Knocking on the Door to the Teaching Profession? Modeling the Entry of Prospective Teachers into the Workforce

DAN GOLDHABER

JOHN M. KRIEG

RODDY THEOBALD

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Dan Goldhaber
University of Washington Bothell

John M. Krieg
Western Washington University

Roddy Theobald
University of Washington

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Acknowledgements

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Abstract

We use a unique longitudinal sample of student teachers ("interns") from six Washington state teacher training institutions to investigate patterns of entry into the teaching workforce. Specifically, we estimate split population models that simultaneously estimate the impact of individual characteristics and student teaching experiences on the timing and probability of initial hiring as a public school teacher. Not surprisingly, we find that interns endorsed to teach in "difficult-to-staff" areas are more likely to be hired as teachers than interns endorsed in other areas. Younger interns, white interns, and interns who did their student teaching in suburban schools are also more likely to find a teaching job. Prospective teachers who do their internships at schools that have more teacher turnover are more likely to find employment, often at those schools. Finally, interns with higher credential exam scores are more likely to be hired by the school where they did their student teaching. Contrary to expectations, few of the measures of the quality or the experience of an intern's cooperating teacher are predictive of workforce entry in the expected direction.

I. The first step of the career path

The past 20 years have seen a proliferation of empirical research into the composition

and distribution of the teacher workforce. Extensive quantitative work investigates where

teachers choose to teach, and the factors that determine whether and when teachers choose to

leave the public teaching workforce.[1] But there is far less research on the first step of a teacher's

career path: who enters the teaching workforce in the first place?

The scarcity of empirical research on entry into the teacher workforce is surprising.

Teacher training has come under increased scrutiny (e.g. Greenberg et al., 2013), and a growing

literature investigates the impact of pre-service training—either the training program itself

(Boyd et al., 2009; Goldhaber et al., 2013; Koedel et al., 2012; Mihaly et al., 2013) or student

teaching experiences (Boyd et al., 2006, 2008; Ronfeldt, 2012; Ronfeldt et al., 2013)—on teacher

mobility and effectiveness. These studies, however, focus on individuals who decided to enter

the teaching workforce and received a teaching job. Many studies do address the factors that

influence the decision to get a teaching degree or the decision to enter the teaching workforce,[2]

but lack detailed information about teacher training experiences, student teaching in particular.

As such, they ignore the potential differential effects of pre-service training experiences on the

probability of workforce entry and outcomes after workforce entry.

There are good reasons to consider the implications of pre-service training for all

prospective teachers, not just those who ultimately end up in the teacher labor market. Those

pursuing a teaching career, for instance, certainly care a great deal about the probability that

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[1] For instance, for research on where teachers choose to teach see Boyd et al. (2005, 2011, 2013), Maier & Youngs (2009), Reininger (2012); and for research on attrition from the public school labor force see Brewer (1996), Boyd et al. (2008), DeAngelis and Presley (2011), Goldhaber et al. (2011), Ingersoll et al. (2012), Krieg (2006), Ronfeldt (2012), Scafidi et al. (2008), Stinebrickner (2001).

[2] See Bacolod (2007), Ballou (1996), Boyd et al. (2007), Boyd et al. (2013), Engel et al. (forthcoming), Goldhaber and Liu (2003), Goldhaber and Walch (2014), Hanushek and Pace (1995), Ingersoll and Perda (2010), and Podgursky et al. (2004).

their training experiences will result in a teaching job at some point in the near future. Moreover, policymakers who approve subsidies for teacher training programs would likely hope that most students in these programs ultimately find employment as a teacher.

There is also a concern that research focusing solely on in-service teachers could provide a misleading picture on the efficacy of training practices. For instance, suppose that a particular pre-service training intervention is found to positively impact the effectiveness and retention of those individuals who enter the workforce, but negatively affects the likelihood that prospective teachers opt to enter the profession. It is conceivable that the benefits of the intervention for in-service teachers are offset by the increased cost associated with having to train more people for a comparable yield. Clearly the yield of teacher trainees must be considered as part of an analysis of the cost-effectiveness of any pre-service intervention.

In this paper we focus on the teacher training experiences of "interns" (i.e., students in traditional teacher training programs who complete student teaching and other requirements to receive a teaching credential) from a sample of six training institutions in Washington state. These interns can be linked with longitudinal data to allow us to estimate the probability that individuals who obtain a teaching credential end up employed in a public school teaching job, employed in a private school teaching job, employed in a public school non-teaching job, or not employed in any public or private school job within the state.

After investigating placement of interns into these four categories, we then consider hiring into a public school teaching position or not being hired at all as a binary outcome (dropping the small number of interns in the other two categories), and estimate split population models that simultaneously model the impact of covariates on the timing and probability that an intern finds a public school teaching job. Controlling for differences in placement rates by training institution and over time, we find that interns endorsed to teach in

"difficult-to-staff areas" like math and science (STEM), special education, and English Language Learning (ELL) find a teaching job faster and with higher probability than interns endorsed in other areas. We also find that younger interns and interns who complete their student teaching in a suburban school are more likely to enter the teaching workforce. Interns who do their student teaching in a school with high teacher turnover are also more likely to enter the teaching workforce, often at their internship school. Finally, the probability that an intern is hired by her internship school increases as the intern's credential exam scores increases. Interestingly, however, we find little evidence that characteristics of an intern's cooperating teacher are predictive of entry into the school workforce.

Our analysis unifies and builds on three strands of the teacher labor market literature: recruitment and retention of teachers in difficult-to-staff subject areas; impacts of teacher training and student teacher experiences; and evidence on teacher workforce entry. We review this literature in section II, describe our data in section III, give an overview of our analytic approach in section IV, and then present our results in section V.

II. Difficult-to-staff areas, pre-service experiences, and workforce entry

The difficulty that school systems face in recruiting and retaining teachers in "difficult-to-staff" areas like STEM, special education, and ELL remains a major policy concern. For example, of the 14 fields (of 62) identified by the American Association for Employment in Education (2008) as "considerable shortage categories", nine fall into the special education field, three into STEM, and one into ELL. The situation is similar in Washington state, as each area with demonstrated teacher shortages falls into math, science, special education, or ELL (OSPI, 2007). Blank et al. (2007) and Ingersoll (2003) also document that there are a surprising number of

individuals who teach in STEM areas that they are not certified to teach, presumably due to the shortages in these areas.

The literature seeking to explain the causes of the above findings blames the "revolving door" of qualified teachers disproportionately leaving teaching positions early for non-retirement reasons like job dissatisfaction or better-paying jobs outside of teaching (Ingersoll, 2001). Liu et al. (2008) focus particularly on the difficulty urban districts face in recruiting and retaining teachers in mathematics, and conclude that administrators in urban districts tend to recruit teachers with strong classroom management skills over math experts when they cannot get both. Fore et al. (2002), McCleskey et al. (2004), and Boe (2006) explore the causes of the national shortage of special education teachers, and conclude that the primary causes are high demand (due to small class sizes), combined with the high attrition of special education teachers due to heavy workloads and "burnout".

While a large literature exists on the impacts of student teaching (see Anderson and Stillman (2013) for a comprehensive review), the vast majority of these studies are case studies with very small sample sizes.[3] For example, Connelly and Graham (2009) focus on a small sample of special education teachers and find that teachers who receive ten or more weeks of training in special education are less likely to burnout and more likely to return for a second year of teaching than teachers who received fewer weeks of training.

A small quantitative literature uses substantially larger samples to link various features of teacher training to data on teacher career paths and effectiveness.[4] Boyd et al. (2006) find evidence that programs that include a capstone project—where teachers relate curriculum learning to actual practices—as part of the student teaching experience tend to produce more

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[3] For example, the largest sample size of the many articles reviewed in Anderson and Stillman (2013) is 335, while the majority has sample sizes under 100.
[4] Several studies also focus on the association between teacher training programs and teacher effectiveness (Boyd et al., 2009; Goldhaber et al., 2013; Koedel et al., 2012; Mihaly et al., 2013).

effective first-year teachers. Boyd et al. (2008) find that, in terms of students' math achievement in particular, teachers who identify similarities between their student teaching experience and their first-year classroom experiences have greater student achievement gains. More recently, Ronfeldt (2012) suggests teacher pre-service placement may be linked both to the length of time a teacher stays in the school district and to teacher value-added gains in student achievement, while Ingersoll et al. (2012), Papay et al. (2012), and Ronfeldt et al. (2013) each find positive effects of more extensive teacher training on teacher retention.

The studies cited to this point aid in our understanding of the value of different aspects of pre-service training, but they also illustrate an important shortcoming: they all focus on a sample of individuals who are already in the teaching workforce. A small literature also investigates the differences between college graduates who do and do not enter teaching. Hanushek and Pace (1995), Goldhaber and Liu (2002), and Podgursky et al. (2004) each demonstrate that college students who opt to go into teaching tend to have lower academic qualifications than their peers, although recent research suggests that the situation may be changing (Goldhaber and Walch, 2014). Goldhaber and Liu (2002), Bacolod (2007), and Ingersoll and Perda (2010) also demonstrate that graduates with degrees in STEM areas are less likely to become teachers.

Each of these studies compares individuals who decide to become teachers with college graduates or attendees who decide not to become teachers, but this may not be the relevant comparison group for all policy questions. For example, if we are interested in the impacts of teacher training experiences, training programs cannot have an impact on students who do not enroll in their programs. Likewise, if we are interested in school hiring practices, schools cannot hire teachers who do not have a teaching degree. Thus we argue that the relevant comparison

group, at least in these cases, is individuals who *did* get a teaching degree but *did not* become a teacher.

To our knowledge, only three papers have focused specifically on the transition of prospective teachers from training programs into the teaching workforce. Ballou (1996) focuses on the school side of the teacher hiring process, and finds little evidence that strong academic credentials help a prospective teacher's job prospects. Engel et al. (forthcoming), on the other hand, focus on the preferences of prospective teachers (as measured by the schools where they choose to apply), and find that schools serving more advantaged students receive more applicants per vacancy. Finally, Boyd et al. (2013) use a two-sided matching model to try to disentangle the preferences of teachers and schools. Their findings run contrary to Ballou (1996) in that they do find evidence that schools demonstrate preferences for prospective teachers with stronger academic credentials, and reinforce the conclusion from Engel et al. (forthcoming) that prospective teachers prefer schools with more advantaged students.

Our analysis unifies and builds on the strands of the teacher labor market literature discussed above. Specifically, we investigate the transition of prospective teachers from training programs into the teaching workforce, focusing on the potential importance of different aspects of training (i.e., areas of specialization and student teaching experiences) as predictors of whether, and when, a prospective teacher ends up teaching. The next section describes the data that allow us to investigate these questions.

III. Data and summary statistics

Data

We compile data from three sources. First, six Washington state universities—Central

Washington University, Pacific Lutheran University, University of Washington-Bothell, University of Washington-Seattle, University of Washington-Tacoma, and Western Washington University—provided data on college students in their teaching training programs who completed student-teaching internships in Washington state public schools. Figure 1 shows that five of the six universities are located in the western third of the state, and none are in the eastern third. As a result, our participating institutions disproportionately serve school systems on the western side of the state (see Figure 2, showing the percentage of teachers in each school district in the state from these training programs). This is not surprising given that teachers tend to be employed close to where they did their training (Boyd et al., 2005; Reininger, 2012).

