Workforce Outcomes of Program Completers in High-Needs Endorsement Areas

EMANUELE BARDELLI and MATTHEW RONFELDT
University of Michigan

Purpose: For decades, federal and state agencies have identified teacher shortages in high-needs endorsement areas (HNEAs), including science, mathematics, and special education, as a critical problem. Many states have implemented policies and practices to recruit HNEA teachers, but little is known about how their workforce outcomes compare with other teachers. **Research Methods:** We leverage statewide longitudinal data in Tennessee to analyze the workforce outcomes of teachers prepared in the state between 2010 and 2016. We model our outcomes of interest using linear and logistic multilevel regression. **Findings:** We observe that the number of teachers who receive HNEA endorsements has increased over time even as the overall number of teachers prepared in the state has declined. HNEA teachers are employed at higher rates and retained at similar rates as other teachers. HNEA teachers have similar student achievement gains as non-HNEA teachers. Though HNEA and non-HNEA teachers also have similar first-year observation ratings, STEM (science, technology, engineering, and mathematics) and special education teachers improve at slower rates subsequently. **Implications:** Our results suggest that potential policy solutions to the recruitment, retention, and development of highly effective HNEA teachers might require policies targeted to individual HNEAs, as each area might have unique needs and challenges. The positive results on preparation and employment of HNEA teachers suggest that Tennessee's policies to train, employ, and retain HNEA teachers have been largely successful. However, our findings also suggest that HNEA teachers may need additional supports in instructional development.

Spurred by enrollment declines in teacher education programs (TEPs) and reports that impending shortages of teachers will affect teacher labor markets in unexpected ways (Cowan et al. 2016; Dee and Goldhaber 2017; Sutcher et al. 2019),

Electronically published October 7, 2021

American Journal of Education, volume 128, number 1, November 2021.
 https://doi.org/10.1086/716486

scholars and policy makers are increasingly focusing on teacher shortages, including their likely extent, causes, and consequences. Although the level of concern has escalated dramatically in recent years, concerns over shortages in certain subjects and contexts are not new. In fact, the US Department of Education has been publishing a list of high-needs endorsement areas (HNEAs) for teachers since 1990. The rapid proliferation of alternative route pathways, such as Teach for America and NYC Teaching Fellows, over the past 2 decades was largely a response to needing qualified teachers in shortage subjects and schools. We know less, though, about the workforce outcomes of teachers who teach in HNEAs. In this article, we provide a descriptive look at the pipeline into teaching for teachers who receive an HNEA endorsement in Tennessee. We follow these program completers (PCs) during the first years of teaching and observe the returns of receiving an HNEA endorsement on hiring rates, instructional effectiveness, and retention.

Given substantial concerns over impending teacher shortages (Sutcher et al. 2019), it is critical to take stock of and learn from ongoing efforts to address the supply, preparation, and retention of teachers in HNEAs. It is also important to consider contextual factors that might lead to teacher shortages and the policies that are enacted to address them. For this reason, we focus on one state, Tennessee, during the end of the Great Recession and the start of the recovery, to investigate teacher shortages in HNEAs. Consistent with national trends, Tennessee has seen a sharp decline in enrollments in TEPs in the years following the Great Recession. During this time, the state has implemented a number of policies and initiatives aimed at increasing the supply of qualified teachers, particularly in HNEAs and shortage schools/districts. For example, Teach for America has two programs in Nashville-Chattanooga and in Memphis. The Tennessee Department of Education has also supported the establishment of partnerships between TEPs and school districts with the explicit goal of supporting hiring of PCs in HNEAs (Tennessee Department of Education 2017).

But have the many efforts to recruit, prepare, employ, and retain HNEA teachers in Tennessee worked? To begin to address this question, this study describes

---

Emanuele Bardelli is a doctoral candidate in educational studies and a fellow of the Institute of Education Sciences (IES) Predoctoral Training Program in Causal Inference in Educational Policy Research at the University of Michigan. His research interests include teacher learning and supports for instructional improvement, with emphasis on early career teachers. Matthew Ronfeldt is associate professor of educational studies and a core faculty member of the IES Predoctoral Training Program in Causal Inference in Educational Policy Research at the University of Michigan. His scholarship focuses on how to improve teaching quality, particularly in schools and districts serving marginalized communities.

the certification, employment, instructional effectiveness, and retention patterns for teachers who receive an HNEA endorsement in comparison with other teachers in the state.[1] Although there has been a steady decline in the number of teachers certified in Tennessee TEPs overall, we observe that there has been an increase in the number of teachers certified to teach specifically in HNEAs during the end of our observation period. In addition, we find that HNEA teachers are getting employed at higher rates than other teachers in Tennessee. Overall, HNEA teachers appear to be retained at similar rates as other teachers in the state, though English as a second language (ESL)/bilingual teachers are significantly more likely to turn over. In terms of instructional effectiveness, results from this study are mixed. Although we observe that HNEA teachers have similar achievement gains as other teachers in the state, they appear to receive significantly lower observation ratings. Taken together, our results provide suggestive evidence that efforts to train and recruit HNEA teachers have helped support the preparation pipeline for these kinds of teachers but that these efforts should likely be paired with continued support though the first years of teaching to ensure that this new supply of teachers is instructionally strong and will persist. Though results from our analysis of Tennessee cannot necessarily be generalized to other states and should not be interpreted causally, they might be of broader policy interest given that many other states have introduced similar policies or strategies for addressing shortages in high-needs teaching areas.

Teachers' Endorsements in HNEAs

Since the 1990s, the US Department of Education has published a list of shortage areas in each state. Teachers who receive endorsements in these areas can qualify for special loan deferment and repayment programs among other local recruitment incentives. The state of Tennessee has reported shortage areas to the US Department of Education for most of the past 20 years. These areas have changed over time, reflecting the changing needs of the state and suggesting that TEPs might adjust to in-state teacher demands. At the same time, special education (SpEd) teachers and STEM (science, technology, engineering, and mathematics) teachers appear to have been in a shortage in the state since the early 1990s and bilingual/ESL teachers have become a shortage area in recent years.

Tennessee has implemented a series of initiatives to address these shortage areas. Among them, in 2014, the State Board of Education has supported the development of partnership agreements between TEPs and local school districts with the goal of strengthening the preparation-to-workforce pipeline (Tennessee Department of Education 2017). Concurrently, the state has supported the development of alternative certification programs that prepare teachers in shortage areas.

Ingersoll (2003) argued that teacher shortages are mostly driven by beginner teachers' attrition rates, with about 44% of new teachers leaving the profession within 5 years (Ingersoll et al. 2018). Other researchers have challenged that beginner teachers' attrition rates are the only cause for the shortages, suggesting that other causes also include a decline in TEP enrollment (Sutcher et al. 2019) and persistent staffing issues in specific subjects and specific settings (Cowan et al. 2016). Dee and Goldhaber (2017) expanded on these insights by arguing that shortages are likely caused by a combination of supply and demand factors. To this point, Podolsky and Sutcher (2016) reported that the shrinking supply of new teachers coupled with teacher retirements are the leading causes for California shortages in SpEd, mathematics, science, and bilingual education.

In this article, we aim to understand how teacher shortages in specific endorsement areas are associated with other factors, including teacher preparation, employment, and evaluation. To this end, we provide one of the first comprehensive, statewide descriptions of the pipeline into teaching among HNEA teachers and their workforce outcomes. Specifically, we ask:

1. What are the characteristics of TEP completers who receive an HNEA endorsement? How do they compare with TEP completers in other endorsement areas?
2. Do employment rates differ between teachers with and without an HNEA endorsement?
3. Do attrition rates differ between teachers with and without an HNEA endorsement?
4. Does instructional effectiveness differ between teachers with and without an HNEA endorsement?
5. Does instructional effectiveness growth differ between teachers with and without an HNEA endorsement?

Literature Review

We organize this literature by considering first what prior literature suggests about enrollment in and completion of preservice certification programs that supply HNEA teachers to the profession. Next, we consider evidence from literature on the workforce outcomes of recently certified teachers, including employment, retention, and performance evaluations.

Teacher Preparation

Enrollment in and graduation from TEPs have been declining over the past 10 years across the United States. Sutcher and colleagues (2019) estimate a

35% decline in undergraduate and postbaccalaureate enrollments between 2009 and 2014. This translates to a 24% drop in the number of graduates/PCs during the same period of time. They also report a similar decline (−29%) in high school students indicating interest in pursuing an education degree on their American College Test (ACT) field of study preference.

Kraft and colleagues (2020) suggest that this recent decline could be a response to the introduction of No Child Left Behind's teacher accountability measures. They report that this decline appears to be concentrated in English, science, and social studies, all tested subjects under No Child Left Behind. They also suggest that state-level changes in teacher labor laws could compound the effect of federal education policies on the decline in interest in teaching. On the other hand, Cowen and colleagues (2017) find that the decline in high school students enrolling into teaching majors is similar to the declines that they observe in comparable professions (i.e., nursing and psychology) during this time period. They conclude that decline in enrollment in education majors and, by proxy, in interest in teaching, at least in Michigan, might be due to a market correction following the surge in interest in teaching during the Great Recession. A decline in the number of graduates from teacher preparation programs might be expected if we assume that people would pursue different careers once the economic climate improves (Altonji et al. 2016; Bedard and Herman 2008).

Teacher Workforce Outcomes

In this section, we review the literature related to the second part of the teacher pipeline—focusing on workforce outcomes once TEP graduates enter the teaching profession. We begin with a review of the literature about employment and retention outcomes for HNEA teachers. We then consider literature on teaching evaluation outcomes for HNEA teachers. For each outcome, we first review literature on findings on overall HNEAs (across endorsement areas) and then we discuss findings to specific endorsement areas, when these are available.

Hiring of HNEA teachers.—Sutcher and colleagues (2019) argued that the hiring of teachers is related to both supply and demand forces within the teacher labor market. Demand for teachers is mostly based on student enrollment and the full-time equivalent teachers needed to teach these students.[2] On the supply side is the interaction of the total number of new teachers being prepared in a subject and geographic area with other factors that make a labor market attractive to potential employees.

Historically, teachers who can fill STEM and SpEd positions have been in high demand (Cross 2017). The US Department of Education has consistently reported these two teaching areas as HNEAs and has incentivized teachers who work in these areas through loan forgiveness or deferment programs. It is less clear, however, how states determine which areas are in high need because the US Department of Education relies on state self-report data to compile its list of HNEAs.

