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WORKING PAPER No. 277 - 0123 • January 2023

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Acknowledgments

This work was produced under financial support from the John S. and James L. Knight Foundation, including helpful feedback and input from Evette Alexander and Ashley Zohn. We gratefully acknowledge the cooperation of Miami-Dade County Public Schools, and especially Gisela Field and Angela Luzon, in providing data access and research support. We acknowledge the cooperation of TFA in helping to accommodate this research effort with the district and provide TFA corps member lists, especially LaKeisha Wells-Palmer and Ryan Kryola.

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CALDER Working Paper No. 277-0123
January 2023

Abstract

This paper examines the impact of Teach For America (TFA) on following-year student test and non-test outcomes in Miami-Dade County Public Schools. This paper measures the extent to which exposure to TFA is followed by improved student outcomes in the future. In particular, this paper measures days missed due to absences or suspensions, course grades in each core subject, and progression in math courses. We find that students taught by TFA math teachers go on to have higher grades in math courses in the following year and are less likely to miss school due to being absent or suspended. However, while students in TFA classrooms score higher on math and ELA assessments in a given year, these test score gains fade out by the following year.

1. Introduction

Teach For America (TFA) is a nonprofit organization that places teachers into classrooms in high-need settings across the United States. TFA operates by recruiting and selecting recent college graduates and midcareer professionals for teaching positions, training them to fill hard-to-staff vacancies as corps members in public schools, and supporting them for the duration of their 2-year commitment. Over the organization's history spanning more than 30 years, TFA has attracted both praise and criticism for its staffing model that disrupts the status quo in public education. Prior evidence from Miami, FL (Backes et al., 2019) and other placement settings nationwide (Clark et al., 2013; Decker et al., 2004; Xu et al., 2011) consistently find that students in TFA classrooms score higher on math assessments in the short term than otherwise similar students in the same schools.

A growing body of work, largely separate from TFA, finds that teacher effects on contemporaneous test scores only capture a fraction of the ways in which teachers impact their students (e.g., Gershenson, 2016; Jackson, 2018), and that there is meaningful differentiation across teachers in affecting the outcomes of their students along dimensions such as student absences, suspensions, and course grades. In addition, measures of teacher effectiveness taken from test-based value added versus non-test value added are only weakly correlated, suggesting that they measure distinct components of teaching skill. In addition, teacher impacts on these non-test outcomes tend to predict future student outcomes at least as well as test-based impacts (e.g., Backes et al., 2022; Jackson, 2018; Liu & Loeb, 2021; Gilraine and Pope, 2021). Several prior studies have found that teacher effects on test scores persist, to some extent, to test scores in future grades (Jacob et al., 2010; Kinsler, 2012), and similar patterns appear to hold for non-tested outcomes (Jackson, 2018). In addition, the extent to which these effects persist may vary across teachers (Candelaria & Bartanen, 2019). Thus, the existing body of evidence on TFA, which largely focuses on test scores in the short run, may by missing important ways in which teachers influence the impacts of their students, both because of the focus on the short term and because of the narrow view on test scores.

This paper extends the existing body of evidence on TFA by examining the relationship between being in a TFA classroom in a given year on both tested and non-tested outcomes in that year as well as in the following year. To our knowledge, only three papers have examined the relationship between TFA and non-test outcomes. Both Decker et al. (2004) and Clark et al. (2013) examine the number of days absent and suspended for students randomly assigned to TFA classrooms relative to those assigned to control classrooms, with the former study conducted in elementary schools and the latter in secondary schools. Neither study found a statistically significant relationship between TFA assignment and days absent or suspended, although their samples are substantially smaller than what is available in the data from Miami-Dade County Public Schools (M-DCPS) utilized for this study. In addition, our data provide information on a broader set of student non-test academic outcomes across a larger span of grade levels. In addition, Backes and Hansen (2018) examine some of the contemporanous non-test outcomes used in M-DCPS in a subset of the data used in this paper (2010–2014), but have a much more limited set of years and do not examine future outcomes.

2. Background on TFA and their Impacts in Miami

TFA began placing corps members in M-DCPS—the site of this study—in 2003, with 35 initial placements, and has continued to place corps members in the district every year since. During the early period of TFA's presence in the district, the placement of corps members in schools did not adhere to an overarching strategy, except for TFA's requirement of placing corps members in schools where 70% or more of students are eligible for free or reduced-price lunch

(FRL), a common proxy for student poverty. Beginning with the 2009–10 school year, TFA rolled out a new staffing strategy (hereafter referred to as the cluster placement strategy) in partnership with M-DCPS; new TFA corps members recruited to the region were eligible for hire only in specific schools within targeted high-need communities. The coincidence of this narrow targeting of corps member placements with a roughly simultaneous surge in the quantity of corps members placed into the region resulted in high concentrations of TFA teachers in targeted schools, providing significantly greater access to quality teachers—as measured by impacts on students' test scores, especially in math (e.g., Backes et al., 2019)—exactly as intended.

