How Do Teachers From Alternative Pathways Contribute to the Teaching Workforce in Urban Areas? Evidence From Kansas City

Yang An
Cory Koedel
University of Missouri-Columbia

We examine how teachers from two alternative preparation programs—Teach for America (TFA) and Kansas City Teacher Residency (KCTR)—contribute to the teacher labor market in and around Kansas City, Missouri. TFA and KCTR teachers are more likely than other teachers to work in charter schools and, more broadly, in schools with more low-income, low-performing, and underrepresented minority (Black and Hispanic) students. Teachers from both programs are more racially/ethnically diverse than the larger local-area teaching workforce, but only KCTR teachers are more diverse than other teachers in the same districts where they work. We estimate value added to achievement for teachers in both programs compared with non-program teachers, with the caveat that our KCTR sample for this analysis is small. In math, we find large positive impacts of TFA and KCTR teachers on test score growth; in English language arts also, we estimate positive impacts, but they are smaller.

Keywords: *Teach for America, Kansas City Teacher Residency, urban teacher labor markets, urban schools, urban schools staffing*

It is well documented that urban school districts have difficulty recruiting and retaining high-quality teachers (Boyd et al., 2005; Boyd et al., 2006; Lankford et al., 2002; Papay et al., 2017). Moreover, accountability policies and improved measures of teaching effectiveness have exacerbated staffing challenges in high-need schools (Bates, 2020; Cullen et al., 2021). Although policy efforts in some states designed to combat these challenges have had some success, teacher recruitment in urban areas remains difficult (Glazerman et al., 2013; Springer et al., 2016; Swain et al., 2019).

Alternative teacher preparation programs (ATPPs) can be a source of labor supply in localized labor markets that face supply-side challenges. Indeed, many ATPPs explicitly build this idea into their mission statements. A well-known example is the national Teach for America (TFA) program, which we study here. Regional programs with similar goals include the New York City Teaching Fellows, Mississippi Teaching Corps, Boston Teacher Residency, and Kansas City Teacher Residency (KCTR; which we also study), among others.

Compared with traditional, university-based preparation programs, which remain the predominant pipeline into the teaching profession nationally, some ATPPs provide an accelerated pathway into the classroom. A rationale for these programs is that rigid licensing requirements create barriers to entry that keep qualified teachers out of the classroom. By reducing these barriers, ATPPs can increase the appeal and accessibility of the profession for a broader population of teachers. There are also economic reasons to expect the expanded pool to include more effective teachers. Sass (2015)

explores this possibility by studying a variety of ATTPs in Florida, and he finds that programs that require the least education-specific training yield the most effective teachers, as measured by value added to student achievement. From this, he concludes that "any benefits from preservice training are overwhelmed by the adverse selection into programs that require [more training specific to the field of education]" (p. 1).

Other ATPPs are not designed to reduce preparation time relative to traditional programs but rather shift the aspects of training that are emphasized during the preparation period. Teacher residency programs fall into this category. For example, Solomon (2009) characterizes the Boston Teacher Residency program as locating "teacher preparation in classrooms rather than in the academy" (p. 478) and writes that residency programs "[do] not question the need for preparation, but rather seek to find better ways to recruit and prepare . . . teachers" (p. 479). Guha et al. (2016) describe residency programs as offering recruits "strong content and clinical preparation specifically for the kinds of schools in which they will teach" (p. 2). Krieg et al. (2020) provide empirical evidence in support of this strategy, finding that first-year teachers are more effective when placed in classrooms with student demographics similar to their student teaching assignments.

We examine how two ATPPs—TFA and KCTR—contribute to the local teacher labor market in and around Kansas City, Missouri. TFA is an example of an "accelerated pathway" program, whereas KCTR is an example of an "intensive but alternative" program. The city school district, Kansas City Public Schools (KCPS), is a high-poverty urban district with low

achievement. The surrounding districts are more advantaged than KCPS, albeit marginally in some cases, and there is a large and vibrant charter sector in the area. The study of Kansas City is useful on its own merits because Kansas City is a major urban area with a large student population. More broadly, when combined with evaluations of ATTPs in other major U.S. cities, our work contributes to an increasingly broad understanding of how ATTPs affect urban teacher labor markets.

We address two primary research questions in our study: First, how are TFA and KCTR teachers deployed in schools in and around Kansas City, and how do they affect local-area teacher diversity?[1] We show that teachers from both programs are placed disproportionately in charter schools—and more broadly in schools with larger shares of low-income, low-performing, and underrepresented minority (URM; which we define as Black and Hispanic) students. In terms of their own diversity, TFA and KCTR teachers are more diverse racially/ethnically than other teachers in the larger local-area labor market. However, only KCTR teachers are more diverse than other teachers working in the same districts, but this result is only suggestive (i.e., the differences are not statistically significant). TFA, KCTR, and the larger teaching workforce in the Kansas City area are all female dominated, although TFA and KCTR are modestly improving their diversity along the dimension of gender.

Our second research question is about the efficacy of TFA and KCTR teachers: Do teachers from these programs outperform other teachers in terms of improving student achievement? We answer this question using estimates of value added to test scores in math and English language arts (ELA) in Grades 4–8. We find that TFA teachers raise student scores by 0.11 and 0.03 standard deviations in math and ELA, respectively, compared with nonprogram teachers, on average. We similarly find that KCTR teachers increase student achievement by 0.15 and 0.05 student standard deviations in math and ELA, respectively, although a caveat to our KCTR results is that the sample of teachers for whom we can estimate value added is small.

In a final, supplementary analysis we examine teacher retention among teachers who enter the labor market via these programs. TFA teachers have higher retention after 1 and 2 years of service, but by Year 5, they are less likely to remain as teachers in the Kansas City area than nonprogram teachers. Early-career retention for KCTR teachers is far above that of other teachers in the same districts, which is consistent with the KCTR's program structure (and the structure of similar residency programs).

Brief Program Descriptions and Prior Research

Teach for America

TFA recruits high-performing college students who commit to teach for 2 years in a low-income community where TFA has partnered with local school districts. TFA emphasizes three aspects of the ideal candidate's mind-set: The candidate (1) shares the program's core belief that all children deserve the opportunities afforded by a high-quality education, (2) has a leadership mind-set, and (3) has the ability to innovate in the classroom. The application process involves completing an online application and a one-on-one interview, which includes delivery of a sample lesson.

Preplacement TFA training occurs during the summer preceding placement. It varies by region but typically involves a 5- to 7-week accelerated training program, which includes teaching practice and coaching, plus a 1- to 2-week regional induction and orientation program. TFA partners with local certification programs to help corps members pursue full teacher certification during the 2-year commitment period. Donaldson and Johnson (2011) find that the majority of TFA teachers continue to teach beyond the 2-year commitment, although the TFA exit rate increases significantly from the second to the third year.

Our investigation of TFA placements follows on existing evidence showing that TFA teachers are more likely to be placed in classrooms with high percentages of low-income and URM students (Backes et al., 2019; Backes & Hansen, 2018; Kane et al., 2008). This is not surprising—as noted by Decker et al. (2004), TFA operates in "schools that serve disadvantaged students, have limited resources, and typically face substantial teacher shortages." (p. 11). These studies also show that TFA teachers are less racially/ethnically diverse than teachers from other pathways in the same districts and schools. We provide new evidence on TFA teachers and their placements from Kansas City.

Our value-added analysis contributes to a large existing evidence base on the efficacy of TFA teachers relative to other teachers. Decker et al. (2004) use a within-school randomized research design to study the effects of TFA teachers on student achievement in math and ELA and find that TFA teachers raise student achievement in math by about 0.15 student standard deviations relative to control teachers in the same schools. Backes et al. (2019) use value-added models and data from Miami-Dade County and find that TFA teachers outperform other teachers by about 0.10 student standard deviations in math. Xu et al. (2011) study TFA effects on achievement in high school and find that TFA teachers increase math test scores by about 0.13 student standard deviations. In terms of effects in ELA, TFA value added is smaller (Backes et al., 2019; Decker et al., 2004; Kane et al., 2008), although in high school, Xu et al. (2011) find that TFA teachers have similar effects on math and English achievement.

Two studies of TFA show results that differ substantively from the findings described in the previous paragraph (Boyd et al., 2006; Kane et al., 2008). Both are from New York City and find small-to-null TFA effects in math and null-to-negative effects in ELA.[2]

Kansas City Teacher Residency

KCTR is an urban teacher residency program operating in the Kansas City area. Residents are college graduates who train with a mentor, receive coaching, and enroll in a master's program through the University of Missouri-Kansas City. KCTR participants earn credit toward their master's (MA) degree and teach 4 days a week for a full academic year in their mentor's classroom during the residency year. At the end of the residency year, residents become certified teachers in Missouri and agree to teach in a high-need school in Kansas City for 3 additional years. During the first postresidency year, program participants complete their MA degree. They continue to receive instructional coaching throughout the 3-year postresidency commitment.

The KCTR recruitment process emphasizes finding individuals whose mind-sets are aligned with program goals—namely, individuals who believe that teachers play an important role in student success and who are interested in personal growth. Teachers are selected into the program through a multistep process that culminates in a rigorous "selection day," where prospective entrants are interviewed by partnering school principals and complete a teaching demonstration. The residency year is demanding as participants are required to attend class and complete their coursework while simultaneously maintaining their responsibilities at their residency schools.

The average age of entrants into KCTR is 30 years. Program staff attribute this in part to the multiyear commitment, which is less appealing to younger candidates. The extended commitment, along with supports to promote teacher improvement and retention during the full KCTR term, is a common feature of residency programs (Solomon, 2009). KCTR allows for what staff refer to as "healthy exit points" in acknowledgment that not everyone who enters the program will succeed (for a variety of reasons), although most entrants complete the program. The most common exit point for those who do leave is after the second year.

Despite the strong interest in the teacher residency model among teacher educators (Guha et al., 2016), our results for KCTR contribute to a very sparse empirical literature on the placements and efficacy of teachers from residency programs. We are aware of just two previous points of empirical evidence. First, Papay et al. (2012) find that teachers from the Boston Residency Program are more demographically diverse (by gender and race/ethnicity) than nonresidency teachers. Residency teachers have negative impacts on student achievement in math but positive performance trajectories. The other efficacy evidence is from the Memphis Teacher Residency, which is evaluated as part of Tennessee's Report Card on the Effectiveness of Teacher Training Programs (Tennessee Higher Education Commission, 2014). The report shows that residency teachers are more demographically diverse than the statewide teaching workforce and presents mixed results on their efficacy relative to other teachers, although the evidence is more positive than negative.

