



A Foot in the Door: Exploring the Role of Student Teaching Assignments in Teachers' Initial Job Placements.

John Krieg
Western Washington University

Roddy Theobald
Center for Education Data & Research
University of Washington Bothell

Dan Goldhaber
American Institutes of Research
Center for Education Data & Research
University of Washington Bothell

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 do their student teaching near their hometowns, but that 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.

** The research presented here utilizes data supplied by the teacher education programs at Central Washington University, Pacific Lutheran University, University of Washington-Bothell, University of Washington-Seattle, University of Washington-Tacoma, and Western Washington University. We gratefully acknowledge the receipt of these data, and we wish to thank Elly Hagen, Cameron Colbo, Kimberly McDaniel, Jim Depaepe, and Joe Koski for their assistance with these data. This work is supported by the National Center for the Analysis of Longitudinal Data in Education Research (CALDER) (grant #R305C120008) and the Bill and Melinda Gates Foundation (grant #OPP1035217). Finally, we wish to thank Jennifer Branstad and Bret Sechrist for research assistance and Jordan Chamberlain for editorial assistance. The views expressed in this paper do not necessarily reflect those of the American Institutes of Research, the University of Washington, or Western Washington University. Responsibility for any and all errors rests solely with the authors.*

Suggested citation:

Krieg, J., Theobald, R., & Goldhaber, D. (2015). A foot in the door: Exploring the role of student teaching assignments in teachers' initial job placements. CEDR Working Paper 2015-2. University of Washington, Seattle, WA.

© 2015 by John Krieg, Roddy Theobald, and Dan Goldhaber. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission, provided that full credit, including © notice, is given to the source

You can access other CEDR publications at
<http://www.CEDR.us/publications.html>

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 public schools (Rich, 2014).¹ Most interventions studied in the existing literature are designed to influence the distribution of teacher quality among *current teachers*, but empirical evidence suggests that policymakers should also be concerned about patterns in hiring new teachers.² Indeed, a growing literature investigating where new teachers choose to teach 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 and 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 (or “internship”) assignments. Student teaching is a nearly universal component of traditional teacher education (Anderson and Stillman, 2013), and programs exercise great discretion over where prospective teachers complete their student teaching (Maier and Youngs, 2009). Moreover, recent evidence (Goldhaber et al., in press a) suggests a close relationship between where prospective teachers do their student teaching and where they find their first teaching job; in fact, nearly 40% of prospective teachers who found a

¹ For evidence on teacher quality gaps, see Clotfelter et al. (2005), Goldhaber et al. (in press b), Isenberg et al. (2013), and Lankford et al. (2002).

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. (in press). For research on locational preferences of teachers, see Boyd et al. (2005), and Reininger (2012).

job were hired into the same district where they completed their student teaching. Other than this, the literature on teacher hiring has largely ignored the relationship between where a teacher does her student teaching and where she finds her first teaching job.

We address this gap in the literature by connecting data on prospective teachers and student teaching assignments from six Washington State teacher education programs to data on all public school teachers in Washington State and provide the first 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 schools, and the process that moves these prospective teachers from their student teaching schools to their first public teaching position—and investigate outcomes from each process separately. The distinction is important for at least two reasons. First, each process could independently contribute to inequities in the distribution of new teacher hires. But perhaps more importantly, unlike nearly every other process that could influence the distribution of teacher quality across schools, the assignment of prospective teachers to student teaching schools is directly manipulable by policymakers.

We find a strong “draw of home” (Boyd et al., 2005) in student teaching assignments; that is, prospective teachers are very likely to student teach near where they grew up. On the other hand, we find that a teacher’s internship district is much more predictive of her first teaching job than her hometown. Put together, these findings suggest that the draw of home phenomenon in new teacher hiring (Boyd et al., 2005; Reiningger, 2012) is actually driven by patterns in student teaching assignments. Moreover, 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 interns, and that (controlling for the spatial relationships

above) the *characteristics* of an intern's student teaching district are quite predictive of the characteristics of her first teaching district. While we cannot distinguish whether these findings are driven by the preferences of interns, teacher education programs, 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.

The paper proceeds as follows. In Section II, we give some background information and review prior work in this area, and then describe our data and present summary statistics in Section III. In Section IV, we outline our analytic models, and present the estimates from these models in Section V. 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; and the process that moves these prospective teachers from their student teaching schools to their first public teaching position. We provide some background and review existing empirical literature about each process before proceeding to our own analyses.

Intern Placement into Student Teaching Positions

In Washington State (the setting for our study), the assignment of prospective teachers to student teaching (“internship”) positions is governed both by state code and contractual arrangements between teacher education programs (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 often interpreted by TEPs as a mandate to place interns in racially diverse internship schools.⁴ Field placement agreements, on the other hand, generally state that the TEP and district will make “cooperative arrangements” to determine interns’ student teaching assignments, and—at least among the contracts we reviewed—contain no further restrictions on the process of assigning interns 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 more affluent schools than the average school in the state, and speculate that the “social networks” created from these student teaching assignments may have implications for these candidates’ subsequent job searches.

Placement of new teachers into first teaching positions

While Maier and Youngs (2009) provide the only existing empirical evidence of placement in student teaching assignments, there is more evidence about the hiring of new teachers into initial teaching jobs, though we stress that only Goldhaber et al. (in press a) 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, and Reininger (2012) shows that this “draw of home” is much stronger for teachers than individuals in other professions. Since teachers disproportionately grow up and attend college in

⁴ 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).

advantaged areas, both papers argue that the draw of home phenomenon handicaps disadvantaged schools in the hiring process.

It is not clear, though, whether this draw of home is driven by the preferences of prospective teachers or hiring districts. Other studies have focused specifically on prospective teacher or district preferences in teacher hiring; for example, Bacolod (2007), Cannata (2010), and Engel et al. (in press) 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. Regardless of the degree to which the employment outcomes for new teachers reflect teacher or school district preferences, Engel and Cannata (2015) note that the outcomes from this process have clear consequences for the staffing of disadvantaged schools.

What is not clear from the existing literature, though, is what policymakers can do to make new teacher hiring more equitable across schools and districts. Surprisingly, despite the fact that the assignment of prospective teachers to student teaching assignments is one of the very few potential “policy levers” in the teacher hiring process, *no paper* in the existing literature considers the characteristics or location of the prospective teacher’s student teaching assignment as an additional factor in determining where prospective teachers begin their teaching careers. In fact, the only paper to consider the role of student teaching schools in teacher hiring is Goldhaber et al. (in press a), who find that more qualified prospective teachers (i.e., 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 dataset combines detailed information about prospective teachers (or “interns”) 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, Pacific Lutheran University, University of Washington-Bothell, University of Washington-Seattle, University of Washington-Tacoma, and Western Washington University—with K-12 data provided by Washington State’s Office of the Superintendent of Public Instruction (OSPI). Our analytic dataset is very similar to the dataset described in Goldhaber et al. (in press a), except with two additional years of K-12 data (from the 2012-13 and 2013-14 school years). We therefore refer readers to Goldhaber et al. (in press a) for descriptive information about the participating TEPs and prospective teachers (or “interns”) from these TEPs.

Our analytic dataset consists of 8,527 interns, 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. We use the full sample of interns to investigate outcomes from the process that assigns prospective teachers to their student teaching internships. To investigate outcomes from the process that moves interns from their student teaching positions to their first teaching jobs, we use the subset of 6,104 interns who are employed as a public school teacher in Washington State by our last year of observation (from the 2013-14 school year).⁵ Some variables of interest—such as scores on the state’s WEST-B credential exam test⁶, undergraduate GPA, and high school attended—are only available for a subset of interns⁷,

⁵ See Goldhaber et al. (in press a) for predictors of which interns enter the public teaching workforce.

