consider district passing rates as a control variable and do not observe any student teaching or hiring into these districts, we omit these districts from the denominator of model 1.

V. Results

Research question #1: What are the determinants of student teaching placement?

We begin by investigating the factors predicting where prospective teachers complete their student teaching. **Table 5** presents seven different specifications of (1) where P_{ij} represents the probability of individual i completing their student teaching in district j. The first column of this table presents results from all 8,527 observations with valid individual and district variables (the "full sample" in Table 1). Positive coefficients signify an increase in the likelihood of student teaching in a district. For instance, student teaching is more likely to occur in large districts and less likely to occur in districts with a high percentage of bilingual students, all else being equal.

Because we model distance from TEP to student teaching district as a cubic, interpreting the distance coefficients in Table 5 is difficult. To aid in this, Panel A of **Figure 3** contrasts the relative probability of student teaching in two districts, subscripted 1 and 2. Consider the case in which district 1 contains the individual's TEP (the solid line of Figure 3). In this case, a prospective teacher is about six times more likely to student teach in district 1 than in a district located 25 miles away and 10 times more likely to train in district 1 than in a district that is 40 miles away. Distance to TEP matters considerably even when comparing the likelihood of student teaching in two districts, neither of which contains the TEP. For instance, prospective teachers are twice as likely to student teach in a district 10 miles from their TEP than one that is 20 miles away and almost six times as likely to student teach in the nearby district as one that is 50 miles away.

The model reported in column 1 of Table 5 includes interactions between two student teacher variables observed for all individuals in the data set (indicators that the individual is male and URM) and distance from TEP. The negative coefficient on the male interaction tells us that men are more likely to student teach close to their TEP than women. In columns 2 and 3 of Table 5, we add additional interactions with WEST-B score and undergraduate GPA (available only for the WEST-B and GPA samples, respectively: see Table 1). The coefficient on each interaction is negative and statistically significant, suggesting that more qualified student teachers are placed closer to their TEPs, all else being equal.

In columns 4–6 of Table 5, we add interactions that explore whether different types of prospective teachers are more or less likely to student teach in disadvantaged districts (we report interactions with district URM in this table, but find similar patterns when we consider other measures of district disadvantage).[15] In column 4, the coefficient on the interaction between individual URM and district URM indicates that minority prospective teachers are more likely to student teach in districts with more minority students. The negative coefficients on the interactions between district URM and average WEST-B score (column 5) and collegiate GPA (column 6) indicate that more qualified student teachers are less likely to student teach in high minority districts, all else being equal.

One possible confounding factor in the results in Table 5 is that student teachers may be placed near their hometowns. If student teachers come from more advantaged locations, then placement based upon home location may create the impression that high-ability student teachers are placed in more advantaged districts. To investigate this possibility, we consider only the 3,038 individuals in the full high school sample (see Table 1) and estimate variants of equation (1) that include measures of the distance between each district and the student teacher's home (high school district). In order to facilitate a comparison of the results in Table 5 with the results in the next table that include measures of distance to home, we reproduce the basic model of Table 5 but apply it only to the high school sample and report the estimates in column 7 of Table 5. Relative to the entire sample, observations in the high school sample are much more likely to student teach in their TEP district. This likely occurs

[15] Results for other measures of district disadvantage are available from the authors upon request.

because the bulk of our high school sample comes from the non-Seattle/Tacoma area TEPs, which have fewer regional districts in which to place student teachers.

Table 6 presents estimates from models that include the distances to each prospective teacher's high school district (note that, although we omit the coefficients from the table, all models control for the same district variables, Z_j, that were presented in Table 5). Panels B and C of **Figure 3** show the relative "pull" of TEP location (Panel B) and home location (Panel C) in student teaching assignments, derived from the estimates in the first column of Table 6. As seen when comparing column 7 of Table 5 and the first column of Table 6, the relationship between TEP location and student teaching location is stronger once we control for hometown location (i.e., once we account for the fact that many individuals return to student teach near where they grew up). Further, Panels B and C of Figure 3 suggest that hometown location and TEP location are both independent and important factors in determining where individuals do their student teaching, although hometown location appears to be a more important predictor. For instance, the solid line in Panel C indicates that a student teacher is about 30 times more likely to student teach in her home district than in a district 30 miles away from her hometown.

The remaining columns of Table 6 parallel columns 2–6 of Table 5. As before, minority student teachers are more likely to train in high minority districts. Student teachers with high collegiate GPAs are more likely to train near both their homes and TEPs. Importantly, the interactions between GPA, WEST-B, and district characteristics are no longer statistically significant. When we estimate models that do not include hometown distance measures on the high school sample,[16] the interaction on GPA is still significant, which suggests that controlling for high school proximity explains some of the relationship between student teaching qualifications and characteristics of districts using student teachers. However,

[16] Results are available from the authors upon request.

all specifications reported in Table 6 suggest that TEP location and hometown location strongly predict student teaching placement.

Research question #2: What role do student teaching placements play in determining first job location?

We now turn to the subset of 6,023 individuals observed to be hired as public teachers in Washington's K–12 public schools (the "hired sample" in Table 1) and investigate the transition from student teaching to first job schools. **Table 7** presents estimates from equation (1) where P_{ij} represents the probability of individual i receiving her first teaching job in district j, estimated for observations across all six participating TEPs. Because we lack high school data for the complete sample, these models only consider the distance between each potential first job district and the individual's student teaching district and TEP district. In **Table 8**, we limit the sample to individuals with high school data and also include measures of the distance between districts and each individual's hometown. All models include the same district controls from Table 5, although we do not report the coefficients for parsimony.[17]

Estimates from the base specification, reported in column 1 of Table 7, illustrate both the close relationship between the location of student teaching and first job and how this relationship varies for different types of teachers.[18] As before, the coefficients on the cubic term of log distances are difficult to interpret, so we explore these relationships graphically in Panel A of **Figure 4**. The solid line in Panel A shows, for example, that an individual is almost 60 times more likely to be hired in her student teaching

[17] Some of these coefficients are worth mentioning. Student teachers are more likely to receive first jobs in large districts (as measured by enrollment) and those that are growing (as measured by annual percent change in enrollment). First jobs are also more likely in districts with lower reading scores and with more minority students, all else being equal.

[18] We focus primarily on the estimates associated with student teaching location, but also note some interesting estimates associated with TEP location. For example, all else being equal, teachers in our sample are *less* likely to be hired into the district of their TEP than other districts. This is primarily due to Western Washington University and Central Washington University being located in very small school districts, as the sign of this coefficient reverses when we exclude teachers from these TEPs. Because of the sensitivity of these estimates to the subset of teachers we consider, we do not interpret the TEP distance results more broadly.

district than in a district 30 miles away, all else being equal (i.e., controlling for the distance of each district from her TEP). Clearly, this is influenced by the 15% of individuals that begin their careers in the building in which they student taught, a fact we will return to shortly. However, consider the dashed line of Panel A, which shows the relative probability of being employed at two districts, neither of which hosted the student teacher. A new teacher is almost 10 times more likely to teach at a district 10 miles from their student teaching as one that is 50 miles from their student teaching suggesting that, even ignoring the high probability of being hired into the student teaching building, first job placement is closely related to the location of student teaching.