TABLE 1

Teacher Counts by Program and the First Postprogram Placement Year

Year	TFA[a]	KCTR
2012	127	
2013	69	
2014	64	
2015	48	
2016	40	
2017	33	
2018	46	32
2019	1	28
2020	2	48
Total	430	108
Total (excluding nonteaching placements)	416[b]	105[b]
Number unmatched	0	0

Note. TFA = Teach for America; KCTR = Kansas City Teacher Residency.
[a]TFA provided placement data for cohorts through 2018. The handful of post-2018 TFA placements are teachers who completed their TFA training in an earlier year but delayed entry into the workforce. [b]Nonteaching positions include central office positions, individuals listed as working in special centers, and teacher coaches, among other positions.

Data and Methods

Data

We received comprehensive lists of the TFA and KCTR participants placed in Missouri schools from the programs themselves. The data include the year and school of each participant's initial placement after the training. Our TFA data cover seven cohorts who received training between Fall 2011 and Fall 2017 (inclusive). KCTR is a newer program, and the first postresidency cohort was not placed until Fall 2017; from KCTR, we received program placement lists for the three cohorts that began their teaching placements in Fall 2017, Fall 2018, and Fall 2019. Hereafter, we refer to each school year by the spring year—for example, 2017–2018 as 2018.

We matched the listed participants to their employment records in administrative data provided by the Missouri Department of Elementary and Secondary Education (DESE). The DESE data provide additional information about the participants themselves, their placements, and their students. We were able to match all of the teachers on the program lists with the DESE data.

Table 1 shows the counts of program participants by the year of the first postprogram placement, again noting that school years are denoted by the spring year (a small number of TFA teachers entered the workforce with a lag, which is why there are a few TFA placements in 2019 and 2020). The table also identifies the number of participants in each program whose first placements were in teaching positions—who are the focus of our analysis. As expected, the vast majority were placed in teaching positions. Exceptions

include a small number of individuals whose initial placements were not in standard teaching roles. For our descriptive analysis, we analyze all teaching placements. For our efficacy analysis based on value added to student achievement, we use teachers of math and ELA in Grades 4–8, for which sample details are provided. The value-added sample includes "self-contained" elementary teachers and subject-specific teachers in higher grades.

Methods: Descriptive Labor Market Analysis

We begin by describing the composition of teachers and their initial teaching placements for each program compared with other public school teachers in the Kansas City area. To define the "local labor market area" or "Kansas City area," we retrieved the address of the central office for each local education agency (LEA) operating over the span of our data from 2012 to 2020. An LEA is a public authority within a state that has administrative control over public elementary or secondary schools; in practice LEAs consist of both traditional school districts and charter school operators. We define the local labor market area as including all LEAs with a Kansas City, Missouri, address. There are 30 such LEAs, including charter authorizers. We also include two additional LEAs with addresses in nearby Independence and Raytown (which are each about 8 miles from central Kansas City). In total, we define the area to include 32 LEAs, which combine to represent the region of effect for the programs we evaluate.[3] For ease of presentation, we use the terms "LEA" and "district" interchangeably in the text that follows.

Table 2 lists the 32 LEAs (or districts), ordered from highest to lowest by the percentage of local-area nonprogram teachers employed. Noting that the vast majority of local-area teachers are nonprogram teachers, the ordering is essentially by size. For each focal program, we report the percentage of teachers in our sample from that program placed in each district. For ease of presentation, the data are aggregated for programs over relevant years in the 2012–2020 range.

The primary takeaway from Table 2 for KCTR and TFA is that they disproportionately place teachers in the central city school district, KCPS. More than 60% of TFA teachers are placed in KCPS, whereas no other LEA has a double-digit share of TFA teachers. KCTR's representation in KCPS is also large—it accounts for about 27.6% of KCTR placements—but smaller than for TFA. Other districts with double-digit shares of KCTR teachers include Hickman Mills and the network of Crossroads Charter Schools. North Kansas City is the largest school district in the region (based on total enrollment and workforce size), but it employs relatively few program teachers, all from KCTR. The North Kansas City student population is much wealthier than the neighboring KCPS population and has a lower share of URM enrollment.

We compare the composition of teachers and their placements from each program with other teachers in terms of (a) the sector (charter or not), level (elementary, middle/junior

high, or high school), and subject of the placement; (b) the characteristics of students in the school; and (c) teachers' own race/ethnicity and gender.[4] Each program is compared with the local area in two different ways. First, we compare program teachers with the teaching workforce in the Kansas City area as a whole using a simple teacher-weighted average from all 32 districts listed in Table 2 over the years 2012–2020. This tells us how teachers from each program compare with the larger teaching workforce in the area.

Second, we make program-specific comparisons using district-by-year weighted averages that are unique to each program. The district-by-year weights are program-specific teacher shares of initial placements. As an extreme (hypothetical) example, suppose that of the 32 districts we identify in the larger Kansas City Area, just two receive any TFA teachers. In this scenario, the program-specific comparison of TFA would involve just the two districts where TFA places teachers (further weighted by the TFA placement shares across the two districts), not all 32 districts. These comparisons tell us how teachers from each program compare with other teachers working in the same districts and years as the program placements. They will differ from the simple comparisons described in the preceding paragraph to the extent that the districts that employ program teachers differ from those that do not within the Kansas City area.

Formally, the district-by-year weighted-average values for the latter comparisons are constructed as follows. For characteristic X and program j, which sends teachers to districts k in years t, the weighted-average value is calculated as

$$\bar{X}_j = \sum_{n=kt}^{N_{kt}} w_{jkt} X_{kt} \qquad (1)$$

The weighting variable w_{jkt} is the fraction of all teachers produced by program j who are placed in district k in year t, and X_{kt} is the value of characteristic X for district k in year t. N_{kt} is the total number of district-by-year cells in which a teacher from any of the two focal programs is placed. In district-years, when no teacher from program j is placed, $w_{jkt} = 0$. For each program j, $\sum_{kt}^{N_{kt}} w_{jkt} = 1$.

Both the simple-average and district-by-year-weighted comparisons are useful for understanding the ways in which the programs influence the regional labor market. For each comparison, we test whether the focal-program mean is statistically different from the comparison-group mean. The weighted comparisons are much less precise due to the weights, meaning that in some cases a substantive difference in means is not statistically detectable in these comparisons. We interpret such instances cautiously in acknowledgment of the ambiguity in their interpretation.[5]

Efficacy Analysis

We estimate the effects of teachers from each program on student achievement in Grades 4 to 8 in math and ELA, on

TABLE 2

Teacher Placement Percentages Across Districts in the Kansas City Area, Combined Across All Years

District	TFA	KCTR	Nonprogram teachers
North Kansas City 74	0	8.57	25.19
Kansas City 33	60.58	27.62	19.14
Independence 30	0	0	16.80
Raytown C-2	1.2	0	10.89
Hickman Mills C-1	0.24	15.24	8.60
Center 58	0	0	4.01
Frontier Schools	0	0	2.16
Hogan Preparatory Academy	6.49	0	1.39
Academie Lafayette	0	0	1.30
University Academy	4.57	3.81	1.21
Guadalupe Centers Schools	6.25	0	1.14
Kansas City International Academy	0.24	0.95	1.09
Brookside Charter School	1.92	7.62	0.81
Lee A. Tolbert Community Academy	0.96	3.81	0.77
Allen Village	0	0	0.67
Crossroads Charter Schools	0	10.48	0.67
Ewing Marion Kauffman School	6.25	5.71	0.57
Benjamin Banneker Academy	0	0	0.44
Gordon Parks Elementary	0	0.95	0.40
Scuola Vita Nuova	0	1.9	0.40
Pathway Academy	1.2	0	0.40
Kipp: Endeavor Academy	2.64	7.62	0.30
Delasalle Charter School	1.92	0	0.29
Genesis School Inc.	2.88	2.86	0.24
Derrick Thomas Academy	1.68	0	0.22
Hope Leadership Academy	0	0	0.20
Renaissance Academy for Math and Science	0.48	0	0.18
Academy for Integrated Arts	0	0.95	0.18
Citizens of the World Charter	0.24	0	0.17
Hope Academy	0	0	0.13
Urban Community Leadership Academy	0.24	0	0.04
Kansas City Girls Preparatory Academy	0	1.90	0.01
Sum	100	100	100

Note. Columns sum to 100%. TFA = Teach for America; KCTR = Kansas City Teacher Residency.

average, compared with nonprogram teachers during the period 2012–2019 using the following value-added model, structured following Koedel, Mihaly, et al. (2015):

$$Y_{igmpqt} = \beta_0 + \mathbf{Y_{imt\text{-}1}}\beta_1 + \mathbf{X_{it}}\beta_2 + \mathbf{\bar{Y}_{mpt\text{-}1}}\beta_3 + \mathbf{\bar{X}_{pt}}\beta_4 \\ + \mathbf{T_{it}}\beta_5 + \mathbf{P_{iqt}}\beta_6 + \gamma_g + \delta_t + \varepsilon_{igmpqt}. \quad (2)$$

In Equation 2, Y_{igmpqt} is a standardized test score (standardized by grade-subject-year) for student i in grade g and subject m, who attended school p and was taught by teacher q in year t.[6] $\mathbf{Y_{imt\text{-}1}}$ is a four-element vector of lagged test score information. The first element is the same-subject lagged score, which we require for all students for inclusion in each subject-specific model (i.e., math or ELA). The second

element is the lagged off-subject score: In our models of math achievement, we include the lagged ELA score, and in the ELA model, we include the lagged math score. To facilitate the inclusion of students who are missing just the off-subject lagged score (but still have the required same-subject score), we impute the missing score to the mean and include an indicator variable that we set equal to 1 if the score is missing. Finally, we add an interaction between the missing indicator variable and the lagged same-subject score, which improves estimation efficiency by allowing the model to rely more heavily on same-subject lagged performance to predict current performance for students who are missing the off-subject lagged score. The vector $\mathbf{\bar{Y}_{mpt\text{-}1}}$ includes school-average values of the lagged test score

variables (lagged math achievement, lagged ELA achievement, and the fraction missing the off-subject test).