⁶ The WEST-B credentialing test consists of three sub-tests: reading, writing, and mathematics. Students may take each sub-test 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.

so we investigate these variables in separate “sub-sample” models.⁸

A key component of our analysis incorporates measures of the distance between each of the state’s 296 public school districts⁹ and between each TEP and these districts. We calculate the distance between two districts as the linear distance between district centroids, 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 intern: (a) the distance from the intern’s TEP to internship district (all interns); (b) the distance from the intern’s high school district (“home”) to internship district (all interns with high school data); (c) the distance from the intern’s TEP to first job district (all hired interns); (d) the distance from the intern’s internship district to first job district (all hired interns); and (e) the distance from the intern’s high school district (“home”) to first job district (all hired interns with high school data). In each case, we also create an indicator for whether the districts are the same; i.e., whether the intern’s first job district is the same as the intern’s internship district.

Table 1 presents summary statistics for these distance measures. Panel A focuses on internship placement. For the 8,527 observations in our data, 51.4% student teach within 25 miles of their TEP and, for interns with high school data, nearly 50% train within 25 miles of their home district. But there are significant differences between TEPs in terms of the proximity of interns’ 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 highly the

⁷ The state has required teacher training applicants to pass the WEST-B credential exam starting in 2002, so we have WEST-B scores for more recent years of data. We received undergraduate GPAs for interns from UW-Tacoma and Western Washington University and partly for UW-Seattle, and received high school information for interns from Central Washington University, Western Washington University and partially for UW-Seattle.

⁸ There are also some variables, such as cooperating teacher characteristics and “network effects” (e.g., having a principal from the same TEP) that we do not include in this version of the analysis for parsimony.

⁹ In 2005, there was a merger between two school districts resulting in 295 districts.

concentrated urban areas, which contain more schools that train interns. This is important because interns from the non-Seattle/Tacoma TEPs constitute the vast majority of what we call our “high school sample”, or interns for whom we received high school data. As shown in the last row of Panel A, interns from our high school sample are less likely to be placed in an internship within 25 or 50 miles of their TEP than the average intern in our full sample.

Panel B of Table 2 presents similar summary statistics for hired interns’ first job location. Consistent with the “draw of home” findings of Boyd et al. (2005) and Reininger (2012), a high proportion hired interns find their first teaching job near home; over half of first jobs are within 25 miles of home and about two-thirds occur within 50 miles. Moreover, nearly one-in-four first jobs occur in the same district from which the intern graduated high school. But Panel B also suggests that the relationship between first job location and internship 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 internship district” are based on the same sample of hired interns. In this row, we see that almost 40% of hired interns 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 interns are also considerably more likely to teach within 25 or 50 miles of their internship district than their home district. Importantly, this is true even when we ignore the 15% of interns who are hired into the same building where they did their internship (in the last row on Panel B). 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 intern’s student teaching district and (for interns who are hired) first job district. We quantify this with four different variables: the percent of underrepresented minority (URM) students¹⁰; the

¹⁰ We define URM as black, Hispanic, or American Indian.

percent of students eligible for free/reduced priced lunch (FRL); the percent of students who passed the state math exam; and the percent of students who passed the state reading exam.¹¹ Since there is considerable variation in these variables across grades and 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 summarize average values of these variables for both internship districts and first job districts in **Table 2** (we focus solely on hired interns in this table so the same interns inform both sets of means). Two patterns emerge from Table 2. First, because these variables are standardized (so the average district in the state has a value of zero), the signs reveal that interns 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, interns tend to do their student teaching in higher-performing districts than the districts where they get their first job.

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 seventeen regions in New York State as a function of the proximity of those regions to the teacher's hometown and college. We build on these models in three important

¹¹ The state of Washington began defining building-level and district-level math and reading passing rates with the passage of NCLB in 2001, so we are missing these variables for the 7% of interns who did their student teaching and/or were hired prior to 2001.

ways. First, we estimate a similar model to Boyd et al. (2005), except predicting the location of each intern's *student teaching* rather than first job. Second, when we predict the location of each intern's first teaching job, we consider the location of her student teaching as an additional predictor. Finally, in each set of analyses, we use school districts as the unit of analysis rather than regions; that is, we predict whether an intern does her student teaching or received her first teaching job in each of the 296 Washington school districts. This allows us to directly control for different school district characteristics that may make it a more attractive district for an internship or job.

In what follows, we describe our models in terms of intern preferences, but we stress that outcomes from the process that assigns interns to student teaching positions reflect intern, TEP, and internship district preferences, and outcomes from the teacher hiring process similarly reflects the preferences of both the interns and hiring districts. Let $U_{ij} = \beta X_{ij} + \lambda Z_j + \varepsilon_{ij}$ be the i^{th} intern's utility for being trained in district j (in our first set of models) or receiving their first job in district j (in our second set of models). The X_{ij} represent the characteristics of individual i relative to district j (so there is one observation per intern and district), including a cubic of the log distance of district j to intern i 's TEP program and, for those observations with data, a cubic of log distance from district j to intern 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, internship 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:

$$(1) \quad P_{ij} = \frac{e^{\beta X_{ij} + \lambda Z_j}}{\sum_{k=1}^{296} e^{\beta X_{ik} + \lambda Z_k}}$$

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).

One 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 interns are more or less likely to intern 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 sub-samples) collegiate GPA and average WEST-B credentialing test score. For models investigating first job placement, we can also consider the intern's age (at time of first hire) and the length of time between their internship and first job, as these variables are only available for hired interns.

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, interns in our sample are more likely to do their student teaching near their TEPs, but this could be because interns prefer to remain near their TEPs, the TEPs themselves assign interns nearby for supervisory reasons, or districts near the TEPs prefer interns from that TEP. Nonetheless, the estimates from model (1) provide useful, descriptive information about patterns in the placement of interns in student teaching positions and their transition from student teaching to their first teaching jobs.

V. Results

Intern Placement into Student Teaching

We begin by investigating the factors predicting where prospective teachers complete their student teaching. **Table 3** presents six different specifications of (1) where P_{ij} represents the probability of intern i completing their student teaching in district j . The first column of this table presents results from all observations with valid individual and district variables. Positive coefficients signify an increase in the likelihood of serving an internship in a district. For instance, internships are more likely to occur in large districts and are less likely in districts with a high percentage of URM students.

Because we model distance from TEP to internship district as a cubic, interpreting the distance coefficients in Table 3 is difficult. To aid in this, Panel A of **Figure 2** contrasts the relative probability of student teaching in two districts, subscripted 1 and 2. Consider the case in which district 1 contains the intern's TEP (the solid line of Figure 2). In this case, an intern is about six times more likely to student teach in district 1 than in a district located twenty-five miles away and ten times more likely to student teach in district 1 than in a district that is thirty-five miles away. Even choosing between two districts, neither of which contains the TEP, suggests that distance to TEP matters considerably. For instance, an intern is twice as likely to student teach in a district ten miles from their TEP than one that is twenty miles away and almost six times as likely to intern in the nearby district as one that is forty miles distant.

The model reported in column 1 of Table 3 includes interactions between two intern variables (indicators that the intern is male and URM) and distance from TEP. The negative coefficient on the male interaction tells us that male interns are more likely to do their student teaching close to their TEP than female interns. In columns 2 and 3 of Table 3, we add additional interactions with variables that are only available for a subset of our sample (WEST-B score and intern undergraduate GPA). The coefficient on each interaction is negative, suggesting that more qualified interns are placed in internships closer to their TEPs, all else equal.