The coefficients on the interactions in column 1 of Table 7 show that these relationships vary considerably for different types of teachers. Specifically, male teachers are more likely to teach farther from their training schools, while older teachers are more likely to teach closer to where they student taught. Teachers who took more time between completing their student teaching and being hired into their first job are also more likely to be hired into districts further from both their student teaching and TEP locations. When we include additional interactions with WEST-B scores (column 2) and undergraduate GPA (column 3)—estimated only for hired individuals with observed WEST-B scores and GPAs, respectively (see Table 1)—we find little evidence that more qualified student teachers end up teaching closer to their student teaching districts. Finally, when we include interactions with hiring district URM in columns 4–6 of Table 7, we see that minority student teachers are more likely to work in high-minority districts.

To investigate the role of home location in teacher hiring, we must limit our sample to the 2,257 individuals who both have high school data and are hired into teaching positions (see Table 1). To understand the implications of examining this hired high school sample, we re-estimate the base model of column 1 of Table 7 using only individuals with high school information. We reproduce this model in column 7 of Table 7. When comparing the results using the subsample with those of the complete sample, there is very little difference in the coefficients relating to student teaching. For both samples, the greater the distance between potential first job district and student teaching district, the lower the probability of being hired into that first job. In the subsample, men, younger teachers, and those taking longer to find jobs are more likely to be hired into districts further from their student teaching just as was the case for the full sample. Like the corresponding models in Table 5, the largest differences between columns 1 and 7 in Table 7 are those relating to distance between TEP and first job; again, this is likely due to the fact that the high school subsample is comprised primarily of individuals from the non-Seattle/Tacoma area TEPs.

We now report estimates from models that consider the distance between individuals' home districts and first job districts in **Table 8**. These models essentially replicate the models reported in Boyd et al. (2005), but add variables related to each individual's student teaching experience including the cubic in distance to the student teaching district. We first note that there are a number of interesting interactions in these models, and some results from Table 7 change once we control for hometown location. For example, we see in column 1 of Table 8 that minorities are actually more likely to begin their teaching careers *closer* to their student teaching district than other teachers, controlling for the proximity of the district to their hometown and TEP. We also see in column 2 of Table 8 that, once we control for proximity to hometown, individuals with higher WEST-B scores tend to find jobs closer to their student teaching districts, all else being equal. Finally, individuals who take longer to find a teaching job ("time to hire") are more likely to teach close to home than individuals who find a teaching job quickly.[19] This is an interesting corollary to the findings from Boyd et al. (2005), as it suggests that the draw of home grows stronger for teachers who take longer to find a teaching job (or perhaps that

[19] We verify that these results change because of the controls for home distances rather than the change of sample by estimating models without home distance on the high school sample. These results are available from the authors upon request.

individuals with a strong preference to live near home limit the scope of their job search and thereby take longer to find a job).

The most striking conclusion from Table 8, however, is that the relationship between first job location and hometown location (reported in Boyd et al., 2005, Reininger, 2012, and Killeen et al., in review) is dwarfed by the relationship between first job location and student teaching location. We illustrate the relative magnitudes of these relationships in Panels B and C of Figure 4; the odds of a teacher beginning her career in her student teaching district relative to another district is consistently about 10 times larger than the corresponding odds of a teacher beginning her career in her hometown district. This reinforces the conclusion from Table 3 that the student teaching location seems to exert a much stronger influence on first job location than the oft-cited draw of home phenomenon.

As already mentioned, about one in six first time teachers receive jobs in the building in which they completed their student teaching. Many of these individuals experience a significantly different job search than those who must cast a wider net to find a teaching position. To ensure that our results aren't driven by these "same building hires" we also estimate models that exclude these individuals. Panels D and E of Figure 4 demonstrate that student teaching location is still much more predictive of first job location than hometown location, even for individuals that are not hired directly into their student teaching district. Our overall conclusion, then, is that student teaching placements play a much larger role in explaining patterns in new teacher hiring than either hometowns or TEP locations.

As a final extension, we use the sample of individuals who are not hired into their student teaching building to investigate the relationship between the *characteristics* of a student teaching district and the *characteristics* of her first job district (we drop perspective teachers hired into their student building so the results are not skewed by same-school hiring). We report estimates from models that include these interactions in columns 2–5 of **Table 9**. For each measure of district disadvantage, we find that those who complete their student teaching in more disadvantaged districts tend to get their first job in more disadvantaged districts, all else being equal. Specifically, each of the bottom four rows of Table 9 demonstrate strong, positive relationships between the URM, FRL, math and reading scores of a first job and the district in which they completed their student teaching. Importantly, these models control for proximity to student teaching, home, and TEP, so the characteristics of a student teaching district are predictive of the characteristics of a first job district even controlling for the spatial relationships we have discussed to this point.

There are a number of possible explanations for the similarities between student teaching districts and first job districts. For example, individuals may have a preference for teaching a particular type of student and select into districts (both for student teaching and first jobs) that have students who meet these preferences. Hiring districts may also give preference to prospective teachers who student taught in districts similar to theirs. Regardless of whether these findings reflect the preferences of teachers or hiring districts, the close relationship between student teaching positions and first job positions has some clear policy implications that we discuss in the next section.

VI. Policy Implications, Limitations, and Directions for Future Work

This study contributes to the growing literature on teacher hiring by providing the first empirical evidence about the process that moves prospective teachers from teacher education programs to student teaching placements and into the teaching workforce. This exploration suggests several policy conclusions, but each of these conclusions comes with a number of caveats due to the limitations of this analysis; hence, we also suggest directions for future research. For example, one conclusion from our analysis of the assignment of individuals to student teaching schools (research question #1) is that more qualified prospective teachers (as measured by undergraduate GPA or WEST-B scores) are disproportionately assigned to do their student teaching in advantaged schools. Unfortunately, we do not know whether the assignment of individuals to student teaching placements reflects the preferences of TEPs, individuals, or student teaching districts. So, we must learn more about how these parties work together to determine student teaching assignments.

Our analysis of the transition from student teaching to first jobs (research question #2) shows quite clearly that a student teaching placement is highly predictive of where an individual finds her first teaching job, and much more predictive than her TEP or hometown. Given this, we view the prior literature on the draw of home as an incomplete picture of initial teacher placement, as this phenomenon appears to be driven by patterns in student teaching assignments. We also take this as preliminary evidence that student teaching serves as a "screening device" for school and districts looking to hire new teachers and could therefore be a policy lever that influences the distribution of teacher quality across schools; that is, if TEPs purposefully sent high-performing (or just more!) student teachers to train in disadvantaged settings, these individuals might be more likely to start their careers in these school and districts.