The evidentiary base of TFA impacts on students spans nearly 2 decades. Multiple randomized control trials have been conducted on the efficacy of TFA corps members across multiple sites, concluding that they are generally as good as or better than other teachers in the same high-need settings in their ability to produce student learning gains, particularly in math (e.g., Clark et al., 2013; Decker et al., 2004). Other studies have used administrative records to identify TFA's impacts on students (e.g., Backes et al., 2019; Boyd et al., 2006; Kane et al., 2008) and produce estimates in similar ranges to experimental studies. When other less commonly tested subjects are evaluated, including science (Xu et al., 2011) and history (Hansen and Sass, 2015), TFA has demonstrated a modest advantage in these outcomes as well. A prior evaluation of TFA in M-DCPS shows corps members outperform peer teachers in both math and—notably—reading, which is not commonly found in the TFA evaluation literature (Backes et al., 2019). Further, prior research in M-DCPS also documents a small reduction in students' unexcused absences and suspensions when assigned to the classrooms of TFA teachers (Backes & Hansen, 2018).

A common critique of the TFA program, however, is that TFA corps members exit the high-need schools into which they are placed (and, frequently, the teaching profession as well) at relatively high rates. Thus, low retention of these relatively effective teachers potentially undermines the ability of the program to effect lasting change. An analysis from Kane et al. (2008) of New York City teachers by different pathways into the profession shows that TFA teachers, indeed, demonstrated the lowest retention among all types. The authors, however, propose a cost–benefit calculation that considers the short-lived benefits of high-performing TFA teachers and lower-performing (often underqualified) teachers that typically staff the same schools. Their results confirm that the performance advantage of TFA in the classroom is strong enough, on average, to justify continuing to hire them even if they turn over at higher rates, a result that has since been replicated (Lovison, 2022). Our own calculations weighing the benefits of TFA performance against increased turnover in M-DCPS reached the same conclusion, even though retention in the district was notably lower than national TFA averages (Backes et al., 2019).

TFA corps members' comparative advantage on classroom performance and lower retention is relevant in all settings in which TFA operates. A unique feature of TFA in M-DCPS is a clustering placement strategy, in which corps members were placed into a limited number of high-need schools. However, the prior studies from the district discussed above find no significant differences in individual TFA corps members' performance or retention associated with clustering intensity across schools. It is important to note, however, that TFA's clustering placement strategy in M-DCPS was, ex ante, hypothesized to accelerate improvements in the targeted communities through two possible mechanisms beyond corps members' performance and retention (see full discussion of the motivations behind the development of the clustering placement strategy in Backes et al., 2019). The first was through positive spillover effects on other peer teachers in schools targeted in the clustering placement strategy; the second was through long-term effects that intensively accumulated to students who would have the opportunity for serial exposure to high-quality TFA teachers over multiple years. Both of these mechanisms hypothesized potential effects that reached beyond the immediate classroom of TFA corps members, enabled by the greater intensity of TFA teachers to create the conditions for systemically larger impacts. The hypothesized spillover effect has been examined in prior work, with Backes et al. (2019) finding no evidence to support spillover occurring on a large enough scale in cluster schools to separate the clustering placement strategy over the incumbent, less-focused placement model.

The research base to this point indicates that the most consequential documented gains associated with TFA corps members are those on student test scores in the year of exposure to a TFA teacher. Yet, teacher-induced test score gains are known to be transitory, with only a small share persisting even into the following year (Jacob et al., 2010); hence, the impacts of TFA could be just as ephemeral. On the other hand, evidence from Chetty et al. (2014b) shows effective teachers in late elementary grades have lasting benefits on students' long-term outcomes beyond test scores, including college attendance, earnings in young adulthood, and the likelihood of having children as teenagers. Since TFA's clustering placement strategy succeeded in providing higher access to quality teachers than students in these schools would have otherwise experienced, it stands to reason that they will be expected to have better long-term trajectories as a result. Ultimately, whether TFA corps members exhibit longer-term effects on students in these communities is an empirical question that we address here. Our primary research question is to as follows: What extent is being in a TFA classroom associated with gains in outcomes not captured by standardized tests, such as grade point average (GPA), above-grade coursetaking, and absences, both in the year of exposure and in the following year?

Prior research of TFA in M-DCPS has touched on similar elements. For example, as noted above, Backes and Hansen (2018) explore some of these outcomes, but only in the years of exposure to a TFA corps member and only in a limited subset of the data used here (2010 through 2014, compared to 2010 through 2021 in this paper). To our knowledge, this is the first study to look specifically at these outcomes in years *after* students are exposed to TFA corps members.

3. Data

We use detailed student-level administrative data that cover M-DCPS students linked to their teachers for 13 academic years (2008–09 through 2020–21).[1] With student enrollment exceeding 300,000 students, M-DCPS is the largest school district in Florida and the fourth largest in the United States. The district has large populations of non-White and disadvantaged students, typical of regions TFA has historically targeted. About 60% of M-DCPS students are Hispanic, 30% Black, and 10% White, and more than 60% of students qualify for FRL service.