To our knowledge, few empirical studies have looked at the link between graduating in a specific HNEA and employment outcomes. This is probably because of data being available only in aggregate form in most teacher preparation data sets (e.g., Title II or School and Staffing Survey data sets). Using data from selected TEPs in Washington State, Goldhaber and colleagues (2014) estimate that PCs with STEM endorsements are about 3 percentage points more likely to be hired in that state than PCs endorsed in elementary education. They do not find differences in the employment rates of teachers endorsed in English-language learning (ELL) compared with PCs endorsed in elementary education. Ingersoll and Perda (2009) show that secondary school leaders are far more likely (three to four times) to report challenges in filling SpEd positions than English/social studies positions. Relatedly, schools are more likely to hire teachers who are not fully certified in SpEd (Boe and Cook 2006).

Retention of HNEA teachers.—Turning to retention instead of employment, more work, albeit mostly qualitative, has focused on differences in teacher retention between HNEA and non-HNEA teachers, finding that HNEA teachers are somewhat more likely to leave teaching than other teachers. Using data from the School and Staffing Survey for the 2011–12 school year, Carver-Thomas and Darling-Hammond (2017) estimate that STEM (7.2%), ESL (6.9%), and SpEd (5.6%) teachers have higher leaving rates than general elementary teachers (4.9%). Nguyen and Redding (2018) expand these analyses to include data from 1988 to 2012. They estimate that there is no difference in the attrition rates of teachers who teach STEM subjects and other teachers. However, they find that STEM teachers are more likely to leave schools with more students eligible for free or reduced-priced lunch than their non-STEM colleagues.

High attrition rates for SpEd teachers have been extensively reported. In their summary of the literature, Billingsley and Bettini (2019) report that SpEd teachers can be up to twice as likely to leave teaching than other teachers. Researchers have suggested the higher rates of turnover among SpEd teachers are likely caused by a number of factors, including experiences during teacher preparation (Connelly and Graham 2009), mentoring during the early career years (Whitaker 2000), job satisfaction (Brownell et al. 1997), and work environment (Billingsley 2004).

Evaluation Outcomes of HNEA Teachers

The drive to recruit new teachers that can teach in HNEAs has raised concerns that these new teachers might not be as effective as the teachers they are replacing, especially given extensive evidence that new teachers are typically less effective than more experienced peers. These concerns may be alleviated somewhat by recent evidence suggesting that new teachers have lower than average achievement gains early in their careers but they rapidly improve during this period (Papay and Kraft 2015). On the other hand, there is little research specifically on the performance evaluations of HNEA teachers versus non-HNEA teachers, though there is some related literature on differences in performance evaluations between teachers who teach in specific subjects/areas and those who teach in other subjects.

STEM endorsements.—In terms of research on how teacher performance evaluations vary by STEM versus non-STEM endorsement, Ronfeldt (2015) finds that teachers with mathematics certification tend to have stronger achievement gains in mathematics than teachers who are certified in other areas. However, prior work in this area has found mixed evidence on whether holding a teacher certification in mathematics, instead of a temporary or emergency credential, has an impact on student scores (Darling-Hammond et al. 2001; Goldhaber and Brewer 2000).

Research in mathematics education has found a positive relationship between teacher content knowledge and student achievement (Hill and Chin 2018; Hill et al. 2005). If we assume that teachers acquire content knowledge during their credentialing program, it would be reasonable to assume that there is a positive relationship between having a STEM credential and student achievement. Consistent with this argument, Monk (1994) finds that program graduates have better mathematics student achievement gains early in their careers when they had completed more mathematics content coursework as part of their teacher certification programs.

As far as observation ratings are concerned, we are not aware of any study that specifically reports on differences by STEM or non-STEM status. Campbell (2014) reports that, on average, mathematics teachers receive lower observation ratings than reading teachers, but this difference appears to be nonsignificant. There is also no prior literature on the possible mechanism that would lead STEM teachers to receive lower observation ratings than non-STEM teachers.

Focusing on HNEA teachers, Henry and colleagues (2012) show that there is a significant variation on the returns to experience for teachers who teach different STEM subjects. Specifically, they find that value-added measures of science teachers grow at about double the rate of value-added measures of mathematics teachers and about four times the rate of value-added measures of non-STEM teachers.

SpEd endorsements.—Isolating the returns of a SpEd endorsement might be difficult to estimate, especially for teachers assigned to students with special needs, as emerging evidence points out that current teacher evaluation systems might not be well suited to evaluate SpEd teachers (e.g., Morris-Mathews et al.

2020). One concern is that misspecification of value-added models might attribute low scores of SpEd students to their teachers (McCaffrey and Buzick 2014; Thurlow et al. 2011).

Consistent with these concerns, Ronfeldt (2015) finds that teachers with SpEd certification have lower average achievement gains in mathematics; importantly, information on student SpEd status was not available so could not be included as a covariate. Feng and Sass (2013) find that returns to experience are lower, on average, for teachers in SpEd courses as compared with teachers in regular education courses. On the other hand, they also report that teachers of SpEd courses who were certified in SpEd have better achievement gains than teachers without SpEd certification.

Buzick and Jones (2015) find that generally teachers' value-added scores are similar with and without SpEd students included, except in classrooms with high proportions of SpEd students—teachers in these classrooms have lower average value-added scores; though the authors suggest that including controls for SpEd students increases these teachers' value-added scores in ways that may mitigate concerns. Campbell and Ronfeldt (2018) show that observation ratings for mathematics and English language arts (ELA) teachers are likely biased to the student composition of the classroom where the evaluation takes place. For example, in some model specifications, they find that teachers with more SpEd students receive lower observation ratings and these differences are unlikely because of differences in actual teaching quality.

ELL endorsements.—There is little literature on differences between ELL and non-ELL-endorsed teachers. That said, ELL students tend to have lower performance on state assessments (Perie et al. 2005), which could lead to similar concerns that teachers of ELL students might receive lower value-added scores, on average. That said, we are not aware of any evidence that teachers with more ELL students receive lower value-added scores. Loeb and colleagues (2014) find that teachers who are effective with ELL students also tend to be effective with non-ELL students, though teachers with bilingual certification and with fluency in their students' home language tend to be more effective with ELL students than with non-ELL students. Moreover, positive effects of having a more effective ELL teacher seem to relate to later test scores rather than same-year scores (Master et al. 2017). In terms of observation ratings, Campbell and Ronfeldt (2018) find that the proportion of ELL students in teachers' classrooms is not significantly related to their observation ratings, though coefficients trend negative.

On one hand, the differences in evaluations between HNEA and non-HNEA teachers, as described above, could very well reflect real differences in instructional quality. On the other hand, some of the literature reviewed above suggests that teacher evaluation outcomes—including observation ratings and value-added scores—may be biased or flawed in ways that could lead to between-subject differences in teacher evaluation outcomes, even where the quality of teaching may not actually differ. These concerns might highlight potential difficulties in trying to separate the contribution of an HNEA endorsement on teacher evaluations from potential bias built into the teacher evaluation system by subject area.

Method

Data Overview

The Tennessee Department of Education provided the data for this project. PC data are collected through TNCompass and include demographic information, program information, and endorsement areas for preservice teachers prepared in the state. We merged onto these data employment records from the Personnel Information Reporting System (PIRS) data set, teacher evaluation outcomes from the evaluation data set, school-level student characteristics from the Tennessee state report card, and teacher-level course information.

Sample

We keep only PCs from programs in the state from 2010 to 2016 that received an apprentice license in our analyses. We categorize high-needs endorsements following the Tennessee State Board of Education's policies. These areas include STEM, bilingual/ESL, and SpEd teaching areas. Table 1 reports the specific endorsements under each area.

Figure 1 shows the number of PCs in each HNEA during our observation period. We notice that the share of PCs that received an HNEA endorsement has

TABLE 1

High-Needs Areas Endorsement Codes

Area	Endorsements
Science, technology, engineering, and mathematics (STEM)	Biology (126, 415)
	Chemistry (127, 416)
	Physics (129, 417)
	Mathematics (125, 413)
Special education	Interventionist (144, 145)
	Modified K–12 (460)
	Comprehensive K–12 (461)
Foreign language	English as a Second Language (409)
	Spanish pre-K–12 (169, 495)

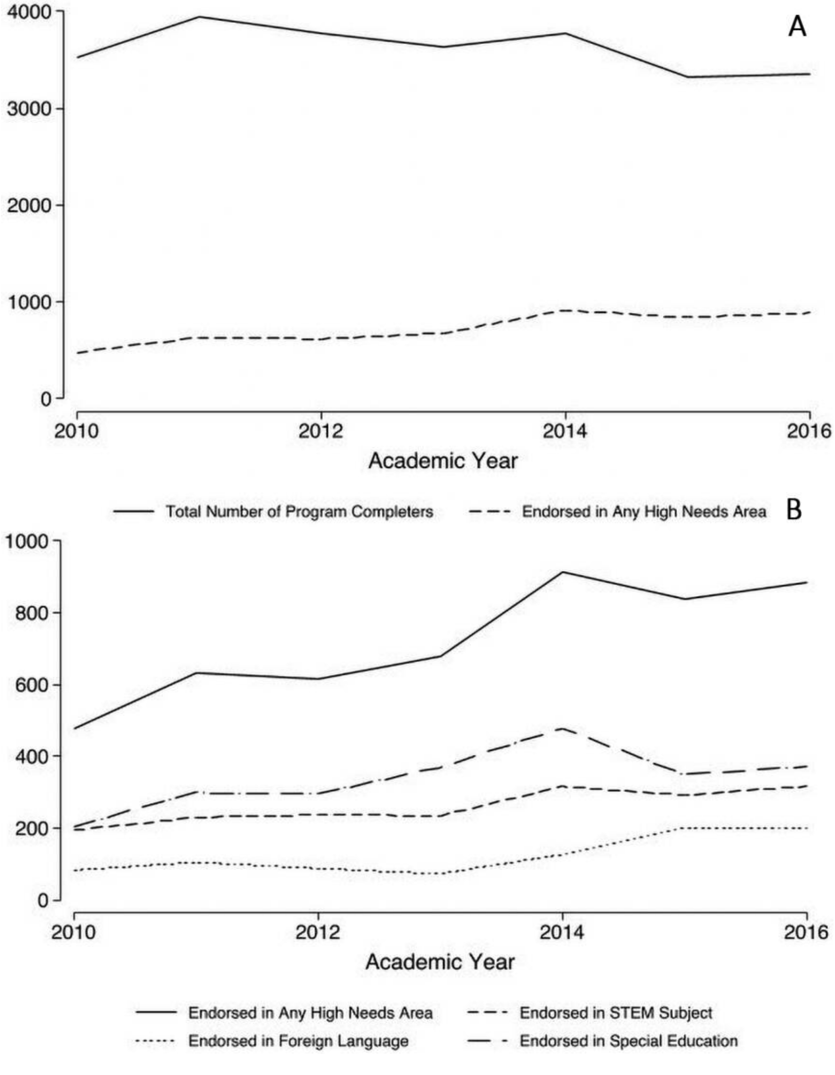

FIG. 1.—Number of graduates by academic year. STEM = science, technology, engineering, and mathematics.

been steadily increasing during our observation period. This is driven by the increase in the preparation of teachers across all three HNEAs. These increases are staggered in time. The share of SpEd endorsements started to increase in 2012, STEM endorsements and bilingual/ESL endorsements in 2013.

