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Teacher Licensing, Teacher Supply, and Student Achievement:
Nationwide Implementation of edTPA *

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Abstract

The educative Teacher Performance Assessment (edTPA) - a performance-based examination for prospective PreK-12 teachers to guarantee teaching readiness - has gained popularity in recent years. This research offers the first causal evidence about the effects of this nationwide initiative on teacher supply and student outcomes of new teachers. We leverage the quasi-experimental setting of different adoption timing by states and analyze multiple data sources containing a national sample of prospective teachers and students of new teachers in the US. We find that the new license requirement reduced the number of graduates from teacher preparation programs by 14%. The negative effect is stronger for non-white prospective teachers at less-selective universities. Contrary to the policy intention, we find evidence that edTPA has adverse effects on student learning.

Keywords: teacher licensing, edTPA, occupational licensing, education policy
JEL Classification: I28, J2, J44, K31, L51

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1 Introduction

The earliest call for teacher entry requirements in the US dates back to the 1960s following widespread concerns over declining student test scores (Rudner and Adelman, 1987). After decades of development, teacher licensure became the primary guaranteer teacher quality in U.S. public schools. Although teacher licensing is universal in the U.S., the requirements have been determined by state legislature and they have varied substantially across jurisdictions. The complex historical development and a lack of concurrent national data create challenges to evaluating the impacts of teacher licensure on teachers and their students on a nationwide scale. Moreover, the net effect of teacher licensure is unclear: license requirements increase entry costs that reduce teacher availability and may distort investments; but a minimum standard of teachers may improve student learning by eliminating incompetent teachers or training teacher skills.

In recent years, the educative Teacher Performance Assessment (edTPA) – a performance-based examination to evaluate the teaching readiness of prospective teachers – has gained popularity across the nation. By 2018, edTPA had become a mandatory testing component for initial teacher licensure and program completion in eight states, providing a contemporaneous quasi-experimental setting to evaluate the effectiveness of teacher licensure.[1]

Unlike the traditional one-time written examinations, edTPA is a semester-long project involving lesson plans, classroom videos, and follow-up reports. The required money and time investment create an additional barrier to entry, potentially exacerbating the existing teacher shortages (Bergstrand Othman et al., 2017; Goldhaber et al., 2017; Petchauer et al., 2018; Gilbert and Kuo, 2019). It is also an open question as to whether the assessment benefits students. A higher requirement filters pre-service teachers at the lower tail of quality distribution, but may lead to negative sorting where higher ability candidates opt for better outside options (Angrist and Guryan, 2004; Goldhaber, 2007; Larsen et al., 2020).[2]

[1]In total, 18 states recognized edTPA as a test option for initial teacher licensure in 2018. We define treatment states as those with edTPA being the only option. See Section 2 about the policy timing.

[2]Kugler and Sauer (2005) also documented that licensing induced negative selection in the physician

Complementarities between the test content and quality of teaching are also key for the new standard to benefit student learning. The overall impacts of edTPA then connect broadly to traditional debates in economics about whether occupational licensing is welfare-improving (Friedman, 1962; Leland, 1979; Shapiro, 1986; Kleiner and Soltas, 2019).

This paper provides the first causal evidence about the effects of edTPA on teacher supply and student outcomes. We build on extant qualitative or case-specific analyses in education literature, providing a quantitative evaluation of edTPA using a national sample of new teachers and their students. Our identification strategy leverages different policy timing, comparing outcomes of interest in treatment states with other states before and after the adoption of edTPA. The analysis applies to the ongoing debate about the implementation/revocation of edTPA in different states, and it speaks to the efficacy of teacher licensure and occupational licensing in general.

We first examine the number of graduates from teacher preparation programs documented in the Integrated Postsecondary Education Data (IPEDS) that captures the majority of potential teacher supply. Analysing graduation years from 2011 to 2019, we find that edTPA reduced the number of teacher graduates by about 14%. This negative effect is stronger in less selective universities and for minority candidates, suggesting issues associated with equity concerns and entry barriers created by edTPA. We are one of the first to document the employment/labor supply effect of teacher licensing (Larsen et al., 2020).

Besides its adverse impacts on teacher supply, we find evidence that edTPA harms student learning of new teachers. We analyze the restricted student data from 2009 to 2017 in the National Assessment of Educational Progress (NAEP) that contains the test scores of a national sample of students in the US. The NAEP is the largest nationally representative assessment in core subjects that provides a common yardstick to compare student progress in different states. Importantly for our analysis, the dataset also links students to the years of experience of their corresponding subject teachers. This unique feature allows us to

profession.

accurately measure the potential benefit of edTPA by focusing on new teachers. Contrary to the policy intention, we find that edTPA decreases student test scores. This negative effect is concentrated on students at higher ability percentiles. The adverse impact is consistent with findings from qualitative studies that onerous workloads hinder prospective teachers from learning how to teach (Greenblatt, 2016; Shin, 2019). Although we also find some positive impacts on reading scores, the estimates are sensitive to the specification. As far as the outcomes (teacher supply and student outcome) we study, the overall impacts of this recent nationwide reform is negative.

In addition to providing a thorough evaluation of one particular policy, this paper contributes to broader interests of teacher licensure. Economists have endeavored to quantify the benefits of teacher licensure (Angrist and Guryan, 2008; Clotfelter et al., 2007, 2010; Goldhaber and Brewer, 2000; Kane et al., 2008; Sass, 2015). Previous results are mixed, reflecting the differences in research design and policy context. We offer complementary evidence that can be generalized to the whole US by looking at the most controversial licensure initiative in recent years. Apart from updating the evidence on students, we also document the extent to which licensure policy is related to teacher shortages, complementing analyses of commonly-discussed factors, including monetary incentives (Goldhaber et al., 2015; Feng and Sass, 2018), work environment (Carter and Carter, 2000; Carroll et al., 2000), support from teacher programs (Liu et al., 2004), and other education reforms (Guarino et al., 2006; Kraft et al., 2020).