Together, our participating institutions graduate roughly one third of the teachers who enter the Washington state teaching workforce each year, and include three of the four largest teacher training institutions in the state (as measured by the average number of workforce entrants from each program).[5] Table 1 provides summary statistics for teachers who entered the workforce between 2005-06 and 2007-08[6] from participating institutions, non-participating institutions from Washington state, and out-of-state institutions. New teachers from our participating institutions are more likely to be endorsed in math or special education, and less likely to be endorsed in elementary education. Overall, while teachers from participating institutions appear to be somewhat representative of all new teachers in the state, we caution that our sample is not a random sample of all teacher training graduates in the state.

Teacher training institutions provided information on each college student who

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[5]There are a total of 20 teacher training institutions in Washington (see Goldhaber et al. (2013) for a full list.) Approximately 15 percent of the state's public school teachers were trained outside the state (see Table 1). See http://program.pesb.wa.gov/reports/reporting_progress/clinicallocation for detailed maps on where Washington teachers tend to do their student teaching.
[6] These are the three years in which we have data on interns from all six participating institutions.

completed a student-teacher internship (referred to as "interns") during a specific range of

years, though the range of years for which data were available varies by university.[7] They also

provided certificate numbers (which are necessary to link interns to the state's administrative

teacher databases), the academic year of the internship, the building and district in which the

internship occurred, and the name of the teacher supervising the internship (the "cooperating

teacher").[8] Some universities also provided additional demographic and extended academic

background data about their interns.[9]

We merge the data on interns with information provided by Washington's Office of the

Superintendent of Public Instruction (OSPI) which includes annual observations of every K-12

employee in the state between 1994 and 2011,[10] linkable both to interns who were hired by

Washington state public schools (either as teachers or in a non-teaching role) and their

supervising (cooperating) teachers. OSPI also provided linkable data for all private school

teachers in the state for the years 2004-2011. We identify interns who do not receive any in-

state public or private school job by their absence in the OSPI data set. These administrative

data also provide information on years of experience, race, and educational background, which

we link to the cooperating teacher of each intern.

We supplement the teacher data from OSPI with data from Washington's Professional

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[7] The longest span provided by a university was every intern between the years 1998 and 2011 and the shortest span was 2006-2011.

[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/she does student teaching. So for these interns, we include the intern's second internship experience in our final dataset.

[9] These include high school information (school attended, class standing, and GPA), standardized test scores (SAT and ACT), collegiate GPA, and demographic information (first generation college student and detailed race/ethnic codes).

[10] When representing years, this paper uses the convention of listing the first year of the academic year. Thus, 1994 represents the 1994-1995 academic year.

Educators Standards Board (PESB) on teacher endorsements.[11] For each intern, we create

indicator variables for each different endorsement the intern received with his or her first

teaching credential, aggregated into eleven categories: elementary education, special

education, math, science, English, ELL (English Language Learners), social studies, arts, health &

PE, languages, and other. We also create a "STEM" category that combines both math and

science. The PESB data also contains the birth year of each intern, which allows us to calculate

the age of each intern during his or her internship year.[12]

Another goal of our analysis is to investigate patterns of workforce entry for prospective

teachers with different student teaching experiences. Teacher training programs enter into

"field placement agreements" with school districts to place their interns in student teaching

positions, and as a result many interns in our sample did their student teaching in the same

school. For example, 107 interns from Western Washington University did their student

teaching at Sehome High School, 87 at Fairhaven Middle School, and 78 at Alderwood

Elementary, all in the Bellingham School District, the school district encompassing the university.

But across our sample, interns did their student teaching in 1162 different schools across the

state, and there is considerable variability in the characteristics of these internship schools, both

within and across our participating institutions. For example, the average intern from Western

Washington University (WWU) did his or her student teaching in a school in which 32.6% of

students were eligible for free/reduced priced lunch (FRL). However, one fourth of WWU interns

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[11] According to the 2006 report "Educator Supply and Demand in Washington State" (OSPI, 2007), there are 14 endorsement areas for which there are "high degrees of shortage," all of which fall into math, science, special education, or ELL. We would thus expect qualified interns who pursue a teaching job in these areas to be more likely to be hired. On the other hand, there is considerable evidence that teachers credentialed in math and science may have better opportunities outside of teaching (Ingersoll, 2001, 2003; Rumberger, 1987). So, we might expect interns credentialed in math or science to be less likely to pursue a teaching job in the first place.
[12] We do not observe degree level for non-hired interns in our sample. For hired interns, the average age of interns entering the workforce with a masters degree (31.5) is somewhat greater than the average age of interns entering the workforce with a bachelor's degree (29.2).

did their student teaching in a school with less than 20% FRL students, while 10% of WWU

interns student taught in a school with more than 60% FRL students.

The information on interns' student teaching schools come from annual data for each

public school in Washington state that includes total enrollment, the percent of students who

pass the state math and reading exams,[13] the percent of students by federal ethnicity

categories, the percent of students enrolled in the free/reduced lunch program, the location of

the school (urban, suburban, town, or rural), and whether the school is in a district that shares a

border with Oregon, Idaho, or Canada. We also compute the number of prior interns that we

observe to have completed their internships at each school, which provides a rough measure of

the school's prior experience with student teachers.

Following Ronfeldt (2012), we use longitudinal teacher employment data to calculate

the "stay ratio" of each internship school, which is a measure of teacher turnover.[14] We modify

Ronfeldt's definition and define a school's stay-ratio in a given school year as the percent of the

school's non-retirement-age teachers who return to the school in the following year.[15]

Therefore, schools with *less* teacher turnover have a *higher* stay ratio. We also use this

longitudinal dataset to create an indicator for whether each intern's student teaching school

hires a new (to the school) teacher the following school year. This is important because a large

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[13] Although Washington state now tests all students in math and reading in grades 3-8 and 10 each year, for many years in our sample the state only tested students in grades 4, 7, and 10. So, to calculate the percent of students passing the state exam in math and reading for each year, we first select the grade in each school (4th, 7th, or 10th) in which the most students took the state exam, and then calculate the percent of students who passed the test in that grade. We standardize these passing rates by grade and year to control for differences in the difficulty of the exams in different grades and years.

[14] Ronfeldt (2012) shows that a school's stay ratio is correlated with other survey-based measures of school functionality, such as administrative quality, staff support, student behavior, and teacher safety.

[15] We follow Ronfeldt (2012) by transforming the stay ratios with an exponential transformation and standardizing within school level (elementary or secondary.) Ronfeldt uses an average of each school's stay ratio over the five-year span of his data, and we experiment with several moving averages, including a three year moving average (the current year and two prior years) and two five-year moving averages (the current year and four prior years, and the current year, two prior years, and two subsequent years.) Our results use the five-year moving average calculated over the current year and four previous years, but the results are robust to the choice of average.

percentage of interns (16%) are hired into the same school where they did their student teaching. We explore this particular outcome further in the next section.

Our population of interest is teachers who participated in traditional student teacher programs in Washington state public schools and receive a credential to teach in the state. To ensure that all interns in our sample completed the requirements to receive a Washington state teaching credential, we limit our sample to those individuals who have a valid Washington certificate. We retain interns who held a non-teaching K-12 position (such as a teacher aide) or a teaching position (such as a non-certificated teacher) prior to their student teaching experience, but we include indicators to distinguish these interns from interns who entered their student teaching placement with no prior experience in Washington public schools.[16]

The full intern sample consists of 8,080 interns who completed student teaching by 2009 and received a teaching credential and endorsements to teach in Washington K-12 public schools. Of the 8,080 interns in the sample, 2,406 do not appear in the OSPI data by 2011. We refer to these interns as "not hired", meaning that they were not hired into a public or private K-12 job during the time that the OSPI data was observed. Note that "not hired interns" may include interns who were hired into a school (or other) position outside of Washington State, or hired into a school position after the last year of our dataset (2011), as well as interns who do not pursue or did not receive any position in a public or private school. We address the issue of right-censoring in our analytic approach.

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[16] There are two significant sources of missing data. First, free/reduced priced lunch data is missing for some schools in some years due to reporting issues. We impute missing school-level FRL values by a linear interpolation on the years of data for that school that are not missing. Second, the percent of students who passed the state exams are missing for teachers in K-2 schools or in grades with 10 or fewer students at the school. If test data is missing for a subset of the years the teacher teaches at a school, we impute the mean of the non-missing passing rates across all the years the teacher taught at the school (for placement school) and the mean over years the school hosted intern teachers (for intern schools). If test data is missing for all years at a school, we impute the mean passing rate for schools in the same district and level. If there is no test score data for that school or any other school in the district, we drop that intern from the analysis.

The 5,674 "hired" interns are observed in three different employment outcomes: public school teacher, public school non-teacher (e.g. paraeducator), and private school teacher. Several interns transition between these outcomes during our years of data, as illustrated by **Figure 3**. For example, 87 interns are first hired as non-teachers in public schools before transitioning to a public teaching role, while 159 interns begin in a public teaching role before transitioning to a non-teaching position. In some of our exploratory analyses, it is useful to define one unique employment outcome for each intern. In these analyses, interns are defined as hired into a private teaching position if we *only* observe them employed in private schools, since our primary interest is in public school hiring. For other hired interns, we define employment outcome as each intern's first position (public school teacher or public school non-teacher). By these definitions, 271 interns (4.7%) are employed only in private K-12 teaching positions, while 185 (3.3%) were initially hired into public, non-teaching positions. The remaining 5,218 – 64.5% of the 8080 interns in the sample – were hired into public, K-12 teaching positions (as their first public school position), a proportion that is broadly consistent with what has been found using nationally representative data.[17]

An important variable that we observe for most, but not all, of the interns in our final sample is ethnicity. We compile intern ethnicity from three sources: the S-275 (which contains all hired interns, with a small amount of missing ethnicity data); the PESB endorsement file (which contains all interns, but with a considerable amount of missing ethnicity data); and the dataset of interns from Western Washington University (with no missing ethnicity data). From these three sources, we are able to create ethnicity indicators (American Indian, Asian, black,

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[17] Ingersoll (2003) finds about 58 percent of new recipients of teaching credentials get a public teaching job within four years.

Hispanic, or white) for 7623 of the 8080 interns in our final sample.[18] For parsimony, we also create a binary variable indicating whether each intern is non-white.

Finally, subsets of our full sample can also be linked to four additional variables. First, interns in the most recent years of our data were required to take the WEST-B teacher credential test in math, reading, and writing. We have WEST-B scores for 4,578 interns in our sample. Since interns in Washington can take the WEST-B as many times as necessary to receive a passing score in each subject, we use the scores from the first time each intern took the test. Second, two programs (Western Washington and UW-Tacoma) provided the undergraduate GPAs of their graduates. Thus, we have the GPA of 4,692 interns in our sample. Third, the supervising teachers of 2,083 interns can be linked to student-level test score data, which allows us to calculate out-of-sample value-added measures of teacher performance for these cooperating teachers. Lastly, 1,392 interns hired into teaching positions can also be linked to student test score data, which allows us to calculate future value-added measures of teacher performance for these interns. We describe these estimates in the next sub-section.