Test scores: The student-level longitudinal data contain English/Language Arts (ELA) and mathematics scores on the Florida Comprehensive Achievement Test (FCAT) through the 2013–14 school year.[2] Beginning in 2014–15, the state introduced the Florida Standards Assessment (FSA), with end-of-grade (EOG) exams administered in math in Grades 3–8 and in

[1] Testing data from the the 2019–20 academic year are not available due to pandemic-induced school closures, though other non-test data for that year are recorded in the data.

[2] From the 2008–09 school year through the 2010–11 school year, all students Grades 3–10 took the FCAT in both mathematics and reading. However, with the introduction of end-of-course (EOC) exams in 2011–12, the mathematics portion of the FCAT was only administered to Grades 3–8 through the end of FCAT testing in 2013–14. We include EOC observations in the analysis in the years they are available, and we consider students' previous year's FCAT scores in the corresponding subject to be their lagged test scores (e.g., eighth grade math is the lagged test score for students taking an EOC Algebra I test as ninth graders).

ELA in Grades 3–10. All scale scores are standardized within the district data to have mean 0, standard deviation 1 in each subject-test-grade-year cell. In addition, the state offers FSA EOC exams in Algebra 1 and Geometry; these exams are considered as math outcomes in the year these courses are taken, typically in Grades 9 and 10 if no EOG exam is available for the student. Algebra 1 and Geometry grades are standardized within the district to have a mean of 0, standard deviation 1 in each subject-test-grade-year cell.

Student demographics: In addition to test scores, we observe a variety of student characteristics that are utilized as explanatory variables in the analysis: race/ethnicity; gender; eligibility for participation in the federal reduced-price lunch program; limited English proficiency status; and whether a student is flagged as having a mental, physical, or emotional disability.

Non-test outcomes: The administrative data contain days missed due to absences and school suspensions in a school year. In addition, transcript data allow for the creation of flags for being assigned to a gifted or honors class, taking above-grade work (e.g., taking Grade 7 math in sixth grade or Algebra 1 in eighth grade), failing a course, and final course grades. Absences and school suspensions are transformed by adding one and taking logs to compute percentage changes in the outcome. We construct several additional variables to capture how students move through the progression of math courses to measure whether students take the next level of math in the following year. These are documented in Appendix B. Finally, following prior work (Jackson, 2018), we use factor analysis to construct a composite measure of non-test outcomes consisting of absences, suspensions, and grade repetition (hereafter referred to as the non-test factor). We also contruct an additional composite factor that includes GPA in core courses in the following year in addition to the other three non-test outcomes.

Teacher-level variables: Students are linked to teachers through data files that contain information on course membership, and teacher personnel files contain information on teachers' backgrounds, including experience and TFA indicators. These TFA flags were generated by using TFA member lists from the regional TFA office on placements during the analysis years.[3] Note that TFA in the data refers to all TFA-affiliated teachers, including both active corps members and alumni who continue to teach in M-DCPS beyond their 2-year commitment (although the large majority of TFA who are linked to students in a classroom are active corps members).

Three analysis samples are used for the study: one in which students are linked to their math teachers, one in which they are linked to their ELA teachers, and one where students are linked to their science and social studies teachers. In these samples, the TFA flag refers to teachers who taught the students in that subject, not teachers of other subjects (e.g., in the case of a middle school student linked to four different teachers for these subjects, and only their math teacher is TFA, the TFA variable will be flagged only in the math sample and not in the other samples where the student appears). Table 1 presents descriptive statistics of key variables for students in the analysis sample broken up into TFA versus non-TFA across the three sample definitions.

Comparing the first two columns of Table 1, it is clear that TFA teachers are much more likely to serve students from high-need backgrounds as measured by FRL eligibility, exhibit lower prior test scores and course grades, and miss more days of school due to absences and

[3] As described in further detail in the methods section, analyses are weighted in proportion to the amount of documented exposure with each relevant teacher they are linked to in course membership data. Outcomes in a particular subject are only linked to teachers associated with that student, subject, and year (e.g., standardized test scores in math only link to that student's math teachers for that year). More general outcomes link to all teachers in the core academic subjects with whom a student is linked during the year (e.g., all documented teachers contribute to school absences).

suspensions. In addition, given the structure of the TFA 2-year commitment, it is no surprise that students in TFA classrooms are exposed to, on average, teachers with far fewer years of experience. Patterns are similar for ELA classrooms (columns 3 and 4) and science/social studies classrooms (columns 5 and 6). The results in Table 1 are all consistent with TFA placement patterns of choosing high-need schools in which to place its corps members. Finally, we note that the concentrations of TFA corps members in the district has varied over time, with the highest concentrations observed during the 2013–14 and 2014–15 school years, as documented in Backes and Hansen (2019).