The vector $\mathbf{X_{it}}$ contains student characteristics. We include indicators for racial/ethnic and gender designations, free and reduced-price lunch (FRL) status, individualized education program (IEP) status, English language learner (ELL) status, and mobility status (i.e., an indicator for whether the student changed schools midyear during year t).[7] We also include school percentages of these variables in the vector $\bar{\mathbf{X}}_{\mathbf{pt}}$.[8] The vector $\mathbf{T_{it}}$ controls for teacher experience. In our preferred specification, we bin teachers into experience groups as in Clotfelter et al. (2006): (1) 0 year prior experience (omitted category), (2) 1–2 years, (3) 3–5 years, (4) 6–12 years, (5) 13–20 years, (6) 21–27 years, and (7) 28+ years. The inclusion of these variables ensures that teacher comparisons are restricted to occur within these experience bands.[9] γ_g and δ_t are grade and year fixed effects, respectively, and ε_{igmpqt} is the error term, which we cluster at the teacher level following Koedel, Parsons, et al. (2015). The vector $\mathbf{P_{iqt}}$ includes the treatment variables of interest: two separate indicator variables for whether student i's teacher in year t is from one of the focal programs. The omitted comparison group consists of nonprogram teachers.[10]

We estimate value added for the subsample of teachers in Grades 4 to 8 in math and ELA. We exclude 2020 data from the value-added analysis because, like other states, Missouri halted 2020 testing due to the COVID pandemic (this has a disproportionate effect on our KCTR sample, per Table 1). In math, our value-added analysis includes 146 TFA teachers and 20 KCTR teachers. In ELA, the analogous teacher sample sizes are 147 and 24, respectively (some of these are overlapping—i.e., self-contained teachers in elementary schools). Due to the clustering structure of the models, the teacher sample sizes are the key determinants of statistical power. Our large TFA sample allows for fairly precise inference regarding program-level value added. Our standard errors for the KCTR estimates are larger; they are still informative, but future research on KCTR (and other teacher residency models) would benefit from analyses at greater scale. A general challenge is that teacher residency programs are often small (Guha et al., 2016) and only a fraction of teachers are placed in tested grades and subjects. For example, the sample of residency teachers in Papay et al. (2012)—the only other published study of a residency program we are aware of that estimates value added—is similarly modest in size ($N \approx 50$).

Results

Descriptive Analysis

Figures 1 to 4 document the compositions of program and nonprogram teachers along the dimensions described above. The figures are structured so that there is one graph for each program in each figure. For a given characteristic, the blue bars show average values for teachers in the focal program. The orange bars show average values for nonprogram teachers in the local area—that is, simple averages across all nonprogram teachers in the districts listed in Table 2. The gray bars show district-by-year weighted-average values for nonprogram teachers as calculated by Equation 1; that is, they show values for the same district-year cells in which teachers from the alternative-certification program were placed.[11] Solid orange and gray bars indicate that the value compared with the blue bar (i.e., the focal-program mean) is statistically different at the 10% level or better. In the appendix, we provide data tables with all of the information presented in the figures (Appendix Tables A1–A3). In addition, the appendix tables show comparisons restricted to only novice teachers (0–2 years experience) and provide some additional details that we omit from the figures for ease of illustration.

We illustrate the substantive difference between the orange and gray bars in the figures using TFA as an example. Returning to Table 2, note that KCPS employs 19.14% of all nonprogram teachers in our sample, and thus the orange bars in our comparisons involving TFA (implicitly) give a 19.14% weight to KCPS when setting the comparison group. However, TFA places 60.58% of its teachers in KCPS. The gray bars reweight KCPS so that it has a 60.58% weight in the TFA-specific comparison group. In other words, the orange bars are for the local area as a whole, while the gray bars are for other teachers in the districts (and years) that match TFA's own placement profile.

Beginning with Figure 1, we document teacher placements in terms of the schooling level and whether the placement is in a charter or noncharter school. About 48% of TFA teachers in our sample were placed in elementary schools. This value is below the simple average of the local area and the TFA-specific weighted-average comparison group in the same districts and years, which are both about 55% (although the comparison with the local-area weighted average is not statistically significant due to the aforementioned reduced precision of the weighted comparisons). Thus, from the first set of bars, we conclude that TFA teachers are less likely than other teachers in the local area to teach in elementary schools. The graph shows that the underrepresentation of TFA teachers in elementary grades is made up in high schools, where TFA teachers are disproportionately likely to be placed. In contrast, the figure shows that KCTR teachers are more likely to be placed in elementary schools and less likely to be placed in high schools relative to the larger local-area labor market.

The final set of bars in each graph in Figure 1 shows the percentages of teachers across all schooling levels placed in charter schools. TFA and KCTR teachers are much more likely to teach in charter schools than the average nonprogram teacher, which highlights the charter sector's disproportionate reliance on these programs for staffing. As indicated by the blue bars, the charter percentages for TFA and KCTR are about 38.0% and
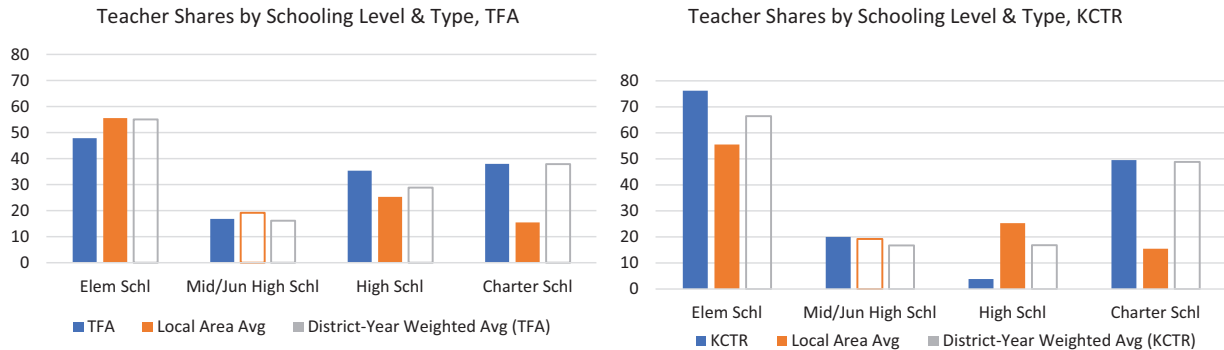
FIGURE 1. *Teacher placements by school type (i.e., charter or not) and level (elementary, middle/junior high, or high school).*
Note. The local-area averages (*orange bars*) are for all teachers in the districts listed in Table 2—they are not program specific, and thus do not change in the graphs. The district-year weighted averages (*gray bars*) are specific to each program. They are weighted based on each program's own placement patterns, so the comparison is with nonprogram teachers in the same districts and years as the program teachers. *Solid orange and gray bars* indicate that the comparison-group mean is statistically different from the focal-program mean, given by the *blue bar* in each three-bar set, at the 10% level; *clear bars* indicate that the difference between the comparison-group mean and focal-program mean is not statistically significant. TFA = Teach for America; KCTR = Kansas City Teacher Residency.
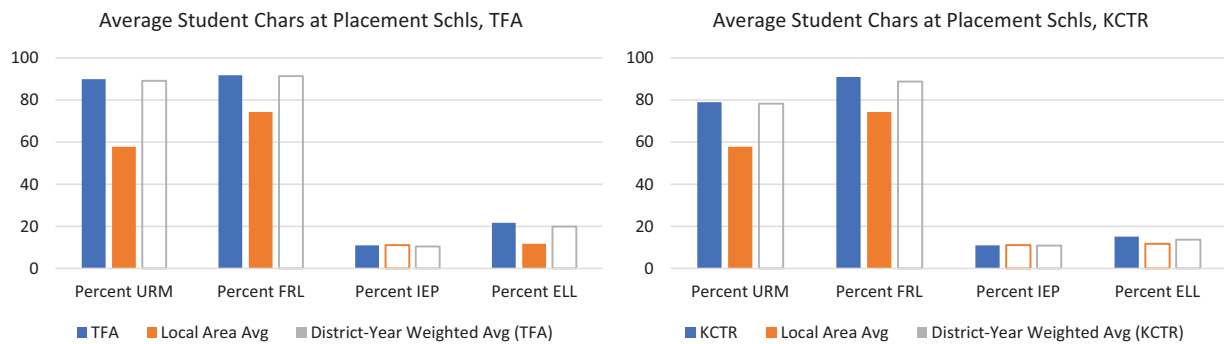

FIGURE 2. *Teacher placements by the characteristics of students attending the initial placement school.*
Note. The local-area averages (*orange bars*) are for all teachers in the districts listed in Table 2—they are not program specific, and thus do not change in the graphs. The district-year weighted averages (*gray bars*) are specific to each program. They are weighted based on each program's own placement patterns, so the comparison is with nonprogram teachers in the same districts and years as the program teachers. *Solid orange and gray bars* indicate that the comparison-group mean is statistically different from the focal-program mean, given by the *blue bar* in each three-bar set, at the 10% level; *clear bars* indicate that the difference between the comparison-group mean and focal-program mean is not statistically significant. TFA = Teach for America; KCTR = Kansas City Teacher Residency; URM = underrepresented minority (Black and Hispanic); FRL = free or reduced-price lunch eligible; IEP = individualized education program; ELL = English language learner.
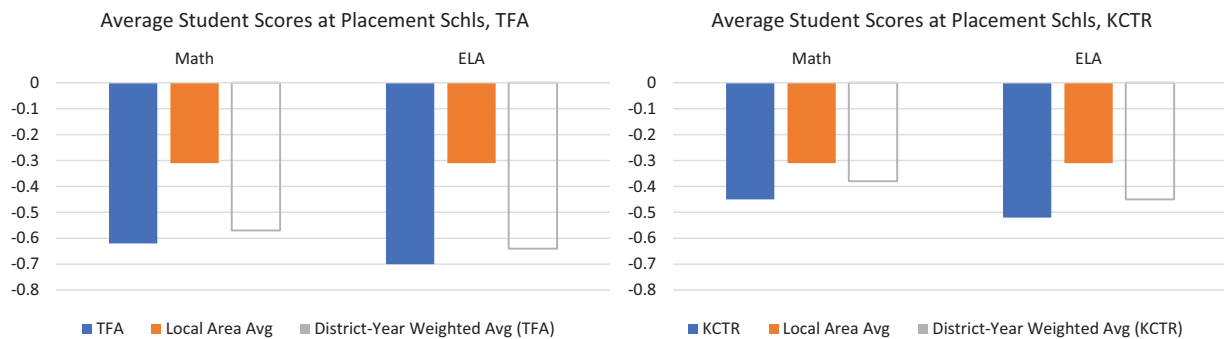

FIGURE 3. *Teacher placements by the standardized achievement level of students attending the initial placement school in math and English language arts (ELA).*
Note. The local-area averages (orange bars) are for all teachers in the districts listed in Table 2—they are not program specific, and thus do not change in the graphs. The district-year weighted averages (*gray bars*) are specific to each program. They are weighted based on each program's own placement patterns, so the comparison is with nonprogram teachers in the same districts and years as the program teachers. *Solid orange and gray bars* indicate that the comparison-group mean is statistically different from the focal-program mean, given by the *blue bar* in each three-bar set, at the 10% level; *clear bars* indicate that the difference between the comparison-group mean and focal-program mean is not statistically significant. TFA = Teach for America; KCTR = Kansas City Teacher Residency.