Value-added estimates of teacher effectiveness

Many specifications of our models include an out-of-sample estimate of each cooperating teacher's value-added performance. We refer to the estimates as "out-of-sample" because they are calculated from student test score data from 2005 through 2011, while many internships in our analytic sample fall outside this date range. Other specifications include an "in-sample" estimate of an intern's future (i.e., post-hiring) value-added performance. These estimates are estimated from variants of the following value-added model for all students linked to their

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[18] In 2011, 3.5% of teachers in Washington were Hispanic, 2.5% were Asian, 1.3% were black, and 1.0% were American Indian. Among interns in our sample for whom we observe ethnicity, 2.9% are Hispanic, 4.4% are Asian, 1.0% are black, and 0.8% are American Indian.

classroom teachers in grades 3–8 from 2005 through 2011 in Washington state[19]:

$$Y_{ijst} = \beta_0 + \beta_1 Y_{i(t-1)} + \beta_2 X_{it} + \tau_{js} + \varepsilon_{ijst} \qquad (1)$$

Y_{ijst} is the state test score for each student i with teacher j in subject s (math or reading) and year

t, normalized within grade and year; $Y_{i(t-1)}$ is a vector of the student's scores the previous year in

both math and reading, also normalized within grade and year; X_{it} is a vector of student

attributes in year t (gender, race, eligibility for free/reduced price lunch, English language

learner status, gifted status, special education status, learning disability status, migrant status,

and homeless status); and τ_{js} is a fixed effect that captures the contribution of teacher j to

student test scores in subject s across all years the teacher is linked to student test score data.

We adjust all teacher effect estimates using empirical Bayes (EB) methods.[20]

We use the estimates $\hat{\tau}_{js}$ as a time-invariant measure of a teacher's contribution to

student test scores in each subject, math and reading. Since many teachers teach both math and

reading, but many secondary teachers only teach math or reading, we use the average of the

value-added estimates in math and reading for teachers who teach both subjects. We

experiment with variants of model (1), including models with student and school fixed effects,

and find that they do not substantively change our findings.

Descriptive picture of interns by labor market outcome

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[19]The proctor of the state assessment was used as the teacher-student link for at least some of the data used for analysis. The 'proctor' variable was not intended to be a link between students and their classroom teachers so this link may not accurately identify those classroom teachers. However, for the 2009-10 school year, we are able to check the accuracy of these proctor matches using the state's new Comprehensive Education Data and Research System (CEDARS) that matches students to teachers through a unique course ID. Our proctor match agrees with the student's teacher in the CEDARS system for about 95 percent of students in math and 94 percent of students in reading. Further, fitting a teacher production function to these data produces similar results to those found elsewhere in the literature (e.g. Jackson and Bruegmann 2009; Clotfelter et al., 2007).

[20] The standard empirical Bayes method shrinks estimates back to the grand mean of the population. Note, however, that standard empirical Bayes adjustment does not properly account for the uncertainty in the grand mean, suggesting the estimates are shrunk too much (McCaffrey et al., 2009). We use the standard approach that's been commonly estimated in the literature (an appendix on empirical Bayes shrinkage is available from the authors by request).

Our primary goal is to identify the teacher training experiences that are correlated with intern entry into the public teaching workforce. However, as we outline above, interns in our sample who are not employed as public school teachers may have been hired into non-teaching positions in public schools, as teachers in private schools, in non-schooling positions in Washington state, or into positions outside of Washington state (teaching or otherwise). We cannot distinguish between interns who are hired out-of-state and interns hired into the state into non-teaching positions (or who are unemployed), but we do know if prospective teachers are employed in private schools or in non-teaching positions in public schools. So, while our primary analysis focus exclusively on the likelihood of becoming a public school teacher (in Washington), we begin by first exploring whether interns end up employed in different positions in public schools or in private schools in the state.

Table 2 compares interns by labor market outcomes along three dimensions: individual intern characteristics; characteristics of the intern's cooperating teacher; and characteristics of the intern's internship school. Interns hired into public or private teaching roles tend to be younger than those hiring into non-teaching roles or who we do not observe in the workforce. There is a large gender discrepancy between interns hired to teach in public versus private schools, and significant difference across endorsement areas, which is not surprising since private schools are not required to staff classes according to teacher endorsements.

There are relatively few differences across groups in terms of the characteristics of the cooperating teachers or internship schools. Interestingly, we do see that interns in schools with more advantaged students (as measured by percent minority students, percent FRL students, and state passing rates) are more likely to be hired as public school teachers than not hired interns. However, interns in schools with *more* teacher turnover are also more likely to be hired into public school positions. This is true in terms of the average stay ratio, but also in terms of

the number of new teachers the internship school needs to hire the following year. This points to the potential importance of interns being hired into the same school where they did their student teaching, an issue we return to in section V.

To further explore the factors that may be correlated with interns being employed in different types of positions, we restrict our sample to only those who receive a job and did their student teaching in 2003 or later (since we only have private school data beginning in 2004), and then estimate multinomial logit models predicting which of the three types of jobs an intern receives. **Table 3** presents the estimated marginal effects from these models, where the reference group is individuals hired into public teaching jobs. As in all models, these estimates control for institution and internship year, as well as a host of other variables (summarized in Table 2) that we omit from the table for parsimony. See the notes of Table 5 for a full list of control variables.

The first column of Table 3 ("Hired Sample") contains estimates from the model based on the full sample of hired interns from 2003-2010. Relative to individuals hired into public teaching positions, and all else equal, interns are less likely to be hired into private school if they are endorsed in STEM or special education.[21] Younger, female, and STEM endorsed interns are also less likely to be hired into a public non-teaching position than into a teaching position, all else equal. The remaining columns of Table 3 report estimates from models adding covariates that are available for only a subset of interns—WEST-B score (averaged across math, science, and writing), undergraduate GPA, and cooperating teacher out-of-sample VAM—and are estimated only for the subset of interns for whom we have the appropriate data. The only notable additional finding from these models is that, all else equal, the probability of being hired into a public non-teaching position (relative to a public teaching position) decreases as the

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[21] So much less so in the case of special education—there is only one intern in this sample endorsed in special education who is hired by a private school—that the coefficient is not identified.

intern's WEST-B score increases.

From this point on we restrict our focus to characteristics predictive of entry into the public teaching workforce (i.e., the reference category in Table 3). One challenge in assessing the connection between training experiences and the labor market is the considerable heterogeneity we observe in the time between when interns complete their internship and when they are observed to be employed (see **Figure 4**). In the next section we discuss the use of split population models to address this challenge, as well as a secondary analysis exploring the factors predicting whether interns are hired into the school in which their internship occurred.

IV. Analytic approach

Split population model

To assess the relationship between internship experiences and employment as a public school teacher, it is typically assumed that the probability of employment for individual i depends on a latent variable, Y_i^*, and the observed outcome depends on whether this latent variable exceeds some threshold, c, that determines the hiring decision:

$$Y_i = \begin{cases} 1 \text{ if } Y_i^* > c, \text{ intern i is employed in a teaching position} \\ 0 \text{ if } Y_i^* \leq c, \text{ intern i is not employed in a teaching position} \end{cases} \quad (2)$$

A common econometric approach is to formulate (2) as a binary choice model and estimate the marginal effect of explanatory variables **X** on the probability of observing $Y_i = 1$. However, this approach ignores three related aspects of the transition from student-internship into the labor market. First, as demonstrated by Figure 4, there is considerable heterogeneity in the time it takes an individual to be hired into a teaching job. Binary choice models produce no information regarding the time it takes to be hired; they simply model whether hiring occurs or

not. But it is conceivable that characteristics of an internship experience differentially impact the likelihood of being hired and the timing of that hire. Binary choice models confound these impacts and tell us nothing of the timing of hire.

Second, our data are right-censored. Specifically, there are likely to be a considerable number of interns, especially those completing their internships late in our sample, who will successfully find a public teaching job after the last year they are observed in our dataset. The standard approach in this setting is to use survival analysis to model the time until each intern is hired into the workforce. But survival analysis assumes that all interns will eventually be hired into the workforce, which brings us to the third issue: many interns never become teachers and never would become teachers even in the absence of censoring. This subpopulation of interns may, or may not, differ in measurable ways from those who search for and do not find employment. To account for the potential differential impacts of observable characteristics on hiring and the timing of hiring, the right-censored data, and the fact that a subset of interns will never find employment, we employ a split-population model.[22]

Split-population models simultaneously estimate the impact of covariates on the timing and probability of an event. Specifically, split population models explicitly account for the possibility that some individuals have a hazard of zero; i.e. those interns who will never have a teaching job, either because they choose not to pursue a job or because they will never be hired. Split population models are popularly used to explore the reoccurrence of cancers[23] and have been used by economists to study job placement and timing (Kyyra & Ollikainen, 2008; Swaim & Podgursky, 1994), criminal recidivism (Schmidt & Witte 1989), survival of financial institutions (DeYoung, 2003; Maggiolini & Mistrulli, 2005), and smoking cessation (Douglas &

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[22] We experiment with both logit and hazard models and find that the primary findings from these models are consistent with the estimates from the split population model.

[23] Split population models are called "cure models" in the medical literature because they assume that a subset of individuals are "cured" and will never have a reoccurrence of cancer, for example.

Hariharan 1994).

As noted in Swaim and Podgursky (1994), a split-population formulation of job placement is stylized in that it assumes that interns make a one-time decision whether or not to pursue a teaching position. This is unrealistic in that it rules out intentional delays to entering the teacher workforce, but as Swaim and Podgursky note, a single-population survival analysis approach makes the even less realistic assumption that all interns who complete student teaching decide to pursue and will ultimately receive a teaching job.

In the split-population framework, we define the latent variable Y_i^* as an indicator of whether intern *i* will eventually be hired into a teaching job, and define T_i^* as the number of years from an intern's student teaching experience to his or her placement in a public K-12 teaching job. T_i^* is defined only for interns who are observed to receive a teaching job ($Y_i^* = 1$). T_i^* is assumed to have a distribution function f(t,Z_i) where Z_i is a vector of observable characteristics for intern *i*. Define F(t,Z_i) = Pr($T_i^* \leq t$), t > 0 as the corresponding cumulative density. Note that because of right-censoring, we do not observe T_i^* and Y_i^* for all the interns in our sample who will eventually be hired. Thus, define T_i as the time to first job for interns who are observed to be hired ($Y_i = 1$) and the time to censoring for interns who are not ($Y_i = 0$). The goal of this part of our analysis is to use our observations of T_i and Y_i for each intern in our sample to make inferences about the factors that influence T_i^* and Y_i^*.