4. Empirical Strategy

We estimate several variations of value-added-type models to address our research question. We begin with the standard model used in the TFA literature (Backes et al., 2019); Chetty et al. (2014a) find that similar models that include prior test scores are sufficient to remove the bias associated with the sorting of students to teachers:

$$(1)\ A_{ist} = \alpha A_{ist-1} + \beta_1 X_{it} + \beta_2 X_{ct} + \beta_3 TFA_{it} + \gamma_s + \varepsilon_{ist}$$

In Equation 1, current student achievement for student *i* in subject *s* in Year *t* (A_{ist}) is modeled as the dependent variable, predicted by explanatory variables representing the student's prior achievement (A_{ist-1}), which contains cubic functions of prior math and ELA scores, a vector of individual characteristics for the student including the experience of the teacher they are assigned to (X_{it}), a vector of classroom characteristics describing the context in which the student learned (X_{ct}), and an indicator variable representing whether a student was exposed to a TFA corps member in that year (TFA_{it}). The variable of interest in our analysis is the point estimate on the TFA indicator, (β_3), with a positive point estimate indicating that student exposure to TFA corps members shows a positive relationship with the dependent variable. Due to nonrandom sorting of TFA to schools, we additionally estimate models that include school fixed effects (γ_s). When the school fixed effects are excluded, TFA teachers are compared against the average of all teachers matched with similar students in the school district; when the school fixed effect is included, TFA corps members' effects are compared against peer teachers in their same schools. Thus the average teacher in the district is likely not the proper counterfactual for who would have been hired in the absence of TFA in a particular school. For example, disadvantaged students tend to be disproportionately taught by inexperienced and relatively less credentialed teachers (Goldhaber et al., 2015), and without TFA, these schools would likely hire teachers with similarly low qualifications. The school fixed effect specification, therefore, is our preferred modeling approach as schools that receive TFA are systematically more disadvantaged than other schools in the district, and this preference is consistent with the broader TFA research.

We estimate Equation 1 across the full sample of students in M-DCPS by tested subject. Since these models generally pool students across multiple grades, grade-specific indicators are interacted with all explanatory variables in Equation 1 except the TFA flag to allow for the explanatory variables to be flexible across different grades. In addition, note that some students will be assigned to multiple teachers of record in the same subject and year. To accommodate for multiple teachers, we use the Full Roster Method described in Hock and Isenberg (2012), where observations in the regression are at the student–teacher link level and are weighted differently by teacher dosage. For example, a student with two math teachers in a given year—one of which is TFA and one is not—would have a 0.5 dosage for each teacher and thus an effective TFA dosage of 0.5.

The baseline model presented in Equation 1 can be readily extended for outcomes beyond student test scores. For example, for the examination of non-test outcomes such as student absences, above-grade coursetaking, and GPA, we simply substitute these outcomes into the dependent variable of Equation 1 and otherwise run the same models, with additional controls for prior-year values of absences, suspensions, and cubic functions of GPA in each of the subject buckets (math, ELA, and science/social studies). When estimating future-year outcomes, we also replace test scores on the left-hand side with some future outcome (e.g., grades in math courses in the following year) as the dependent variable on the same set of explanatory variables (i.e., regressing a student outcome in time $t+1$ on a TFA indicator in time t and a set of baseline controls from time $t-1$).

5. Results

5.1 Contemporaneous Test Scores

Impacts on test scores in math and ELA are presented in Table 2. Relative to prior work in M-DCPS (Backes and Hansen, 2019), the results in Table 2 include three additional school years: 2017–18, 2018–19, and 2020–21 (with testing in 2019–20 canceled due to the pandemic). The top panel combines observations from all school years and finds coefficients in the same ballpark as prior published studies (Backes et al., 2019), with an estimate of 0.091 standard deviations in math and 0.032 in ELA, both statistically significant. As in prior work, models with school fixed effects tend to find a more positive view of TFA as the set of comparison teachers is restricted to other teachers in the schools that TFA is placed into rather than all teachers in the district. As noted above, TFA teachers were clustered into some of the most disadvantaged schools in the district, which were targeted for school turnaround efforts due to being deemed as low performing. Because these schools tend to be disadvantaged, by the design of TFA's placement strategy, school fixed effects lead to comparisons with, on average, weaker teachers than the non-fixed effects version. The school fixed effects models likely serve as a better counterfactual for who would be hired if not for TFA's presence in these schools.

This paper is the third wave of an ongoing evaluation of TFA in the district. Panel 2 of Table 2 breaks down results separately by each of the three study periods, with the prior two covered by Backes et al. (2019) for 2009–2014 and by Backes and Hansen (2019) for 2015–2017. The results for the school fixed effects models for 2018–2021 (column 2 for math and 4 for ELA) are similar to the results from the data obtained in the prior study period, 2015–2017. Overall, there is now evidence spanning more than a decade that, relative to other teachers in the schools in which they are placed, TFA teachers in M-DCPS have been effective at raising the test scores of their students in math and ELA.

Panel 3 of Table 2 splits the math test score results by end-of-*grade* versus end-of-*course* exams (all ELA results are from end-of-grade tests, so no corresponding ELA results are shown).[4] Available EOC tests in math include Algebra I and Geometry. While there are positive results for both math test types, TFA effects are largest for EOC exams. This is consistent with other evidence from TFA studies; for example, Xu et al. (2011) find very large TFA effects in math and science using EOC exams in high school and a student fixed effects model.