In columns 4-6 of Table 3, we add interactions that explore whether different types of interns are more or less likely to do their student teaching in disadvantaged districts (we report interactions with district %URM in this table, but find similar patterns when we consider other measures of district disadvantage).¹² In column 4, the coefficient on the interaction between intern URM and district %URM indicates that minority interns are more likely to serve as interns in districts with more minority students. The negative coefficients on the interactions between district %URM and intern average WEST-B score (column 5) and intern GPA (column 6) indicate that more qualified interns are less likely to serve internships in high minority districts, all else equal.

One possible confounding factor in the results in Table 3 is that student teachers may be receiving internship placements near their hometowns. If interns come from more advantaged locations, then internship placement based upon home location may create the impression that high ability interns are placed in more advantaged districts. To control for this possibility, we limit our sample to interns for whom we received high school data and estimate variants of equation (1) that include measures of the distance between each district and the intern's home (high school district).

The estimates from these models are reported in **Table 4** (note that, though we omit the coefficients from the table, all models control for the same district variables, Z_j , that were presented in Table 3). Panels B and C of **Figure 2** show the relative “pull” of TEP location (Panel B) and home location (Panel C) in internship assignments, estimated from the first column of Table 4. It is clear from these figures that, while TEP location is still predictive of student teaching placements, home location has a much stronger relationship with the location of an intern's student teaching district. The solid line in Panel C, for example, indicates that an

¹² Results for other measures of district disadvantage are available from the authors upon request.

intern is 50 times more likely to student teach in her home district than in a district 50 miles away from her home, all else equal. These findings strongly echo the findings of Boyd et al. (2005) about initial teacher hiring, and suggest that the “draw of home” is quite strong in student teaching assignments as well.

The remaining columns of Table 4 parallel columns 2-6 of Table 3. As before, minority interns are more likely to student teach in high minority districts. Interns with high collegiate GPAs are more likely to serve as interns near both their homes and TEPs. Importantly, the interactions between intern GPA, WEST-B, and district characteristics are no longer statistically significant. This could be because of the reduced sample size associated the high school subset, the different characteristics of interns in the high school subset, or possibly because controlling for high school proximity explains some of the relationship between internship qualifications and internship district characteristics. However, in all specifications reported in Table 4, the finding that the “draw to home” is a strong predictor of internship placement remains.

The transition from student teaching to first teaching jobs

We now turn to the subset of 6,104 interns observed to be hired as public teachers in Washington’s K-12 public schools and investigate the transition from student teaching to first job schools. **Table 5** presents estimates from equation (1) where P_{ij} represents the probability of intern i receiving her first teaching job in district j , estimated for observations across all six participating TEPs. Since we lack high school data for the complete sample of interns, these models only consider the distance between the 296 districts and each intern’s internship school and TEP. In **Table 6**, we limit the sample to interns with high school data and also include

measures of the distance between districts and each intern's hometown. All models include the same district controls from Table 3, although we do not report the coefficients for parsimony.¹³

Estimates from the base specification, reported in column 1 of Table 5, illustrate both the close relationship between the location of a teacher's internship district and first job district and how this relationship varies for different types of teachers.¹⁴ 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 3**. The solid line in Panel A shows, for example, that an intern is almost 50 times more likely to first teach in her internship district than in a district 30 miles away from her internship district, all else equal (i.e., controlling for the distance of each district from her TEP). Clearly, this is influenced the 15% of interns that begin their careers in the building in which they served as interns. However, consider the dashed line of Panel A which shows the relative probability of being employed at two districts, neither of which hosted their internship. A new teacher is almost four times more likely to teach at a district ten miles from their internship as one that is 25 miles from their internship suggesting that, even ignoring the high probability of being hired into an internship building, internship placement is closely related to first job placement.

The coefficients on the interactions in column 1 of Table 5 show that these relationships vary considerably for different types of teachers. Specifically, male teachers are more likely to teach farther from their internship schools, while older teachers are more likely to teach closer to their internship schools. Teachers who took more time between completing their internship and

¹³ Some of these coefficients are worth mentioning. Interns 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 equal.

¹⁴ We focus primarily on the estimates associated with internship school location, but also note some interesting estimates associated with TEP location. For example, all else 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.

being hired into their first job are also more likely to be hired into districts further from both their internship and TEP locations. When we include additional interactions with WEST-B scores (column 2) and undergraduate GPA (column 3), we find little evidence that more qualified interns receive jobs closer or further from either than TEPs or internship locations. However, when we include interactions with hiring district %URM in columns 4-6 of Table 5, we see that minority interns are more likely to receive jobs in high minority districts, while interns with higher WEST-B scores are less likely to be hired into high minority districts.

We now turn to the subset of interns for whom we observe high school data and report estimates from models that consider the distance between interns' home districts and first job districts in Table 6.¹⁵ These models essentially replicate the models reported in Boyd et al. (2005), but add variables related to each intern's student teaching experience. We first note that there are a number of interesting interactions in these models, and some results from Table 5 change once we control for hometown location. For example, we see in column 1 of Table 6 that minority interns are actually more likely to begin their teaching careers *closer* to their internship district than other teachers, controlling for the proximity of the district to their hometown and TEP. We also see in column 2 of Table 6 that, once we control for proximity to hometown, interns with higher WEST-B scores tend to find jobs closer to their internship districts, all else equal. Finally, interns who take longer to find a teaching job ("intern time to hire") are more likely to teach close to home than interns who find a teaching job quickly. 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.

¹⁵ We note that estimating the same models reported in Table 5 for this sample of interns produces very similar results as those reported in Table 5. We also note that we omit the coefficients related to distance from interns' TEPs from this table, but these coefficients are also similar to those reported in Table 5.

The most striking conclusion from Table 6, though, is that the relationship between first job location and hometown location (reported in Boyd et al., 2005 and Reininger, 2012) is dwarfed by the relationship between first job location and internship school location. We illustrate the relative magnitudes of these relationships in Panels B and C of Figure 3; the odds of a teacher beginning her career in her internship district relative to another district is consistently about ten times larger than the corresponding odds of a teacher beginning her career in her hometown district. This reinforces the conclusion from Table 1 that the location of a teacher’s internship seems to exert a much stronger influence on her 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 internship. Many of these interns experience a significantly different job search than interns 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 interns. Panels D and E of Figure 3 demonstrate that internship location is still much more predictive of first job location than hometown location, even for interns that are not hired directly into their internship school. Our overall conclusion, then, is that internship 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 interns who are not hired into their internship building to investigate the relationship between the *characteristics* of an intern’s internship district and the *characteristics* of her first job district (we focus on this sub-sample 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 7**. For each measure of district disadvantage, we find that the interns who do their student teaching in more disadvantaged district tend to get their first job

in more disadvantaged districts. Importantly, these models control for proximity to internship, home, and TEP, so the characteristics of an intern's student teaching district are predictive of the characteristics of an intern's 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 internship districts and first job districts. For example, interns may have a preference for teaching a particular type of student and select into districts, both for internships and first jobs, that have students who meet these preferences. Hiring districts may also give preference to prospective teachers who served internships in districts similar to theirs. Regardless of whether these findings reflect the preferences of teachers or hiring districts, though, the close relationship between internship 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

Our exploration of the process that moves prospective teachers from teacher education programs to student teaching placements and into the teaching workforce suggests several policy conclusions. But each of these conclusions comes with a number of caveats due the limitations of this analysis; hence we also suggest directions for future research. For example, one conclusion from our analysis of the assignment of interns to student teaching schools 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 interns to student teaching placements reflects the preferences of TEPs, interns, or internship 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 shows quite clearly that an intern's student teaching placement is highly predictive of where she finds her first teaching job, and much more predictive than her TEP or hometown. Given that an intern's hometown *is* highly predictive of where she does her student teaching, we see this as compelling evidence that the well-documented "draw of home" phenomenon is actually 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!) interns to do their student teaching in disadvantaged settings, these interns 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 interns to student teaching assignments: we cannot distinguish between the preferences of interns 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 interns' "preference" to work close to where they student taught is invariant to the type of district where they do their student teaching. That is, if a TEP decided to send all of their interns to do student teaching in disadvantaged schools and districts, we cannot know if these interns would still be as likely to stay in these schools and districts.