FIGURE 4. *Teachers' racial/ethnic and gender designation percentages.*

Note. The local-area averages (*orange bars*) are for all teachers in the districts listed in Table 2—they are not program specific, and thus do not change in the graphs. The district-year weighted averages (*gray bars*) are specific to each program. They are weighted based on each program's own placement patterns, so the comparison is with nonprogram teachers in the same districts and years as the program teachers. *Solid orange and gray bars* indicate that the comparison-group mean is statistically different from the focal-program mean, given by the *blue bar* in each three-bar set, at the 10% level; *clear bars* indicate that the difference between the comparison-group mean and focal-program mean is not statistically significant. TFA = Teach for America; KCTR = Kansas City Teacher Residency.
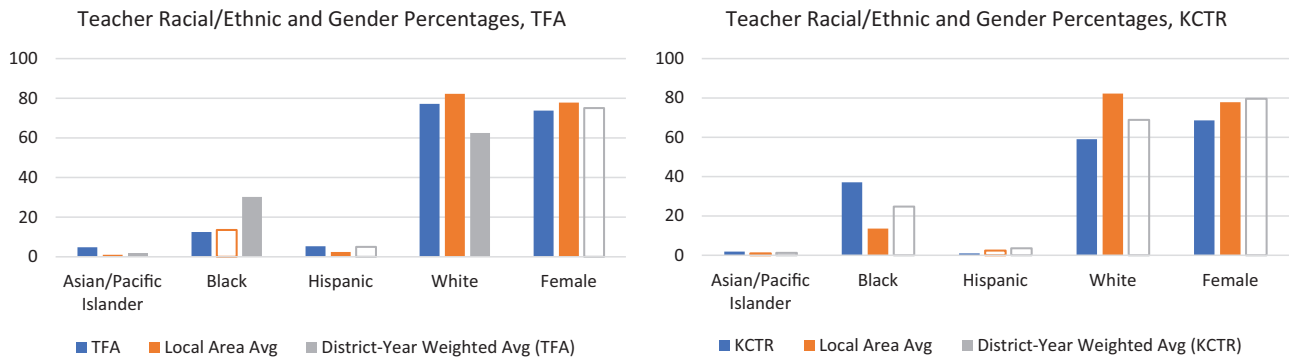
49.5%, respectively. In comparison, just 15.5% of non-program teachers in the area teach in charter schools (as indicated by the orange bars).[12]

Next, in Figure 2, we document average student characteristics at the teachers' placement schools. The structure of the figure is the same as for Figure 1. We compare the program teachers' placement schools using four school-level student characteristics: (1) the URM enrollment percentage (note that given the demographics of the local area, the URM percentage primarily captures the percentage of students who are Black), (2) the FRL-eligible enrollment percentage, (3) the percentage of students on an IEP, and (4) the percentage of ELL students.[13]

Program teachers are much more likely than nonprogram teachers to work in schools with higher URM student populations. This can be seen by the large gap between the blue and orange bars in each graph corresponding to the URM percentages. However, this gap disappears when we compare the blue and gray bars (i.e., the blue and gray bars show nearly identical values). This is informative about the mechanism by which program teachers are disproportionately working with high URM populations. Specifically, it means that the sorting is all occurring at the district level. Or put another way, conditional on the district and year of the placement, teachers from the focal programs are working in schools with similar URM percentages as other, nonprogram teachers. But because the districts in which they are placed are high-URM districts, their exposure to URM students is higher than the local-area average.

With respect to student FRL and ELL percentages, a qualitatively similar pattern plays out for each program, with modest variability in the magnitude of exposure gaps between program and nonprogram teachers. There are no differences in schools' IEP percentages between program and nonprogram teachers.

Figure 3 provides related evidence using average standardized test scores at the teachers' placement schools. We make two notes about these comparisons. First, average test scores in all teachers' schools, even in the larger sample of nonprogram teachers, are large and negative in both subjects. This is because we standardize scores using the state distribution. The implication is that the average student in the Kansas City area (as we have defined it) performs below the state average. Second, the test score results in Figure 3 are descriptive only. They may embody some program effects to the extent that program teachers affect test scores, about which we provide some evidence below. However, noting that nonschooling factors explain the majority of the variance in student test score levels (Nye et al., 2004), and since program teachers represent just a small fraction of the local-area workforce, our primary use of school-average test scores here, as in the previous figures, is to provide information about placement context.

Figure 3 shows that both TFA and KCTR teachers are placed in schools with substantially lower test score levels compared with other local-area teachers, as indicated by the large gaps between the blue and orange bars for these programs in Figure 3. Again, the gaps shrink and become statistically insignificant when we use the program-specific weighted averages (gray bars), although they do not completely close as in the comparisons in Figure 2. The fact that they mostly close points to district placements, and not school placements within districts, as the primary mechanism that drives the sorting of TFA and KCTR teachers into schools with lower achievement. But the suggestive evidence that the gaps do not close all the way indicates that there may be additional (albeit modest) within-district sorting of TFA and KCTR teachers that leads them to teach in lower-achieving schools compared with other teachers in the same districts and years. In Appendix Tables A2b and A2c, we show that the small, insignificant gaps that remain in the weighted-average
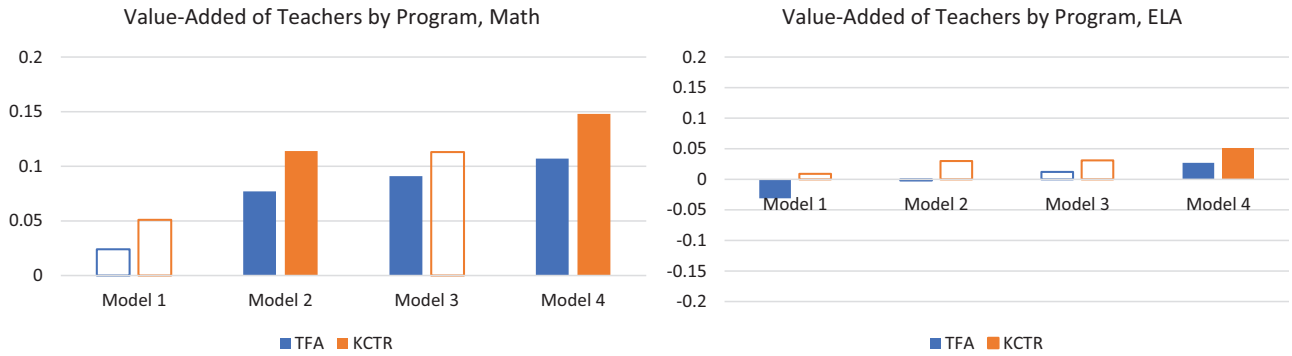
Value-Added of Teachers by Program, Math

Value-Added of Teachers by Program, ELA

■ TFA   ■ KCTR

FIGURE 5. *Value added to achievement in math and English language arts (ELA) in Grades 4 to 8 for program teachers compared with nonprogram teachers, using different value-added specifications as described in the text.*
Note. Moving from Model 1 to Model 4 increases the comprehensiveness of the value-added model. Model 1 is a base specification that only controls for individual lagged achievement ($\mathbf{Y_{imt-1}}$) and grade and year fixed effects. Model 2 adds the individual student characteristics in the vector $\mathbf{X_{it}}$. Model 3 further adds the school-level control vectors $\mathbf{\bar{Y}_{pmt-1}}$ and $\mathbf{\bar{X}_{pt}}$. The last component of the full model is the vector of teacher experience bins, denoted by $\mathbf{T_{it}}$, added to Model 4, which is the full, preferred specification. *Solid bars* indicate differences between focal-program teachers and other teachers that are statistically significant at the 10% level or higher; *clear bars* indicate statistically insignificant differences. Note that the comparison group is the omitted comparison group in the value-added models, and thus the comparison-group mean is normalized to 0 in these results. TFA = Teach for America; KCTR = Kansas City Teacher Residency.

comparisons are partly explained by teacher experience. Specifically, noting that TFA and KCTR teachers are themselves inexperienced, if we restrict the weighted comparison group for each program to include only inexperienced nonprogram teachers, the nominal achievement gaps between program and nonprogram teachers decline further.[14]

We additionally note one other finding from the achievement comparisons not shown in Figure 3 but given in the appendix: The sorting patterns of program teachers in tested grades and subjects largely mirror the sorting patterns of all program teachers discussed thus far. This presents useful context for the subsequent results from the value-added models.

Finally, Figure 4 documents the racial/ethnic and gender compositions of program teachers relative to the local area. We divide teachers into the following racial/ethnic groups: Asian/Pacific Islander, Black, Hispanic, White, and Other (the Other category is suppressed in Figure 4 for ease of presentation, but results are available in Appendix Tables A3a–A3c). Compared with local-area teacher demographics overall, as represented by the orange bars, both programs are at least modestly diversifying, with generally larger percentages of Asian/Pacific Islander, Black, and Hispanic teachers, and smaller percentages of White teachers, than the local-area average. KCTR is the most diverse program, particularly with respect to the percentage of Black teachers (37%, which is about 2.5 times higher than the local-area average of about 13.6%). When we compare program teachers with other teachers in the same districts and years (gray bars), KCTR teachers are at least suggestively more diverse racially/ethnically than their nonprogram teaching peers; however, TFA teachers are a less diverse group.[15]

We also examine gender diversity. Like the national teaching workforce, the workforce in the Kansas City area is

female dominated, as is each focal program. That said, both TFA and KCTR are modestly diversity-improving along the dimension of gender.

Efficacy Analysis

Figure 5 shows the value-added results for teachers in Grades 4 to 8. We estimate four different models for each subject, which are all variants of Equation 2. Nonprogram teachers are the holdout group, which normalizes their (average) value added to 0. A solid bar in the figure indicates that the estimate for the program is statistically distinguishable from the average value added of nonprogram teachers at the 10% level or higher, and a clear bar indicates that the estimate cannot be distinguished from the value added of nonprogram teachers. The results underlying the figure are also available in tabular form in Appendix Tables A4 (for math) and A5 (for ELA).

The four different value-added specifications are labeled as Models 1 to 4 in the figure. Model 4 is the full specification shown in Equation 2, and Models 1 to 3 are sparser variants that build up to the full model. First, Model 1 is a base specification that only controls for individual lagged achievement ($\mathbf{Y_{imt-1}}$) and grade and year fixed effects. Model 2 adds the individual student characteristics in the vector $\mathbf{X_{it}}$. Model 3 further adds the school-level control vectors $\mathbf{\bar{Y}_{mpt-1}}$ and $\mathbf{\bar{X}_{pt}}$ to account for schooling context. The last component of the full model is the vector of teacher experience bins, denoted by $\mathbf{T_{it}}$, which is added to Model 4.