5.2 Contemporaneous Non-Test Outcomes

Table 3 shows the relationship between TFA exposure and non-test outcomes in a given year. Because some outcomes are no longer specific to a given subject (i.e., math test scores for math teachers), we extend the math and ELA view from Table 2 to include the other core

[4] End-of-grade exams are tied to a specific grade and subject (e.g., grade 8 math), while end of course exams are tied to a specific course (e..g,. Geometry).

academic subjects, science and social studies. Note that each row in this table corresponds to a regression model using the listed measure as the dependent variable in our analysis and with the analysis sample defined by the column headings. The point estimates reported in the table are those corresponding to that for TFA teachers in the model specification defined by the row and column position. In the combined sample (labeled “All” in columns 1 and 2), the TFA point estimates correspond to TFA exposure in any subject.

The first two outcomes, absences and suspensions, are an update of Backes and Hansen (2018), which measured TFA effects on absences and suspensions from 2010–2014, although not broken down by subject. Adding seven additional school years (2015–2021; 2020 non-test measures were recorded despite the pandemic closures) and splitting results by math, ELA, and social studies/science, we largely recover the same pattern, with students in TFA classrooms less likely to miss school due to absences and suspensions in the school fixed effects models. Interestingly, these effects are largely concentrated in the non-math classrooms. This pattern of teachers who raise test scores not necessarily being the same as those who improve other student outcomes is consistent with a growing literature on non-test outcomes (e.g., Jackson, 2018; Backes et al., 2022). When examining the non-test factor that combines absences, suspensions, and grade repetition as used in Jackson (2018), students in TFA classrooms in a given year are about 0.01 standard devisions higher in this non-test factor in each subject, although none is statistically significant.

Table 3 also displays the relationship between TFA and course grades in a given year, which is in effect a measure of grading standards and not necessarily an outcome of interest (the next section contains measurements of course grades in the following year). The only notable pattern from this investigation is that it appears TFA teachers in ELA have harder grading standards than other teachers in the school.

5.3 Future Non-Test Outcomes

Table 4 turns to the relationship between being in a TFA classroom in a given year and non-test outcomes in the *following* year. Because each outcome is conditional on being observed in the district in the following year, the first row shows the change in likelihood of being in the district in the following year for students in TFA classrooms relative to other classrooms as a check for differential sample attrition. Results in the fixed effects models contain very precisely estimated zeroes.

Student absences and suspensions in the year *after TFA exposure* generally follow the same pattern as in the year of exposure. In the school fixed effects models, seven out of eight coefficients are negative (with the positive one being 0.001)—that is, less likely to miss school—and four of eight are significant at the 5% level, mostly driven by days suspended in the following year. In addition, the non-test factor consisting of absences, suspensions, and grade repetition is higher by 0.029 standard deviations and statstically significant. Examing the subject-specific columns, this again is due to the non-math TFA teachers. Thus, the impact on student non-test outcomes in a given year appears to persist to some degree into the following year.[5]

For course grades, students taught by math TFA teachers tend to have better math grades in the following year, although this is only significant at the 10% level in both models (columns

[5] A potential concern about these following-year estimates is that they could be captuing to some degree conditional sorting based on student experience in Year *t*. For example, students assigned to TFA in *t* are about 5 percentage points more likely to be assigned to TFA in *t+1*, conditional on the observables in Equation 1 and school fixed effects. One solution would be to include classroom fixed effects for *t+1*, but this is intractable due to students being in multiple classrooms in *t+1*, even in the same subject, and especially in high school. Thus, estimates in this section may be better thought of as the effect of TFA exposure in *t* encompassing different course assignments in *t+1* (including differential exposure to TFA in *t+1*).

3 and 4). This offers some evidence that the gains in math test scores for students in TFA classrooms represent actual student learning rather than some alternative explanation like teaching to the test. However, these gains in course grades in the following year are not seen in other subjects (recall that test score point estimates in ELA are roughly one-third the size of those in math).

5.4 More Future Math Outcomes

This section contains a deeper investigation into the ways in which math TFA teachers may influence the future outcomes of their students. We focus on math in particular for three reasons. First, the test score results and future course grade results indicate that this is the subject in which TFA teachers most influence student learning outcomes, both in the present year and in the future (in the case of course grades). Second, math follows a more linear progression than other studies—for example, progressing from Algebra I to Geometry to Algebra II—making it natural to examine whether students in TFA classrooms are more likely to advance to the next course in a sequence. Finally, Algebra II is a requirement for freshman admissions into the University of Florida, meaning that progressing through the math sequence is essential for reaching the next level.