But this conclusion comes with (at least) three caveats. The first is similar to our caveat about the assignment of individuals to student teaching assignments: we cannot distinguish between the preferences of individuals and hiring schools in determining first job placements. One potential solution is to estimate a two-sided matching model (e.g., Boyd et al., 2013) that seeks to distinguish between these preferences, but even then there is a second caveat: we cannot know whether student teachers' "preference" to work close to where they student taught is invariant to the type of district where they do their student teaching. Specifically, suppose that a TEP decides to send all of their student teachers to train in disadvantaged schools and districts. On the one hand, these prospective teachers may be less likely to stay in the student teaching school and district than our results suggest, but on the other hand, there is evidence from the behavioral economics literature that similar "nudge policies" (Thaler &

Sunstein, 2008) can have considerable impacts on decision making. So until a TEP decides to implement such a policy, it is difficult to know whether it would improve equity in teacher hiring as much as our results suggest.

A final caveat concerns the generalizability of our findings. Specifically, all of our results that contrast relationships between hometowns, student teaching, and first jobs are based on a sample of individuals from three Washington state TEPs (see Table 1) that may not be representative of all TEPs in the state, let alone in the country. We therefore caution against generalizing our results to student teachers from all TEPs, even in Washington state, particularly given evidence that teacher workforce policies can have very different effects on different types of teachers (Clotfelter et al., 2011). That said, this limitation simply underscores the need for more research and better data systems about student teaching experiences and workforce outcomes. Given the paucity of existing research, we view this study as the most comprehensive empirical evidence about the role of student teaching in new teacher hiring.

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Tables

Table 1. Sample sizes by institution and sample

	Total	CWU	PLU	UWB	UWS	UWT	WWU
Panel A: Full Sample (all individuals)							
All	8527	2048	417	414	877	236	4535
WEST-B sub-sample	4575	1685	311	222	453	172	1732
GPA sub-sample	4736	0	1	0	0	200	4535
Panel B: Full High School Sample (all individuals with high school data)							
All	3038	451	1	0	28	0	2558
WEST-B sub-sample	1306	348	1	0	13	0	944
GPA sub-sample	2559	0	1	0	0	0	2558
Panel C: Hired Sample (all individuals hired into teaching positions)							
All	6023	1383	316	291	693	183	3157
WEST-B sub-sample	3264	1189	243	165	363	136	1168
GPA sub-sample	3309	0	1	0	0	151	3309
Panel D: Hired High School Sample (all individuals hired into teaching positions with high school data)							
All	2257	299	1	0	23	0	1934
WEST-B sub-sample	941	244	1	0	12	0	684
GPA sub-sample	1935	0	1	0	0	0	1934

*Participating institutions: Central Washington University (CWU); Pacific Lutheran University (PLU); University of Washington – Bothell (UWB); University of Washington – Seattle (UWS); University of Washington – Tacoma (UWT); Western Washington University (WWU).

Table 2: Individual variable summary statistics

	Full Sample	Hired Sample	Full High School Sample	Full WEST-B Sample	Full GPA Sample
N	**8,527**	**6,023**	**3,038**	**4,575**	**4,736**
Individual characteristics					
Age	29.82 (7.73)	29.73 (7.73)	26.79 (5.29)	29.60 (7.71)	29.88 (7.66)
Proportion male	.233	.238	.210	.243	.231
Proportion URM	.041	.043	.034	.047	.037
Collegiate GPA	3.23 (1.01)	3.23 (1.02)	3.34 (.637)	3.32 (.897)	3.23 (1.01)
West-B score	271.58 (11.69)	271.65 (11.74)	271.52 (10.83)	271.58 (11.69)	273.43 (10.81)
Endorsement area					
Proportion STEM	.120	.134	.092	.128	.098
Proportion SPED	.105	.126	.131	.099	.130
Proportion ELL	.054	.057	.048	.060	.038
Proportion elementary	.651	.636	.652	.642	.666
Teacher Education Program					
CWU	.240	.230	.148	.368	--
PLU	.049	.053	.0003	.067	.0002
UWB	.049	.048	--	.048	--
UWS	.102	.115	.009	.099	--
UWT	.027	.030	--	.037	.042
WWU	.532	.524	.842	.378	.957

*Standard deviations of continuous variables in parentheses.

Table 3: Distance summary statistics

Panel A: Distances to student teaching district (all observations)						
	Distance from TEP district			Distance from home district		
	Same	Within 25 mi	Within 50 mi	Same	Within 25 mi	Within 50 mi
CWU	7.1%	20.7%	40.8%	21.5%	50.8%	61.6
PLU	23.7%	87.8%	97.3%	--	--	--
UW Bothell	22.4%	100%	100%	--	--	--
UW Seattle	44.4%	99.8%	100%	7.1%	53.6%	78.5
UW Tacoma	48.7%	100%	100%	--	--	--
WWU	23.6%	45.3%	50.8%	21.3%	48.3%	55.8
All TEPs	22.5%	51.4%	59.4%	21.2%	48.7%	56.8
High School Sample	24.5%	46%	52.9%	21.2%	48.7%	56.8

Panel B: Distances to first job district (hired individuals only)									
	Distance from TEP district			Distance from home district			Distance from student teaching district		
	Same	Within 25 mi	Within 50 mi	Same	Within 25 mi	Within 50 mi	Same	Within 25 mi	Within 50 mi
CWU	0.5%	8.1%	30.1%	28.4%	53.2%	65.9%	36.6%	65.5%	78.8%
PLU	11.7%	82.2%	93.6%	--	--	--	38.6%	85.1%	95.2%
UW Bothell	13.0%	96.2%	97.9%	--	--	--	45.3%	93.8%	97.6%
UW Seattle	21.9%	92.0%	96.5%	4.3%	65.2%	86.9%	35.6%	89.3%	96.2%
UW Tacoma	20.2%	90.1%	97.2%	--	--	--	29.5%	90.1%	97.8%
WWU	8.3%	23.8%	32.6%	22.7%	54.3%	66.7%	40.7%	70.1%	79.4%
All TEPs	8.8%	36.9%	47.7%	23.3%	54.3%	66.6%	39.0%	74.2%	83.7%
All TEPs, Less Same Building Hires	7.9%	35.7%	46.8%	22.5%	52.9%	66.4%	28.6%	69.8%	80.9%
High School Sample	7.9%	23.2%	33.4%	23.3%	54.3%	66.6%	37.5%	65.7%	75.7%
High School Sample, Less Same Building Hires	6.8%	21.4%	31.8%	22.5%	52.9%	66.4%	26.5%	59.7%	71.4%