A final caveat is about the generalizability of our findings. Specifically, all of our results that contrast relationships between hometowns, internships, and first jobs are based on a sample of interns from just three Washington State TEPs that may not be representative of all TEPs in the state, let alone in the country. We therefore caution against generalizing our results to interns

from all TEPs, even in Washington State. 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.

References

- Anderson, L. M. & Stillman, J.A. (2013). Student teaching's contribution to preservice teacher development: A review of research focused on the preparation of teachers for urban and high-needs contexts." *Review of Educational Research* 83(1), 3-69.
- Bacolod, M. (2007). Who teaches and where they choose to teach: College graduates of the 1990s. *Educational Evaluation and Policy Analysis*, 29(3), 155-168.
- Boyd, D., Lankford, H., Loeb, S., & Wyckoff, J. (2005). The draw of home: How teachers' preferences for proximity disadvantage urban schools. *Journal of Policy Analysis and Management*, 24(1), 113-132.
- Boyd, D., Grossman, P., Lankford, H., Loeb, S., Michelli, N., & Wyckoff, J. (2006). Complex by design: Investigating pathways into teaching in New York City schools. *Journal of Teacher Education*, 57(2), 155-166.
- Boyd, D. J., Grossman, P. L., Lankford, H., Loeb, S., & Wyckoff, J. (2009). Teacher preparation and student achievement. *Educational Evaluation and Policy Analysis*, 31(4), 416-440.
- Boyd, D., Lankford, H., Loeb, S., Ronfeldt, M., & Wyckoff, J. (2011). The role of teacher quality in retention and hiring: Using applications-to-transfer to uncover preferences of teachers and schools. *Journal of Policy and Management*, Vol. 30(1), pp. 88-2011.
- Boyd, D., Lankford, H., Loeb, S., & Wyckoff, J. (2013). Analyzing the determinants of the matching of public school teachers to jobs: Disentangling the preferences of teachers and employers. *Journal of Labor Economics*, 31(1), 83-117.
- Cannata, M. (2010). Understanding the teacher job search process: Espoused preferences and preferences in use. *Teachers College Record* 112(12), 2889-2934.
- Clotfelter, C. T., Ladd, H. F., & Vigdor, J.L. (2005). Who teaches whom? Race and the distribution of novice teachers. *Economics of Education Review*, 24(4), 377-392.
- Clotfelter, C., Glennie, E., Ladd, H., & Vigdor, J. (2008a). Teacher bonuses and teacher retention in low-performing schools evidence from the North Carolina \$1,800 teacher bonus program. *Public Finance Review*, 36(1), 63-87.
- Clotfelter, C., Glennie, E., Ladd, H., & Vigdor, J. (2008b). Would higher salaries keep teachers in high-poverty schools? Evidence from a policy intervention in North Carolina. *Journal of Public Economics*, 92(5), 1352-1370.
- Engel, M., & Cannata, M. (2015). Localism and teacher labor markets: How geography and decision making may contribute to inequality. *Peabody Journal of Education*, 90(1), 84-92.
- Fulbeck, E. S. (2014). Teacher mobility and financial incentives: A descriptive analysis of Denver's ProComp. *Educational Evaluation and Policy Analysis*, 36(1), 67-82.
- Glazerman, S., Protik, A., Teh B., Bruch, J., and Max, J. (2013). Transfer incentives for high performing teachers: Final results from a multisite experiment (NCEE 2014-4003). Washington, DC: National Center for Education Evaluation and Regional Assistance, Institute of Education Sciences, U.S. Department of Education.

Goldhaber, D., Gross, B., & Player, D. (2011). Teacher career paths, teacher quality, and persistence in the classroom: Are public schools keeping their best? *Journal of Policy Analysis and Management*, 30(1), 57-87.

Goldhaber, D., Krieg, J., & Theobald, R. (in press a). Knocking on the door to the teaching profession? Modeling the entry of prospective teachers into the workforce. *Economics of Education Review*.

Goldhaber, D., Lavery, L., & Theobald, R. (in press b). Uneven playing field? Assessing the teacher quality gap between advantaged and disadvantaged students. *Educational Researcher*.

Grissom, J. A., Loeb, S., & Nakashima, N. A. (2014). Strategic involuntary teacher transfers and teacher performance: Examining equity and efficiency. *Journal of Policy Analysis and Management*, 33(1), 112-140.

Hanushek, E. A., Kain, J. F., & Rivkin, S. G. (2004). Why public schools lose teachers. *Journal of Human Resources*, 39(2), 326-354.

Hinrichs, P. (2013). What kind of teachers are schools looking for? Evidence from a randomized field experiment. In 38th Annual AEFP Conference.

Isenberg, E., Max, J., Gleason, P., Potamites, L., Santillano, R., Hock, H., & Hansen, M. (2013). Access to effective teaching for disadvantaged students. *National Center for Education Evaluation and Regional Assistance*, U.S. Department of Education.

Lankford, H., Loeb, S., & Wyckoff, J. (2002). Teacher sorting and the plight of urban schools: A descriptive analysis. *Educational Evaluation and Policy Analysis*, 24(1), 37-62.

Maier, A., & Youngs, P. (2009). Teacher preparation programs and teacher labor markets: How social capital may help explain teachers' career choices. *Journal of Teacher Education*, 60(4), 393-407.

National Council for Accreditation of Teacher Education (2010). Transforming teacher education through clinical practice: a national strategy to prepare effective teachers. Report of the Blue Ribbon Panel on Clinical Preparation and Partnerships for Improved Student Learning, Washington D.C.

Reininger, M. (2012). Hometown disadvantage? It depends on where you're from. Teachers' location preferences and the implications for staffing schools. *Educational Evaluation and Policy Analysis*, 34(2), 127-145.

Rich, M. (2014). U.S. to focus on equity in assigning of teachers. *The New York Times*, November 10, 2014.

Scafidi, B., Sjoquist, D. L., & Stinebrickner, T. R. (2007). Race, poverty, and teacher mobility. *Economics of Education Review*, 26(2), 145-159.