Results are displayed in Table 5, which examines the relationship between being in a TFA math classroom in Year t versus math outcomes in Year $t+1$. Because the outcomes concern math courses and test scores in the following year, we first display the likelihood of taking a math course in the following year (conditional on being observed in the district). The format of Table 5 contains three columns. The first two are identical to Tables 2–4, with the first column including the base set of controls and the second column adding school fixed effects. In Table 5, we add an additional column that adds controls for whether a student took an advanced (honors, AP, IB, gifted) or above-grade (e.g., Grade 7 math in Grade 6 or Geometry in Grade 9) course in Year *t*. These controls may be important if, for example, being assigned to an advanced course in *t* is associated with both (a) outcomes in *t+1* and (b) being in a TFA classroom in *t*. Because the TFA assignment itself is unlikely to have caused the advanced course assignment in *t*, these controls may help avoid conflating course-taking with TFA effects. Returning to the discussion of taking math in the following year, all three specifications are very close to zero.

The following row shows math scores in the year following exposure to TFA in math. Despite large gains in math test scores in the TFA exposure year, there do not appear to be any gains that persist to the following year (in results available from the authors, there is also no change in ELA scores in the following year). Given the large literature on the fadeout of test score gains (e.g., Chetty et al., 2014a), this perhaps does not come as a surprise. For example, if one used a fadeout value of 0.3 (Cascio and Staiger, 2012), we might expect the coefficient on math scores in following year math to be 0.092 * 0.3 = 0.028.

The final four rows examine future course-taking in math. There is no TFA effect on whether a student advances to the next math course in the sequence (e.g., from Algebra I to Geometry), which is consistent from the summary statistics in Table 1, where 96% (non-TFA) and 95% (TFA) of students advance, on average, to the next math course. TFA exposure also not appear to affect whether or not a student goes into an above grade math course the following year (defined for Grades 6 through 10). Turning to taking an advanced math course (AP, IB, gifted, honors) in the following year, results are sensitive to specification. There is a large association in the column 1 model with no school fixed effects. However, this coefficient is substantially attenuated when adding school fixed effects. This is likely because the typical student in schools where TFA is placed is low in the achievement distribution of the district and would be unlikely to take advanced math courses if in another school. However, these students are higher in the achievement distribution of their own schools and thus more likely to be enrolling in advanced courses. When adding controls for advanced and above-grade course-taking in Year *t* in column 3, the results again attenuate and are no longer significant. Thus, the association between TFA and advanced course-taking in the following year shown in column 1 are likely the result of school selection and TFA teachers being more likely to teach advanced courses in *t*, and not actually a causal TFA impact.

The final results in Table 5 show whether a student ever passed Algebra II, for students who had not yet reached Algebra II (or higher) and who could have plausibly reached Algebra II during the sample period. For example, a student in seventh grade in 2020 would not be counted because reaching Algebra II by 2021 is not feasible, though a seventh-grade student in 2015 would be included since Algebra II by 2021 would be the expected course progression. As with the other course-taking results, we do not find any TFA effect. Summing up the results from Table 5, there does not appear to be a persistent impact of TFA on math test scores or the math courses that students take in the future. However, there is some evidence that students earn better grades in their next math course in the year after TFA exposure (Table 4).

6. Discussion

Prior evidence spanning several locales and including randomized control trials has found that students in TFA classrooms score higher on math assessments in the short term than otherwise similar students in the same schools (Clark et al., 2013; Decker et al., 2004; Xu et al., 2011). In a study spanning more than a decade of data, we find the same to be true in Miami. In addition, we find small, but statistically significant, effects of TFA teachers on reading test scores. While prior research has found that teachers who raise student test scores also improve the long-run outcomes of their students, including college-going and labor-market earnings (Chetty et al., 2014b; Backes et al., 2022), prior to this study, there has been no direct evidence on the question of whether exposure to TFA improves student outcomes in ways that extend beyond test scores in the short term.

The results presented here suggest that exposure to TFA may also lead students to missing fewer days of school, both in the year of exposure and the year following. Further, TFA teachers that had the greatest association with reduced absences and suspensions were not the same who had the greatest impact on test scores, suggesting that TFA teachers are impacting students in varied ways and focusing on test scores alone misses important dimensions of TFA effects. Prior work has found that students see gains in longer term outcomes when they are taught by teachers who improve the non-test outcomes of their students in the short term (Jackson, 2018; Backes et al., 2022). These gains in non-test outcomes—along with marginally better course grades in math in the year following TFA exposure—suggest that short-run improvements in test scores following TFA exposure are not solely driven by teaching to the test or some other explanation that does not benefit students to the extent that the test score gains would suggest. Together, these results add to a growing body of literature showing that a narrow focus on test scores alone misses some of the ways in which teachers impact the outcomes of their students.