Table 4: Standardized district measures of disadvantage

Panel A: All hired individuals			
	First job	Student Teaching	Difference
FRL students	-0.324	-0.330	0.006
URM students	0.103	0.086	0.017
Pass Math	0.448	0.583	-.136***
Pass Reading	0.32	0.485	-.165***
Panel B: All hired individuals, less same building hires			
	First job	Student Teaching	Difference
FRL students	-0.314	-0.328	0.014
URM students	0.110	0.082	0.028*
Pass Math	0.434	0.585	-.151***
Pass Reading	0.308	0.489	-.180***

Table 5: Predictors of student teaching district (all TEPs)

	1	2	3	4	5	6	7
ln(distance from TEP)	-3.069*** (0.555)	-3.333*** (0.812)	-1.941** (0.987)	-3.044*** (0.555)	-3.234*** (0.811)	-2.004** (0.985)	5.732*** (1.391)
ln(distance from TEP)^2	0.782*** (0.167)	1.152*** (0.235)	0.521* (0.279)	0.773*** (0.167)	1.121*** (0.235)	0.523* (0.279)	-1.706*** (0.385)
ln(distance from TEP)^3	-0.102*** (0.016)	-0.141*** (0.023)	-0.079*** (0.026)	-0.102*** (0.016)	-0.138*** (0.023)	-0.080*** (0.025)	0.124*** (0.034)
TEP in same district	-3.459*** (0.589)	-4.596*** (0.805)	-2.530** (1.119)	-3.442*** (0.588)	-4.516*** (0.803)	-2.582** (1.116)	6.359*** (1.620)
TEP district and district same type	-0.018 (0.039)	0.054 (0.054)	0.070 (0.049)	-0.020 (0.039)	0.056 (0.055)	0.071 (0.049)	0.318*** (0.083)
ln(distance from TEP) * male	-0.036** (0.016)	-0.010 (0.022)	-0.062*** (0.019)	-0.035** (0.016)	-0.010 (0.022)	-0.061*** (0.019)	-0.064*** (0.024)
ln(distance from TEP) * individual URM	0.048 (0.035)	0.045 (0.048)	0.079* (0.045)	0.036 (0.037)	0.045 (0.050)	0.048 (0.047)	-0.055 (0.056)
ln(distance from TEP) * WEST-B		-0.003*** (0.001)			-0.003*** (0.001)		
ln(distance from TEP) * GPA			-0.034*** (0.009)			-0.018** (0.009)	
ln(district enrollment)	1.375*** (0.022)	1.430*** (0.031)	1.317*** (0.032)	1.378*** (0.022)	1.437*** (0.031)	1.324*** (0.032)	1.362*** (0.040)
Growth in district enrollment	-0.000*** (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000** (0.000)	0.000** (0.000)
District FRL	0.045 (0.041)	0.113** (0.056)	0.415*** (0.063)	0.049 (0.041)	0.117** (0.056)	0.433*** (0.063)	0.202*** (0.071)
District URM	0.044 (0.047)	-0.195*** (0.068)	0.159** (0.063)	0.044 (0.047)	-0.198*** (0.068)	0.146** (0.063)	0.134* (0.075)
District Math Test	0.007 (0.061)	0.297*** (0.094)	-0.068 (0.085)	0.004 (0.061)	0.292*** (0.094)	-0.048 (0.085)	-0.042 (0.101)
District Reading Test	0.064* (0.038)	0.006 (0.051)	-0.396*** (0.069)	0.027 (0.039)	0.986* (0.519)	0.232** (0.105)	-0.165** (0.068)
District is urban	-0.064* (0.037)	-0.226*** (0.048)		-0.061 (0.037)	-0.224*** (0.048)		-0.382*** (0.084)
District is rural	0.540*** (0.059)	0.657*** (0.079)	0.138 (0.084)	0.542*** (0.059)	0.662*** (0.080)	0.130 (0.084)	0.517*** (0.099)
District is in town	-0.060 (0.047)	-0.191*** (0.070)	-0.098 (0.060)	-0.060 (0.047)	-0.191*** (0.070)	-0.107* (0.060)	-0.062 (0.073)
District URM * individual URM				0.506*** (0.071)	0.423*** (0.085)	0.485*** (0.154)	
District URM * individual WEST-B					-0.004* (0.002)		
District URM * individual GPA						-0.214*** (0.028)	
Observations	2,283,966	1,238,627	1,260,919	2,283,966	1,238,627	1,260,919	808,092
# of Individuals	8527	4575	4736	8527	4575	4736	3038

NOTES: p-values from two-sided t-test: *p<.10; **p<.05; ***p<.01.

Table 6: Predictors of student teaching district (high school subset)

	1	2	3	4	5	6
ln(distance from home)	1.410* (0.768)	-1.283 (1.327)	1.229 (0.828)	1.399* (0.768)	-1.343 (1.329)	1.251 (0.828)
ln(distance from home)^2	-0.978*** (0.226)	-0.852** (0.352)	-0.880*** (0.242)	-0.975*** (0.226)	-0.847** (0.352)	-0.886*** (0.242)
ln(distance from home)^3	0.111*** (0.021)	0.099*** (0.033)	0.104*** (0.023)	0.111*** (0.021)	0.099*** (0.033)	0.104*** (0.023)
Home in same district	1.213 (0.831)	0.542 (1.303)	0.849 (0.888)	1.200 (0.832)	0.521 (1.303)	0.869 (0.889)
Home district and district same type	-0.109** (0.049)	-0.034 (0.074)	-0.169*** (0.054)	-0.111** (0.049)	-0.036 (0.074)	-0.170*** (0.054)
ln(distance from home) * male	0.029 (0.035)	0.069 (0.056)	0.021 (0.040)	0.030 (0.035)	0.070 (0.056)	0.020 (0.040)
ln(distance from home) * individual URM	0.098 (0.078)	0.131 (0.116)	0.019 (0.095)	0.112 (0.080)	0.117 (0.119)	0.020 (0.096)
ln(distance from home) * WEST-B		0.008*** (0.002)			0.009*** (0.002)	
ln(distance from home) * GPA			-0.057** (0.025)			-0.058** (0.025)
ln(distance from TEP)	10.090*** (1.451)	12.111*** (2.409)	11.187*** (1.537)	10.092*** (1.449)	12.064*** (2.404)	11.141*** (1.538)
ln(distance from TEP)^2	-3.107*** (0.402)	-3.646*** (0.652)	-3.425*** (0.423)	-3.110*** (0.401)	-3.656*** (0.650)	-3.419*** (0.423)
ln(distance from TEP)^3	0.261*** (0.036)	0.308*** (0.058)	0.292*** (0.037)	0.261*** (0.036)	0.310*** (0.058)	0.292*** (0.037)
TEP in same district	10.967*** (1.685)	13.064*** (2.706)	11.599*** (1.792)	10.948*** (1.683)	13.044*** (2.697)	11.558*** (1.792)
TEP district and district same type	0.117 (0.088)	0.145 (0.121)	0.023 (0.072)	0.116 (0.088)	0.151 (0.121)	0.024 (0.072)
ln(distance from TEP) * individual male	-0.039 (0.030)	0.004 (0.044)	-0.042 (0.033)	-0.039 (0.030)	0.004 (0.044)	-0.041 (0.033)
ln(distance from TEP) * individual URM	-0.046 (0.067)	0.051 (0.101)	-0.094 (0.079)	-0.093 (0.072)	-0.003 (0.109)	-0.135 (0.083)
ln(distance from TEP) * WEST-B		-0.001 (0.002)			-0.000 (0.002)	
ln(distance from TEP) * GPA			-0.040* (0.021)			-0.033 (0.022)
District URM * individual URM				0.533*** (0.156)	0.512** (0.201)	0.566** (0.258)
District URM * individual WEST-B					-0.003 (0.005)	
District URM * individual GPA						-0.108 (0.070)
Observations	808,092	352,745	679,451	808,092	352,745	679,451
# of Individuals	3038	1306	2559	3038	1306	2559