Tables and Figures

Table 1: Distance summary statistics

Panel A: Distances to internship district (all interns)									
	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 interns only)									
	Distance from TEP district			Distance from home district			Distance from internship 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 2: Standardized district measures of disadvantage

Panel A: All hired interns			
	First job	Internship	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 interns, less same building hires			
	First job	Internship	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 3: Predictors of internship district (all TEPs)

	1	2	3	4	5	6
ln(distance from TEP)	-3.377*** (0.605)	-3.103*** (0.817)	-3.191*** (1.123)	-3.351*** (0.604)	-3.018*** (0.816)	-3.271*** (1.122)
ln(distance from TEP) ²	0.842*** (0.185)	1.080*** (0.237)	0.813** (0.322)	0.833*** (0.184)	1.049*** (0.237)	0.820** (0.322)
ln(distance from TEP) ³	-0.107*** (0.018)	-0.136*** (0.023)	-0.102*** (0.030)	-0.106*** (0.018)	-0.132*** (0.023)	-0.103*** (0.030)
TEP in same district	-3.878*** (0.632)	-4.373*** (0.810)	-4.317*** (1.252)	-3.859*** (0.631)	-4.297*** (0.808)	-4.370*** (1.250)
TEP district and district same type	-0.023 (0.044)	0.071 (0.055)	0.067 (0.062)	-0.024 (0.044)	0.074 (0.055)	0.068 (0.062)
ln(distance from TEP) * intern male	-0.036** (0.018)	-0.013 (0.022)	-0.072*** (0.024)	-0.036* (0.018)	-0.012 (0.022)	-0.071*** (0.024)
ln(distance from TEP) * intern URM	0.055 (0.040)	0.044 (0.049)	0.103* (0.055)	0.046 (0.042)	0.038 (0.051)	0.095* (0.057)
ln(distance from TEP) * WEST-B		-0.003*** (0.001)			-0.003*** (0.001)	
ln(distance from TEP) * GPA			-0.036*** (0.012)			-0.020 (0.013)
ln(district enrollment)	1.380*** (0.025)	1.418*** (0.031)	1.294*** (0.040)	1.384*** (0.025)	1.424*** (0.031)	1.300*** (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)
District %FRL	0.018 (0.022)	0.047* (0.027)	0.270*** (0.040)	0.020 (0.022)	0.049* (0.027)	0.276*** (0.040)
District %URM	-0.222*** (0.038)	-0.249*** (0.045)	-0.254*** (0.070)	-0.223*** (0.038)	-0.249*** (0.045)	-0.259*** (0.070)
District % pass math test	0.020 (0.055)	-0.123* (0.070)	0.148* (0.085)	0.020 (0.055)	-0.125* (0.070)	0.153* (0.085)
District % pass reading test	0.085 (0.072)	0.238** (0.095)	0.046 (0.111)	0.082 (0.072)	0.232** (0.095)	0.044 (0.111)
District % bilingual	0.139*** (0.024)	0.119*** (0.029)	-0.127*** (0.047)	0.124*** (0.024)	0.524** (0.226)	0.186*** (0.072)
District is urban	-0.125*** (0.040)	-0.242*** (0.049)		-0.123*** (0.040)	-0.241*** (0.049)	
District is rural	0.619*** (0.066)	0.639*** (0.079)	0.043 (0.105)	0.620*** (0.066)	0.643*** (0.079)	0.039 (0.105)
District is in town	-0.128** (0.056)	-0.273*** (0.072)	-0.233*** (0.081)	-0.130** (0.056)	-0.276*** (0.072)	-0.242*** (0.081)
District %URM * intern URM				0.197*** (0.033)	0.178*** (0.037)	0.064 (0.092)
District %URM * intern WEST-B					-0.002* (0.001)	
District %URM * intern GPA						-0.099*** (0.018)
Observations	1,809,996	1,235,104	822,743	1,809,996	1,235,104	822,743

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

Table 4: Predictors of internship district (high school subset)

	1	2	3	4	5	6
ln(distance from home)	1.935** (0.984)	-1.308 (1.333)	1.708 (1.116)	1.919* (0.984)	-1.350 (1.334)	1.706 (1.116)
ln(distance from home) ²	-1.121*** (0.289)	-0.863** (0.354)	-1.005*** (0.325)	-1.117*** (0.289)	-0.858** (0.354)	-1.000*** (0.325)
ln(distance from home) ³	0.123*** (0.027)	0.100*** (0.033)	0.114*** (0.030)	0.123*** (0.027)	0.099*** (0.033)	0.114*** (0.030)
Home in same district	1.691 (1.070)	0.570 (1.311)	1.220 (1.200)	1.672 (1.070)	0.550 (1.310)	1.219 (-1.200)
Home district and district same type	-0.108* (0.061)	-0.040 (0.074)	-0.216*** (0.073)	-0.109* (0.061)	-0.042 (0.074)	-0.216*** (0.073)
ln(distance from home) * intern male	0.038 (0.045)	0.064 (0.057)	0.037 (0.055)	0.038 (0.045)	0.064 (0.056)	0.036 (0.055)
ln(distance from home) * intern URM	0.129 (0.095)	0.136 (0.116)	0.023 (0.127)	0.147 (0.096)	0.128 (0.118)	0.022 (0.127)
ln(distance from home) * WEST-B		0.009*** (0.002)			0.008*** (0.002)	
ln(distance from home) * GPA			-0.069* (0.038)			-0.069* (0.038)
ln(distance from TEP)	8.927*** (1.847)	12.333*** (2.467)	9.876*** (2.067)	8.947*** (1.844)	12.264*** (2.463)	9.871*** (2.067)
ln(distance from TEP) ²	-2.859*** (0.515)	-3.720*** (0.669)	-3.124*** (0.571)	-2.867*** (0.515)	-3.722*** (0.667)	-3.124*** (0.571)
ln(distance from TEP) ³	0.243*** (0.046)	0.313*** (0.060)	0.273*** (0.051)	0.244*** (0.046)	0.313*** (0.059)	0.273*** (0.051)
TEP in same district	9.371*** (2.124)	13.391*** (2.773)	9.237*** (2.393)	9.377*** (2.120)	13.341*** (2.764)	9.236*** (2.393)
TEP district and district same type	0.073 (0.101)	0.185 (0.122)	-0.017 (0.099)	0.072 (0.101)	0.190 (0.122)	-0.017 (0.099)
ln(distance from TEP) * intern male	-0.031 (0.038)	-0.006 (0.045)	-0.039 (0.043)	-0.031 (0.038)	-0.005 (0.045)	-0.038 (0.043)
ln(distance from TEP) * intern URM	0.040 (0.086)	0.050 (0.102)	-0.008 (0.109)	0.009 (0.090)	-0.011 (0.111)	-0.006 (0.110)
ln(distance from TEP) * WEST-B		-0.000 (0.002)			0.000 (0.002)	
ln(distance from TEP) * GPA			-0.100*** (0.032)			-0.098*** (0.032)
District %URM * intern URM				0.154** (0.075)	0.218** (0.087)	-0.014 (0.168)
District %URM * intern WEST-B					-0.001 (0.002)	
District %URM * intern GPA						-0.016 (0.048)
Observations	521,616	350,089	392,975	521,616	350,089	392,975

NOTES: p-values from two-sided t-test: *p<.10; **p<.05; ***p<.01. All models include district controls from Table 3.