It is also worth pointing out that the total number of graduates from Tennessee's TEPs has been mostly constant over our observation period. We can see that the total number of graduates from TEPs in the state is constant at around 3,500 PCs. However, the number of PCs with an HNEA endorsement is steadily increasing over the same time frame.

Measures

Measures of teacher preparation.—Teacher preparation measures include data that TEPs report in recommending PCs for teacher certification. These measures include teacher certification and endorsements granted, program grade point average, and PC demographic characteristics. Some TEPs also report admission data, such as high school grade point average (GPA), SAT/ACT scores, and teacher certification exam scores.

Measures of employment.—We measure employment by merging teacher evaluation data to the PC data set. Tennessee policy mandates that all teachers be evaluated each school year. We code teachers as employed in the state if they have a valid evaluation score during that school year. These scores include both observation ratings and value-added measures. We develop a measure for ever being employed that codes teachers as employed in the state if they have a valid evaluation score during any time after they graduate from a TEP. As a robustness check, we use data from the PIRS to identify school personnel who are reported to be teachers.[3]

Measures of instructional quality.—Measures of instructional quality include teacher observation ratings and value-added measures. Most school districts in Tennessee use the Tennessee Educator Acceleration Model (TEAM) rubric to evaluate classroom instruction.[4] This rubric includes 19 indicators over three domains (instruction, planning, and environment) plus four items measuring professionalism. Value-added measures are available for teachers who teach in tested grade levels and subjects.[5] We first standardize these raw scores within each grade level/subject (and year) and then average the standardized scores into a single composite score for each teacher. This also allows us to calculate separate math and ELA scores for elementary school teachers.

Measures of attrition.—We code teachers as leavers during their last year of employment in the state using the employment record data we described above. We code for attrition in multiple ways. Our main approach is to assume a teacher is a "leaver" in year $t + 1$ when they appear in the state data as a teacher in year t but not in year $t + 1$. In our main analytic approach, we do not allow teachers to return (e.g., temporary leave); after they are coded as "leaving" then they are treated as missing henceforth. A limitation of this approach is that it is likely to misidentify some teachers who go on leave temporarily as permanent "leavers."

As a robustness check, we treat individuals who leave temporarily but return in subsequent years as "stayers," and treat their year(s) of absence as missing. A limitation of the latter approach is that teachers employed in more recent years have fewer opportunities (years) to return to teaching, so we are unable to distinguish temporary leavers from permanent leavers. As for employment, we use teacher evaluation data to identify employed teachers in the state and use the PIRS database as a robustness check for this decision.

Analytic Approach

We use linear and logistic mixed regression to explicitly model the nested nature of our observations and to account for binary and continuous outcome variables. Conceptually, our preferred model is

$$\text{Outcome} = \beta \times \text{High Needs} + \text{Controls} + \text{Random Intercepts},$$

where β is our coefficient of interest. It estimates the observed difference in the outcome for PCs who received an HNEA endorsement compared with PCs who did not receive the same HNEA endorsement. As a result, we are comparing the outcomes of HNEA-endorsed teachers with all other teachers who do not have the same endorsement. As discussed above, we interpret this coefficient as the descriptive difference in the outcome of interest between teachers with and without any given HNEA endorsement.

The set of controls and random terms that we include in our models depends upon whether the outcome of interest is a TEP-based outcome (i.e., characteristics and employment rates of PCs in HNEAs) or workforce-based outcomes (i.e., teacher evaluation outcomes, growth trajectories, and attrition rates of PCs in HNEAs). We include a vector of PC demographic characteristics and TEP features in all models. The addition of these controls allows us to parse out some possible sources of external variation in the workforce outcomes that are unrelated to receiving an HNEA endorsement. Nevertheless, we are unable to control for all endogenous sources of variation, and we caution the reader against interpreting our results causally.

We discuss these different models in more detail for each research question in the following sections.

Question 1—What Are the Characteristics of TEP Completers Who Receive an HNEA Endorsement?

We estimate the relative odds ratios of receiving an HNEA endorsement by nesting teacher observation within TEPs, adjusting for PC and time-varying TEP characteristics. Our preferred estimation model is

$$\ln\left(\frac{p(\text{HighNeeds}_{ipt})}{1 - p(\text{HighNeeds}_{ipt})}\right) = \beta_0 + X_i\Gamma + Y_p\Theta + \text{Year}_t + \delta_j + \epsilon_{ipt},$$

where X_i is a vector of PC covariates including gender and race/ethnicity indicators and final program GPA, Y_p is a vector of TEP covariates including program level and field placement type indicators, Year_t is a year fixed effect, and δ_j is a TEP-level random intercept term.

Question 2—Do Employment Rates Differ between Teachers with and without an HNEA Endorsement?

We estimate the relative odds of being employed after receiving an HNEA endorsement by nesting teacher observations within TEPs. Our preferred model is

$$\begin{aligned}\ln\left(\frac{p(\text{Employed}_{ipt})}{1 - p(\text{Employed}_{ipt})}\right) &= \beta_0 + \beta_1\text{HighNeeds}_i \\ &\quad + X_i\Gamma + Y_p\Theta + \text{Year}_t + \delta_j + \epsilon_{ipt},\end{aligned}$$

where Employed_i is an indicator variable for whether the PC is employed as a teacher. The variable HighNeeds_i indicates whether the PC is endorsed to teach an HNEA. All other covariates are the same as in the models we discussed previously.

Question 3—Do Attrition Rates Differ between Teachers with and without an HNEA Endorsement?

We estimate the following equation:

$$\begin{aligned}\ln\left(\frac{p(\text{Leaver}_{ipsdt})}{1 - p(\text{Leaver}_{ipsdt})}\right) &= \beta_0 + \beta_1\text{HighNeeds}_i + \tau f(\text{Exp}_t) \\ &\quad + X_i\Gamma + Y_p\Theta + S_s\Psi + \text{TEP}_i\Lambda + \rho\text{Year}_t \\ &\quad + \nu_d + \sigma_s + \epsilon_{ipsdt},\end{aligned}$$

where Leaver_{ipsdt} is an indicator variable for whether we observe teacher i as not being employed in the state during year $t + 1$.

X_i is a vector of time-invariant basic PC characteristics, Y_p is the TEP covariate vector, and S_s is a vector of time-varying school characteristics.[6] TEP_i is a set of TEP-level fixed effects entered as a level 2 (teacher-level) predictor. Year_t is a set of year fixed effects.

ν_d and σ_s are random-effect terms for district and school, respectively. ϵ_{ipsdt} is the individual error term. These random effects account for unobserved differences in teacher evaluation outcomes at the district level (e.g., evaluation rubric used to observe a teacher or testing schedule for students), at the school level (e.g., principal leadership or professional development opportunities), or at the teacher level (e.g., undergraduate preparation or personal beliefs about teaching).

Question 4—Does Instructional Effectiveness Differ between Teachers with and without an HNEA Endorsement?

We move to workforce-based outcomes starting from instructional effectiveness. These data have a different structure than the data described above. As a result, we nest teacher-year observation (level 1) within teachers (level 2), schools (level 3), and districts (level 4). In an equation,

$$\begin{aligned}\text{EVAL}_{ipsdt} = {} & \beta_0 + \beta_1 \text{HighNeeds}_i + \tau f(\text{Exp}_t) + X_i \Gamma \\ & + Y_p \Theta + S_s \Psi + \text{TEP}_i \Lambda + \rho \text{Year}_t + \nu_d + \sigma_s + \varphi_i + \epsilon_{ipsdt},\end{aligned}$$

where EVAL_{ipsdt} is the evaluation outcome of interest (i.e., observation rating or TVAAS score), HighNeeds_i is an indicator variable taking the value 1 if the PC received an HNEA endorsement, $f(\text{Exp}_t)$ includes two measures for experience: (1) a continuous measure for years of experience that candidates are reported to have prior to completing their teaching endorsement at their TEP and (2) indicator variables for each year of employment in a Tennessee school since receiving their endorsement. These two measures allow us to model both initial experience and time from graduation and to resolve issues of collinearity between years of teaching experience and years from graduation. The rest of the model specification follows the model for question 3 except that we also add an individual-level random effect φ_i nested within schools and districts.

Question 5—Does Instructional Effectiveness Growth Differ between Teachers with and without an HNEA Endorsement?

We use an indicator variable model (see Harris and Sass 2014; Papay and Kraft 2015) to model teacher growth in teacher evaluation outcomes for teachers endorsed in HNEAs. The preferred model is

$$\begin{aligned}\mathrm{EVAL}_{ipsdt} = \beta_0 + \sum_{j=0}^{6} \beta_j(\mathrm{HighNeeds}_i \times \mathrm{Exper}_i) + X_i\Gamma + Y_p\Theta \\ + S_s\Psi + \mathrm{TEP}_i\Lambda + \rho\mathrm{Year}_t + \nu_d + \sigma_s + \varphi_i + \epsilon_{ipsdt},\end{aligned}$$

where EVAL_{ipsdt} is the evaluation outcome of interest for teacher i in year t. Exper_i is an indicator variable for years of employment in Tennessee for teacher i during year t. We parameterize this experience variable with six indicator variables, five of them indicating 1–5 years of experience and a sixth one pooling together 6+ years of experience. All other covariates and random effects structure match the ones we included for the model described for question 4.