We consider a model for T_i^* and Y_i^* that splits our observations into two groups of interns, one of which will eventually be hired and the other of which will not.[24] The conditional density and distribution functions for T_i^* are defined as:

$$f(t_i \mid Y_i^* = 1, Z_i) = \Pr(T_i^* = t_i \mid Y_i^* = 1, Z_i) = g(t, Z_i) \quad (3)$$

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[24] We assign Y = 1 to individuals finding a job which, in traditional split population terminology, are "failures."

$$F(t_i \mid Y_i^* = 1, Z_i) = \Pr(T_i^* < t_i \mid Y_i^* = 1, Z_i) = G(t, Z_i) \quad (4)$$

Let $\delta_i = \Pr(Y_i^* = 1 \mid \mathbf{Z_i})$. For interns who are hired during the sample period, we observe $Y_i = Y_i^* = 1$

and $T_i = T_i^* = t_i$. Thus can write joint density of the observed data for these interns as:

$$\Pr(Y_i = 1, T_i = t_i \mid Z_i) = \Pr(Y_i^* = 1 \mid Z_i)\Pr(T_i^* = t_i \mid Y_i^* = 1, Z_i) = \delta_i g(t_i, Z_i) \quad (5)$$

In contrast, the interns who are not hired during the sample period ($Y_i = 0$) might never be hired

($Y_i^* = 0$) or might be hired after the sample period ($Y_i^* = 1$ and $T_i^* > t_i$). The joint density of the

observed data for interns with $Y_i = 0$ is:

$$\Pr(Y_i = 0, T_i = t_i \mid Z_i) = \Pr(Y_i^* = 0 \mid Z_i) + \Pr(Y_i^* = 1 \mid Z_i)\Pr(T_i^* > t_i \mid Y_i^* = 1, Z_i)$$
$$= (1 - \delta_i) + \delta_i(1 - G(t_i, Z_i)) \quad (6)$$

Combining (5) and (6) and assuming independence across observations yields the likelihood

function for the observed data Y_i and T_i:[25]

$$L = \prod_{i=1}^{n} [\delta_i g(t_i, \mathbf{Z_i})]^{y_i} [1 - \delta_i + \delta_i(1 - G(t_i, \mathbf{Z_i}))]^{1-y_i} \quad (7)$$

Within this likelihood, we can specify a functional form for both δ_i and G and estimate

coefficients relating the observed characteristics of each intern to the probability of getting

hired (δ_i) and the time to hire ($G(t_i, \mathbf{Z_i})$). The split-population literature provides a number of

options. For the results presented below, we model δ_i as a logit in Z:

$$\log\left(\frac{\delta_i}{1 - \delta_i}\right) = \gamma \mathbf{Z_i} + \varepsilon_i$$
$$\Rightarrow \delta_i = \frac{\exp(\gamma \mathbf{Z_i} + \varepsilon_i)}{1 + \exp(\gamma \mathbf{Z_i} + \varepsilon_i)} \quad (8)$$

In (8), γ is a vector of coefficients representing the correlation between each observable intern

characteristic and the log odds of the intern eventually being hired.

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[25] We maximize this likelihood using the user-written STATA module CUREREGR (Buxton 2007). We do not cluster standard errors at the institution level because we are not interested in any institution-level covariates.

Our primary results use an exponential model for the "fail density" G():

$$G(t_i, \mathbf{Z_i}) = 1 - \exp(-\frac{t_i}{\exp(\beta\mathbf{Z_i})}) \qquad (9)$$

In (9), β is a vector of coefficients representing the correlation between each observable intern characteristic and the slope of the hazard curve representing time-to-hire. We do experiment with other specifications of G() and find that the results are robust to the choice of fail density.[26]

We discuss our estimates of γ and β in the next section, but these coefficients can be difficult to interpret because they describe related dimensions of the same outcome: the former describes the probability of eventually getting a public teaching job, while the latter describes the time until the intern is hired. To ease the interpretation of our results, we calculate marginal effects for each covariate at one and five years after student teaching.[27] These marginal effects can be interpreted as the expected change in the probability of being hired one or five years after completing the internship for each unit change in the covariate.

Hiring into internship school

One intriguing finding from our exploratory analysis is that 806 of the 5218 interns hired into public schools (15.4%) were hired by the school where they did their student teaching, suggesting that student teaching may serve not only training purposes, but also provides schools with information about the ability and fit of prospective teachers. We employ a logit model to explore the probability, θ_i, that an intern is hired into his or her internship school:

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[26] Specifically, when we allow the time to hire to have both a shape and scale parameter using a Weibull or a Gamma distribution, the estimates for the scale parameter are very similar to the estimates for the scale parameter using the exponential distribution while the estimates for the shape parameter are largely not statistically significant.

[27] We calculate the marginal effect of each covariate at the mean of other covariates using the "predict" command in the STATA module CUREREGR (Buxton 2007).

$$\log\left(\frac{q_i}{1 - q_i}\right) = \mathit{l}\,\mathbf{Z_i} + e_i \quad (10)$$

We first estimate this model for all hired teachers, so the dependent variable (in equation 10) is the log odds of being hired at one's internship school, relative to being hired at another school. This, however, ignores the fact that internships may have occurred in schools that did not have any available openings when interns were seeking employment. Given this, we also estimate this model for the subset of interns who did their student teaching at a school that hired at least one new teacher the following year, and further control for the number of interns the school hired. We transform all logit coefficients to marginal effects (calculated at the intern level) to ease in interpretation of our results.

V. Results

Probability and timing of hiring as public school teacher

Table 4 reports the selected estimated coefficients and marginal effects from four specifications of the split population model described in section IV. For each model, we report the vector of estimated coefficients $\hat{g}$ in the "Hired" column (these coefficients are on the log odds scale). We stress that these coefficients should not necessarily be interpreted as reflecting the hiring preferences of employers or employees. Positive values of these coefficients represent a positive correlation between the variable and the probability of eventually entering the teaching workforce. We also report the vector of estimated coefficients $\hat{\mathit{L}}$ in the "Time" column, which represent the relationship between each variable and the time-to-hire. The "Hired" and "Time" coefficients can be difficult to interpret together: the first represents the probability of *eventual* hire, while the second determines the slope of the hazard curve for

hiring for interns who eventually be hired. Because of this, we also report marginal effects for each coefficient for the probability of hiring one and five years after student teaching.[28] These marginal effects can be interpreted as the impact of a one unit change in the covariate on the probability of being hired into a public school job one or five years after completing an internship. To further solidify intuition, we plot fitted probabilities of hire over time for selected covariates in **Figure 5**. In these plots, the vertical distance between the curves at each time point corresponds to the marginal effect at that time.[29]

The first set of results in Table 4 reports selected estimates from a split population model estimated for the full sample of interns (columns 1-3). The full list of control variables is noted at the bottom of Table 5; all models control for an intern's training institution, internship year, and internship term. This is important because we observe large disparities in placement rates between participating institutions and internship years.[30]

Several intern characteristics are correlated with the probability and timing of an intern being employed in a public teaching job. All else equal, younger interns are more likely to be in a public teaching job: an increase of 10 years of age is correlated with a 2.8 percentage point decrease in the probability of being employed in a public school after one year, and is correlated with a 4.6 percentage point decrease in the probability of being in a public school after five years. These marginal effects—the vertical distance between the time-to-hire curves for interns of average age (28 years old) and ten years older than average age (38 years old)—can be seen increasing over time in Figure 5a. One possible explanation for the age finding is that school

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[28] The marginal effects are estimated by calculating the difference in the survival probabilities for a hypothetical intern who experiences a unit increase in the covariate under consideration. This intern is given the sample means for all other covariates.

[29] The line plots in Figure 5 show the fitted probability for each variable, holding all other variables in the model at its mean value. Thus the vertical distances correspond exactly to the marginal effects reported in Table 4.

[30] For example, not surprisingly given the economic downturn, our estimates suggest that there was a sharp drop in the probability of getting hired for interns who graduated in 2008 or later.

systems prefer to hire younger interns believing in the traditional model of hiring recent college

graduates who can dedicate an entire career to teaching (Hess, 2009). But, it is also possible that

older interns are career changers who may not be as likely to seek a teaching job, even having

obtained a teaching credential.[31]

Although the raw difference in observed employment rates for white and non-white

interns is not statistically significant (72.5% for white vs. 70.0% for non-white, p = 0.130), the

split population estimates in Table 4 suggest that non-white interns are significantly less likely

(1.3 percentage points after one year and 5.8 percentage points after five years) to be hired, all

else equal, than white interns (these differences are also plotted over time in Figure 5b).[32] This

seemingly runs contrary to the rhetoric about the desirability of diversifying the teacher

workforce and existing empirical evidence (Boyd et al., 2011). To dig deeper into this finding we

estimate models that interact the non-white indicator with indicators for each institution to

assess whether it is consistent across training programs. In these specifications each interaction

term (and the main effect) is negative; that is, non-white interns are less likely to be hired, all

else equal, regardless of the institution they attended.[33] We also interact the non-white

indicator with indicators for internship school geographic location (west of Puget Sound area,

Puget Sound area, western half of state, and other) and find that the interaction between non-

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[31] Also, as we note in the data section, teachers who obtain a Masters degree (and we do not observe the type of degree for non-hired interns) tend to be older so the age result may also be picking up some of the supply or demand effects associated with the receipt of an MA versus a BA degree.

[32] One possible explanation for why we see non-white intern are less likely to find employment in the split population model, even though there is little difference in average employment rates, is that non-white interns are more likely to teach in schools with higher teacher turnover. As we will discuss later, interns from schools with high teacher turnover are more likely to find employment, all else equal. This means that non-white interns are disproportionately compared to other interns from internship schools with high placement rates in the regression. The average standardized internship school stay ratio is -0.23 for non-white interns and -0.17 for white interns (p = 0.022).

[33] There are some sizeable differences in the proportion of minority interns graduating from the six institutions in our sample – for example, 15.0% of interns from UW-Seattle are non-white, compared to only 7.6% of interns at Western Washington – but the findings on non-whites cannot be driven by differences in employment prospects associated with institution since the model includes training program fixed effects.

white and the western half of state is significant and negative, though why employment prospects for prospective minority teachers ought to be diminished in the part of the state with higher minority student populations, particularly in the Puget Sound region, is not clear.

Finally, and perhaps most importantly, we estimate a number of specifications of the split population model that include separate identifiers for the race/ethnicity of the interns: American Indian, Asian, black, and Hispanic interns (with the reference category being white interns). Interns of each non-white ethnicity are less likely to be hired than white students, all else equal, but only the coefficients for American Indian and Asian are statistically significant.[34] These findings are mostly robust to the inclusion of internship district-by-year fixed effects in the split population model (i.e., American Indian and Asian interns are still significantly less likely to be hired, all else equal), although the sign for Hispanic interns flips in this model.[35]

The bottom line is that the race/ethnicity results are a bit puzzling and difficult to interpret as it is not clear whether they are driven by the preferences of hiring officials or prospective employees, who might have differential employment opportunities outside of public schools. Of course it is also possible that the findings reflect some omitted variable that is correlated with both the non-white indicator and probability of employment. For example, each minority intern sub-group has significantly lower average WEST-B scores than white interns.[36] We return to this point below when we discuss the findings for models that control for measures of academic proficiency.

Not surprisingly given the evidence that school systems tend to report greater difficulty

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[34] The log odds coefficients for probability of eventual hire and corresponding standard errors for each category are -0.839 (SE = 0.38) for American Indian, -0.57 (SE = 0.19) for Asian, -0.05 (SE = 0.42) for black, and -0.33 (SE = 0.23) for Hispanic.

[35] The log odds coefficients from the model with internship district-by-year fixed effects for probability of eventual hire and corresponding standard errors for each category are -0.821 (SE = 0.38) for American Indian, -0.44 (SE = 0.18) for Asian, -0.29 (SE = 0.36) for black, and 0.18 (SE = 0.26) for Hispanic.

[36] The average standardized WEST-B score is 0.028 white interns, -0.093 for Asian interns, -0.276 for American Indian interns, -0.390 for black interns, and -0.426 for Hispanic interns.

recruiting and retaining teachers with certain endorsements, we see strong evidence that a

teacher's endorsement area predicts the probability of employment.[37] Relative to interns

endorsed in elementary education, interns endorsed in STEM and special education are far more

likely to be employed all else equal (11.7 percentage points after one year and 13.7 percentage

points after five years for STEM, shown relative to elementary in Figure 5c; 10.8 percentage

points after one year and 13.5 percentage points after five years for special education). Interns

with an endorsement to teach ELL classes are also more likely to be employed, all else equal,

than interns without an ELL endorsement (4.8 percentage points after one year and 8.2

percentage points after five years).[38]

One might expect that cooperating teachers or internship schooling characteristics would

influence the likelihood of workforce entry, either directly through the training that interns

receive or because the reputation of a school or recommendation of the cooperating teacher

would carry weight when interns sought a job. In particular, discussions with school hiring

officials suggest it is common for cooperating teachers to write letters of recommendation for

prospective teachers, few of these internship variables are significant predictors of the

probability and timing of workforce entry.[39] Interestingly, the only cooperating teacher

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[37] Since interns can hold an endorsement in more than one area, our model contains interactions between an indicator for whether an intern holds multiple endorsements and the STEM, special education, other, and elementary indicators. ELL, unlike the other categories, is a secondary endorsement, which means that interns endorsed in ELL *must* be endorsed in another area. We therefore do not interact the ELL and multiple endorsement variables. The STEM and special education coefficients are therefore interpreted relative to elementary education, while the ELL coefficients are measured relative to all interns not endorsed in ELL.