Table 5: Predictors of first job district (all TEPs)

	1	2	3	4	5	6
ln(distance from internship)	6.429*** (0.669)	5.510*** (0.913)	6.007*** (1.028)	6.417*** (0.668)	5.460*** (0.913)	6.008*** (1.028)
ln(distance from internship) ²	-2.362*** (0.205)	-2.096*** (0.260)	-2.284*** (0.310)	-2.359*** (0.205)	-2.086*** (0.260)	-2.284*** (0.310)
ln(distance from internship) ³	0.229*** (0.020)	0.200*** (0.025)	0.225*** (0.030)	0.228*** (0.020)	0.199*** (0.025)	0.225*** (0.030)
Internship in same district	6.894*** (0.694)	6.248*** (0.878)	6.150*** (1.083)	6.880*** (0.693)	6.213*** (0.876)	6.149*** (1.082)
Internship district and district same type	-0.068* (0.041)	-0.053 (0.051)	-0.079 (0.061)	-0.067* (0.041)	-0.052 (0.051)	-0.079 (0.061)
ln(distance from internship) * intern male	0.137*** (0.025)	0.143*** (0.031)	0.221*** (0.040)	0.136*** (0.025)	0.142*** (0.031)	0.219*** (0.040)
ln(distance from internship) * intern age	-0.008*** (0.001)	-0.008*** (0.002)	-0.008*** (0.002)	-0.008*** (0.001)	-0.009*** (0.002)	-0.008*** (0.002)
ln(distance from internship) * intern time to hire	0.058*** (0.006)	0.065*** (0.009)	0.067*** (0.009)	0.058*** (0.006)	0.066*** (0.009)	0.067*** (0.009)
ln(distance from internship) * intern URM	0.022 (0.049)	0.024 (0.059)	-0.116 (0.092)	0.033 (0.050)	0.032 (0.060)	-0.121 (0.094)
ln(distance from internship) * WEST-B		0.001 (0.001)			0.001 (0.001)	
ln(distance from internship) * GPA			-0.033* (0.017)			-0.033* (0.017)
ln(distance from TEP)	-4.066*** (0.739)	-2.472** (1.122)	-0.220 (1.548)	-4.043*** (0.739)	-2.431** (1.120)	-0.230 (1.547)
ln(distance from TEP) ²	1.343*** (0.224)	0.899*** (0.286)	0.473 (0.435)	1.335*** (0.223)	0.877*** (0.286)	0.472 (0.435)
ln(distance from TEP) ³	-0.135*** (0.022)	-0.088*** (0.028)	-0.071* (0.040)	-0.134*** (0.022)	-0.085*** (0.028)	-0.071* (0.040)
TEP in same district	-5.099*** (0.772)	-4.052*** (0.983)	0.474 (1.760)	-5.087*** (0.771)	-4.019*** (0.980)	0.463 (1.759)
TEP district and district same type	0.275*** (0.053)	0.264*** (0.064)	-0.221*** (0.065)	0.270*** (0.053)	0.259*** (0.064)	-0.219*** (0.065)
ln(distance from TEP) * intern male	-0.135*** (0.041)	-0.155*** (0.052)	-0.239*** (0.059)	-0.133*** (0.041)	-0.153*** (0.052)	-0.236*** (0.059)
ln(distance from internship) * intern age	-0.008*** (0.003)	-0.008*** (0.003)	-0.005 (0.004)	-0.008*** (0.003)	-0.008** (0.003)	-0.005 (0.004)
ln(distance from internship) * intern time to hire	0.020* (0.011)	0.015 (0.016)	0.002 (0.015)	0.020* (0.011)	0.014 (0.016)	0.002 (0.015)
ln(distance from TEP) * intern URM	-0.113 (0.089)	-0.066 (0.114)	0.180 (0.149)	-0.137 (0.089)	-0.080 (0.115)	0.103 (0.151)
ln(distance from TEP) * WEST-B		-0.001 (0.002)			-0.001 (0.002)	
ln(distance from TEP) * GPA			0.025 (0.030)			0.029 (0.031)
District %URM * intern URM				0.189*** (0.040)	0.151*** (0.046)	0.259*** (0.084)
District %URM * intern WEST-B					-0.002** (0.001)	
District %URM * intern GPA						-0.014 (0.019)
Observations	1,330,323	847,537	641,733	1,330,323	847,537	641,733

NOTES: p-values from two-sided t-test: *p<.10; **p<.05; ***p<.01. All models include district controls from Table 3.

Table 6: Predictors of first job district (high school sample)

	1	2	3	4	5	6
ln(distance from internship)	4.783*** (1.319)	7.220*** (2.016)	5.376*** (1.516)	4.753*** (1.319)	7.209*** (2.017)	5.373*** (1.516)
ln(distance from internship) ²	-1.689*** (0.393)	-1.745*** (0.554)	-1.836*** (0.451)	-1.680*** (0.393)	-1.737*** (0.554)	-1.837*** (0.451)
ln(distance from internship) ³	0.164*** (0.038)	0.164*** (0.053)	0.176*** (0.043)	0.163*** (0.038)	0.163*** (0.053)	0.176*** (0.043)
Internship in same district	5.163*** (1.404)	5.772*** (1.970)	5.591*** (1.600)	5.133*** (1.404)	5.744*** (1.970)	5.596*** (1.600)
Internship district and district same type	0.018 (0.073)	0.106 (0.096)	-0.034 (0.083)	0.018 (0.073)	0.105 (0.096)	-0.033 (0.083)
ln(distance from internship) * intern male	0.162*** (0.050)	0.193*** (0.066)	0.149** (0.060)	0.161*** (0.050)	0.192*** (0.066)	0.146** (0.060)
ln(distance from internship) * intern age	-0.019*** (0.004)	-0.020*** (0.007)	-0.016*** (0.005)	-0.019*** (0.004)	-0.020*** (0.007)	-0.016*** (0.005)
ln(distance from internship) * intern time to hire	0.092*** (0.014)	0.075*** (0.022)	0.093*** (0.015)	0.092*** (0.014)	0.075*** (0.022)	0.093*** (0.015)
ln(distance from internship) * intern URM	-0.189* (0.107)	-0.289** (0.137)	-0.376** (0.152)	-0.184* (0.108)	-0.287** (0.138)	-0.399** (0.157)
ln(distance from internship) * WEST-B		-0.007*** (0.003)			-0.007*** (0.003)	
ln(distance from internship) * GPA			-0.064 (0.040)			-0.062 (0.041)
ln(distance from home)	0.215 (1.083)	-0.585 (1.615)	0.009 (1.209)	0.208 (1.083)	-0.637 (1.618)	-0.026 (1.211)
ln(distance from home) ²	-0.549* (0.312)	-0.339 (0.419)	-0.386 (0.344)	-0.547* (0.312)	-0.339 (0.419)	-0.382 (0.345)
ln(distance from home) ³	0.055* (0.029)	0.035 (0.039)	0.036 (0.032)	0.055* (0.029)	0.035 (0.039)	0.036 (0.032)
Home in same district	1.204 (1.185)	0.516 (1.602)	0.769 (1.302)	1.194 (1.185)	0.515 (1.603)	0.757 (1.303)
Home district and district same type	0.120* (0.068)	0.190** (0.090)	0.102 (0.077)	0.120* (0.068)	0.191** (0.090)	0.100 (0.077)
ln(distance from home) * intern male	0.003 (0.050)	0.022 (0.065)	-0.056 (0.059)	0.004 (0.050)	0.022 (0.065)	-0.055 (0.059)
ln(distance from home) * intern age	0.030*** (0.006)	0.035*** (0.008)	0.029*** (0.006)	0.030*** (0.006)	0.035*** (0.008)	0.028*** (0.006)
ln(distance from home) * intern time to hire	-0.028** (0.012)	-0.013 (0.019)	-0.017 (0.013)	-0.028** (0.012)	-0.013 (0.019)	-0.017 (0.013)
ln(distance from home) * intern URM	-0.058 (0.111)	-0.052 (0.145)	-0.049 (0.165)	-0.050 (0.112)	-0.051 (0.145)	-0.053 (0.165)
ln(distance from home) * WEST-B		-0.000 (0.002)			0.000 (0.003)	
ln(distance from home) * GPA			-0.060 (0.050)			-0.052 (0.050)
District %URM * intern URM				0.082 (0.081)	0.047 (0.099)	0.181 (0.134)
District %URM * intern WEST-B					-0.001 (0.002)	
District %URM * intern GPA						-0.074** (0.036)
Observations	432,623	246,276	349,688	432,623	246,276	349,688

NOTES: p-values from two-sided t-test: *p<.10; **p<.05; ***p<.01. All models include district controls from Table 3 and institution distances and interactions from Table 5.