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Tables

Table 1. Summary Statistics

	Math		ELA		Sci. + Soc. Stud.	
	Non-TFA	TFA	Non-TFA	TFA	Non-TFA	TFA
Student demographics and days present						
White	0.09	0.02	0.09	0.02	0.09	0.01
Black	0.21	0.68	0.21	0.70	0.21	0.71
Hispanic	0.70	0.31	0.70	0.28	0.70	0.27
FRL	0.71	0.89	0.71	0.88	0.71	0.88
ELL	0.13	0.13	0.13	0.06	0.13	0.14
Mental disability	0.06	0.05	0.06	0.05	0.06	0.06
Physical disability	0.02	0.02	0.02	0.02	0.02	0.02
Emotional disability	0.01	0.01	0.01	0.01	0.02	0.01
Days absent	9.04	12.70	9.05	13.51	9.12	12.90
Days suspended	0.31	0.72	0.32	0.51	0.32	0.62
Prior year non-test factor	0.04	-0.19	0.04	-0.14	0.04	-0.17
Prior year non-test factor (with GPA)	0.01	-0.37	0.01	-0.31	0.01	-0.36
Prior achievement						
Prior math scores	0.05	-0.30	0.05	-0.20	0.05	-0.33
Prior ELA scores	0.03	-0.46	0.03	-0.30	0.03	-0.49
Prior-year math GPA	2.45	2.10	2.45	2.14	2.45	2.09
Prior-year ELA GPA	2.66	2.30	2.66	2.37	2.66	2.33
Prior-year sci+SS GPA	2.74	2.37	2.74	2.40	2.74	2.33
Teacher experience	15.72	1.62	15.92	1.30	15.65	1.21
In district next year	0.83	0.86	0.83	0.79	0.82	0.76
For students in district next year						
Took math course next year	0.99	0.98				
Took next math course in sequence next year	0.96	0.95				
Took above-grade math next year (Grades 6–10)	0.33	0.20				
Ever passed Algebra 2 in M-DCPS	0.52	0.41				

Note. Unit of observation is student-year. Compares students in TFA classrooms to non-TFA classrooms.

Table 2. Effect of TFA on Contemporaneous Test Scores

	Math		ELA	
	(1)	(2)	(3)	(4)
Panel 1: All				
TFA 2010–2021	0.081***	0.092***	0.021***	0.034***
	(0.013)	(0.011)	(0.008)	(0.007)
Panel 2: By time period				
2010–14	0.100***	0.114***	0.016	0.018*
	(0.021)	(0.016)	(0.010)	(0.009)
2015–17	0.068***	0.075***	0.031**	0.037***
	(0.019)	(0.018)	(0.015)	(0.014)
2018–21	0.046*	0.075***	0.003	0.031***
	(0.024)	(0.021)	(0.012)	(0.011)
Panel 3: By test level				
End of grade	0.064***	0.078***		
	(0.016)	(0.016)		
End of course	0.098**	0.110**		
(Algebra I, Geometry)	(0.019)	(0.018)		
School FE		X		X

Note. Regression controls for student-level and class average demographics and cubic previous test scores, and their interactions with grade. Other controls include class size and teacher experience.

Table 3. Effect of TFA on Contemporaneous Non-Test Outcomes

	All		Math		ELA		Other (sci + ss)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Days absent	0.014	-0.015*	0.027*	-0.007	0.020	-0.011	0.004	-0.023*
	(0.014)	(0.009)	(0.016)	(0.011)	(0.014)	(0.013)	(0.020)	(0.013)
Days suspended	-0.004	-0.015**	-0.003	-0.009	-0.015**	-0.024***	0.001	-0.014*
	(0.007)	(0.006)	(0.010)	(0.009)	(0.007)	(0.007)	(0.008)	(0.009)
Grade repetition	-0.002	0.002**	-0.003	0.002*	-0.002	0.002*	-0.002	0.002
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
GPA this year in subject	-0.011	-0.026	0.025	0.013	-0.031	-0.058**	-0.001	-0.025
	(0.019)	(0.019)	(0.034)	(0.035)	(0.025)	(0.023)	(0.025)	(0.025)
Overall GPA	0.015	-0.008	0.013	-0.003	0.006	-0.021*	0.022	-0.003
	(0.013)	(0.011)	(0.018)	(0.015)	(0.015)	(0.012)	(0.016)	(0.017)
Non-test factor	0.007	0.012	0.011	0.009	0.008	0.012	0.005	0.014
	(0.015)	(0.009)	(0.020)	(0.016)	(0.015)	(0.012)	(0.018)	(0.010)
School FE		X				X		X

Note. Regression controls for student-level and class average demographics and cubic previous test scores and grades in each subject, prior absenses and suspensions, and their interactions with grade. Other controls include class size and teacher experience. Non-test factor contains absences, suspensions, and whether a student repeated a grade.

Table 4. Effect of TFA on Following-Year Non-Test Outcomes

	All		Math		ELA		Other (sci + ss)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In district next year	0.003	-0.002	0.004*	-0.001	0.002	-0.003	0.004	-0.002
	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
Grade repetition after next year	-0.001	0.000	-0.001	0.001	-0.002	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Days absent next year	0.037***	-0.012	0.051***	0.001	0.037**	-0.010	0.028	-0.022**
	(0.014)	(0.007)	(0.015)	(0.009)	(0.015)	(0.013)	(0.018)	(0.010)
Days suspended next year	-0.007	-0.021***	0.003	-0.006	-0.018**	-0.030***	-0.008	-0.027***
	(0.007)	(0.007)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)
GPA next year in subject			0.044*	0.037*	-0.005	-0.017	0.007	-0.015
			(0.026)	(0.021)	(0.019)	(0.016)	(0.022)	(0.019)
Overall GPA next year	0.012	0.001	0.016	0.021*	-0.004	-0.012	0.021	-0.000
	(0.011)	(0.009)	(0.017)	(0.011)	(0.014)	(0.013)	(0.014)	(0.012)
Non-test factor next year	-0.004	0.029***	-0.021	0.004	0.001	0.028**	0.006	0.046***
	(0.016)	(0.009)	(0.021)	(0.015)	(0.017)	(0.013)	(0.020)	(0.012)
Non-test factor (w/ GPA) next year	0.003	0.018**	-0.006	0.016	-0.004	0.009	0.015	0.027**
	(0.015)	(0.008)	(0.019)	(0.013)	(0.017)	(0.013)	(0.019)	(0.011)
School FE		X				X		X