[38] When we explore models with interactions between endorsement areas and year of internship, only one of the 22 interactions is statistically significant at the 95 percent confidence level, which is about what we would expect by random chance. Thus we conclude that the impact of endorsement area on probability of hiring is consistent over the years in our sample.

[39] Similarly, one might have hypothesized that the training experience of interns would be enhanced by a race/ethnicity or gender match between cooperating teacher and intern or, perhaps most importantly, by being matched to a cooperating teacher with the same endorsements. There is evidence that matches between teacher and student demographics can influence teacher productivity and speculation that this may be related to teachers ability to connect with students given similar backgrounds/perspectives (Dee 2004; Ehrenberg et al., 1995), so it is not outlandish to imagine we would see these sort of effects with

characteristic that is a significant predictor of employment is the number of interns from participating institutions mentored by each cooperating teacher in prior years during the period of our data, which is negatively correlated with probability of employment. It is unclear whether this might be related to the nature of the training received by interns or the guidance they might receive from more experienced cooperating teachers. For instance, one could imagine that more experienced cooperating teachers are teachers that school systems feel need extra help in the classroom so they are assigned more interns, possibly affecting the quality of the training interns receive and hence their desirability as applicants. On the other hand, more experienced cooperating teachers may provide interns with different information about their prospects as teachers, affecting their supply decisions.

Just as Ronfeldt (2012) finds little correlation between the characteristics of the students in a teacher's internship school and workforce outcomes, we find little evidence that internship school student characteristics are predictive of hiring outcomes. However, two other internship school characteristics do seem to matter for K-12 employment prospects. First, interns who did their student teaching in cities, towns, and rural areas are all less likely to eventually be employed in a public teaching position than interns who did their student teaching in suburban areas, all else equal. Second, probability of employment decreases as the average amount of teacher turnover in an intern's internship school decreases (i.e., as the school's stay ratio increases): a one standard deviation increase in the stay ratio is correlated with a 1.9 percentage point decrease in the probability of employment after one year and a 3.2 percentage point decrease after five years (these differences are shown over time in Figure 5d). This finding is interesting in that it conflicts with Ronfeldt (2012), who finds that teachers who did their student teaching in schools with low teacher turnover are both more effective (in

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cooperating teachers and interns. But, as it turns out, this does not to be the case at least in terms of the probability of eventual K-12 public school employment.

terms of value added) and stay in teaching longer, attributes that should make interns more

desirable job candidates.

It is possible that hiring officials are unaware of the connection between internship school

and the outcomes of interns as teachers. It is also possible that Ronfeldt's findings on

effectiveness and attrition are biased by sample selection. For example, if only the most

motivated teachers from schools with low teacher turnover enter the workforce, and the most

motivated teachers are more effective and more likely to stay in the profession longer, then

Ronfeldt's findings may be driven by the impact of student teaching on workforce entry, not the

impact of the student teaching on effectiveness and retention. Another possibility exists: it is

possible that schools use internships as screening devices for future hiring. If this is the case,

then students completing internships at schools with a higher stay ratio would be less likely to

be hired at their internship school because of its low teacher turnover and these individuals

would not be able to demonstrate their effectiveness at a school that was about to hire a

teacher. We explore this possibility in the next sub-section.[40]

The regression estimated for the full sample contains little in the way of controls for

individual heterogeneity, and as we discussed in regards to the non-white findings, omission of

these controls may bias the estimates from the full sample. With this in mind, the final three

columns in Table 4 report estimates from models that add covariates that are available for only

a subset of interns—WEST-B score (averaged across math, science, and writing), undergraduate

GPA, and cooperating teacher out-of-sample VAM—and are estimated only for the subset of

interns for whom we have the these additional data elements. WEST-B and GPA are available for

different subsets of interns (WEST-B for recent interns, and GPA for interns from Western

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[40] We also estimate a split population model that drops interns who are hired into their internship school, and find that the stay ratio is no longer significant correlated with probability of hire. Full results are available from the authors upon request.

Washington University and UW-Tacoma), so we report estimates from both models even though the goal of each model is to control for a measure of intern qualifications. For each of these subsets we find little evidence that measures of intern academic proficiency, or the effectiveness of an intern's cooperating teacher, are correlated with the probability of hiring as a public school teacher.[41] Importantly, non-white interns are still less likely to be hired even in models that control for intern academic proficiency[42], although this does not rule out other omitted variables (i.e., other workforce opportunities) that may be biasing this estimate.

Internship as screening device: probability of being hired into internship school

Of the 5,218 interns hired into the public K-12 system, 806 (15.4%) performed their internship in the building that ultimately hired them. This raises the possibility that schools may use student teaching as a screening process for their own hiring. Our finding that interns who did their student teaching in schools with higher teacher turnover are more likely to be hired lends credence to this notion. We explore this possibility further in Table 5, which reports estimated marginal effects from a logistic regression predicting intern hiring into their internship school (relative to hiring into another school).

The first column of Table 5 reports estimates from a model estimated for all hired interns. In an interesting reversal, non-white interns are more 4.7 percentage points *more* likely to be

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[41] We also experiment with a split population model that includes internship district-by-year fixed effects, and find that most of our are qualitatively similar: the probability of hire decreases as age increases; interns endorses in STEM and special education are more likely to be hired than interns endorsed in elementary education; and interns endorsed in ELL are more likely to be hired than interns not endorsed in ELL. One important result that changes is the coefficient in internship school stay ratio; the probability of hire still increases as teacher turnover increases, but the coefficient is less than half as large and not statistically significant. This is not surprising given that much of the variation in the stay ratio is cross district (40%) rather than within.

[42] When we decompose the non-white indicator into individual ethnicity indicators, we find that (as in the full model) Asian and American Indian interns are less likely to find employment than white interns, even controlling for WEST-B scores or undergraduate GPA.

hired into their internship school than white interns, all else equal.[43] Given that non-white interns are *less* likely to be hired overall, this suggests that non-white interns are particularly unlikely to find a job outside of their internship school. We also find that the probability of employment in the internship school decreases as the stay ratio increases, which matches our hypothesis: interns who do their student teaching at schools with more teacher turnover are more likely to be hired into that school.

Column 2 of Table 5 reports estimates from a model estimated only for interns who did their student teaching at a school that hired at least one new (to the school) teacher the following year (i.e., who had a chance of being hired by their internship school). One intriguing finding from this model is that interns who are endorsed in the same area as their cooperating teacher are more 4.5 percentage points more likely to be hired by their internship school, perhaps reflecting the influence of the cooperating teacher in the hiring process.

The last four columns of Table 5 report estimates from models for the four subsets of data we discuss in section III: interns with WEST-B scores, an undergraduate GPA, a future VAM estimate, or a cooperating teacher VAM estimate (all of whom were hired and did their student teaching at a school that hired at least one new teacher the following year). Interestingly, a ten-point increase in average WEST-B score is correlated with a 2.3 percentage point increase in the probability of being hired by the internship school, which suggests that schools are more likely to hire their student teachers permanently if they have stronger qualifications. The same is not true of GPA, though, and while future intern VAM and cooperating teacher VAM are both positively correlated with the probability of being hired by the internship school, neither result is close to statistically significant.

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[43] We also experiment with a model that interacts the intern non-white indicator with the percent of non-white students at the internship school, and find that non-white interns who do their student teaching at schools with a high percent of non-white students are particularly likely to be hired by their internship schools. Full results are available from the authors on request.

VI. Discussion and conclusions

In recent years there has been growing attention paid to the role of student teaching in the formulation and progression of an individual's teaching career. Much of this research has investigated the role of student teaching for individuals who already have become teachers, thus ignoring the role these internships may play on the decision to become a teacher and their effect on hiring and placement decisions. In this paper, we observe the outcomes of all interns from six teacher training institutions, and whether or not they are hired into the K-12 workforce. This is the first study that uses a sample of teacher training program graduates and detailed information of student teaching experiences to investigate patterns of entry into the teacher workforce.[44] We find that the endorsements earned by interns, as well as the characteristics of the schools in which internships take place, are important predictors of whether and when interns are hired into the K-12 system.

Interns who receive an endorsement in a STEM field, special education, or ELL are much more likely to be hired into the K-12 system than interns receiving endorsements in other areas. These findings conform to the conventional wisdom that these teachers are in high demand. Moreover, the job market success of these interns suggests that the shortage of STEM and special education teachers may not be the result of inefficiencies in the labor market at time of hire. Rather, shortages in STEM, for example, may be driven by demonstrated differences in the probability that STEM majors pursue teaching degrees (Goldhaber and Liu, 2002; Bacolod, 2007; and Ingersoll and Perda, 2010) and by the higher attrition rates of teachers in high-demand areas (Boe, 2006; Fore et al., 2002; Ingersoll, 2001; McCleskey et al., 2004).

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[44] It is worth again emphasizing that we can observe the correlation between intern and intership characteeristics and hiring outcomes, but hiring is a two-stage process: a prospective teacher must first decide to pursue a teaching job, and then a school must decide to hire the prospective teacher once he or she has applied. Recent work (Boyd et al., 2013) has developed a theoretical framework that considers the preferences of both teachers and schools in the matching of teachers to jobs.

Prior research has called into question whether public schools hire more academically talented job applicants (e.g., Ballou, 1996). Our results generally support this conclusion, as we do not observe a strong correlation between licensure exam scores, or grade point average, and the likelihood of being employed in a public teaching position.[45] Note, however, that we cannot rule out the possibility that interns with better licensure scores opt for employment outside of K-12 schools. Interestingly, we do find that interns with higher licensure scores are somewhat more likely to be hired by their internship schools (the estimated coefficient is relatively small in magnitude but statistically significant). This is consistent with the notion that these test scores are correlated with attributes observable through student teaching, but perhaps not through the general job application process, and are correlated with the attributes that make interns desirable job candidates.

Some of the non-significant findings are also worth emphasizing. Our research is novel in that we can identify teachers who supervised student internships. Characteristics of these cooperating teachers—such as experience, endorsements, gender, race, educational background and, for a subset of them, value-added—do not appear to be correlated with the probability of an intern's later employment, at least in expected ways. Given the policy interest in improving student teaching (CAEP, 2013; Greenberg et al., 2013) and the perception that student teaching and the quality of the cooperating teacher plays an important role in teacher preparation, these findings are somewhat discouraging as they offer little in the way of direct guidance about how to improve teacher preparation. The one piece of evidence suggesting cooperating teacher effects indicates that interns assigned to cooperating teachers with more

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[45] This is not terribly surprising given that school systems in Washington (and to our knowledge in other states) do not ask candidates about their scores as part of the teacher application process. Even if licensure scores are predictive of teacher effectiveness, it is possible that they do not strongly correlate with the information collected from teacher applicants at the point of application so would not be correlated with hiring. See Goldhaber (2007) for a focus how licensure scores are used, and on the relationship between licensure scores and teacher effectiveness.

experience helping supervise internships are less likely to be employed. Clearly this dynamic

merits future investigation, possibly in an assessment of whether this (or another cooperating

teacher characteristic) is correlated with the effectiveness of teachers who make it into the

teacher labor market.