Robustness Checks

We conduct several robustness checks of our results to how we define our outcomes of interest and how we specify the regression models.

For employment outcomes, we check the robustness of our results to our definition of employment as being evaluated as a teacher using PIRS employment records. In this case, we define a PC as being employed in the state when they are reported as being a teacher in the PIRS data set rather than receiving an evaluation score through classroom observation or student state tests. Similarly, we check the robustness of our results to our definition of leaver as not being employed as a teacher using PIRS employment records. The results of these analyses are reported in appendix tables 1 and 4 (appendix is available online). Overall, it appears that our results are robust to how we identify employed or leaver PCs.

For teacher evaluation outcomes, differential student assignment to HNEA and non-HNEA-endorsed teachers could explain part of the performance differences between these two groups of teachers. We test the robustness of our results to sorting of students into classes by controlling for classroom student composition, student prior achievement, and school type. Results of these robustness checks are reported in appendix table 1 and appendix figures 1 and 2. The results are mixed and somewhat difficult to interpret as we only have student characteristics for a subsample of the teachers that are in our main estimation sample. For this reason, we can only partially test the impact of student assignments on outcomes because our access to student-level covariates is limited to only a few years of our panel. Our robustness checks seem to suggest that student characteristics might explain in part the differences in teacher evaluation outcomes that we observe between HNEA and non-HNEA-endorsed teachers. We expand on this observation in the Results section.

Results

Question 1—What Are the Characteristics of Preservice Teachers Who Receive a High-Needs Endorsement?

Table 2 summarizes results from *t*-tests comparing the characteristics of PCs who received and did not receive an endorsement in an HNEA. We find that

TABLE 2

Characteristics of Program Completers by Endorsement Area

	All	Other	HNEA	Differences	Effect Size
Woman	.788	.793	.767	−.026	.065***
White	.868	.886	.793	−.093	.277***
Asian or Pacific Islander	.011	.010	.019	.009	.085***
Black–not Hispanic	.077	.070	.103	.033	.124***
Hispanic	.016	.014	.028	.014	.114***
Other	.027	.020	.057	.037	.225***
Undergraduate degree	.637	.666	.520	−.146	.306***
Postbacc. degree	.303	.288	.366	.078	.170***
Postbacc. nondegree	.059	.046	.114	.068	.291***
Grade point average	3.522	3.520	3.532	.012	.032^{+}
In-state resident	.892	.899	.862	−.036	.116***
Age	27.720	27.430	28.450	1.020	.135***
Alternative program	.076	.053	.169	.116	.443***
No prior work experience	.793	.806	.746	−.059	.360***
1 year of experience	.152	.150	.162	.012	.147***
2 years of experience	.028	.023	.047	.024	.035^{+}
3 years of experience	.010	.008	.020	.012	.144***
4 years of experience	.005	.004	.009	.005	.122***
5 years of experience	.003	.002	.003	.001	.080***
6+ years of experience	.009	.008	.013	.005	.015
N	25,229	20,211	5,018		

NOTE.—Teachers who are endorsed in any high-needs area are included in the high-needs endorsement area (HNEA) group. Effect sizes are reported in standard deviation units.

$^{+}$ $p < .10$.

*** $p < .001$.

PCs who receive an endorsement in an HNEA are more likely to be teachers of color and male. They are also more likely to complete a graduate degree, to be from out of state, to be older, and much more likely to have completed an alternative certification program. Finally, we find that PCs in an HNEA are more likely to have some years of teaching experience prior to receiving their endorsements.

We suspect that some of these trends are related. For example, we know from prior research that PCs from alternative certification programs tend to be people of color, male, in graduate programs, and older. Thus, in table 3, we report results from logistic regression models estimating the probability to receive an endorsement in an HNEA as a function of all PC characteristics in the same model.[7] After adjusting for other PC characteristics, PCs with HNEA endorsements are significantly more likely to be male, Hispanic, Asian, and identify as other race/ethnicity.

We also find that the characteristics predicting completion differ across the three HNEAs. PCs that receive a STEM endorsement are more likely to be Asian or Pacific Islander and to complete alternative certification and postbaccalaureate programs; they are less likely to be women and Black–not Hispanic. PCs that receive a bilingual or ESL endorsement are more likely to be women, of Hispanic origin, and have higher GPAs. PCs who receive a SpEd endorsement are more likely to be women, Black–not Hispanic and to identify as "other" race/ethnicity; they also tend to have lower GPAs. We also note the high intercluster correlation at the TEP level for PCs in bilingual/ESL and SpEd. This suggests that the TEPs that PCs attend explain much of the variation in completion of bilingual/ESL and SpEd endorsements; this means that there is likely a subset of TEPs in Tennessee that produce teachers in these areas.

Overall, these two tables point out significant variation in the characteristics of PCs across the three HNEAs. Results for STEM endorsements suggest that the state's recent push for alternative certification routes might have helped to increase the supply of PCs in STEM TEPs. To explore this finding further, we graph the total number of PCs that receive a STEM endorsement from traditional and alternative routes in figure 2. We notice that, although the number of PCs who receive a STEM endorsement from traditional routes is decreasing, there is a corresponding expansion of alternative certification routes that grant STEM endorsements.

Question 2—What Are the Employment Outcomes of PCs in HNEAs?

Table 4 reports estimates, as odds ratios, for the likelihood of gaining employment as a teacher in Tennessee as a function of endorsement area. We estimate

TABLE 3

Odds Ratios to Complete a TEP with an HNEA Endorsement

	Any HNEA (1)	STEM (2)	Bilingual/ESL (3)	Special Education (4)
Alternative program	1.857***	2.140***	1.304	1.491**
	(.194)	(.309)	(.242)	(.214)
Postbacc. degree	1.267***	1.475***	1.674***	.978
	(.056)	(.098)	(.165)	(.061)
Postbacc. nondegree	1.341**	1.415*	1.610*	.989
	(.148)	(.217)	(.314)	(.161)
Woman	.849***	.415***	1.769***	1.560***
	(.035)	(.023)	(.194)	(.102)
Asian or Pacific Islander	1.617***	1.659**	2.475***	.911
	(.224)	(.308)	(.584)	(.195)
Black–not Hispanic	1.004	.755*	.647*	1.312***
	(.066)	(.084)	(.113)	(.107)
Hispanic	1.789***	.815	6.627***	.924
	(.208)	(.166)	(1.090)	(.170)
Other	2.046***	1.046	1.929***	2.115***
	(.178)	(.168)	(.336)	(.216)
GPA	1.129*	1.242**	2.373***	.781***
	(.056)	(.092)	(.286)	(.052)
Constant	.080***	.043***	.000***	.028***
	(.018)	(.012)	(0)	(.011)
Academic year FE	Yes	Yes	Yes	Yes
TEP ICC	.173	.084	.362	.509
N	24,539	24,539	24,539	24,539

NOTE.—This table reports the estimates (as odds ratios) of logistic regression of receiving a high-needs endorsement area (HNEA) on program completer (PC) characteristics. PC covariates include indicators for gender, race, in-state status, and final program grade point average (GPA). Teacher education program (TEP) covariates include indicator for alternative programs and program type (undergraduate/graduate). These models cluster observations within TEPs using random intercepts. Standard errors are in parentheses. STEM = science, technology, engineering, and mathematics; ESL = English as a second language; FE = fixed effects; ICC = intraclass correlation coefficient.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

that the odds of receiving employment among PCs who received an endorsement in an HNEA are about 1.7 greater than the odds among PCs with endorsements in other areas. This is equivalent to about a 10 percentage point increase in the marginal employment rate for teachers with HNEA endorsements. Likelihood of employment is significantly higher for SpEd- and STEM-endorsed PCs

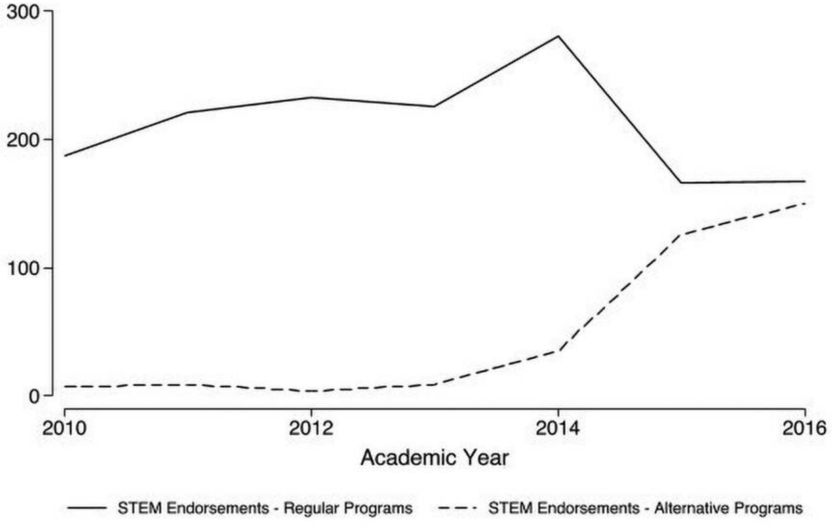

FIG. 2.—Number of program completers in STEM (science, technology, engineering, and mathematics) by program type.

when compared with non-HNEA PCs; bilingual/ESL teachers are also hired at somewhat higher rates but not at statistically significant levels.

We also observe significant variation among graduation cohorts. Although we do not have conclusive evidence for these year-to-year differences in employment rates, we suspect that lower than average employment rates for the first cohorts in our data set could be in part explained by PCs graduating toward the end of the Great Recession, and the higher employment rates for later cohorts might suggest a rebound in the statewide teacher labor market.[8] If this is the case, then the positive coefficients on the 2012–13 and 2013–14 cohorts suggest that the rebound was greater among HNEA-endorsed teachers as compared with non-HNEA teachers.

Figure 3 visually displays the employment rates differences of PCs with and without an HNEA endorsement. We notice that PCs in an HNEA endorsement (gray lines) are more likely to be employed than PCs in other endorsement areas (black lines). The employment rates over time are improving for both teachers endorsed and not endorsed in an HNEA. Once we break this down by each HNEA, we find that PCs in STEM and SpEd areas are more likely to be employed than other teachers and that PCs who are endorsed in bilingual/ESL follow a similar employment rate as other, non-HNEA PCs.