NOTES: p-values from two-sided t-test: *p<.10; **p<.05; ***p<.01. All models include district controls from Table 5.

Table 7: Predictors of first job district (all TEPs)

	1	2	3	4	5	6	7
ln(distance from student teaching)	6.360*** (0.614)	5.749*** (0.898)	5.954*** (0.879)	6.163*** (0.612)	5.569*** (0.897)	5.852*** (0.877)	5.001*** (1.059)
ln(distance from student teaching)^2	-2.350*** (0.189)	-2.128*** (0.256)	-2.276*** (0.266)	-2.289*** (0.188)	-2.081*** (0.256)	-2.244*** (0.266)	-1.946*** (0.317)
ln(distance from student teaching)^3	0.228*** (0.018)	0.203*** (0.025)	0.223*** (0.026)	0.222*** (0.018)	0.198*** (0.025)	0.220*** (0.026)	0.190*** (0.030)
Student taught in same district	6.827*** (0.636)	6.341*** (0.864)	6.222*** (0.921)	6.627*** (0.634)	6.180*** (0.862)	6.127*** (0.919)	5.532*** (1.123)
Student teaching district and district same type	-0.072* (0.038)	-0.067 (0.050)	-0.074 (0.053)	-0.064* (0.038)	-0.059 (0.050)	-0.069 (0.053)	-0.032 (0.062)
ln(distance from student teaching) * male	0.127*** (0.023)	0.142*** (0.030)	0.171*** (0.033)	0.125*** (0.023)	0.142*** (0.030)	0.169*** (0.033)	0.154*** (0.039)
ln(distance from student teaching) * age	-0.007*** (0.001)	-0.008*** (0.002)	-0.008*** (0.002)	-0.007*** (0.001)	-0.008*** (0.002)	-0.008*** (0.002)	-0.008** (0.003)
ln(distance from student teaching) * time to hire	0.048*** (0.005)	0.049*** (0.007)	0.065*** (0.008)	0.047*** (0.005)	0.048*** (0.007)	0.064*** (0.008)	0.070*** (0.011)
ln(distance from student teaching) * individual URM	-0.004 (0.046)	0.025 (0.057)	-0.177** (0.083)	-0.001 (0.047)	0.028 (0.058)	-0.172** (0.083)	-0.140 (0.092)
ln(distance from student teaching) * WEST-B		0.000 (0.001)			0.000 (0.001)		
ln(distance from student teaching) * GPA			-0.012 (0.013)			-0.010 (0.013)	
ln(distance from TEP)	-4.557*** (0.693)	-2.551** (1.106)	-0.758 (1.379)	-4.420*** (0.691)	-2.352** (1.105)	-1.250 (1.368)	2.513 (1.983)
ln(distance from TEP)^2	1.513*** (0.209)	0.939*** (0.282)	0.655* (0.387)	1.461*** (0.208)	0.883*** (0.282)	0.780** (0.385)	-0.204 (0.540)
ln(distance from TEP)^3	-0.153*** (0.020)	-0.091*** (0.027)	-0.090** (0.035)	-0.148*** (0.020)	-0.086*** (0.027)	-0.101*** (0.035)	-0.016 (0.048)
TEP in same district	-5.442*** (0.727)	-4.213*** (0.967)	0.000 (1.578)	-5.434*** (0.724)	-4.142*** (0.963)	-0.772 (1.566)	3.712 (2.348)
TEP district and district same type	0.261*** (0.049)	0.295*** (0.064)	-0.208*** (0.056)	0.236*** (0.049)	0.276*** (0.064)	-0.173*** (0.057)	0.254** (0.113)
ln(distance from TEP) * male	-0.112*** (0.037)	-0.151*** (0.051)	-0.176*** (0.050)	-0.109*** (0.037)	-0.150*** (0.051)	-0.173*** (0.050)	-0.214*** (0.061)
ln(distance from student teaching) * age	-0.007*** (0.002)	-0.008** (0.003)	-0.001 (0.003)	-0.007*** (0.002)	-0.008** (0.003)	-0.001 (0.003)	-0.006 (0.006)
ln(distance from student teaching) * time to hire	0.025** (0.010)	0.022 (0.014)	0.001 (0.014)	0.025** (0.010)	0.023* (0.014)	-0.000 (0.014)	0.004 (0.018)
ln(distance from TEP) * individual URM	-0.036 (0.085)	-0.062 (0.112)	0.312** (0.138)	-0.042 (0.086)	-0.067 (0.113)	0.306** (0.137)	0.221 (0.155)
ln(distance from TEP) * WEST-B		-0.001 (0.002)			-0.002 (0.002)		
ln(distance from TEP) * GPA			-0.005 (0.024)			-0.006 (0.024)	
District URM * individual URM				0.065*** (0.009)	0.046*** (0.012)	0.066*** (0.016)	
District URM * WEST-B					-0.003 (0.002)		
District URM * GPA						-0.006 (0.035)	
Observations	1,615,736	878,933	886,737	1,615,736	878,933	886,737	603,994
# of Individuals	6023	3264	3309	6023	3264	3309	2257

NOTES: p-values from two-sided t-test: *p<.10; **p<.05; ***p<.01. All models include district controls from Table 5.