The location of a student's internship is also an important determinant in his or her

labor market outcome. Specifically, interns who do their student teaching in suburban schools

are more likely to enter the workforce, all else equal. The increased likelihood of being hired

from a suburban school may be a result of non-random placement of interns into perceived

"healthy" suburban schools and a preference for principals to hire current interns. But, it is also

possible that our findings reflect a preference to hire interns in schools in which student

teaching occurred, which would be consistent with the literature showing that teachers tend to

be employed near where they did their training (Boyd et al, 2005), if there are more teaching

openings in suburban schools. It also suggests that the process by which internships are

determined may be an important to understanding the distribution of teacher quality across

schools, an important topic for future research.

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Figures

Figure 1. Participating and Non-Participating Institutions
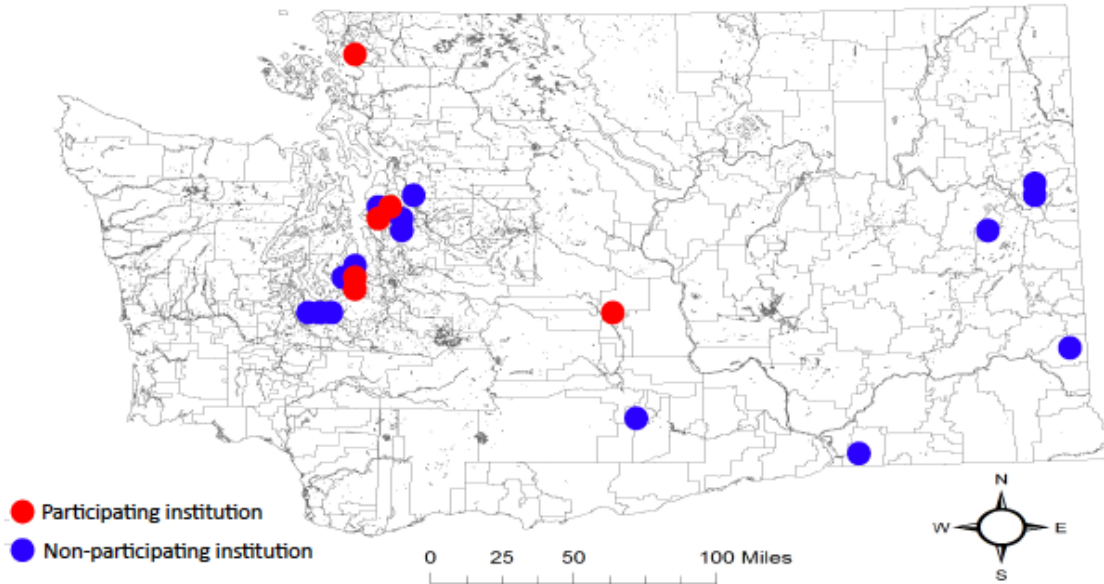

Figure 2. Proportion of New Teachers from Participating Institutions
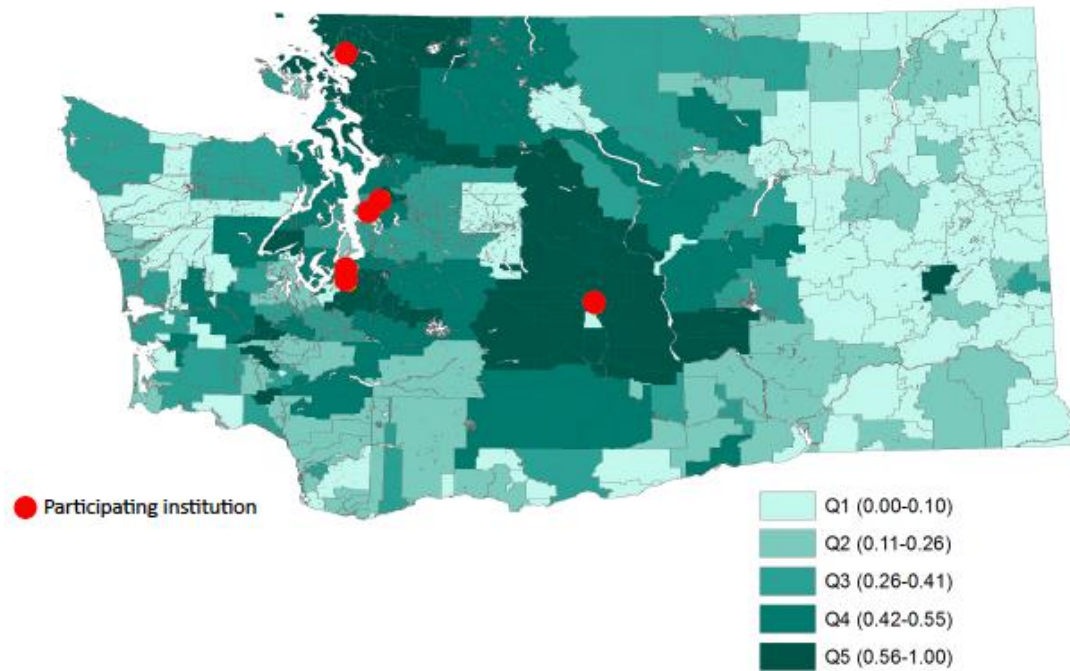
Figure 3: Transitions of Interns Between Observed Hiring Outcomes
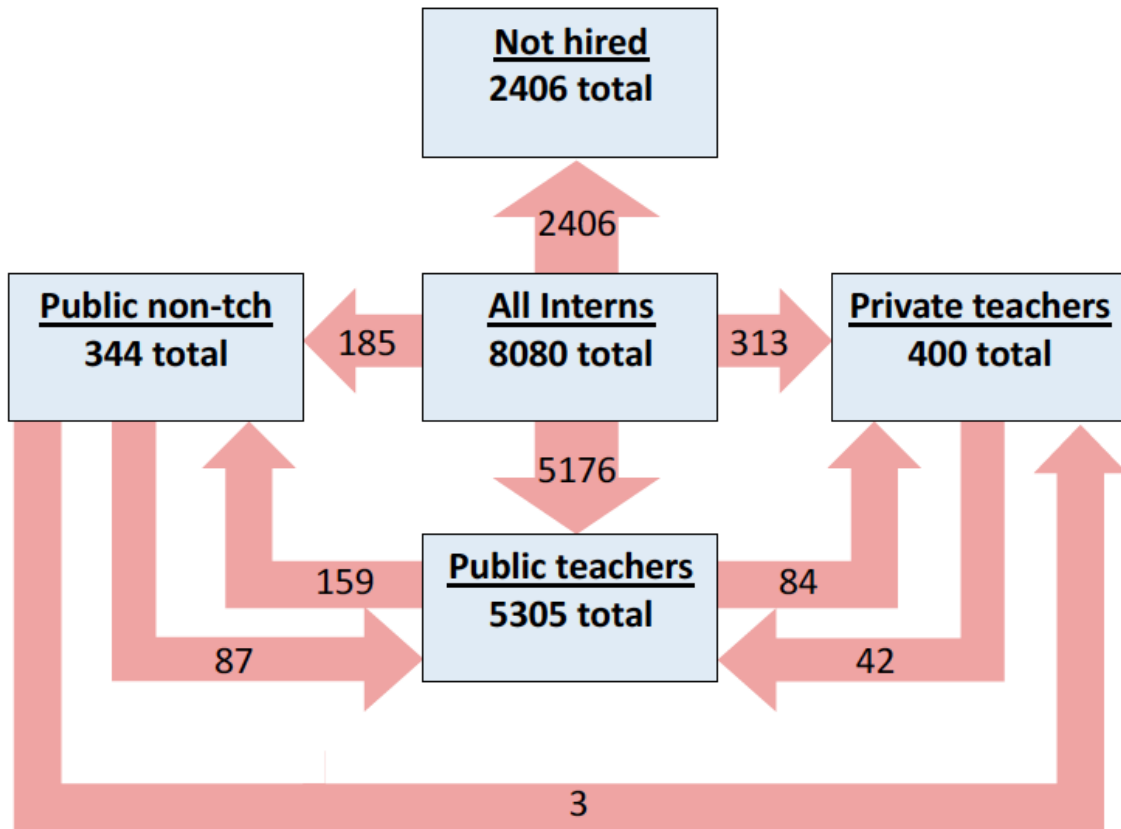
Figure 4: Time to First Teaching Job for Interns Hired into Teaching Job
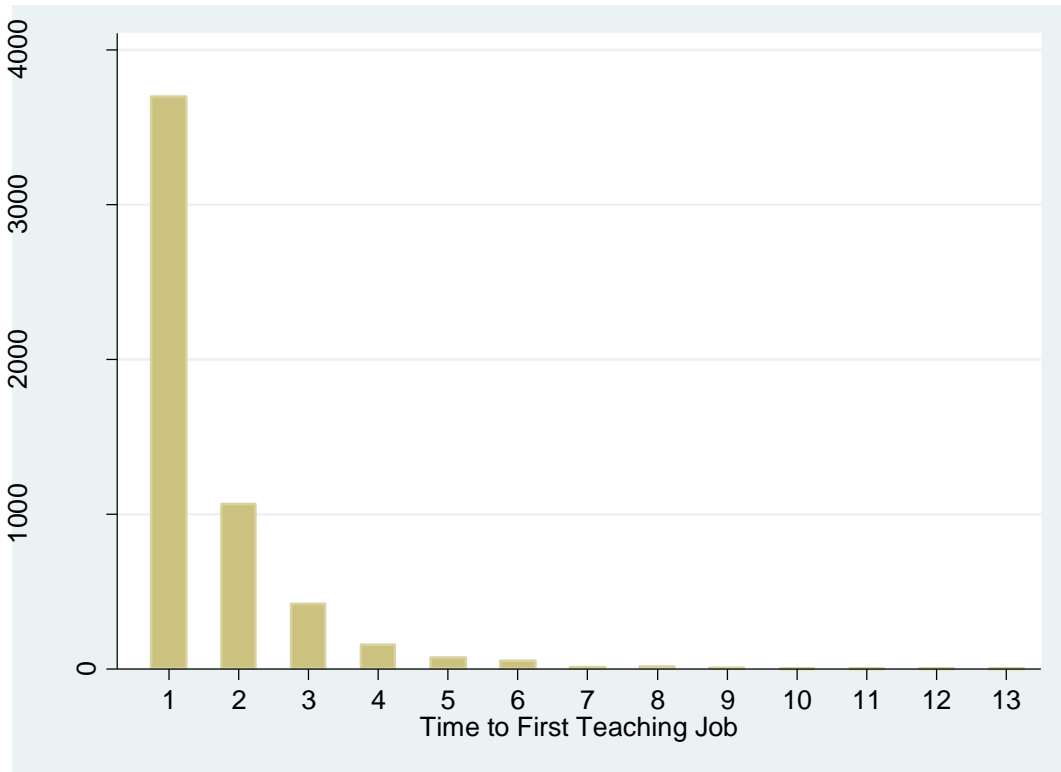
Figure 5: Fitted Probabilities of Hire for Selected Variables (at the Means)
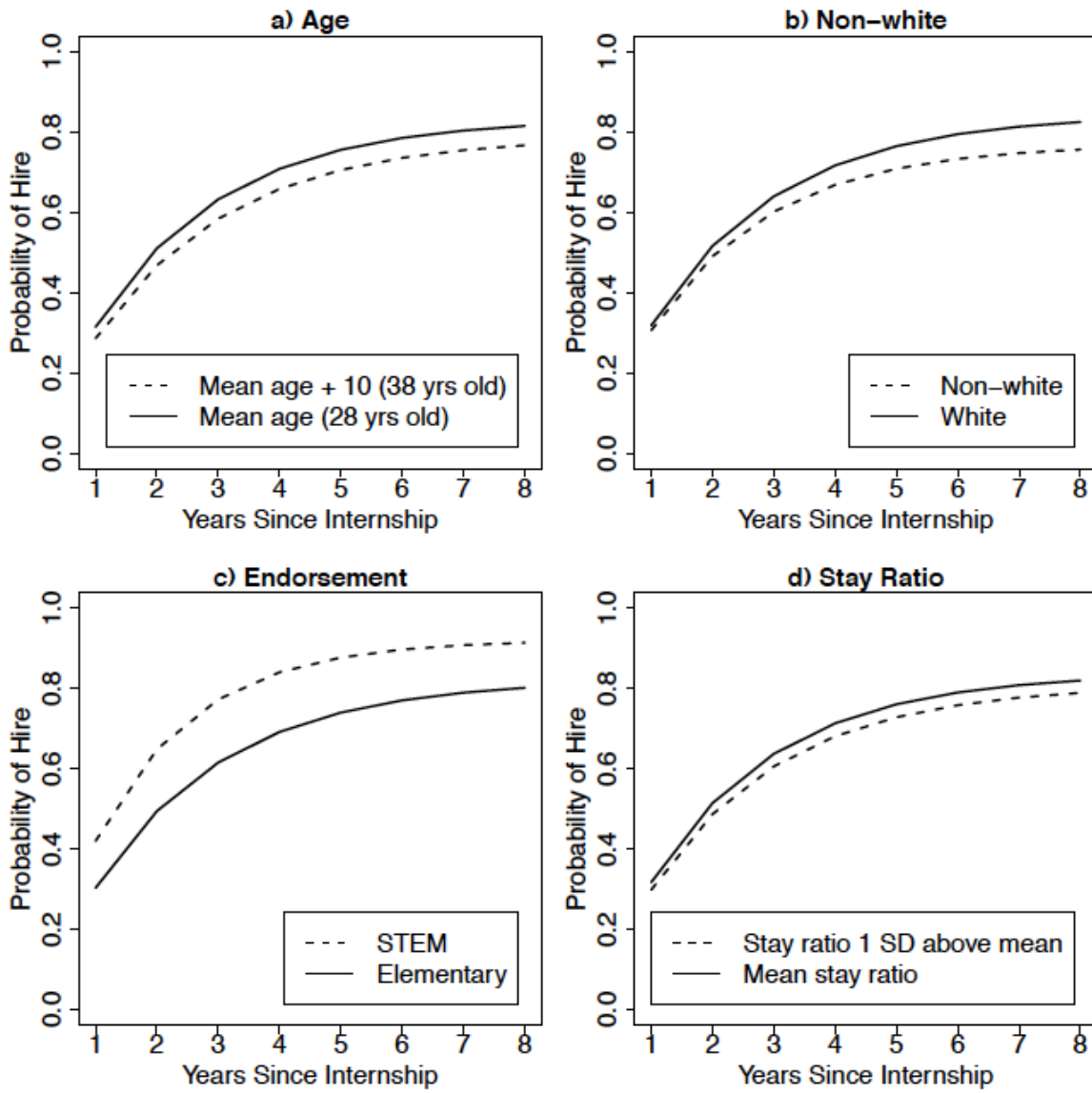
Tables