TABLE 4

Odds Ratios to Be Ever Employed by Endorsement Area

	Any HNEA (1)	STEM (2)	Bilingual/ESL (3)	Special Education (4)
Endorsed	1.679***	1.531***	1.184	1.778***
	(.069)	(.097)	(.103)	(.103)
Woman	1.043	1.058	1.028	1.014
	(.038)	(.039)	(.038)	(.037)
Asian or Pacific Islander	.567***	.584***	.592***	.599***
	(.074)	(.076)	(.077)	(.078)
Black–not Hispanic	1.664***	1.674***	1.667***	1.640***
	(.113)	(.114)	(.113)	(.111)
Hispanic	.807	.851	.833	.852
	(.093)	(.097)	(.095)	(.097)
Other	.933	1.003	1.001	.941
	(.086)	(.092)	(.092)	(.087)
GPA	1.104*	1.110*	1.112*	1.123**
	(.047)	(.047)	(.048)	(.048)
Alternative cert.	2.412***	2.487***	2.543***	2.506***
	(.290)	(.299)	(.305)	(.301)
Postbacc. degree	.977	.984	.989	.997
	(.038)	(.038)	(.039)	(.039)
Graduate degree	1.302*	1.302*	1.309*	1.328*
	(.150)	(.150)	(.151)	(.153)
Grad. 2010–11	1.075	1.084	1.086	1.077
	(.057)	(.057)	(.057)	(.057)
Grad. 2011–12	1.111	1.124*	1.128*	1.113*
	(.060)	(.060)	(.060)	(.060)
Grad. 2012–13	1.198***	1.224***	1.229***	1.200***
	(.065)	(.067)	(.067)	(.065)
Grad. 2013–14	1.263***	1.310***	1.320***	1.270***
	(.069)	(.072)	(.072)	(.070)
Grad. 2014–15	1.113	1.150*	1.150*	1.126*
	(.065)	(.067)	(.067)	(.066)
Grad. 2015–16	.889*	.922	.924	.899
	(.052)	(.054)	(.054)	(.053)
Constant	1.065	1.070	1.107	1.064
	(.207)	(.207)	(.214)	(.206)
TEP ICC	.145	.144	.145	.142
N	24,539	24,539	24,539	24,539

NOTE.—This table reports the estimates of the odds ratios of being ever employed in the state on being endorsed in a high-needs endorsement area (HNEA). These models cluster observations within teacher education programs (TEPs) using random intercepts. Standard errors are in parentheses. STEM = science, technology, engineering, and mathematics; ESL = English as a second language; GPA = grade point average; ICC = intraclass correlation coefficient.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

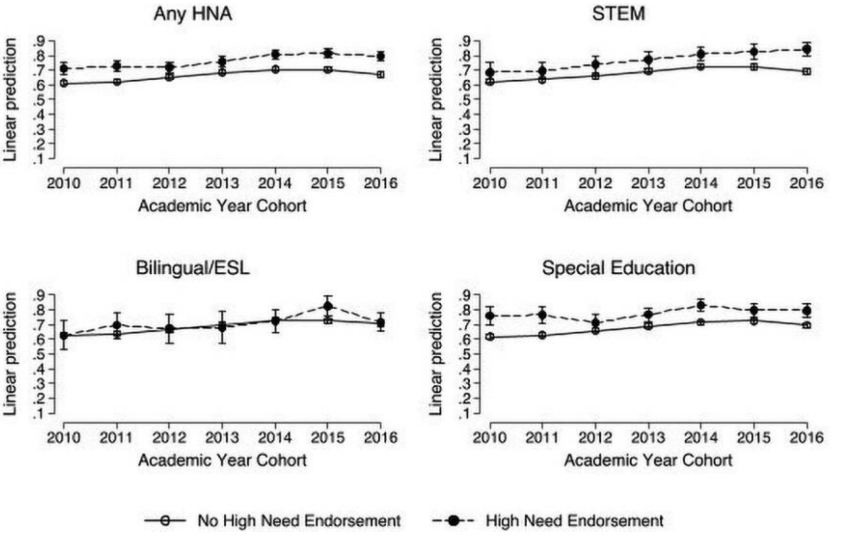

FIG. 3.—Employment rates within 3 years of graduation by high-needs endorsement area (HNEA). STEM = science, technology, engineering, and mathematics; ESL = English as a second language.

As a robustness check, we reproduce the same analytic strategy but restrict the outcome to employment within 3 years of graduation. As seen in appendix table 2, the results from these models are virtually identical to the results for models where we do not restrict the time window for employment.

Question 3—Do Teachers Who Are Endorsed in HNEAs Leave Teaching at Similar Rates as Other Teachers?

Table 5 reports the estimates, in odds ratios, for the likelihood of leaving teaching as a function of endorsement area. In column 1, we observe that the odds of leaving teaching for HNEA and non-HNEA teachers are statistically similar. When we compare the estimates across the HNEA endorsements, though, we find that bilingual/ESL teachers are more likely to leave teaching than other teachers. That is, bilingual/ESL teachers are 1.28 times as likely as nonbilingual/ESL teachers to leave teaching during our period of observation. This translates into about a 1.5 percentage point increase in their yearly average attrition rates.

TABLE 5

Odds Ratios to Leave Teaching by Endorsement Area

	Any HNEA (1)	STEM (2)	Bilingual/ESL (3)	Special Education (4)
Endorsement	1.098	1.088	1.283*	1.010
	(.053)	(.078)	(.131)	(.065)
Woman	.965	.969	.961	.967
	(.046)	(.047)	(.046)	(.046)
Asian or Pacific Islander	1.148	1.151	1.147	1.154
	(.200)	(.200)	(.199)	(.201)
Black–not Hispanic	.786**	.786**	.789**	.785***
	(.058)	(.058)	(.058)	(.058)
Hispanic	.670*	.681*	.646*	.679*
	(.119)	(.121)	(.116)	(.121)
Other	1.104	1.121	1.110	1.122
	(.129)	(.131)	(.130)	(.131)
GPA	1.012	1.013	1.008	1.014
	(.058)	(.058)	(.058)	(.058)
Alternative certification	1.426*	1.439*	1.430*	1.443*
	(.209)	(.210)	(.209)	(.211)
School covariates	Yes	Yes	Yes	Yes
PC covariates	Yes	Yes	Yes	Yes
Experience FE	Yes	Yes	Yes	Yes
TEP FE	Yes	Yes	Yes	Yes
District ICC	.018	.018	.018	.018
School ICC	.023	.022	.023	.022
N	37,251	37,251	37,251	37,251

NOTE.—This table reports the estimates of logistic models to leave using evaluation data on being endorsed in a high-needs endorsement area (HNEA). Experience covariates include indicators for number of years of experience during the first year of work in the state and time-varying indicators for total experience teaching in the state. These models cluster observations within schools and districts using random intercepts. Standard errors are in parentheses. STEM = science, technology, engineering, and mathematics; ESL = English as a second language; GPA = grade point average; PC = program completer; FE = fixed effects; TEP = teacher education program; ICC = intraclass correlation coefficient.

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

Question 4—What Are the Evaluation Outcomes for Teachers with HNEA Endorsements? How Do They Compare with Non-HNEA Teachers?

We now turn to measures of instructional performance for teachers who received HNEA endorsements. Table 6 reports the estimates of the differences in

TABLE 6

Evaluation Outcomes for Teachers who Received Endorsements in High-Needs Areas

	Any HNEA (1)	STEM (2)	Bilingual/ESL (3)	Special Education (4)
Observation ratings	−.042***	−.056***	−.001	−.030**
	(.008)	(.012)	(.018)	(.010)
Average TVAAS scores	−.076***	.023	.091	−.308***
	(.020)	(.023)	(.068)	(.034)
Mathematics TVAAS scores	.032	.180***	.219	−.222***
	(.035)	(.041)	(.133)	(.049)
ELA TVAAS scores	−.153***	−.184	.078	−.219***
	(.038)	(.146)	(.078)	(.044)

NOTE.—This table reports the estimated differences between teachers endorsed in high-needs endorsement areas (HNEA) and teachers not endorsed in HNEA on multiple evaluation outcomes. Observation ratings report the difference in observation points; Tennessee Valued-Added Assessment System (TVAAS) scores report the difference in student standard deviation units. Experience covariates include indicators for number of years of experience during the first year of work in the state and time-varying indicators for total experience teaching in the state. Program completer covariates include indicators for gender, race, in-state status, and final program grade point average. School time-varying covariates include indicators for school level, percentage of students who are African American, Hispanic, Asian, and Native American, percentage of students participating in the Free and Reduced Lunch program, average daily attendance rate, and 3-year teacher turnover. Teacher education program covariates include indicator for alternative programs and program type (undergraduate/graduate). These models cluster observations within teachers, schools, and districts using random intercepts. Standard errors are in parentheses. Our analytic sample includes $N = 47{,}623$ for observation ratings, $N = 19{,}770$ for TVAAS scores, $N = 9{,}871$ for mathematics TVAAS, and $N = 10{,}753$ for English language arts (ELA) TVAAS. STEM = science, technology, engineering, and mathematics; ESL = English as a second language.

** $p < .01$.

*** $p < .001$.

teacher evaluation outcomes between teachers who received an endorsement in an HNEA and teachers who did not, after controlling for teaching experience, school-level time-varying characteristics, and TEP-level covariates that might affect teacher evaluation outcomes.

We find that teachers who received an endorsement in an HNEA receive lower observation ratings than teachers who did not have an endorsement in an HNEA ($d = -0.042$, $p < .001$). Teachers endorsed in STEM and SpEd areas receive significantly lower observation ratings ($d = -0.056$, $p < .001$ and $d = -0.030$, $p < .01$), whereas bilingual/ESL teachers receive statistically similar observation ratings as non-HNEA teachers ($d = -0.001$, $p > .10$). To put these effect sizes into perspective, we estimate that difference between a first- and a second-year teacher is about 0.20 observation rubric points, so both of those differences are about the same growth on observation ratings that first-year teachers experience in 2 months of instruction.

When we consider TVAAS scores, we find that teachers endorsed in HNEA areas have lower TVAAS scores than teachers in non-HNEA areas ($d = -0.078$, $p < .001$). This appears to be largely driven by the fact that teachers with SpEd endorsements consistently receive lower TVAAS scores than teachers who did not receive a SpEd endorsements ($d = -0.308$, $p < .001$). Again, we estimate that difference between a first- and a second-year teacher is about 0.15 student-level standard deviations, so the difference between HNEA teachers and other teachers is about the difference in the growth that teachers experience during half a year of experience and about 2 years of experience for teachers with a SpEd endorsement.