Before describing the results, we first note that our value-added estimates reflect the combined effects of (a) any selection into the programs and (b) any incremental improvement in teaching caused by the programs conditional on who enrolls. A program can have high value added through either

or both channels. For example, if a program recruits individuals who are predisposed to be strong teachers (i.e., positive selection) but does nothing via training to improve their performance, teachers from that program will have high value added; similarly, a program that recruits average teachers but offers exemplary training will also have high value added. While our inability to disentangle the "selection" and "training" effect mechanisms is a limitation for some research questions, the combined effect is likely of first-order policy interest for districts looking to hire effective teachers.[16]

We first focus on the results from Model 4, which is our preferred specification. In math, we find that TFA and KCTR teachers substantially outperform nonprogram teachers in the Kansas City area. Their value-added estimates are 0.11 and 0.15 student standard deviations higher, on average, respectively. For ELA, the results from Model 4 suggest small positive effects of TFA and KCTR teachers on the order of about 0.03 to 0.05 student standard deviations.

Looking at the estimates for TFA and KCTR across the models in Figure 5 is instructive. Again starting with math, in the sparse model—Model 1—there are no statistically detectable differences between program and nonprogram teachers. However, once we control for student characteristics in Model 2, the differences emerge and persist as the specifications become richer. A similar but more muted pattern of modestly increasing estimates across models is present for ELA. This finding is previewed by the descriptive analysis above, which shows that TFA and KCTR teachers are more likely to be placed in schools with more disadvantaged and lower-achieving students. Model 1 does not account for these placement differences except to the extent that they are captured by students' own lagged test scores. The more robust accounting for teaching context in Models 2 to 4 reveals important performance gaps between TFA and KCTR teachers compared with other teachers.

Another aspect of the cross-model estimates that merits attention is the difference between Models 3 and 4. These models differ only by whether we control for teacher experience. The experience-conditional comparisons in Model 4 are useful for gauging the efficacy of TFA and KCTR teachers relative to their similarly experienced nonprogram peers. However, it is also desirable to compare TFA and KCTR teachers with other teachers without conditioning on experience. Model 3 does not separately control for experience, so it implicitly makes the comparison with *all* nonprogram teachers, who are much more experienced on average. The estimates from both models are informative about TFA and KCTR treatment effects.

Practically speaking, our estimates change little going from Models 3 to 4 for both TFA and KCTR (although for ELA the small change is at the threshold of statistical significance). On further investigation, the reason is that the experience-efficacy gradient among nonprogram teachers is modest and effectively flat over a large range of the experience distribution after the first year (results are suppressed for brevity).

While this result is not entirely out of line with what has been found elsewhere in the literature (Clotfelter et al., 2006; Wiswall, 2013), the gradient in Kansas City is especially flat.[17] Thus, whether we condition on teacher experience in our comparisons has little bearing on the findings.

Extension: Teacher Retention

We briefly extend our analysis to assess whether program teachers are more or less likely to remain in the Kansas City area compared with nonprogram teachers. For KCTR, we can perform the retention analysis for the 2018 placement cohort only—the 2019 and 2020 cohorts are too new to credibly study retention. We look to see if teachers from the 2018 KCTR cohort remain in the workforce in 2019 and 2020 ($N = 31$, noting that one 2018 placement was in a nonteaching position). Because we have more cohort data for TFA, we expand the retention analysis to look forward up to 5 years for TFA teachers whose initial placements were between 2012 and 2016 (inclusive; $N = 340$).

Retention rates in the Kansas City area for both programs compared with retention rates for nonprogram first-year teachers in the same years are reported in Figure 6. We define the Kansas City area more broadly for examining retention than in the previous analysis. Specifically, we consider a teacher as retained in the Kansas City area if they are observed teaching in a public school in the Missouri portion of the formal metropolitan statistical area as defined by the U.S. Census. We also report retention rates in the larger Missouri workforce in the appendix (which are slightly higher but similar; see Appendix Tables A6 and A7).

In the figure, retention after 1 year indicates that the teacher was observed working in the year following the initial placement (i.e., in Year 2). Retention rates after Years 2, 3, and 4 are similarly defined and cumulative (e.g., a value of 50 after Year 3 would indicate that 50% of the entering teachers were still teaching in the area into the fourth year). As in previous figures, we compare KCTR and TFA teachers with the simple average of teachers in the districts listed in Table 2 and the program-specific weighted averages based on the districts and years in which the TFA and KCTR teachers were placed. We restrict the comparison groups to new teachers only for this analysis.

For TFA, more than 99% of teachers return after the first year, which is consistent with the 2-year program commitment. However, there is a stark drop going into Year 3, with only 57% of teachers remaining beyond the second year. Retention after the fourth year—that is, the percentage of TFA teachers who are still teaching in Year 5—is just 32.35%. These retention rates are similar to the rates calculated using national TFA data (Donaldson & Johnson, 2011).

For KCTR, the 1- and 2-year retention rates are above the local-area simple average and the weighted average based on KCTR placements. The retention gaps over the first 2 years are quite large: After 1 year, KCTR teachers are more
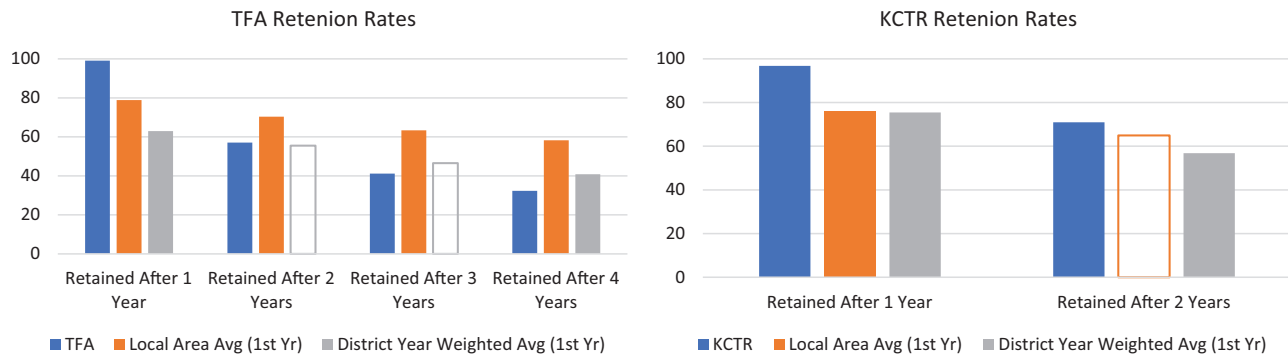
FIGURE 6. *Retention rates for KCTR and TFA teachers relative to novice nonprogram teachers in the Kansas City Area, as defined by the Missouri portion of the metropolitan statistical area.*

Note. The local-area averages (*orange bars*) are for all teachers in the districts listed in Table 2—they are not program specific, and thus do not change in the graphs. The district-year weighted averages (*gray bars*) are specific to each program. They are weighted based on each program's own placement patterns, so the comparison is with nonprogram teachers in the same districts and years as the program teachers. The retention rates reported in the figure are cumulative (e.g., the "Retained After 3 Years" percentage for TFA reports the number of originally placed TFA teachers who are still working in the Kansas City metropolitan statistical area in the fourth year after the initial placement). Retention rates for KCTR are reported for the 2018 placement cohort only; retention rates for TFA are reported for the 2012–2016 placement cohorts. *Solid orange and gray bars* indicate that the comparison-group mean is statistically different from the focal-program mean, given by the *blue bar* in each three-bar set, at the 10% level; *clear bars* indicate that the difference between the comparison-group mean and focal-program mean is not statistically significant. TFA = Teach for America; KCTR = Kansas City Teacher Residency.

than 20 percentage points more likely to remain teaching in the area relative to nonprogram new teachers in the same districts and years. After 2 years, the gap shrinks but remains sizeable, at about 14 percentage points.

Discussion and Conclusion

We contribute to the growing evidence base on the placements and efficacy of alternative teacher certification programs by assessing two such programs—TFA and KCTR—in Kansas City, Missouri. Descriptively, we document program placements in terms of school types and levels, characteristics of students taught, and the racial/ethnic and gender diversity of the teachers themselves. Although there is some heterogeneity across the two programs, common themes are that these programs disproportionately place teachers in charter schools and, more broadly, in schools serving disadvantaged students. Teachers from both programs are also more diverse racially/ethnically than the larger local-area teaching population, although only KCTR teachers are more diverse than other teachers in the same districts in which they are placed. KCTR seems to be particularly effective as a pathway for Black teachers to enter the profession.

We also estimate the value added of program teachers relative to nonprogram teachers. We find that students in Grades 4 to 8 whose teachers are from TFA and KCTR have much higher achievement growth in math than similar students in similar schools who are taught by nonprogram teachers. To give our estimates context, the best research on teacher quality indicates that a 1-standard-deviation move in the distribution of teacher quality as measured by math value added—for example, a move from about the 50th to the 85th percentile—corresponds to a move in the student test distribution of about

0.10 to 0.15 standard deviations. Thus, our estimates of 0.11 and 0.15 for TFA and KCTR, respectively, imply that these teachers are about 0.70 to 1.50 teacher standard deviations more effective than comparable nonprogram teachers, on average, in math. We also find evidence of small, positive impacts of teachers from these programs on ELA achievement.[18] Our smaller findings in ELA for both programs are consistent with the broad empirical regularity that teacher effects in math are larger than in ELA (e.g., Goldhaber et al., 2013; Hanushek & Rivkin, 2010; Lefgren & Sims, 2012).

Our findings for TFA in math are qualitatively consistent with similar estimates using data from other TFA sites outside of New York City. Inclusive of the New York City estimates, our findings fall somewhere in the middle of the range of what has been found in previous research (as discussed above). Our result that the TFA effect is larger in math than in ELA also aligns with prior research (e.g., Backes et al., 2019; Decker et al., 2004; Kane et al., 2008).[19]

Our study is the first to provide efficacy evidence on KCTR. More broadly, our estimates contribute to a very sparse literature on the efficacy of teachers from residency programs. Although our estimates should be interpreted cautiously given the relatively small sample of KCTR teachers in tested grades and subjects, our hope is that over time they can be combined with estimates from other studies of residency programs to inform our general understanding of their effectiveness.[20]

It is notable that we find that teachers from both TFA and KCTR are more effective, on average, than nonprogram teachers in the local area. As described in the introduction, the training models for TFA and KCTR are quite different. The former is an example of an "accelerated pathway" program, while the latter involves lengthy and intensive

training, albeit with a very different structure from what is typical of university-based programs. Our findings suggest that both strategies offer promise as alternatives to traditional teacher preparation.