Table 1. Summary Statistics for All New Teachers in WA, 2005-06 through 2007-08

	Participating Institutions N=2180	Non-Participating Institutions N=2745	Out-of-State Institutions N=966
Average age at first hire	30.46 (8.73)	30.92 (8.60)	30.39 (8.48)
Percent male	25.83%	26.67%	25.47%
Percent with math endorsement	7.80%	6.27%*	8.07%
Percent with science endorsement	8.58%	9.22%	10.25%
Percent with English endorsement	18.39%	20.62%	12.63%**
Percent with social studies endorsement	9.86%	10.67%	9.32%
Percent with elementary endorsement	56.74%	62.04%**	30.75%**
Percent with special education endorsement	14.31%	10.49%**	8.18%**
Percent with arts endorsement	7.29%	6.12%	6.52%
Percent with health/P.E. endorsement	4.17%	2.19%	3.21%

*Significance levels for two-sided t-test relative to first column. *p<.05; **p<.01. Standard deviations of continuous variables are in parentheses.

Table 2. Intern, cooperating teacher, and internship school characteristics by outcome

	Public teaching role	Private teaching role	Public non-teaching role	Not observed hired
FULL SAMPLE (N=8080)	N = 5218	N = 271	N = 185	N = 2406
Intern characteristics				
Age	27.96**	27.60*	30.18	29.06
	(7.66)	(7.53)	(9.37)	(9.01)
Male	23.78%	14.02%	34.05%**	22.98%
Non-white	8.80%	9.50%	8.11%	9.80%
Intern endorsement area				
STEM	13.97%**	6.27%	2.16%**	8.40%
Special education	13.11%**	0.37%**	6.49%	6.57%
ELL	5.39%	4.06%	5.41%	4.36%
Elementary	63.53%**	81.55%**	57.84%**	67.87%
Other	37.01%*	21.03%**	48.11%**	34.50%
Cooperating teacher characteristics				
Age	44.95*	45.10	44.30	45.49
	(9.70)	(10.05)	(9.77)	(9.81)
Experience	15.02	15.16	14.54	15.15
	(8.59)	(9.13)	(8.23)	(8.74)
Number prior observed interns	0.38**	0.66*	0.46	0.51
	(0.93)	(1.17)	(1.01)	(1.12)
Male	23.34%	13.28%**	32.43%**	22.32%
Master's degree	60.94%*	60.15%	56.22%	63.42%
Gender match	71.90%	81.18%**	73.51%	73.65%
Endorsement match	77.27%	75.65%	75.14%	79.14%
Internship school characteristics				
Percent minority students	21.04**	21.07	22.03	22.74
	(17.46)	(15.49)	(16.47)	(17.88)
Percent FRL students	34.35**	35.54	37.67	37.91
	(20.61)	(19.72)	(19.44)	(20.64)
Standardized Avg. Passing Rate	0.28**	0.32	0.26	0.22
	(0.83)	(0.85)	(0.81)	(0.84)
Standardized Stay Ratio	-0.20**	-0.20*	-0.14	-0.12
	(0.60)	(0.67)	(0.71)	(0.66)
Number prior observed interns	7.68**	11.42*	10.74	9.34
	(12.13)	(15.75)	(18.39)	(13.53)
Number new teachers hired next year	1.21**	0.88	1.01	0.93
	(1.54)	(1.24)	(1.31)	(1.29)
WEST-B SAMPLE (N=4575)	N=2837	N=173	N=107	N=1458
Avg. WEST-B Score	272.14**	272.18	267.03**	270.75
	(11.68)	(11.14)	(11.98)	(11.68)
VAM SAMPLE (N=2083)	N=1290	N=80	N=47	N=666
Cooperating teacher VAM	0.05	0.04	0.04	0.04
	(0.18)	(0.17)	(0.21)	(0.17)
GPA SAMPLE (N=4535)	N=2983	N=145	N=105	N=1302
Undergraduate GPA	3.21	3.46*	3.29	3.24
	(1.06)	(0.66)	(0.73)	(1.02)

*Significance levels for two-sided t-test relative to last column. *p<.05; **p<.01.

Table 3: Multinomial Marginal Effect Estimates for Hiring as Private Teacher and Hiring as Public Non-Teacher vs. Hiring as Public School Teacher (2003-2010)

	Hired Sample (N=3840)		WEST-B Sample (N=3101)		GPA Sample (N=1720)		Coop VAM Sample (N=1048)	
	Private Tch (SD)	Public Non-Tch (SD)	Private Tch (SD)	Public Non-Tch (SD)	Private Tch (SD)	Public Non-Tch (SD)	Private Tch (SD)	Public Non-Tch (SD)
Intern age * 10	-0.001 (0.001)	0.014*** (0.004)	-0.009 (0.006)	0.017*** (0.004)	-0.001 (0.001)	0.017** (0.006)	0.000 (0.010)	0.012 (0.007)
Intern male (ref female)	-0.011 (0.012)	0.016* (0.007)	-0.008 (0.012)	0.024** (0.008)	0.013 (0.019)	0.018 (0.011)	-0.020 (0.021)	0.024 (0.015)
Intern non-white	-0.016 (0.014)	-0.005 (0.011)	-0.017 (0.015)	0.001 (0.010)	0.014 (0.023)	0.005 (0.018)	-0.002 (0.030)	0.008 (0.020)
Intern endorsed in STEM (ref elem)	-0.041* (0.019)	-0.059** (0.021)	-0.041* (0.020)	-0.042* (0.020)	-0.128 (2.633)	-0.500 (30.258)	0.034 (0.032)	-0.034 (0.032)
Intern endorsed in SPED (ref elem)	- (-)	-0.043 (1.509)	- (-)	-0.034 (1.928)	- (-)	- (-)	- (-)	- (-)
Intern endorsed in ELL (ref not ELL)	-0.022 (0.018)	-0.005 (0.012)	-0.014 (0.018)	0.000 (0.012)	-0.039 (0.038)	-0.009 (0.020)	-0.013 (0.034)	-0.025 (0.029)
Intern avg. WEST-B * 10			0.000 (0.004)	-0.011*** (0.003)				
Intern undergraduate GPA					-0.002 (0.010)	-0.002 (0.005)		
Int school percent FRL Students* 10	0.000 (0.000)	0.004 (0.002)	-0.004 (0.003)	0.002 (0.003)	0.000 (0.001)	0.000 (0.000)	0.001 (0.006)	0.006 (0.005)
Int school avg. passing rate (std)	0.001 (0.001)	0.004 (0.006)	0.004 (0.007)	0.002 (0.006)	0.001 (0.001)	0.001 (0.001)	0.006 (0.014)	0.001 (0.011)
Int school stay Ratio (std)	0.001 (0.001)	0.004 (0.005)	0.010 (0.007)	0.002 (0.005)	0.002 (0.001)	0.000 (0.001)	0.005 (0.013)	0.014 (0.010)
Int school in city (ref suburb)	-0.005 (0.009)	-0.010 (0.007)	-0.004 (0.009)	-0.013 (0.008)	0.003 (0.014)	-0.005 (0.010)	0.008 (0.018)	-0.027 (0.015)
Int school in town (ref suburb)	-0.024 (0.018)	0.000 (0.011)	-0.029 (0.020)	0.001 (0.011)	-0.004 (0.026)	0.015 (0.015)	-0.049 (0.047)	-0.015 (0.025)
Int school rural (ref suburb)	-0.016 (0.015)	-0.019 (0.012)	-0.033 (0.019)	-0.013 (0.012)	-0.017 (0.024)	-0.008 (0.017)	0.020 (0.027)	-0.014 (0.023)
Coop tch experience * 10	0.000 (0.001)	-0.005 (0.004)	-0.005 (0.005)	-0.005 (0.004)	0.000 (0.001)	0.000 (0.001)	-0.004 (0.010)	0.000 (0.008)
Coop tch gender match	0.007 (0.012)	0.010 (0.007)	0.002 (0.013)	0.015 (0.008)	0.035 (0.019)	0.018 (0.011)	0.008 (0.021)	0.000 (0.014)
Coop tch endorsement match	-0.011 (0.011)	-0.021* (0.008)	-0.010 (0.012)	-0.016 (0.009)	0.014 (0.019)	-0.007 (0.013)	-0.042 (0.022)	-0.024 (0.016)
Coop tch avg. VAM							-0.066 (0.047)	0.029 (0.034)

*Samples include hired interns who did their student teaching in 2002 or later. See Table 5 for other notes.