Table 7: Predictors of first job district (all TEPs, less same building hires)

	1	2	3	4	5
ln(distance from internship)	6.568*** (0.682)	6.490*** (0.691)	6.512*** (0.689)	6.642*** (0.680)	6.688*** (0.682)
ln(distance from internship) ²	-2.377*** (0.210)	-2.351*** (0.213)	-2.350*** (0.212)	-2.389*** (0.209)	-2.405*** (0.209)
ln(distance from internship) ³	0.230*** (0.021)	0.227*** (0.021)	0.227*** (0.021)	0.231*** (0.020)	0.233*** (0.021)
Internship in same district	6.424*** (0.707)	6.354*** (0.715)	6.376*** (0.713)	6.474*** (0.705)	6.522*** (0.706)
Internship district and district same type	-0.060 (0.041)	-0.076* (0.042)	0.188*** (0.030)	0.180*** (0.029)	0.180*** (0.029)
ln(distance from internship) * intern male	0.178*** (0.029)	0.187*** (0.030)	-0.010*** (0.002)	-0.010*** (0.002)	-0.010*** (0.002)
ln(distance from internship) * intern age	-0.010*** (0.002)	-0.010*** (0.002)	0.040*** (0.008)	0.042*** (0.007)	0.043*** (0.007)
ln(distance from internship) * intern time to hire	0.043*** (0.007)	0.040*** (0.008)	0.027 (0.058)	0.025 (0.058)	0.026 (0.058)
ln(distance from internship) * intern URM	0.026 (0.058)	0.030 (0.058)	-0.078* (0.042)	-0.055 (0.041)	-0.059 (0.041)
ln(distance from TEP)	-4.008*** (0.765)	-3.923*** (0.774)	-3.893*** (0.772)	-4.008*** (0.761)	-4.020*** (0.763)
ln(distance from TEP) ²	1.312*** (0.232)	1.280*** (0.235)	1.264*** (0.234)	1.305*** (0.230)	1.307*** (0.231)
ln(distance from TEP) ³	-0.132*** (0.022)	-0.128*** (0.023)	-0.126*** (0.023)	-0.131*** (0.022)	-0.131*** (0.022)
TEP in same district	-4.942*** (0.798)	-4.890*** (0.805)	-4.851*** (0.803)	-4.929*** (0.793)	-4.967*** (0.795)
TEP district and district same type	0.249*** (0.054)	0.254*** (0.055)	-0.163*** (0.044)	-0.158*** (0.043)	-0.157*** (0.043)
ln(distance from TEP) * intern male	-0.155*** (0.043)	-0.161*** (0.044)	-0.008*** (0.003)	-0.007*** (0.003)	-0.007*** (0.003)
ln(distance from internship) * intern age	-0.008*** (0.003)	-0.008*** (0.003)	0.026** (0.012)	0.021* (0.012)	0.021* (0.012)
ln(distance from internship) * intern time to hire	0.021* (0.012)	0.026** (0.012)	-0.082 (0.100)	-0.077 (0.098)	-0.075 (0.099)
ln(distance from TEP) * intern URM	-0.079 (0.098)	-0.085 (0.100)	0.247*** (0.055)	0.239*** (0.054)	0.235*** (0.054)
District %URM * intern URM	0.183*** (0.041)	0.175*** (0.042)	0.172*** (0.043)	0.175*** (0.042)	0.173*** (0.042)
District %URM * Internship district %URM		0.015*** (0.006)			
District % FRL * Internship District % FRL			0.031*** (0.007)		
District % Pass Math * Internship District % Pass Math				1.026*** (0.196)	
District % Pass Read * Internship District % Pass Read					1.677*** (0.317)
Observations	1,137,842	1,110,438	1,110,438	1,137,842	1,137,842

NOTES: p-values from two-sided t-test: *p<.10; **p<.05; ***p<.01. All models include district controls from Table 3.

Figure 1. Proportion of New Teachers from Participating Institutions

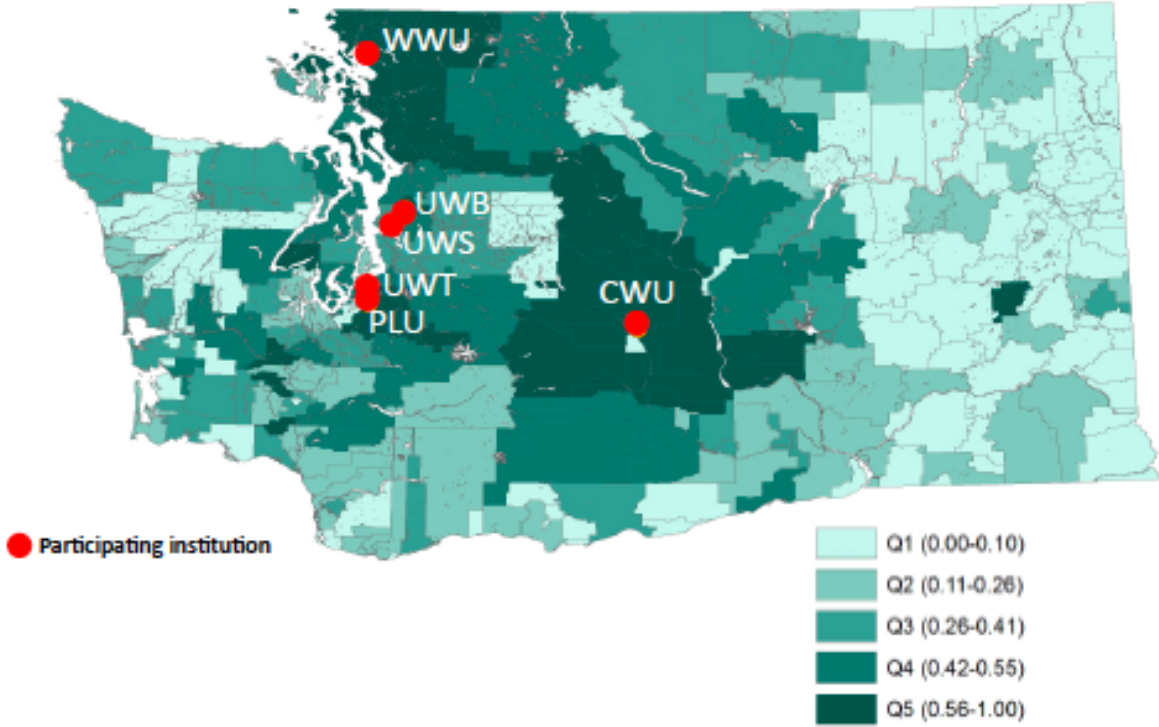
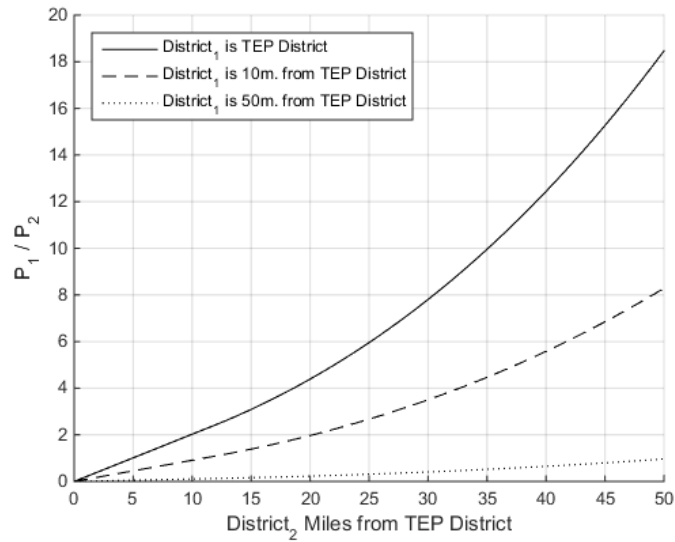
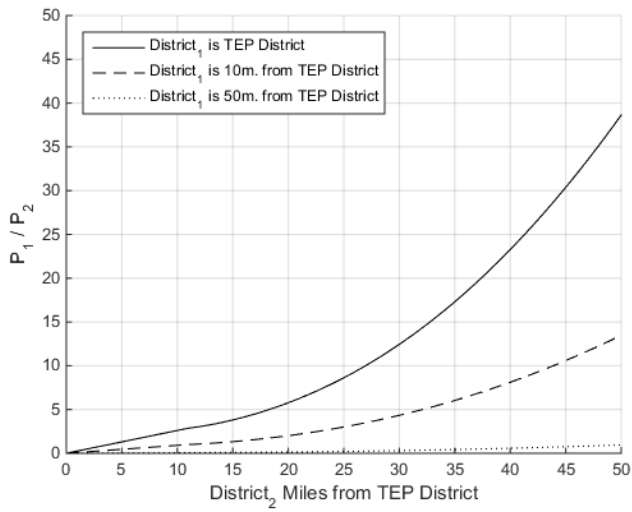