Finally, we analyze teacher retention for TFA and KCTR teachers. TFA teachers are more likely be retained after the first year, but their retention rate falls thereafter. The retention rate after 4 years for TFA teachers is below the comparable rate for nonprogram teachers in the same districts but not markedly so (32% vs. 41%). As discussed by Donaldson and Johnson (2011), this suggests that the high turnover rate among TFA teachers is less about the TFA program per se and more about the difficult teaching environments faced by TFA teachers.

KCTR teachers are more likely to be retained than comparable nonprogram teachers over the first 3 years posttraining. This finding is consistent with similar evidence on Boston Residency teachers from Papay et al. (2012). The higher retention rate of KCTR teachers over our evaluation period is in line with expectations given that program residents agree to teach in a high-need school in the Kansas City area for at least 3 years. That said, it bears mentioning that no one can be forced to remain in a position (teaching or otherwise), and regardless of the mechanism driving the lower turnover of KCTR teachers, this will be an appealing feature of the program for school administrators faced with the challenge of staffing high-need urban schools.

APPENDIX

TABLE A1a

Teacher Placement Percentages by Grade Span and Subject for Initial Postprogram Placements, Combined Across All Years, Compared With the Simple Region Average

Grade/subject	TFA	KCTR	All nonprogram teachers	All nonprogram teachers (novices only)
Elementary total	47.84	76.19	55.53	58.67
Tested grades and subjects (4–8)	12.02	28.57	10.05	11.97
PK–3	24.28	36.19	21.94	26.06
Language specialist	4.33	0.95	3.8	2.21
Special education	4.33	0	6.15	5.97
Other	2.88	10.48	13.58	12.46
Middle school/junior high school total	16.83	20	19.19	19.18
Tested grades and subjects (4–8)	8.89	12.38	6.82	7.54
Language specialist	1.68	0.95	0.47	0.52
Special education	1.2	0	2.15	1.5
Science	2.88	3.81	2.03	2.14
Social studies	0.48	0.95	1.77	1.66
Other	1.68	1.9	5.94	5.82
High school total	35.34	3.81	25.28	22.16
Tested grades and subjects (7–8)	7.93	0	0.56	0.55
English language arts	6.25	0.95	4.05	4.15
Math	4.33	1.9	2.78	2.66
Science	7.21	0.95	2.61	3.1
Social studies	1.92	0	2.77	2.08
Special education	4.81	0	2.93	1.97
Other	2.88	0	9.58	7.64
Sum (totals)	100	100	100	100
Total charter percentage	37.98	49.52	15.47	23.60

Note. Schooling levels are defined as described in the text. The "other" category at each level comprises a number of sparsely populated positions, including physical education, health, music, and other specialty subjects and nontraditional assignments. The "Total charter percentage" row combines charter placements across all schooling levels and subjects. Novice teachers (last column) are teachers with 0–2 years of experience. TFA = Teach for America; KCTR = Kansas City Teacher Residency.

TABLE A1b

Detailed Analogue to Table A1a for TFA, With Program-Specific Weighted-Average Comparison

Grade/subject	TFA	TFA weighted	
		All nonprogram teachers	All nonprogram teachers (novices only)
Elementary total	47.84	55.03	54.62
Tested grades and subjects (4–8)	12.02	9.77	9.51
PK–3	24.28	23.55	27.64
Language specialist	4.33	3.60	1.39
Special education	4.33	6.52	5.79
Other	2.88	11.59	10.28
Middle school/junior high school total	16.83	16.14	17.77
Tested grades and subjects (4–8)	8.89	5.75	7.17
Language specialist	1.68	1.45	1.11
Special education	1.2	1.49	0.86
Science	2.88	1.69	1.93
Social studies	0.48	0.96	1.74
Other	1.68	4.80	4.95
High school total	35.34	28.83	27.62
Tested grades and subjects (7–8)	7.93	2.34	4.18
English language arts	6.25	4.12	4.09
Math	4.33	2.64	2.48
Science	7.21	2.86	3.71
Social studies	1.92	3.60	2.26
Special education	4.81	2.85	1.23
Other	2.88	10.42	9.67
Sum (totals)	100	100	100
Total charter percentage	37.98	37.89	37.91

Note. Novice-only teachers (last column) are teachers with 0–2 years of experience. Program-specific weighted averages are calculated as shown in Equation 1. The weights are the district-by-year initial placement shares of program teachers, and the characteristics are weighted across all nonprogram teachers (i.e., all teachers who are not from one of the two focal programs). TFA = Teach for America.

TABLE A1c

Detailed Analog to Table A1a for KCTR, With Program-Specific Weighted-Average Comparison

Grade/subject	KCTR	KCTR weighted	
		All nonprogram teachers	All nonprogram teachers (novice only)
Elementary total	76.19	66.42	67.01
Tested grades and subjects (4–8)	28.57	11.52	13.23
PK–3	36.19	23.70	26.41
Language specialist	0.95	5.15	2.83
Special education	0	7.55	7.91
Other	10.48	18.49	16.63
Middle school/junior high school total	20.00	16.74	15.62
Tested grades and subjects (4–8)	12.38	5.86	6.01
Language specialist	0.95	1.38	1.30
Special education	0	2.28	0.92
Science	3.81	1.24	1.72
Social studies	0.95	1.40	1.17
Other	1.90	4.58	4.50

TABLE A1c (continued)

| Grade/subject | KCTR | KCTR weighted | |
		All nonprogram teachers	All nonprogram teachers (novice only)
High school total	3.81	16.84	17.37
Tested grades and subjects (7–8)	0	0.41	0.33
English language arts	0.95	2.83	3.56
Math	1.90	1.82	1.97
Science	0.95	1.89	3.62
Social studies	0	1.79	1.41
Special education	0	1.96	1.08
Other	0	6.15	5.40
Sum (totals)	100	100	100
Total charter percentage	49.52	48.85	47.45

Note. Novice-only teachers (last column) are teachers with 0–2 years of experience. Program-specific weighted averages are calculated as shown in Equation 1. The weights are the district-by-year initial placement shares of program teachers, and the characteristics are weighted across all nonprogram teachers (i.e., all teachers who are not from one of the two focal programs). KCTR = Kansas City Teacher Residency.

TABLE A2a

Average Characteristics of Students in the Schools and Years of Teachers' First Placements, Compared With the Simple-Average School Characteristics (Teacher Weighted) in the Region

Characteristic	TFA	KCTR	All nonprogram teachers	All nonprogram teachers (novice only)
Percent Asian/Pacific Islander	2.40	3.31	2.91	2.71
Percent Black	64.21	62.00	39.90	45.51
Percent Hispanic	25.71	16.95	17.90	19.86
Percent White	6.28	12.46	33.83	27.09
Percent Other	1.40	5.27	5.46	4.84
Percent FRL	91.78	90.97	74.31	80.80
Percent IEP	10.94	10.97	11.05	11.08
Percent ELL	21.67	15.08	11.68	14.06
Average math achievement (standardized)	−0.62	−0.45	−0.31	−0.41
Average ELA achievement (standardized)	−0.70	−0.52	−0.31	−0.40
Among teachers in tested grades and subjects only (4–8)				
Average math achievement (standardized)	−0.61	−0.49	−0.32	−0.43
Average ELA achievement (standardized)	−0.69	−0.54	−0.31	−0.41

Note. Novice-only teachers (last column) are teachers with 0–2 years of experience. TFA = Teach for America; KCTR = Kansas City Teacher Residency; FRL = free or reduced-price lunch eligible; IEP = individualized education program; ELL = English language learner; ELA, English language arts.

TABLE A2b

Detailed Analogue to Table A2a for TFA, With Program-Specific Weighted-Average Comparison

| Characteristic | TFA | TFA weighted | |
		All nonprogram teachers	All nonprogram teachers (novice only)
Percent Asian/Pacific Islander	2.40	2.46	2.11
Percent Black	64.21	65.55	69.55
Percent Hispanic	25.71	23.55	20.85
Percent White	6.28	6.95	5.99
Percent Other	1.40	1.49	1.50

(continued)

TABLE A2b (continued)

Characteristic	TFA	TFA weighted	
		All nonprogram teachers	All nonprogram teachers (novice only)
Percent FRL	91.78	91.38	91.40
Percent IEP	10.94	10.45	10.51
Percent ELL	21.67	19.87	17.35
Average math achievement (standardized)	−0.62	−0.57	−0.60
Average ELA achievement (standardized)	−0.70	−0.64	−0.66
Among teachers in tested grades and subjects only (4–8)			
Average math achievement (standardized)	−0.61	−0.55	−0.67
Average ELA achievement (standardized)	−0.69	−0.62	−0.72

Note. Novice-only teachers (last column) are teachers with 0–2 years of experience. Program-specific weighted averages are calculated as shown in Equation 1. The weights are the district-by-year initial placement shares of program teachers, and the characteristics are weighted across all nonprogram teachers (i.e., all teachers who are not from one of the two focal programs). TFA = Teach for America; FRL = free or reduced-price lunch eligible; IEP = individualized education program; ELL = English language learner; ELA, English language arts.

TABLE A2c

Detailed Analogue to Table A2a for KCTR, With Program-Specific Weighted-Average Comparison

Characteristic	KCTR	KCTR weighted	
		All nonprogram teachers	All nonprogram teachers (novice only)
Percent Asian/Pacific Islander	3.31	2.71	2.66
Percent Black	62.00	61.35	62.31
Percent Hispanic	16.95	16.92	16.66
Percent White	12.46	14.04	13.87
Percent Other	5.27	4.98	4.49
Percent FRL	90.97	88.77	89.43
Percent IEP	10.97	10.84	11.14
Percent ELL	15.08	13.69	13.15
Average math achievement (standardized)	−0.45	−0.38	−0.41
Average ELA achievement (standardized)	−0.52	−0.45	−0.48
Among teachers in tested grades and subjects only (4–8)			
Average math achievement (standardized)	−0.49	−0.38	−0.40
Average ELA achievement (standardized)	−0.54	−0.45	−0.48

Note. Novice-only teachers (last column) are teachers with 0–2 years of experience. Program-specific weighted averages are calculated as shown in Equation 1. The weights are the district-by-year initial placement shares of program teachers, and the characteristics are weighted across all nonprogram teachers (i.e., all teachers who are not from one of the two focal programs). KCTR = Kansas City Teacher Residency; FRL = free or reduced-price lunch eligible; IEP = individualized education program; ELL = English language learner; ELA, English language arts.