Table 4: Split Population Estimates for Hiring as Public School Teacher vs. Not Observed Hired (1998-2010)

	Full Sample (N=7624)			WEST-B Sample (N=4295)			GPA Sample (N=4433)			Coop VAM Sample (N=1956)		
	Hired (SD)	Time (SD)	*1yr ME* *5yr ME*	Hired (SD)	Time (SD)	*1yr ME* *5yr ME*	Hired (SD)	Time (SD)	*1yr ME* *5yr ME*	Hired (SD)	Time (SD)	*1yr ME* *5yr ME*
Intern age * 10	-0.299***	0.050*	*-0.028*	-0.443***	0.052	*-0.027*	-0.329***	0.066*	*-0.025*	-0.300**	0.018	*-0.004*
	(0.050)	(0.023)	*-0.046*	(0.111)	(0.042)	*-0.052*	(0.052)	(0.030)	*-0.033*	(0.095)	(0.046)	*-0.004*
Intern male (ref female)	-0.011	0.029	*-0.008*	-0.122	-0.015	*-0.004*	-0.036	0.020	*-0.007*	0.250	0.103	*0.018*
	(0.105)	(0.042)	*-0.007*	(0.190)	(0.063)	*-0.0005*	(0.108)	(0.055)	*-0.007*	(0.222)	(0.098)	*0.012*
Intern non-white	-0.484***	-0.070	*-0.012*	-0.550*	-0.220**	*0.029*	-0.586***	0.060	*-0.034*	-0.468	0.144	*0.026*
	(0.135)	(0.057)	*-0.056*	(0.223)	(0.081)	*-0.011*	(0.150)	(0.089)	*-0.057*	(0.244)	(0.123)	*0.007*
Intern endorsed in STEM (ref elem)	0.924***	-0.281***	*0.117*	0.701*	-0.343***	*0.110*	0.972***	-0.327***	*0.115*	1.188*	-0.218	*0.089*
	(0.181)	(0.062)	*0.137*	(0.291)	(0.092)	*0.126*	(0.191)	(0.086)	*0.093*	(0.490)	(0.163)	*0.054*
Intern endorsed in SPED (ref elem)	0.974**	-0.246*	*0.108*	0.655	-0.464**	*0.144*	0.839**	-0.202	*0.075*	1.187	-0.266	*0.140*
	(0.297)	(0.096)	*0.135*	(0.445)	(0.135)	*0.143*	(0.298)	(0.117)	*0.075*	(1.118)	(0.271)	*0.065*
Intern endorsed in ELL (ref not ELL)	0.700**	-0.069	*0.048*	0.533	-0.188	*0.063*	0.510*	-0.046	*0.019*	0.204	-0.044	*0.034*
	(0.245)	(0.073)	*0.082*	(0.438)	(0.111)	*0.082*	(0.242)	(0.101)	*0.033*	(0.405)	(0.171)	*0.017*
Intern avg. WEST-B * 10				-0.006	0.049*	*0.011*						
				(0.076)	(0.025)	*0.011*						
Intern undergraduate GPA							0.040	0.015	*-0.003*			
							(0.042)	(0.022)	*-0.002*			
Int school percent FRL Students* 10	-0.046	-0.003	*-0.002*	0.002	0.006	*-0.001*	-0.058	-0.017	*0.001*	-0.006	-0.013	*0.003*
	(0.035)	(0.014)	*-0.005*	(0.090)	(0.024)	*-0.001*	(0.036)	(0.019)	*-0.001*	(0.064)	(0.029)	*0.001*
Int school avg. passing rate (std)	-0.105	-0.023	*0.000*	-0.065	-0.037	*0.007*	-0.154*	-0.030	*0.0004*	0.042	-0.082	*-0.020*
	(0.076)	(0.031)	*-0.009*	(0.218)	(0.059)	*0.003*	(0.077)	(0.038)	*-0.005*	(0.141)	(0.066)	*-0.011*
Int school stay Ratio (std)	-0.199**	0.034	*-0.019*	-0.147	0.084	*-0.024*	-0.194**	-0.002	*-0.006*	-0.143	-0.068	*-0.017*
	(0.068)	(0.029)	*-0.032*	(0.152)	(0.049)	*-0.035*	(0.072)	(0.037)	*-0.013*	(0.129)	(0.058)	*-0.013*
Int school in city (ref suburb)	-0.232*	0.047	*-0.024*	-0.361	0.021	*-0.017*	-0.170	0.025	*-0.008*	-0.207	0.080	*0.013*
	(0.102)	(0.039)	*-0.037*	(0.210)	(0.063)	*-0.037*	(0.106)	(0.051)	*-0.014*	(0.185)	(0.084)	*0.008*
Int school in town (ref suburb)	-0.445**	-0.056	*-0.013*	-0.663*	-0.182	*0.014*	-0.504**	-0.009	*-0.014*	-0.087	0.101	*-0.009*
	(0.145)	(0.067)	*-0.052*	(0.262)	(0.101)	*-0.033*	(0.148)	(0.083)	*-0.030*	(0.322)	(0.150)	*-0.011*
Int school rural (ref suburb)	-0.394**	0.063	*-0.037*	-0.533	0.036	*-0.029*	-0.423*	0.046	*-0.034*	-0.509	0.035	*0.004*
	(0.146)	(0.068)	*-0.065*	(0.326)	(0.110)	*-0.063*	(0.138)	(0.074)	*-0.042*	(0.285)	(0.145)	*-0.006*
Coop tch number prior interns	-0.142**	-0.047*	*0.004*	-0.120	-0.045	*0.009*	-0.143**	-0.025	*-0.002*	-0.133	-0.047	*0.010*
	(0.046)	(0.022)	*-0.010*	(0.087)	(0.032)	*0.002*	(0.050)	(0.027)	*-0.015*	(0.098)	(0.043)	*0.000*
Coop tch gender match	-0.048	0.030	*-0.010*	-0.170	-0.060	*0.009*	0.007	0.059	*-0.016*	0.075	0.027	*0.010*
	(0.106)	(0.042)	*-0.011*	(0.194)	(0.063)	*0.0004*	(0.100)	(0.050)	*-0.0105*	(0.218)	(0.096)	*0.007*
Coop tch endorsement match	0.046	-0.019	*0.007*	-0.053	0.015	*-0.005*	0.164	-0.001	*0.002*	0.541*	0.095	*0.025*
	(0.112)	(0.047)	*0.009*	(0.246)	(0.082)	*-0.008*	(0.109)	(0.055)	*0.008*	(0.214)	(0.100)	*0.024*
Coop tch avg. VAM										0.455	0.162	*0.017*
										(0.478)	(0.229)	*0.014*

*Samples include all interns hired as public school teachers or not observed hired into any position. See Table 5 for other notes.

Table 5: Logit Marginal Effect Estimates for Hiring into Internship School vs. Hiring into Other School (1998-2010)

Sample	Hired	Open	WEST-B	GPA	Int VAM	Coop VAM
Sample Size	N = 5218	N = 2970	N = 1524	N = 1824	N = 727	N = 664
	ME (SD)	ME (SD)	ME (SD)	ME (SD)	ME (SD)	ME (SD)
Intern age * 10	0.001 (0.007)	0.012 (0.010)	0.017 (0.015)	0.000 (0.014)	0.025 (0.020)	0.052** (0.019)
Intern male (ref female)	-0.010 (0.013)	-0.022 (0.019)	-0.060* (0.027)	-0.023 (0.024)	-0.065 (0.042)	-0.053 (0.041)
Intern non-white	0.047** (0.016)	0.045 (0.025)	0.046 (0.035)	0.026 (0.038)	0.010 (0.053)	-0.079 (0.064)
Intern endorsed in STEM (ref elem)	-0.002 (0.018)	-0.001 (0.027)	-0.005 (0.038)	-0.039 (0.038)	0.025 (0.064)	0.011 (0.063)
Intern endorsed in SPED (ref elem)	0.009 (0.028)	-0.011 (0.044)	-0.022 (0.062)	-0.025 (0.059)	-0.102 (0.131)	0.030 (0.105)
Intern endorsed in ELL (ref not ELL)	-0.029 (0.023)	-0.030 (0.035)	-0.031 (0.045)	-0.021 (0.047)	-0.081 (0.076)	-0.144 (0.096)
Intern avg. WEST-B * 10			0.023* (0.011)			
Intern undergraduate GPA				0.000 (0.010)		
Intern future VAM					0.095 (0.079)	
Int school percent FRL Students* 10	-0.002 (0.004)	0.000 (0.006)	0.001 (0.009)	0.002 (0.009)	0.004 (0.012)	-0.002 (0.013)
Int school avg. passing rate (std)	-0.012 (0.009)	-0.014 (0.014)	-0.014 (0.021)	-0.024 (0.018)	0.004 (0.027)	-0.012 (0.029)
Int school stay Ratio (std)	-0.028** (0.009)	-0.020 (0.015)	-0.006 (0.022)	-0.043* (0.020)	-0.029 (0.029)	-0.017 (0.030)
Int school in city (ref suburb)	-0.025* (0.012)	-0.027 (0.018)	-0.010 (0.026)	-0.034 (0.023)	-0.019 (0.037)	-0.038 (0.038)
Int school in town (ref suburb)	0.041* (0.019)	0.081** (0.030)	0.126** (0.042)	0.087* (0.037)	0.205 (0.058)	0.138* (0.059)
Int school rural (ref suburb)	0.054** (0.018)	0.055 (0.029)	0.053 (0.043)	0.081* (0.037)	0.051 (0.051)	0.072 (0.053)
Coop tch experience * 10	-0.003 (0.006)	-0.003 (0.010)	0.003 (0.013)	-0.023 (0.013)	-0.018 (0.020)	-0.002 (0.021)
Coop tch gender match	0.002 (0.013)	-0.016 (0.019)	-0.019 (0.027)	-0.017 (0.024)	-0.042 (0.042)	-0.024 (0.041)
Coop tch endorsement match	0.022 (0.015)	0.045* (0.022)	0.048 (0.033)	0.004 (0.029)	-0.044 (0.040)	0.025 (0.045)
Coop tch avg. VAM						0.080 (0.085)

*Samples include all interns hired into public schools. Significance levels from two-sided t-test: *p<.05; **p<.01; ***p<.001. All models include indicators for internship year, training institution, and internship term, as well as: intern gender, interactions between the number of multiple endorsements and teacher endorsement areas, indicators for intern prior and current school experience, and missing race indicator; internship school enrollment, indicators for Idaho/Oregon borders, and observed number of prior interns; and indicators for cooperating teacher masters degree, male, and observed number of prior interns.