Figure 2: Relationships Between Distance Measures and Internship Placement

A. All TEPs



B. High School Sample



C. High School Sample

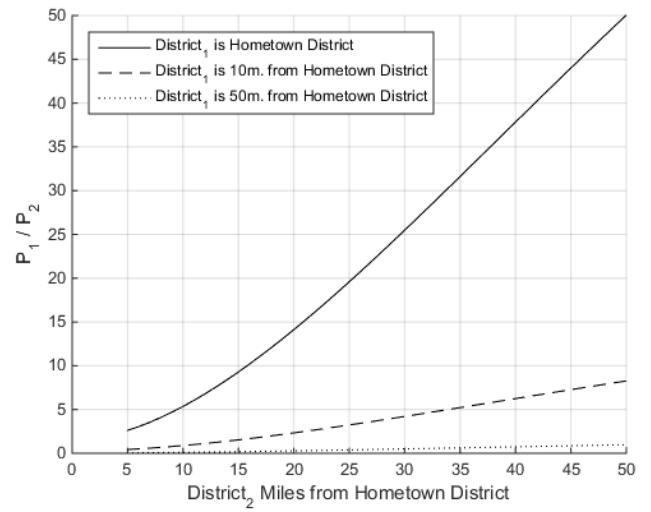
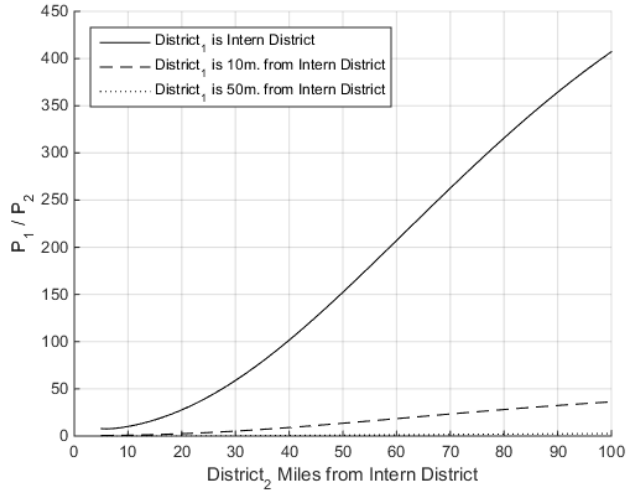
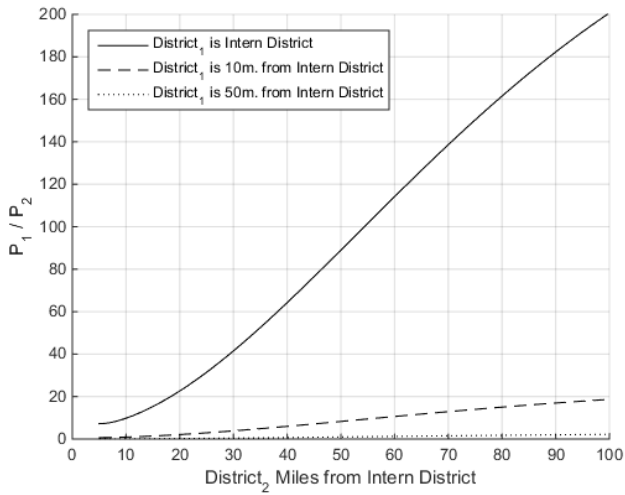


Figure 3: Relationships Between Distance Measures and First-Job Placement

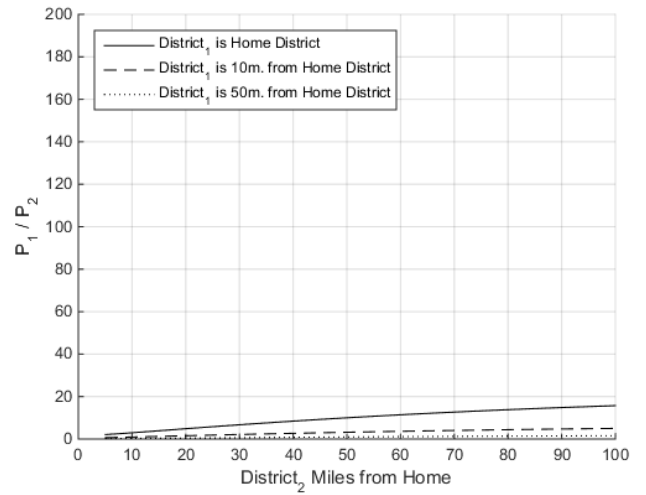
A. All TEPs



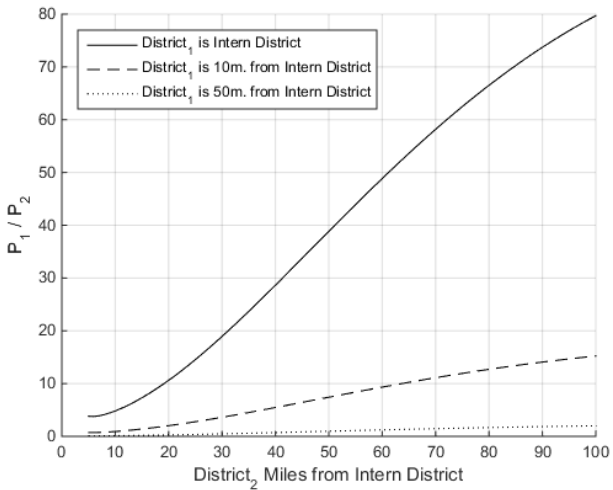
B. High School Sample



C. High School Sample



D. High School Sample, less same building hires



E. High School Sample, less same building hires