TABLE A3a

Program Teachers' Race/Ethnicity and Gender Percentages Compared With the Simple Average (Teacher Weighted) in the Region

Characteristic	TFA	KCTR	All nonprogram teachers	All nonprogram teachers (novice only)
Percent Asian/Pacific Islander	4.81	1.90	1.00	1.24
Percent Black	12.50	37.14	13.55	13.83
Percent Hispanic	5.29	0.95	2.40	3.18
Percent White	77.16	59.05	82.26	80.78
Percent Other	0.24	0.95	0.79	0.97
Percent female	73.80	68.57	77.83	77.68

Note. Novice-only teachers (last column) are teachers with 0–2 years of experience. TFA = Teach for America; KCTR = Kansas City Teacher Residency.

TABLE A3b

Detailed Analogue to Table A3a for TFA, With Program-Specific Weighted-Average Comparison

Characteristic	TFA	TFA weighted	
		All nonprogram teachers	All nonprogram teachers (novice only)
Percent Asian/Pacific Islander	4.81	1.76	2.70
Percent Black	12.50	30.20	29.42
Percent Hispanic	5.29	5.00	5.79
Percent White	77.16	62.48	61.09
Percent Other	0.24	0.56	1.00
Percent female	73.80	75.08	74.06

Note. Novice-only teachers (last column) are teachers with 0–2 years of experience. Program-specific weighted averages are calculated as shown in Equation 1. The weights are the district-by-year initial placement shares of program teachers, and the characteristics are weighted across all nonprogram teachers (i.e., all teachers who are not from one of the two focal programs). TFA = Teach for America.

TABLE A3c

Detailed Analogue to Table A3a for KCTR, With Program-Specific Weighted-Average Comparison

Characteristic	KCTR	KCTR weighted	
		All nonprogram teachers	All nonprogram teachers (novice only)
Percent Asian/Pacific Islander	1.90	1.25	1.77
Percent Black	37.14	24.77	25.27
Percent Hispanic	0.95	3.55	4.54
Percent White	59.05	68.84	67.84
Percent Other	0.95	1.59	0.57
Percent female	68.57	79.61	75.17

Note. Novice-only teachers in the last column are teachers with 0–2 years of experience. Program-specific weighted averages are calculated as shown in Equation 1. The weights are the district-by-year initial placement shares of program teachers, and the characteristics are weighted across all nonprogram teachers (i.e., all teachers who are not from one of the two focal programs). KCTR = Kansas City Teacher Residency.

TABLE A4

Value Added to Student Achievement by Program, Grades 4–8, Math

Program	Model 1	Model 2	Model 3	Model 4
TFA	0.024 (0.036)	0.077 (0.037)**	0.091 (0.038)**	0.107 (0.039)***
KCTR	0.051 (0.069)	0.114 (0.068)*	0.113 (0.069)	0.148 (0.066)**
Lagged test scores, grade and year fixed effects	×	×	×	×
Student-level controls		×	×	×
School-level controls			×	×
Teacher experience controls (bins)				×
R^2	0.580	0.589	0.593	0.594
N (student-year observations)	185,284	185,284	185,284	185,284
N (TFA teachers)	146	146	146	146
N (KCTR teachers)	20	20	20	20
N (nonprogram teachers)	1,953	1,953	1,953	1,953

Note. The models control for teacher experience using indicators for the following experience bins as reported in the main text: (1) 0 year prior experience (omitted), (2) 1–2 years, (3) 3–5 years, (4) 6–12 years, (5) 13–20 years, (6) 21–27 years, and (7) 28+ years. Standard errors clustered by teacher are reported in parentheses. The teacher counts reported at the bottom of the table indicate the number of unique teachers (i.e., clusters). TFA = Teach for America; KCTR = Kansas City Teacher Residency.
*$p < .10$. **$p < .05$. ***$p < .01$.

TABLE A5

Value Added to Student Achievement by Program, Grades 4–8, ELA

Program	Model 1	Model 2	Model 3	Model 4
TFA	−0.031 (0.014)**	−0.002 (0.014)	0.012 (0.013)	0.027 (0.013)**
KCTR	0.009 (0.044)	0.030 (0.036)	0.031 (0.026)	0.051 (0.028)*
Lagged test scores, grade and year fixed effects	×	×	×	×
Student-level controls		×	×	×
School-level controls			×	×
Teacher experience controls (bins)				×
R^2	0.665	0.673	0.676	0.676
N (student-year observations)	186,614	186,614	186,614	186,614
N (TFA teachers)	147	147	147	147
N (KCTR teachers)	24	24	24	24
N (nonprogram teachers)	2,178	2,178	2,178	2,178

Note. The models control for teacher experience using indicators for the following experience bins as reported in the main text: (1) 0 year prior experience (omitted), (2) 1–2 years, (3) 3–5 years, (4) 6–12 years, (5) 13–20 years, (6) 21–27 years, and (7) 28+ years. Standard errors clustered by teacher are reported in parentheses. The teacher counts reported at the bottom of the table indicate the number of unique teachers (i.e., clusters). TFA = Teach for America; KCTR = Kansas City Teacher Residency; ELA = English language arts.
*$p < .10$. **$p < .05$. ***$p < .01$.

TABLE A6

KCTR Teacher Retention Rates Compared With Other Teachers in the Region

Region	KCTR	All nonprogram teachers (first-year teachers only)	All nonprogram teachers (first-year teachers only, district-year weighted average)
Kansas City area 1-year retention rate	96.77	76.24	75.48
Kansas City area 2-year retention rate	70.97	64.95	56.82
Missouri 1-year retention rate	96.77	78.02	76.44
Missouri 2-year retention rate	74.19	67.92	58.79

Note. KCTR = Kansas City Teacher Residency.

TABLE A7

TFA Teacher Retention Rates Compared With Other Teachers in the Region

Region	TFA	All nonprogram teachers (first-year teachers only)	All nonprogram teachers (first-year teachers only, district-year weighted average)
Kansas City area 1-year retention rate	99.12	78.86	62.95
Kansas City area 2-year retention rate	57.06	70.35	55.51
Kansas City area 3-year retention rate	41.18	63.37	46.53
Kansas City area 4-year retention rate	32.35	58.22	40.84
Missouri 1-year retention rate	99.12	80.94	65.04
Missouri 2-year retention rate	58.82	73.27	58.08
Missouri 3-year retention rate	43.24	66.78	49.49
Missouri 4-year retention rate	33.82	61.88	43.99

Note. TFA = Teach for America.

Notes

1. The latter line of inquiry is motivated by the large minority enrollment share in the Kansas City area and a rapidly evolving body of research demonstrating the importance of demographic representation in the teaching workforce (e.g., Dee, 2005; Egalite et al., 2015; Egalite & Kisida, 2017; Holt & Gershenson, 2019; Lindsay & Hart, 2017; Papageorge et al., 2020).

2. A third notable study is of a major expansion of TFA funded by a scale-up grant from the U.S. Department of Education (Clark et al., 2017). Using a random assignment–based strategy similar to that of Decker et al. (2004), Clark et al. (2017) estimate the null effects of TFA teachers relative to other teachers in math and reading, on average. However, it is incorrect to say that these results conflict with the positive evidence on TFA described in the preceding paragraph because the estimates in both subjects are imprecise and cannot rule out effects in the same range.

3. We made one exception in our geographic definition of the Kansas City area, which is to exclude the Park Hill school district. While Park Hill has a Kansas City address, it is about 13 miles away from central Kansas City and is a highly advantaged school district. Park Hill did not receive any TFA or KCTR teachers during the period of study.

4. We use DESE's rules to categorize each school as an elementary school, middle/junior high school, or high school as follows: Elementary schools are defined as schools with any combination that includes Grades K–8; middle schools are those with any combination that includes Grades 4–8, which are at least partly departmentalized; junior high schools have any combination that includes departmentalized Grades 7–9; and high schools typically include Grades 9–12 but may include Grades 7–12.

5. We conduct the statistical tests using unweighted and weighted univariate linear regressions, where the dependent variable is a characteristic X and the independent variable is a focal-program binary indicator variable. In the regressions, the intercept is the comparison-group mean, and the coefficient on the focal-program indicator gives the difference in means.

6. Some students take the algebra I end-of-course test in the eighth grade instead of the standard grade-level test. We include these students in the analysis, and their scores on the algebra I test are separately standardized.

7. The racial/ethnic categories we include are American Indian, Asian/Pacific Islander, Black, Hispanic, and multirace (White is the omitted group).

8. For parsimony, we condense the racial/ethnic school percentage variable to capture just the percentage of non-White, non-Asian/Pacific Islander students; this has no substantive effect on our results.

9. In results omitted for brevity, we also confirm that all of our main findings are qualitatively upheld if we control for experience using linear and quadratic terms in place of the bins.

10. The comparison group includes teachers from a subset of the 32 LEAs listed in Table 2. This is because a few LEAs do not cover Grades 4–8 during the period 2012–2019 (e.g., a K–3 charter school). A small data issue also arises for teachers who start in one of the 32 focal districts but subsequently move to a different district. For our main models, we include all teacher-year observations in any of the 32 focal school districts and drop all observations outside of these districts (e.g., when a teacher moves out of the area but remains in Missouri). That said, how we handle data outside of the 32 focal districts is inconsequential to our results, and we have confirmed that the results are qualitatively insensitive to including teacher-years from outside districts when teachers move. The robustness of our results to modifying the sample inclusion criteria is consistent with the model's ability to control for student and school circumstances to isolate teacher effects on student learning (Koedel, Mihaly, et al., 2015).

11. The nonprogram group in each chart excludes teachers from both TFA and KCTR to facilitate consistency across comparisons.

12. For the charter school comparison in particular, the weighted averages given by the gray bars are not especially informative because almost all charter school operators are coded as their own districts in Missouri. Because the weighted-average comparison group forces weights proportional to each program's own district placements, it is by construction that the percentage of teachers in charter schools for each program virtually matches its program-specific weighted-average value as indicated by the gray bar.

13. The FRL percentage is measured imperfectly because of the community eligibility provision, or CEP (Koedel & Parsons, 2021). The CEP-induced measurement error in the FRL percentage is likely to understate the differences between program and nonprogram teachers along this dimension, but directionally the comparisons are still informative.

14. This is consistent with well-documented evidence that inexperienced teachers, on average, are more likely to work in disadvantaged schools (Clotfelter et al., 2006; Goldhaber et al., 2018).

15. None of the weighted-average racial/ethnic differences in Figure 4 are statistically significant for KCTR teachers, but this is partly due to imprecision in the statistical tests with the weights. Note that the weighted racial/ethnic differences in the share of Black and White teachers for KCTR in particular are nominally large. This is at least suggestive of a meaningful diversity effect, despite the fact that our weighted comparisons are not sufficiently powered to detect it statistically.