Note. Regression controls for student-level and class average demographics and cubic previous test scores and grades in each subject, and their interactions with grade. Other controls include class size and teacher experience.

Table 5. Effect of TFA on Future Math Outcomes

	(1)	(2)	(3)
Take math next year	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)
Math scores next year	0.005	0.013	0.001
	(0.016)	(0.018)	(0.021)
Above-grade math next year	0.003	-0.004	0.006
(Grades 6–10)	(0.016)	(0.014)	(0.009)
Advance to next math course	0.002	0.002	-0.003
	(0.004)	(0.004)	(0.005)
Advanced course this year	0.074***	0.025	
	(0.020)	(0.017)	
Advanced course next year	0.057***	0.025**	0.016
	(0.015)	(0.012)	(0.012)
Ever pass Algebra 2	-0.002	0.005	0.003
	(0.011)	(0.008)	(0.010)
School FE		X	X
Controls: advanced math & above-grade math this year			X

Note. Regression controls for student-level and class average demographics and cubic previous test scores and grades in each subject, and their interactions with grade. Other controls include class size and teacher experience.

Appendix A. Variable Definitions and Sample Construction

Table A1. Most Frequent TFA Courses

Rank	Math	ELA	Other
1	HS Intensive Math	HS Intensive Reading	Biology 1
2	Geometry	English 2	M/J Comp Science 2
3	M/J Intensv Math	English 1	Chemistry 1
4	M/J Grade 7 Math	M/J Intens Read (MC)	World History
5	Algebra 1	Speech 1	American History
6	M/J Grade 8 Pre-Alg	English 3	M/J Comp Sci 3
7	M/J Math 1	English Honors 2	Physical Sci
8	Algebra 1 Honors	M/J Lang Arts 3	Chemistry 1 Hon
9	Geometry Honors	English Honors 1	M/J Comp Sci 1
10	ALG 1-B	M/J Lang Arts 2	Social Studies Grade 4
11	ALG 1-A	M/J Lang Arts 1	Science Grade 5
12	Math Grade 4	Language Arts g4	Science Grade 4
13	Math Grade 3	Language Arts g3	M/J Civics & Car Pl
14	Math Grade 5	Language Arts g5	Science Grade 3
15	M/J Math 1 Adv	M/J Lang Arts 1 Adv	Biology 1 Honors

Notes: Most common 15 course codes as measured by the number of student–teacher links over the sample.

Table A2. Variable construction

Outcome	Sample Grades	Definition
Days absent	4–11	ln(1 + days absent).
Days absent	4–11	ln(1 + days suspended).
Math grade	4–11	Courses coded with the typical grade a course would be taken in (e.g., Grade 6 for M/J math 1, Grade 7 for M/J math 2, Grade 8 for M/J math 3, Grade 9 for Algebra 1, Grade 10 for Geometry, Grade 11 for Algebra 2, and Grade 12 for any of Pre-calculus, Calculus, or AP Statistics). A student is coded as advancing if they move to a higher math grade level from 1 year to the next OR if they take a course coded as Grade 12 in the following year (e.g., a student is coded as advancing when going from Pre-calculus to Calculus even though both are coded as Grade 12). For courses where grade or level cannot be obtained (e.g., M/J Intensive Math), the course is coded for a student at the level of that student's enrolled grade.
Advanced to next math course	4–11	A student is coded as advancing if they move to a higher math grade level from 1 year to the next OR if they take a course coded as Grade 12 in the following year (e.g., a student is coded as advancing when going from Pre-calculus to Calculus even though both are coded as Grade 12).
Above-grade math	7–11	A student is coded as taking above-grade math if their math grade (described above) exceeds their actual enrolled grade.
Above-grade math next year	6–10	Whether a student is in an above-grade (see above) math course next year.
Advanced math course	4–11	Gifted, honors, AP, IB course.
Ever passes Algebra 2	Math grade is between 4 and 10 (Algebra 2 is math grade 11), who could have reached Algebra 2 in the sample period (i.e., students in grade early grades in recent years are coded as missing)	Time-invariant, student-level variable for whether student ever passes Algebra 2.
Non-test factor	4–11	Principle component analysis of grade repetition, days absent, and days suspended. An additional version contains GPA.

Note: all next-year outcomes conditional on being observed in district in following year (i.e., missing for students no in district).