Though we generally find that HNEA-endorsed teachers receive lower TVAAS, STEM-endorsed teachers appear to be an exception. We find that STEM teachers have, on average, higher mathematics TVAAS scores than teachers not endorsed in STEM ($d = 0.180$, $p < .001$). Though this finding is encouraging, it is somewhat at odds with finding that STEM-endorsed teachers receive lower observation ratings ($d = -0.056$, $p < .001$). More research is needed to understand these seemingly contradictory results, especially given that teachers in Tennessee have to reach a given benchmark on their observation rating scores to transition their probationary teaching license to a professional teaching license.

Finding that HNEA teachers typically receive lower observation ratings and TVAAS scores than non-HNEA teachers does not necessarily mean they are less effective teachers. We know from prior literature, discussed above, that secondary teachers and teachers who work with marginalized student populations tend to get worse observation ratings, on average, and that these lower ratings may reflect factors other than teachers' instructional quality.

Another possible explanation for the difference in teacher evaluation outcomes is that STEM and SpEd teachers initially begin their careers at similar performance levels but improve at slower rates than teachers with other endorsements. These different improvement trajectories could explain the average results that we discussed above. To examine these possibilities, we next turn to analyses of growth trajectories of HNEA teachers.

Question 5—What Are the Performance Growth Trajectories of HNEA Teachers? How Do They Compare with Non-HNEA Teachers?

Figure 4 displays the average growth trajectories in observation ratings for teachers who received an endorsement in an HNEA and teachers who did not.

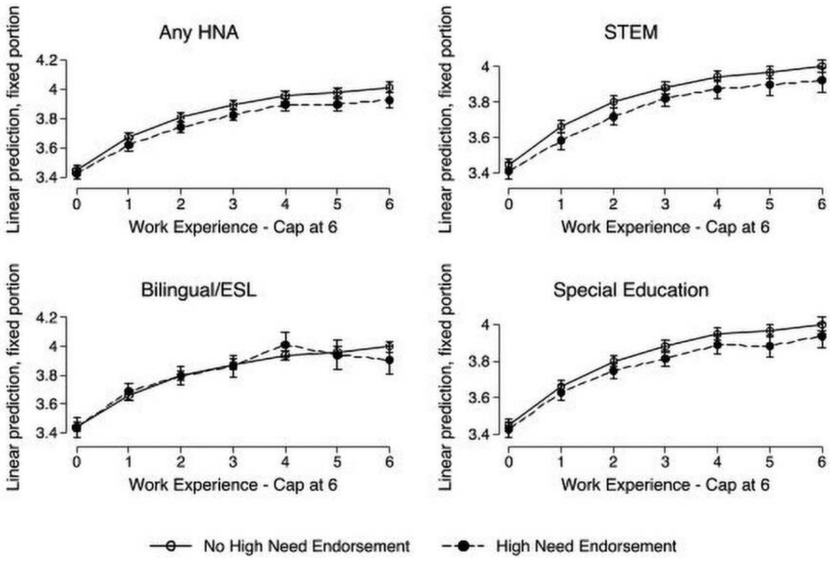

FIG. 4.—Growth trajectories in observation ratings. This figure reports the marginal expected observation ratings for high-needs endorsement area (HNEA) teachers. All other covariates in the model are set at their means. STEM = science, technology, engineering, and mathematics; ESL = English as a second language.

Overall, we find that teachers across endorsement categorizations started their careers with similar observation ratings. That is, first-year performance does not differ significantly between teachers with HNEA and non-HNEA endorsements. On the other hand, we find that observation ratings start to diverge with experience, where HNEA teachers, on average and all else equal, grow at lower rates than their non-HNEA colleagues. It appears that the lower growth rate trajectories are mostly concentrated among STEM and SpEd teachers. These results allow for a more nuanced interpretation of the results for observation ratings that we discussed in the previous section. The lower performance for STEM and SpEd teachers does not appear to stem from differences in initial (first-year) quality; rather, it appears that these teachers' observation ratings do not increase as rapidly as those of other teachers.[9]

Because estimates for TVAAS are noisy, we have less confidence in them and do not prioritize them here. However, we display results in appendix figure 3 that suggest a general improvement pattern that differs from that using observation ratings: HNEA teachers appear to receive lower first-year TVAAS estimates and to grow at a faster rate than non-HNEA teachers, leading them to close their evaluation gap by their third year of experience. In contrast, teachers with SpEd endorsements appear to follow a different improvement trajectory. They still have lower first-year TVAAS scores than their colleagues but follow a flatter growth trajectory during their early careers, leading them to receive lower TVAAS scores later in their careers.

Robustness Checks

We run several robustness checks to explore the relationship between HNEA endorsements and teacher evaluation outcomes more in depth. We first rerun the results for the teacher evaluation outcomes by school type because we suspected that placement in a particular school level (e.g., middle school) might differentially affect teachers' evaluation outcomes. The results of these models are reported in appendix table 3. We find that the negative effects for observation ratings are concentrated in high schools for STEM-endorsed teachers, in middle schools for bilingual/ESL-endorsed teachers, and in elementary schools for SpEd-endorsed teachers. We find that the negative effects on TVAAS scores are mainly driven by SpEd teachers' scores, regardless of the school level they teach. TVAAS scores for other HNEAs do not appear to differ by school level.

Another alternative explanation for the differences in teacher evaluation outcomes is that HNEA teachers might be assigned classrooms that differ from other teachers in the same schools. In particular, we suspected that SpEd teachers are likely to be assigned to students with lower average achievement, which may, in turn, affect their observation ratings and TVAAS scores. Thus, we include controls for prior student achievement and student characteristics in our preferred models to test whether or not estimates on observation ratings change.[10] We visually report the results of these analyses in appendix figures 1 and 2. These figures report on three different point estimates. On the left-hand side, we report the point estimate for the main effect of having an HNEA endorsement on observation ratings. In the middle, we report the same estimate once we restrict the estimation sample to teachers for whom we have student information. On the right-hand side, we report the point estimate of the effect of having an HNEA endorsement after controlling for student characteristics.

Overall, the results of these robustness checks are mixed. We find that the lower observation ratings for STEM teachers persist even after we adjust for prior student achievement. On the other hand, observation ratings of SpEd PCs were no longer significantly lower than they were for other teachers; differences in TVAAS scores are reduced by about half, but they are still negative. It is difficult to know what to conclude from the latter results. Though existing data do not allow us to reach a clear conclusion, these robustness checks should urge readers to be cautious about assuming that worse evaluation outcomes among HNEA teachers necessarily means they are actually less prepared or less effective. Consistent with recent evidence (Jones and Brownell 2014), these results may suggest instead that the kind of classrooms that are assigned to SpEd teachers might play a role in their evaluations. However, we are not able to investigate this further using available data.

Another possible alternative explanation for lower evaluation outcomes among HNEA teachers is that more HNEA teachers are teaching in fields outside of those in which they received endorsements; prior studies have found these "out-of-field" teachers typically perform worse than teachers who teach in subjects in which they were endorsed (Dee and Cohodes 2008; Goldhaber and Brewer 2000). We assess the sensitivity of our results to out-of-field teaching in two ways. First, we drop from our estimation sample both HNEA teachers who do not teach courses that match their endorsed area and non-HNEA-endorsed teachers who teach HNEA courses. In other words, we drop from the estimation sample teachers who teach out-of-subject courses and we compare the evaluation outcomes for in-subject HNEA teachers to in-subject non-HNEA teachers. Second, we use an instrumental variable regression to instrument in-field teaching using receiving an endorsement in the field in which teachers currently teach. We interpret these estimates as the association between evaluation outcomes and teaching HNEA courses after adjusting the estimates for teachers who were teaching in-subject according to their endorsement area. Intuitively, these estimates are a reweighting of the estimates from our preferred models using the percentage of HNEA teachers who teach HNEA courses.

The sensitivity analyses described above are reported in appendix table 4. Reading the table from left to right, we report the results of the instrumental variable regression first, followed by the results for the conditional regression where we limit our estimation sample to teachers who teach in their endorsed area. The first three columns report the results of the reduced form regression. These results are similar to the results from our preferred estimation models. The second column reports the results of the instrumental variable first stage regression. These results can be interpreted as estimating the fraction of HNEA teachers who teach in-subject. We find some heterogeneity in the fraction of teachers who teach in-subject across the endorsement areas—about 75% of the teachers endorsed in STEM, 32% of teachers endorsed in bilingual/ESL, and about 97% of the teachers endorsed in SpEd teach in-subject.[11]

The third column reports the estimates of the instrumental variable regression where receiving an HNEA endorsement is an instrument for teaching in-subject. These estimates report the differences in evaluation outcomes for teachers who were teaching in-subject according to their endorsement area. The fourth column reports the estimates of the conditional regression where the estimation sample for the reduced form regression is limited to teachers who teach in-subject. Overall, results suggest that teaching in- or out-of-subject does not seem to affect overall results. As before, HNEA teachers appear to receive lower observation ratings and TVAAS estimates than non-HNEA teachers.

Discussion and Implications

For decades, federal and state agencies have identified teacher shortages in HNEAs, including science, mathematics, and SpEd, as a critical problem. Many states have implemented policies and practices to recruit HNEA teachers, but little is known about how their workforce outcomes compare with other teachers. In this article, we provide a comprehensive descriptive analysis of the labor market outcomes for program graduates with HNEA endorsements in one state, Tennessee. To our knowledge, our work is among the first papers that provide a deep descriptive analysis of the teacher pipeline for HNEA teachers, from endorsement during initial teacher preparation through entry into teaching and subsequent workforce outcomes (instructional performance, retention).

It is important to stress that our analyses are descriptive in nature, so we discourage the reader from interpreting results as causal effects of receiving HNEA endorsements on workforce outcomes. We do what we can to adjust our models for various forms of selection, and we investigate alternative, noncausal explanations. Despite our efforts, we are not able to adjust for all forms of selection, for example, the possibility that more promising PCs may prefer and select into different HNEA endorsements. Nevertheless, our descriptive analyses provide insights into HNEA-endorsed teachers and into the variation in their workforce outcomes.