16. That is, districts will care more about whether effective teachers come out of a particular pipeline than why one pipeline produces stronger teachers than another. Disentangling the mechanisms is of greater interest from the perspective of informing teacher-training organizations, for which knowing more about what aspects of training lead to greater teacher efficacy in participants is important. See Koedel, Parsons, et al. (2015) for further discussion on this subject.

17. Wiswall (2013) shows that one explanation for the generally flat or only slightly upward-sloping experience-performance gradient is negative selection into who remains in

teaching. That said, for our purposes, the distinction of mechanisms is not critical.

18. We can only estimate value added for teachers in tested grades and subjects. Noting that teacher placements are determined by hiring districts, our findings could be biased if districts know which teachers will be most effective (which is uncertain) and strategically place better TFA and KCTR teachers in tested grades and subjects. However, for this to cause bias in our comparative estimates in the direction of our findings, districts would need to strategically place the best TFA and KCTR teachers in this way but not make similar strategic placements of nonprogram teachers. We view this as unlikely, although we cannot rule it out with certainty.

19. Decker et al. (2004) and Kane et al. (2008) find no statistical evidence of a TFA effect in ELA, although their standard errors also cannot rule out modest positive impacts; Backes et al. (2019) estimate a statistically significant TFA effect on ELA of 0.02 student standard deviations (which is very close to our estimate).

20. As noted previously, teacher residency programs are generally small, at least speaking from a statistical perspective (Guha et al., 2016). Given this, perhaps the most feasible path toward assembling general evidence about the efficacy of the residency model is for researchers to collectively produce estimates from a large number of programs and combine the evidence across sites.

References

Backes, B., & Hansen, M. (2018). The impact of Teach for America on non-test academic outcomes. *Education Finance and Policy*, *13*(2), 168–193. https://doi.org/10.1162/edfp_a_00231

Backes, B., Hansen, M., Xu, Z., & Brady, V. (2019). Examining spillover effects from Teach for America corps members in Miami-Dade County Public Schools. *Journal of Teacher Education*, *70*(5), 453–471. https://doi.org/10.1177/0022487117752309

Bates, M. (2020). Public and private employer learning: Evidence from the adoption of teacher value added. *Journal of Labor Economics*, *38*(2), 375–420. https://doi.org/10.1086/705881

Boyd, D., Grossman, P., Lankford, H., Loeb, S., & Wyckoff, J. (2006). How changes in entry requirements alter the teacher workforce and affect student achievement. *Education Finance and Policy*, *1*(2), 176–216. https://doi.org/10.1162/edfp.2006.1.2.176

Boyd, D., Lankford, H., Loeb, S., & Wyckoff, J. (2005). The draw of home: How teachers' preferences for proximity disadvantage urban schools. *Journal of Policy Analysis and Management*, *24*(1), 113–132. https://doi.org/10.1002/pam.20072

Clark, M. A., Isenberg, E., Liu, A. Y., Makowsky, L., & Zukiewicz, M. (2017). *Impacts of the Teach for America investing in innovation scale-up* (Policy report). Mathematica Policy Research.

Clotfelter, C., Ladd, H., & Vigdor, J. (2006). Teacher-student matching and the assessment of teacher effectiveness. *Journal of Human Resources*, *41*(4), 778–820. https://doi.org/10.3368/jhr.XLI.4.778

Cullen, J. B., Koedel, C., & Parsons, E. (2021). The compositional effect of rigorous teacher evaluation on workforce quality. *Education Finance and Policy*, *16*(1), 7–41. https://doi.org/10.1162/edfp_a_00292

Decker, P., Mayer, D. P., & Glazerman, S. (2004). *The effects of Teach for America on students: Findings from a national evaluation*. Mathematica Policy Research.

Dee, T. S. (2005). A teacher like me: Does race, ethnicity, or gender matter? *American Economic Review*, *95*(2), 158–165. https://doi.org/10.1257/000282805774670446

Donaldson, M. L., & Johnson, S. M. (2011). Teach for America teachers: How long do they teach? Why do they leave? *Phi Delta Kappan*, *93*(2), 47–51. https://doi.org/10.1177/003172171109300211

Egalite, A. J., & Kisida, B. (2017). The effects of teacher match on students' academic perceptions and attitudes. *Educational Evaluation and Policy Analysis*, *40*(1), 59–81. https://doi.org/10.3102/0162373717714056

Egalite, A. J., Kisida, B., & Winters, M. A. (2015). Representation in the classroom: The effect of own-race teachers on student achievement. *Economics of Education Review*, *45*, 44–52. https://doi.org/10.1016/j.econedurev.2015.01.007

Glazerman, S., Protik, A., Teh, B. R., Bruch, J., & Max, J. (2013). *Transfer incentives for high-performing teachers: Final results from a multisite randomized experiment* (NCEE 2014-4004). National Center for Education Evaluation and Regional Assistance.

Goldhaber, D., Cowan, J., & Walch, J. (2013). Is a good elementary teacher always good? Assessing teacher performance estimates across subjects. *Economics of Education Review*, *36*(1), 216–228. https://doi.org/10.1016/j.econedurev.2013.06.010

Goldhaber, D., Quince, V., & Theobald, R. (2018). Has it always been this way? Tracing the evolution of teacher quality gaps in U.S. public schools. *American Educational Research Journal*, *55*(1), 171–201. https://doi.org/10.3102/0002831217733445

Guha, R., Hyler, M. E., & Darling-Hammond, L. (2016). *The teacher residency: An innovative model for preparing teachers*. Learning Policy Institute.

Hanushek, E. A., & Rivkin, S. G. (2010). Generalizations about using value-added measures of teacher quality. *American Economic Review*, *100*(2), 267–271. https://doi.org/10.1257/aer.100.2.267

Holt, S. B., & Gershenson, S. (2019). The impact of demographic representation on absences and suspensions. *Policy Studies Journal*, *47*(4), 1063–1093. https://doi.org/10.1111/psj.12229

Kane, T. J., Rockoff, J. E., & Staiger, D. O. (2008). What does teacher certification tell us about teacher effectiveness? Evidence from New York City. *Economics of Education Review*, *27*(6), 615–631. https://doi.org/10.1016/j.econedurev.2007.05.005

Koedel, C., Mihaly, K., & Rockoff, J. E. (2015). Value-added modeling: A review. *Economics of Education Review*, *47*, 180–195. https://doi.org/10.1016/j.econedurev.2015.01.006

Koedel, C., & Parsons, E. (2021). The effect of the community eligibility provision on the ability of free and reduced-price meal data to identify disadvantaged students. *Educational Evaluation and Policy Analysis*, *43*(1), 3–31. https://doi.org/10.3102/0162373720968550

Koedel, C., Parsons, E., Podgursky, M., & Ehlert, M. (2015). Teacher preparation programs and teacher quality: Are there real differences across programs? *Education Finance and Policy*, *10*(4), 508–534. https://doi.org/10.1162/EDFP_a_00172

Krieg, J., Goldhaber, D., & Theobald, R. (2020). *Disconnected development? The importance of specific human capital in the transition from student teaching to the classroom* (CALDER Working Paper No. 236-0520). https://eric.ed.gov/?id=ED605737

Lankford, H., Loeb, S., & Wyckoff, J. (2002). Teacher sorting and the plight of urban schools: A descriptive analysis. *Educational Evaluation and Policy Analysis*, *24*(1), 37–62. https://doi.org/10.3102/01623737024001037

Lefgren, L., & Sims, D. P. (2012). Using subject test scores efficiently to predict teacher value-added. *Educational Evaluation and Policy Analysis*, *34*(1), 109–121. https://doi.org/10.3102/0162373711422377

Lindsay, C. A., & Hart, C. M. D. (2017). Exposure to same-race teachers and student disciplinary outcomes for Black students in North Carolina. *Educational Evaluation and Policy Analysis*, *39*(3), 485–510. https://doi.org/10.3102/0162373717693109

Papageorge, N., Gershenson, S., & Kang, K. M. (2020). Teacher expectations matter. *Review of Economics and Statistics*, *102*(2), 234–251. https://doi.org/10.1162/rest_a_00838

Papay, J. P., Bacher-Hicks, A., Page, L. C., & Marinell, W. H. (2017). The challenges of teacher retention in urban schools: Evidence of variation from a cross-site analysis. *Educational Researcher*, *46*(8), 434–448. https://doi.org/10.3102/0013189X17735812

Papay, J. P., West, M. R., Fullerton, J. B., & Kane, T. J. (2012). Does an urban teacher residency increase student achievement? Early evidence from Boston. *Educational Evaluation and Policy Analysis*, *34*(4), 413–434. https://doi.org/10.3102/0162373712454328

Nye, B., Konstantopoulos, S., & Hedges, L. (2004). How large are teacher effects? *Educational Evaluation and Policy Analysis*, *26*(3), 237–257. https://doi.org/10.3102/01623737026003237

Sass, T. R. (2015). Licensure and worker quality: A comparison of alternative routes to teaching. *Journal of Law and Economics*, *58*(1), 1–35. https://doi.org/10.1086/682904

Solomon, J. (2009). The Boston Teacher Residency: District-based teacher education. *Journal of Teacher Education*, *60*(5), 478–488. https://doi.org/10.1177/0022487109349915

Springer, M. G., Swain, W. A., & Rodriguez, L. A. (2016). Effective teacher retention bonuses: Evidence from Tennessee. *Educational Evaluation and Policy Analysis*, *38*(2), 199–221. https://doi.org/10.3102/0162373715609687

Swain, W. A., Rodriguez, L. A., & Springer, M. G. (2019). Selective retention bonuses for highly effective teachers in high-poverty schools: Evidence from Tennessee. *Economics of Education Review*, *68*, 148–160. https://doi.org/10.1016/j.econedurev.2018.12.008

Tennessee Higher Education Commission. (2014). *2014 report card on the effectiveness of teacher training programs*. Tennessee Department of Education.

Wiswall, M. (2013). The dynamics of teacher quality. *Journal of Public Economics*, *100*, 61–78. https://doi.org/10.1016/j.jpubeco.2013.01.006

Xu, Z., Hannaway, J., & Taylor, C. (2011). Making a difference? The effects of Teach for America in high school. *Journal of Policy Analysis and Management*, *30*(3), 447–469. https://doi.org/10.1002/pam.20585

Authors

YANG AN received his PhD in economics from the University of Missouri-Columbia. His research interests include a variety of topics in K–12 and higher education.

CORY KOEDEL is an associate professor of economics and public policy at the University of Missouri-Columbia. His research interests include a variety of topics in K–12 and higher education.