Table 8: Predictors of first job district (high school sample)

	1	2	3	4	5	6
ln(distance from student teaching)	5.104*** (1.119)	7.180*** (2.016)	5.366*** (1.513)	4.466*** (1.313)	6.930*** (2.006)	5.336*** (1.510)
ln(distance from student teaching)^2	-1.773*** (0.337)	-1.736*** (0.554)	-1.832*** (0.451)	-1.592*** (0.392)	-1.631*** (0.551)	-1.823*** (0.449)
ln(distance from student teaching)^3	0.171*** (0.032)	0.163*** (0.053)	0.176*** (0.043)	0.155*** (0.038)	0.153*** (0.053)	0.174*** (0.043)
Student teaching in same district	5.510*** (1.186)	5.741*** (1.969)	5.587*** (1.597)	4.819*** (1.397)	5.362*** (1.958)	5.560*** (1.594)
Student teaching district and district same type	0.019 (0.063)	0.103 (0.096)	-0.035 (0.083)	0.025 (0.073)	0.108 (0.096)	-0.031 (0.083)
ln(distance from student teaching) * male	0.132*** (0.042)	0.194*** (0.066)	0.149** (0.060)	0.161*** (0.050)	0.198*** (0.066)	0.144** (0.059)
ln(distance from student teaching) * age	-0.019*** (0.003)	-0.020*** (0.007)	-0.016*** (0.005)	-0.019*** (0.004)	-0.020*** (0.007)	-0.016*** (0.005)
ln(distance from student teaching) * time to hire	0.092*** (0.012)	0.075*** (0.022)	0.093*** (0.015)	0.092*** (0.014)	0.075*** (0.022)	0.092*** (0.015)
ln(distance from student teaching) * individual URM	-0.246** (0.100)	-0.290** (0.137)	-0.375** (0.152)	-0.168 (0.108)	-0.272** (0.139)	-0.363** (0.152)
ln(distance from student teaching) * WEST-B		-0.007*** (0.003)			-0.007*** (0.002)	
ln(distance from student teaching) * GPA			-0.063 (0.040)			-0.062 (0.040)
ln(distance from home)	0.004 (0.933)	-0.584 (1.614)	0.022 (1.208)	0.254 (1.084)	-0.629 (1.621)	0.042 (1.211)
ln(distance from home)^2	-0.449* (0.271)	-0.335 (0.418)	-0.389 (0.344)	-0.562* (0.313)	-0.335 (0.419)	-0.407 (0.345)
ln(distance from home)^3	0.045* (0.025)	0.034 (0.039)	0.036 (0.032)	0.057* (0.029)	0.031 (0.039)	0.038 (0.032)
Home in same district	0.995 (1.014)	0.494 (1.601)	0.784 (1.300)	1.222 (1.186)	0.456 (1.604)	0.823 (1.303)
Home district and district same type	0.091 (0.058)	0.190** (0.090)	0.102 (0.077)	0.129* (0.068)	0.197** (0.089)	0.104 (0.076)
ln(distance from home) * male	-0.014 (0.044)	0.021 (0.065)	-0.056 (0.059)	-0.002 (0.050)	0.016 (0.064)	-0.057 (0.059)
ln(distance from home) * age	0.029*** (0.005)	0.035*** (0.008)	0.029*** (0.006)	0.030*** (0.006)	0.035*** (0.008)	0.028*** (0.006)
ln(distance from home) * time to hire	-0.034*** (0.011)	-0.014 (0.019)	-0.016 (0.013)	-0.028** (0.012)	-0.027 (0.019)	-0.017 (0.013)
ln(distance from home) * individual URM	-0.191* (0.098)	-0.055 (0.144)	-0.053 (0.165)	-0.057 (0.112)	-0.061 (0.145)	-0.048 (0.165)
ln(distance from home) * WEST-B		-0.000 (0.002)			-0.000 (0.003)	
ln(distance from home) * GPA			-0.059 (0.050)			-0.049 (0.049)
District URM * individual URM				0.092*** (0.018)	0.086*** (0.022)	0.073*** (0.024)
District URM * WEST-B					-0.001 (0.002)	
District URM * GPA						-0.161** (0.080)
Observations	603,994	246,276	349,688	432,623	246,276	349,688
# of Individuals	2257	934	1,315	1,628	934	1,315

NOTES: p-values from two-sided t-test: *p<.10; **p<.05; ***p<.01. All models include district controls from Table 5 and institution distances and interactions from Table 7.

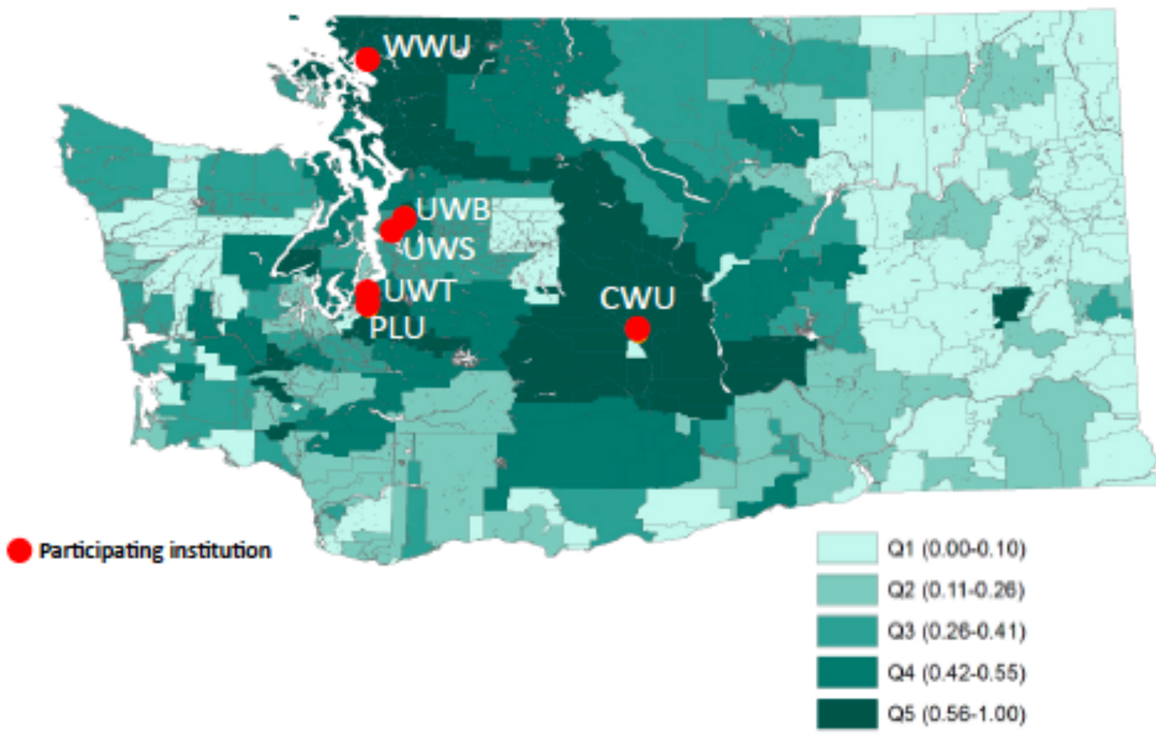
Table 9: Predictors of first job district (all TEPs, less same building hires)