On the supply side, we find an increase over time in the number of new teachers who received an HNEA endorsement, whereas the overall number of teachers prepared statewide decreased. At face value, this finding may indicate that the various state, district, and TEP efforts to increase the supply of HNEA teachers in Tennessee have been successful. A few mechanisms are likely to account for this finding. First, efforts to recruit teachers into HNEAs (e.g., new, alternative certification routes focused on HNEAs) could have induced new people to enter the teacher profession who would not have entered it otherwise. For example, an undergraduate chemistry major might have chosen to become a high school chemistry teacher instead of a chemist for a pharmaceutical company because an alternative route certification program opened at their university and/or offered a desirable pathway into teaching. Second, this finding could suggest there has been reshuffling of current PCs from non-HNEA endorsements into HNEA endorsements. TEPs could have responded to labor market demand for teachers with HNEA endorsements by creating/expanding programs that endorse PCs into these areas or by emphasizing/incentivizing recruitment into these programs. This response would shift the current PC population within programs without necessarily attracting new potential teachers into the workforce. Finally, mechanisms outside of the control of TEPs are also possible. For example, state or district efforts to target recruitment specifically of HNEA teachers into schools could have caused prospective teachers to seek out and enroll in HNEA endorsements programs at differentially higher rates. This explanation would not account for the decline in non-HNEA endorsements, but these declines are consistent with national trends. Our data set does not allow us to tease apart these possible mechanisms. Future work into the supply of HNEA-endorsed teachers should aim to disentangle these hypotheses to better understand whether programs designed to attract teachers to HNEA expand the available pool of potential teachers or reshuffle students interested in a teaching career to HNEAs.

Receiving an HNEA endorsement is correlated with being male and a person of color, suggesting that efforts to increase HNEA endorsements may also be helping to diversify the Tennessee teaching workforce. We find evidence that alternative route TEPs are more likely than traditional route TEPs to graduate students with HNEA endorsements. For example, as STEM endorsements have declined in recent years among traditional route providers, in recent years they have substantially increased among alternative providers. These findings suggest that efforts to recruit HNEA-endorsed teachers can successfully be paired with efforts to prepare and recruit a diverse teacher workforce. These findings suggest also that alternative providers, which have been shown to increase the diversity of the teaching workforce in other labor markets (Boyd et al. 2008; Matsko et al., 2021), may be playing a similar role in Tennessee.

Finding that HNEA-endorsed teachers have higher employment rates than non-HNEA-endorsed teachers is consistent with both prior literature and intuition that teachers with HNEA endorsement would be in greater demand than other teachers. On the other hand, finding that HNEA retention rates are comparable to non-HNEA rates is inconsistent with most prior literature, which has often found lower retention rates among HNEA teachers. More research is needed to understand why HNEA teacher retention results differ in Tennessee than in other labor markets, as being able to stop, or at least slow down, the revolving door of turnover among HNEA teachers means also reducing the need to continually recruit and prepare new HNEA teachers.

One potential concern is that—in the push to increase the supply of HNEA teachers—instructional quality may be sacrificed. At least initially, this does not seem to be the case; observation ratings among HNEA teachers are statistically similar to non-HNEA teachers during the first year of teaching. In subsequent years, HNEA teachers' observation ratings grow more slowly, especially among STEM- and SpEd-endorsed teachers. TVAAS scores tell a slightly different story. HNEA teachers appear to start their careers underperforming compared with non-HNEA-endorsed peers, but their TVAAS scores catch up later in their careers. Improvement in STEM teachers' TVAAS scores appears to be behind this latter result, as TVAAS scores for SpEd teachers seem to lag behind their colleagues' teacher evaluation scores throughout our observation period.

The HNEA subgroup that consistently received both lower observation ratings and TVAAS scores was SpEd teachers (see table 6, right column). Though we observe that SpEd teachers receive consistently lower evaluation outcomes, we are unable—given the nature of this study and the available data—to discern whether they are actually less instructionally effective teachers or observation protocols and value-added models are less suited for measuring SpEd teacher quality. This latter explanation appears particularly relevant given prior evidence that these evaluation measures appear to disadvantage teachers who work with the marginalized student populations that are often overrepresented in SpEd classrooms (Campbell and Ronfeldt 2018; Jones and Brownell 2014; Steinberg and Garrett 2016). Finding differences between SpEd and non-SpEd teachers to reduce by half with the inclusion of student achievement as a covariate provides some evidence in support of this, but more research is needed to better understand whether the source of the difference in evaluation outcomes between HNEA and non-HNEA teachers is based on different instructional performance or a hidden bias in the teacher evaluation system. It is also possible that differential retention rates could explain observed differences in teacher evaluation scores by endorsement area. However, we do not find significant differences in attrition/retention rates between teachers endorsed in SpEd/STEM and other teachers. Thus, differential attrition is unlikely to explain our results. More research is needed to fully understand the dynamic between teacher evaluation scores and teacher retention.

Another possible limitation in our work is that we cannot explain the reason why HNEA teachers leave the teaching profession and whether there is heterogeneity in these reasons across HNEA subgroups. In fact, research into teacher attrition has shown that teachers who teach different subjects might leave the profession for different reasons. For example, Ingersoll and May (2012) discussed how mathematics teachers who left the profession reported that the strongest factor in their decision was the degree of autonomy in making instructional decisions in their classroom, whereas science teachers indicated that salary was the main factor in their decision for leaving teaching. In our work, we can only observe that a teacher left the profession, without knowing the reasons why. This remains a limitation in our work, and future, likely qualitative, work should aim to better understand if there is variation in the reasons why teachers leave across HNEAs.

Overall, the HNEA endorsement, employment, and retention patterns in Tennessee seem promising. Compared with non-HNEA graduates, HNEA graduates are being endorsed and employed at higher rates, suggesting an increasing supply into Tennessee classrooms. This, coupled with retention rates being comparable to non-HNEA teachers, indicates that relative shortages in HNEA subjects are being closed. That said, ESL/bilingual teachers appear to have different trends than other HNEA teachers. Unlike other HNEA teachers, ESL/bilingual teachers have similar endorsement and employment rates as non-HNEA teachers. This is likely to be concerning to Tennessee policy makers, especially given that ESL/bilingual teacher turnover rates are also higher than all other non-HNEA and HNEA groups. Taken together, these trends suggest that potential policy solutions to the recruitment, retention, and development of highly effective HNEA teachers might require policies targeted to individual HNEAs, as each area might have unique needs and challenges.

Notes

We appreciate the generous financial support that was provided for this research by the IES, US Department of Education, through the Statewide, Longitudinal Data Systems Grant (PR/Award R372A150015). Emanuele Bardelli received predoctoral support from the IES, US Department of Education (PR/Award R305B150012). We also appreciate comments on earlier drafts of this article from Kevin Schaaf, Matthew Truwit, Jason Grissom, the reviewers from the Tennessee Education Research Alliance (TERA), and conference attendees at the 2019 American Educational Research Association conference in Toronto, Ontario. This project would not have been possible without the partnership, support, and data provided by the Tennessee Department of Education. Please note that the views expressed are those of the authors and do not necessarily reflect those of this study's sponsors, the Tennessee Department of Education, or the institutions to which the authors are affiliated.

1. During our observation period, the Tennessee Department of Education has identified as HNEAs secondary mathematics, science and technology (e.g., computer science and career technical education), special education, bilingual education, and English as a second language.
2. Local and state policies that mandate maximum student-to-teacher ratios, graduation requirements, as well as retirement and retention benefits all affect the overall local demand of teachers.
3. Our partners at the Tennessee Department of Education have recommended using the evaluation data as the primary way to identify which teachers are employed in the state (and not), indicating that the data may be more dependable than the PIRS data.
4. School districts can develop their own observation rubrics and receive a waiver from the state department of education to use them to evaluate teachers. About 20% of the teachers in the state are evaluated using these alternative rubrics. We rely on the equated scores among these rubrics and the TEAM rubric that Tennessee Department of Education uses to calculate teachers' level of effectiveness.
5. Tennessee uses a version of the SAS EVAAS (Education Value-Added Assessment System) models called the Tennessee Valued-Added Assessment System (TVAAS). The most notable difference between TVAAS models and traditional value-added models (VAMs) is the fact that TVAAS scores are not adjusted for student socioeconomic factors.

6. These covariates are individual-level variables identifying PCs who completed an alternative clinical placement (i.e., residency or job-embedded placement) or who completed a graduate program. As such, these are not collinear with the TEP fixed effects, which are at the institution (e.g., university) level. That is, each institution can have multiple programs within it. Effectively, the interaction between TEP fixed effects and these individual covariates identifies individual programs within a larger institution. For example, the same institution could have an undergraduate elementary program, a graduate STEM program, and a job-embedded graduate program. These covariates allow us to account for further variation within an institution.

7. Column 1 shows estimates for all HNEA endorsements combined, so it is similar to table 2 in that regard. However, in table 2, all PC characteristics are entered into the same model, so estimates on any given characteristic can be interpreted as adjusting for other covariates.

8. Note that the negative result for the 2015–16 graduation cohort is also expected, as this group of PCs has been on the labor market for only 1 year. Their employment rates will be mechanically lower than the other cohorts that had more time to seek and gain employment.

9. Differential sorting of students to STEM versus non-STEM teachers could explain this difference. At this time, we are unable to test the extent to which student sorting can explain these differences in observation rating growth rates because we do not have access to student-level characteristics for all teachers in our sample.

10. Due to data availability issues, we are only able to do these analyses on a subset of teachers whom we can link to student-level data.

11. This might be due to the fact that about 47% of the teachers endorsed in bilingual/ESL have another non-HNEA endorsement, whereas only 9.5% of STEM-endorsed teachers and 24.5% of SpEd-endorsed teachers have another non-HNEA endorsement. These non-HNEA secondary endorsements usually include generalist grade-band endorsements such as elementary education, middle grades (4–8) education, or secondary grades (7–12) education.

References

Altonji, J. G., P. Arcidiacono, and A. Maurel. 2016. "The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects." In *Handbook of the Economics of Education*, vol. 5, ed. Eric A Hanushek, Stephen Machin, and Ludger Woessmann. Amsterdam: Elsevier.

Bedard, Kelly, and Douglas A. Herman. 2008. "Who Goes to Graduate/Professional School? The Importance of Economic Fluctuations, Undergraduate Field, and Ability." *Economics of Education Review* 27 (2): 197–210.

Billingsley, Bonnie. 2004. "Special Education Teacher Retention and Attrition: A Critical Analysis of the Research Literature." *Journal of Special Education* 38 (1): 39–55.

Billingsley, Bonnie, and Elizabeth Bettini. 2019. "Special Education Teacher Attrition and Retention: A Review of the Literature." *Review of Educational Research* 89 (5): 697–744.

Boe, Erling E., and Lynne H. Cook. 2006. "The Chronic and Increasing Shortage of Fully Certified Teachers in Special and General Education." *Exceptional Children* 72 (4): 443–60.

Boyd, Donald J., Hamilton Lankford, Susanna Loeb, Jonah Rockoff, and James Wyckoff. 2008. "The Narrowing Gap in New York City Teacher Qualifications and Its Implications for Student Achievement in High-Poverty Schools." *Journal of Policy Analysis and Management* 27 (4): 793–818.

Brownell, Mary T., Stephen W. Smith, Janet R. McNellis, and M. David Miller. 1997. "Attrition in Special Education: Why Teachers Leave the Classroom and Where They Go." *Exceptionality* 7 (3): 143–55.

Buzick, Heather M., and Nathan D. Jones. 2015. "Using Test Scores from Students with Disabilities in Teacher Evaluation." *Educational Measurement: Issues and Practice* 34 (3): 28–38.

Campbell, Shanyce L. 2014. "Quality Teachers Wanted: An Examination of Standards-Based Evaluation Systems and School Staffing Practices in North Carolina Middle Schools." PhD diss., University of North Carolina at Chapel Hill Graduate School, https://search.proquest.com/docview/1612601875.

Campbell, Shanyce L., and Matthew Ronfeldt. 2018. "Observational Evaluation of Teachers: Measuring More Than We Bargained For?" *American Educational Research Journal* 55 (6): 1233–67.

Carver-Thomas, Desiree, and Linda Darling-Hammond. 2017. "Teacher Turnover: Why It Matters and What We Can Do about It." Learning Policy Institute, https://www.fcis.org/uploaded/Data_Reports/Teacher_Turnover_REPORT.pdf.

Connelly, Vincent, and Suzanne Graham. 2009. "Student Teaching and Teacher Attrition in Special Education." *Teacher Education and Special Education* 32 (3): 257–69.

Cowan, James, Dan Goldhaber, Kyle Hayes, and Roddy Theobald. 2016. "Missing Elements in the Discussion of Teacher Shortages." *Educational Researcher* 45 (8): 460–62.

Cowen, Joshua, Katharine Strunk, Eric Brunner, and Steven Drake. 2017. "Did Policy Change Block the Teacher Pipeline? Evidence on the Impact of Labor Market Reforms in Michigan." Paper presented at the 39th annual fall research conference of the American Public Policy Analysis and Management (APPAM) Association, Chicago.

Cross, Freddie. 2017. "Teacher Shortage Areas: Nationwide Listing 1990–1991 through 2016–2017." US Department of Education, https://www2.ed.gov/about/offices/list/ope/pol/bteachershortageareasreport201718.pdf.

Darling-Hammond, Linda, Barnett Berry, and Amy Thoreson. 2001. "Does Teacher Certification Matter? Evaluating the Evidence." *Educational Evaluation and Policy Analysis* 23 (1): 57–77.

Dee, Thomas S., and Sarah R. Cohodes. 2008. "Out-of-Field Teachers and Student Achievement: Evidence from Matched-Pairs Comparisons." *Public Finance Review* 36 (1): 7–32.

Dee, Thomas S., and Dan Goldhaber. 2017. "Understanding and Addressing Teacher Shortages in the United States." 2017–05, The Hamilton Project, http://www.hamiltonproject.org/assets/files/understanding_and_addressing_teacher_shortages_in_us_pp.pdf.

Feng, Li, and Tim R. Sass. 2013. "What Makes Special-Education Teachers Special? Teacher Training and Achievement of Students with Disabilities." *Economics of Education Review* 36 (October): 122–34.

Goldhaber, Dan, and Dominic J. Brewer. 2000. "Does Teacher Certification Matter? High School Teacher Certification Status and Student Achievement." *Educational Evaluation and Policy Analysis* 22 (2): 129–45.
Goldhaber, Dan, John M. Krieg, and Roddy Theobald. 2014. "Knocking on the Door to the Teaching Profession? Modeling the Entry of Prospective Teachers into the Workforce." *Economics of Education Review* 43 (December): 106–24.
Harris, Douglas N., and Tim R. Sass. 2014. "Skills, Productivity and the Evaluation of Teacher Performance." *Economics of Education Review* 40 (June): 183–204.
Henry, Gary T., C. Kevin Fortner, and Kevin C. Bastian. 2012. "The Effects of Experience and Attrition for Novice High-School Science and Mathematics Teachers." *Science* 335 (6072): 1118–21.
Hill, Heather C., and Mark Chin. 2018. "Connections between Teachers' Knowledge of Students, Instruction, and Achievement Outcomes." *American Educational Research Journal* 55 (5): 1076–112.
Hill, Heather C., Brian Rowan, and Deborah L. Ball. 2005. "Effects of Teachers' Mathematical Knowledge for Teaching on Student Achievement." *American Educational Research Journal* 42 (2): 371–406.
Ingersoll, Richard M. 2003. "The Teacher Shortage: Myth or Reality?" *Educational Horizons* 81 (3): 146–52.
Ingersoll, Richard M., and Henry May. 2012. "The Magnitude, Destinations, and Determinants of Mathematics and Science Teacher Turnover." *Educational Evaluation and Policy Analysis* 34 (4): 435–64.
Ingersoll, Richard M., Lisa Merrill, Daniel Stuckey, and Gregory Collins. 2018. "Seven Trends: The Transformation of the Teaching Force." CPRE Research Reports, https://repository.upenn.edu/cgi/viewcontent.cgi?article=1109&context=cpre_researchreports.
Ingersoll, Richard M., and David Perda. 2009. "The Mathematics and Science Teacher Shortage: Fact and Myth." Research Report #RR-62, CPRE Research Reports.
Jones, Nathan D., and Mary T. Brownell. 2014. "Examining the Use of Classroom Observations in the Evaluation of Special Education Teachers." *Assessment for Effectiveness Intervention* 39 (2): 112–24.
Kraft, Matthew A., Eric J. Brunner, Shaun M. Dougherty, and David J. Schwegman. 2020. "Teacher Accountability Reforms and the Supply and Quality of New Teachers." *Journal of Public Economics* 188 (August): 1–24. https://doi.org/10.1016/j.jpubeco.2020.104212.
Loeb, Susanna, James Soland, and Lindsay Fox. 2014. "Is a Good Teacher a Good Teacher for All? Comparing Value-Added of Teachers with Their English Learners and Non-English Learners." *Educational Evaluation and Policy Analysis* 36 (4): 457–75.
Master, Benjamin, Susanna Loeb, and James Wyckoff. 2017. "More than Content: The Persistent Cross-Subject Effects of English Language Arts Teachers' Instruction." *Educational Evaluation and Policy Analysis* 39 (3): 429–47. https://doi.org/10.3102/0162373717691611.
Matsko, Kavita Kapadia, Matthew Ronfeldt, and Hillary Greene Nolan. 2021. "How Different Are They? Comparing Teacher Preparation Offered by Traditional, Alternative, and Residency Pathways." *Journal of Teacher Education*. https://doi.org/10/gmkbcn.
McCaffrey, Daniel F., and Heather M. Buzick. 2014. "Is Value-Added Accurate for Teachers of Students with Disabilities? What We Know Series: Value-Added Methods and Applications." Knowledge Brief 14, Carnegie Foundation for the Advancement of

Teaching (ERIC Document Reproduction Service no. ED556478), http://files.eric.ed.gov/fulltext/ED556478.pdf.
Monk, David H. 1994. "Subject Area Preparation of Secondary Mathematics and Science Teachers and Student Achievement." *Economics of Education Review* 13 (2): 125–45.
Morris-Mathews, Hannah, Kristabel R. Stark, Nathan D. Jones, Mary T. Brownell, and Courtney A. Bell. 2020. "Danielson's Framework for Teaching: Convergence and Divergence with Conceptions of Effectiveness in Special Education." *Journal of Learning Disabilities* 54 (1): 66–78.
Nguyen, Tuan D., and Christopher Redding. 2018. "Changes in the Demographics, Qualifications, and Turnover of American STEM Teachers, 1988–2012." *AERA Open* 4 (3), https://doi.org/10.1177/2332858418802790.
Papay, John P., and Matthew A. Kraft. 2015. "Productivity Returns to Experience in the Teacher Labor Market: Methodological Challenges and New Evidence on Long-Term Career Improvement." *Journal of Public Economics* 130 (October): 105–19.
Perie, Marianne, W. Grigg, and P. Donahue. 2005. "The Nation's Report Card: Reading, 2005." NCES 2006-451, National Center for Education Statistics, https://eric.ed.gov/?id=ED486463.
Podolsky, Anne, and Leib Sutcher. 2016. "California Teacher Shortages: A Persistent Problem." Learning Policy Institute, https://learningpolicyinstitute.org/sites/default/files/product-files/California_Teacher_Shortages_Persistent_Problem_BRIEF.pdf.
Ronfeldt, Matthew. 2015. "Field Placement Schools and Instructional Effectiveness." *Journal of Teacher Education* 66 (4): 304–20.
Steinberg, Matthew P., and Rachel Garrett. 2016. "Classroom Composition and Measured Teacher Performance: What Do Teacher Observation Scores Really Measure?" *Educational Evaluation and Policy Analysis* 38 (2): 293–317.
Sutcher, Leib, Linda Darling-Hammond, and Desiree Carver-Thomas. 2019. "Understanding Teacher Shortages: An Analysis of Teacher Supply and Demand in the United States." *Educational Policy Analysis Archives* 27 (April): 35.
Tennessee Department of Education. 2017. "Preparation through Partnership: Strengthening Tennessee's New Teacher Pipeline." Tennessee Department of Education, https://www.tn.gov/content/dam/tn/education/reports/Preparation_through_Partnership.pdf.
Thurlow, Martha L., Chris Bremer, and Deb Albus. 2011. "2008–09 Publicly Reported Assessment Results for Students with Disabilities and ELLs with Disabilities." Technical Report 59, National Center on Educational Outcomes, University of Minnesota (ERIC Document Reproduction Service no. ED527067), https://eric.ed.gov/?id=ED527067.
Whitaker, Susan D. 2000. "Mentoring Beginning Special Education Teachers and the Relationship to Attrition." *Exceptional Children* 66 (4): 546–66.