	1	2	3	4	5
ln(distance from student teaching)	6.292*** (0.624)	6.284*** (0.623)	6.281*** (0.622)	6.338*** (0.625)	6.466*** (0.625)
ln(distance from student teaching)^2	-2.299*** (0.192)	-2.295*** (0.192)	-2.287*** (0.192)	-2.306*** (0.192)	-2.343*** (0.192)
ln(distance from student teaching)^3	0.223*** (0.019)	0.223*** (0.019)	0.222*** (0.019)	0.224*** (0.019)	0.227*** (0.019)
Student teaching in same district	6.144*** (0.645)	6.126*** (0.645)	6.117*** (0.644)	6.165*** (0.647)	6.291*** (0.647)
Student teaching district and district same type	-0.060 (0.038)	-0.061 (0.038)	-0.064* (0.038)	-0.054 (0.038)	-0.059 (0.038)
ln(distance from student teaching) * male	0.179*** (0.027)	0.180*** (0.027)	0.181*** (0.027)	0.180*** (0.027)	0.180*** (0.027)
ln(distance from student teaching) * age	-0.010*** (0.001)	-0.010*** (0.001)	-0.010*** (0.001)	-0.010*** (0.001)	-0.010*** (0.001)
ln(distance from student teaching) * time to hire	0.038*** (0.006)	0.038*** (0.006)	0.038*** (0.006)	0.038*** (0.006)	0.038*** (0.006)
ln(distance from student teaching) * individual URM	-0.017 (0.053)	-0.009 (0.054)	-0.009 (0.054)	-0.012 (0.054)	-0.011 (0.054)
ln(distance from TEP)	-4.435*** (0.714)	-4.387*** (0.714)	-4.306*** (0.714)	-4.386*** (0.713)	-4.468*** (0.713)
ln(distance from TEP)^2	1.451*** (0.216)	1.432*** (0.216)	1.401*** (0.216)	1.433*** (0.215)	1.455*** (0.215)
ln(distance from TEP)^3	-0.147*** (0.021)	-0.145*** (0.021)	-0.142*** (0.021)	-0.146*** (0.021)	-0.148*** (0.021)
TEP in same district	-5.338*** (0.747)	-5.293*** (0.747)	-5.195*** (0.747)	-5.264*** (0.746)	-5.369*** (0.745)
TEP district and district same type	0.204*** (0.051)	0.198*** (0.051)	0.193*** (0.051)	0.187*** (0.051)	0.192*** (0.051)
ln(distance from TEP) * male	-0.134*** (0.040)	-0.135*** (0.040)	-0.137*** (0.040)	-0.137*** (0.040)	-0.137*** (0.040)
ln(distance from student teaching) * age	-0.007*** (0.002)	-0.006*** (0.002)	-0.006** (0.002)	-0.006*** (0.002)	-0.006** (0.002)
ln(distance from student teaching) * time to hire	0.023** (0.010)	0.023** (0.010)	0.022** (0.010)	0.022** (0.010)	0.022** (0.010)
ln(distance from TEP) * individual URM	0.014 (0.094)	0.009 (0.094)	0.009 (0.094)	0.009 (0.094)	0.010 (0.094)
District %URM * individual URM	0.067*** (0.009)	0.060*** (0.010)	0.054*** (0.010)	0.058*** (0.010)	0.058*** (0.009)
District %URM * student teaching district %URM		0.031** (0.012)			
District % FRL * student teaching district % FRL			0.073*** (0.014)		
District % Pass Math * student teaching district % Pass Math				1.174*** (0.182)	
District % Pass Read * student teaching district % Pass Read					1.750*** (0.282)
Observations	1,377,340	1,377,340	1,377,070	1,354,480	1,373,668
# of Individuals	6023	6023	6021	6023	6023

NOTES: p-values from two-sided t-test: *p<.10; **p<.05; ***p<.01. All models include district controls from Table 5.

Figures

Figure 1. Proportion of New Teachers from Participating Institutions



NOTE: Figure 1 illustrates the proportion of newly hired teachers in each district over the past 10 years who graduated from one of the six participating institutions in this study. The legend shows how these proportions are binned into five quintiles.

Figure 2: Student teaching assignments by year of student teaching

Central Washington University
Pacific Lutheran University
UW Bothell
UW Seattle
UW Tacoma
Western Washington University

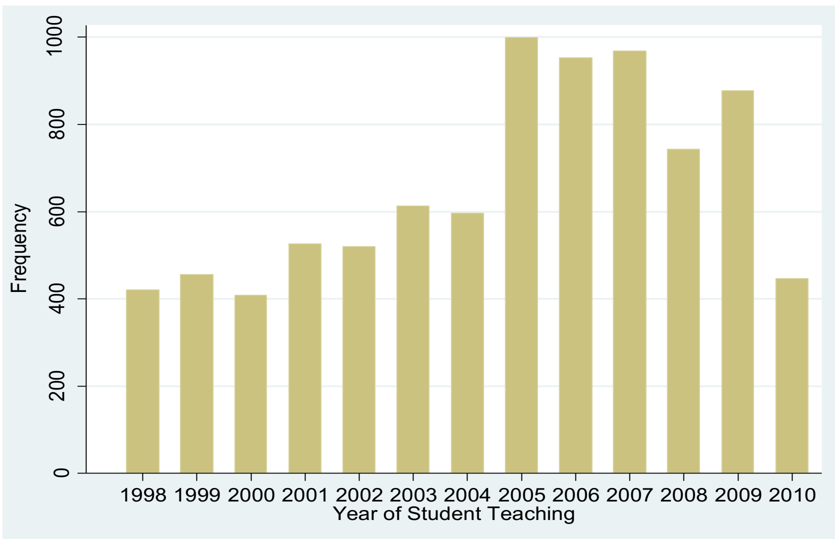
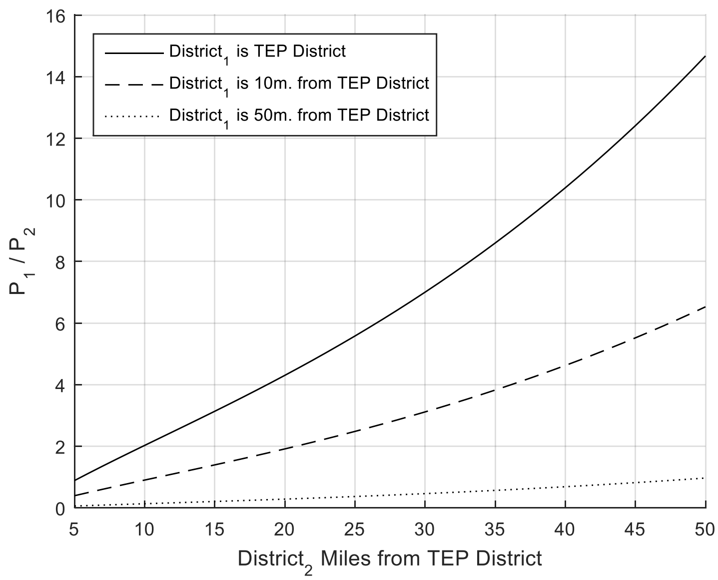
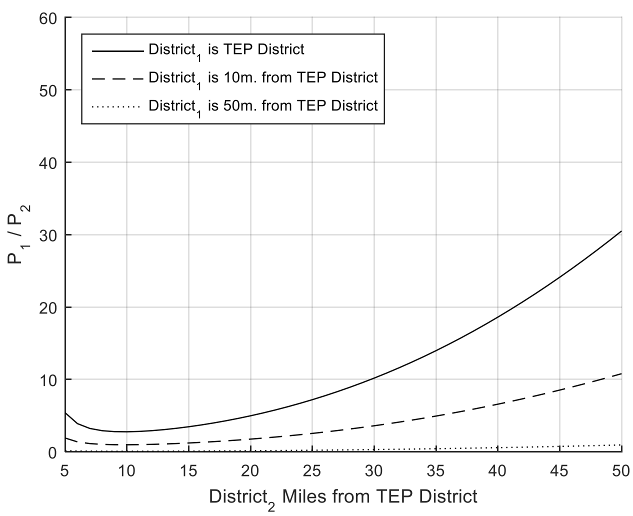


Figure 3: Relationships Between Distance Measures and Student Teaching Placement

A. All TEPs



B. High School Sample



C. High School Sample

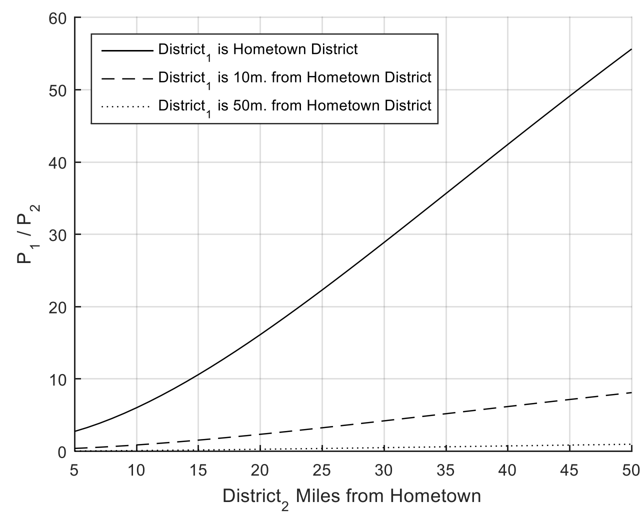
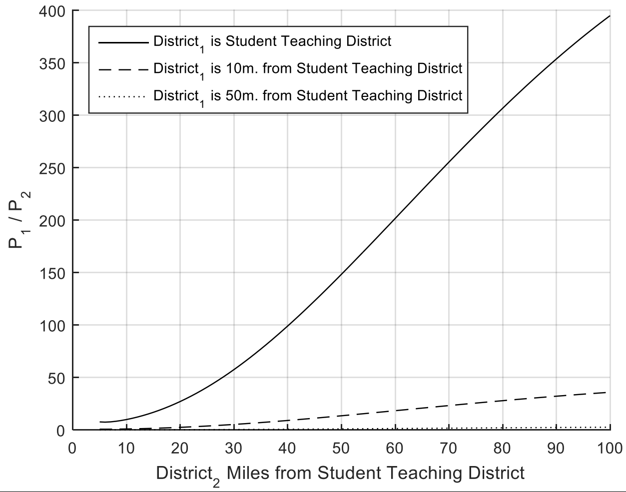
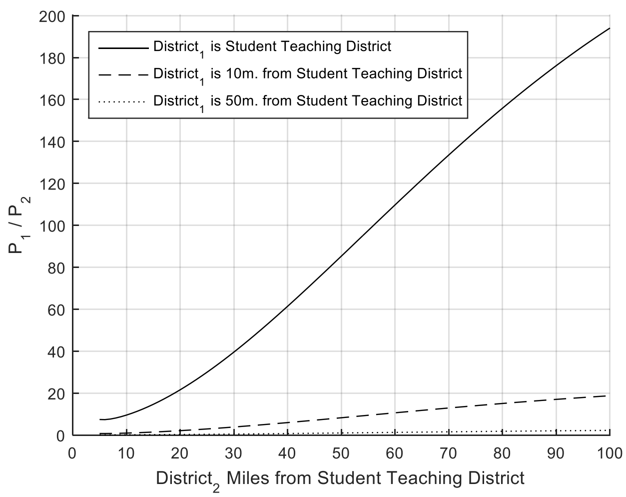


Figure 4: Relationships Between Distance Measures and First-Job Placement

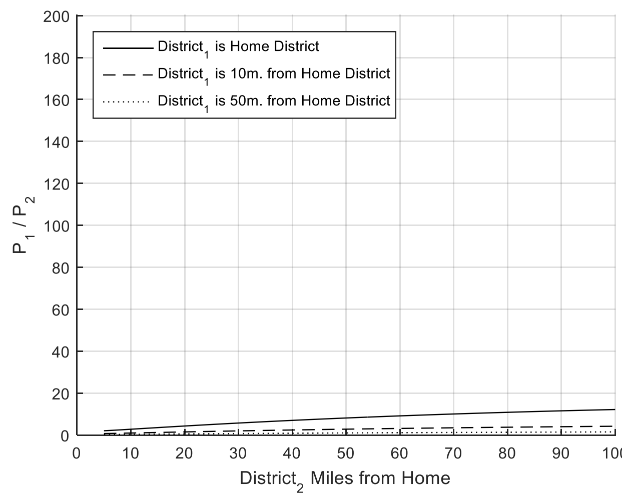
A. All TEPs



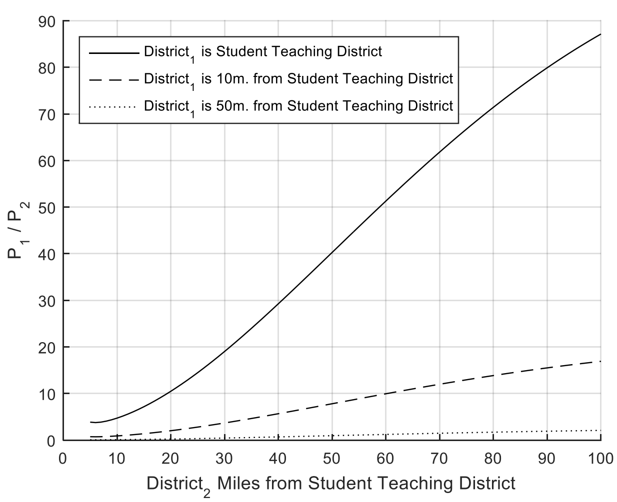
B. High School Sample



C. High School Sample



D. High School Sample, less same building hires



E. High School Sample, less same building hires