Our results also speak to the efficacy of occupational licensing. Researchers found that licensing reduces employment (Blair and Chung, 2019; Chung, 2020), increases price/wage (Kleiner, 2000; Kleiner and Krueger, 2013; Thornton and Timmons, 2013), and has minimal improvement on quality (Carpenter and Dick, 2012; Kleiner et al., 2016; Anderson et al., 2020; Farronato et al., 2020).[3] Several studies have pointed to the signaling value of licensing (Law and Marks, 2009; Blair and Chung, 2018, 2020; Xia, 2021). Most empirical work on licensing

[3] Anderson et al. (2020) are among the few to find a positive quality effect.

uses cross-sectional variation or historical data. In contrast, we exploit a unique contemporary policy change in an important profession to provide sharper identification. To the extent that public school teachers comprise a large and socially influential workforce, our paper offers three important results with regard to the welfare consequences of occupational licensing: the policy reduces labor supply and creates shortages; exacerbates diversity concerns; and, does not benefit consumers (students in our setting).

Lastly, our results speak to the unintended consequences of high-stake teacher assessments. The goal of performance-based evaluations in the public schools is to improve teacher performance by providing incentives. Unfortunately, studies have found ample evidence that high-stakes on-the-job evaluations exerted pressure on teachers, hampering teacher recruitment and retention (Reback et al., 2014; Dee and Wyckoff, 2015; Sartain and Steinberg, 2016; Kraft et al., 2020; Cullen et al., 2021). We evaluate a new performance-based assessment for pre-service teachers and offer complementary findings that high-stake assessments dampen new teacher supply.

2 Background of edTPA

Modern licensure tests for prospective teachers mostly cover three areas: basic skills (such as reading, writing, grammar, mathematics), subject matter, and pedagogical knowledge (Larsen et al., 2020). For pedagogical knowledge, the education community in the 1990s started to recognize the need for performance evaluation rather than written examinations to guarantee the teaching readiness of prospective teachers (Sato, 2014).

The earliest attempt to incorporate a performance evaluation process into the teacher licensure system was in 1998 in California.[4] Borrowing from the experience and models in California, the American Association of Colleges of Teacher Education (AACTE), which is the leading organization representing educator preparation programs in the US, cooperated

[4]The legislation is 'CA Senate Bill 2042'. Among a variety of models, popular options include the California Teaching Performance Assessment (CalTPA) and the Performance Assessment for California Teachers (PACT)

with the Stanford Center for Assessment to develop a standardised assessment called the educative Teacher Performance Assessment (edTPA) for nation-wide adoptions.[5]

Unlike the usual form of written examinations, edTPA requires candidates to show competency in preparing classes by submitting detailed lesson plans, delivering instruction effectively by recording the lesson during the internship, and properly assessing student performance to guide future instruction via a thorough analysis of student learning outcomes. The experts at Pearson then score a candidate's materials in three areas: 'Planning for Instruction and Assessment', 'Instructing and Engaging Students in Learning', and 'Assessing Student Learning'.[6] Preparation for edTPA takes place alongside the teaching internship. The entire whole process can take semesters.

Some education scholars contend that this performance-based format better reflects the complexity of teaching better than written examinations and prepare teachers to focus on student learning (Darling-Hammond and Hyler, 2013). However, ample qualitative evidence suggests that edTPA discourages new teachers from entering the teaching profession. Gilbert and Kuo (2019) find that the test fee together with miscellaneous expenses add a significant burden to students who have already struggled financially. Bergstrand Othman et al. (2017) find that time commitment and the uncertainty about passing the exam created mental stress to the teacher candidates. Besides, Greenblatt (2016) and Shin (2019) suggest that teacher candidates often found themselves focusing too much on catching up the scoring rubrics and deadline at the expense of teaching opportunities. Worse still, the negative impacts fall disproportionately on minority and lower-income candidates (Greenblatt and O'Hara, 2015; Goldhaber et al., 2017; Petchauer et al., 2018).[7]

By 2018, eight states had implemented edTPA to evaluate teaching effectiveness for

[5]EdTPA is now administered by Pearson Education, Inc.

[6]Interested readers can refer to the official edTPA document (`http://www.edtpa.com/Content/Docs/edTPAMGC.pdf`) for a more detailed description on the assessment scheme.

[7]From the latest official statistics of edTPA (`https://secure.aacte.org/apps/rl/res_get.php?fid=3621&ref=rl`), the average pass rate is between 75% and 92%. The pass rate for ethnic minorities is significantly lower than for their white counterparts.

prospective public school teachers (see Figure 1).[8] Washington and New York were among the earliest states mandated edTPA as a necessary component for program completion and initial teacher licensure in January and May 2014, respectively. Prospective teachers have to satisfy a cutoff score to graduate from the teacher preparation program and qualify for a teacher license.[9] Later, the mandatory nature of edTPA expanded to Georgia (September 2015), Illinois (September 2015), Wisconsin (September 2016), New Jersey (September 2017), Alabama (September 2018) and Oregon (September 2018).[10]

Not all states consider edTPA as the sole assessment choice. By 2018, ten other states had recognized edTPA as an assessment option. Since teacher candidates in these states may opt for existing options other than edTPA, we do not include the optional states in the baseline analysis.[11] To check sensitivity of this sample criteria, we add them as control states in a robustness analysis.

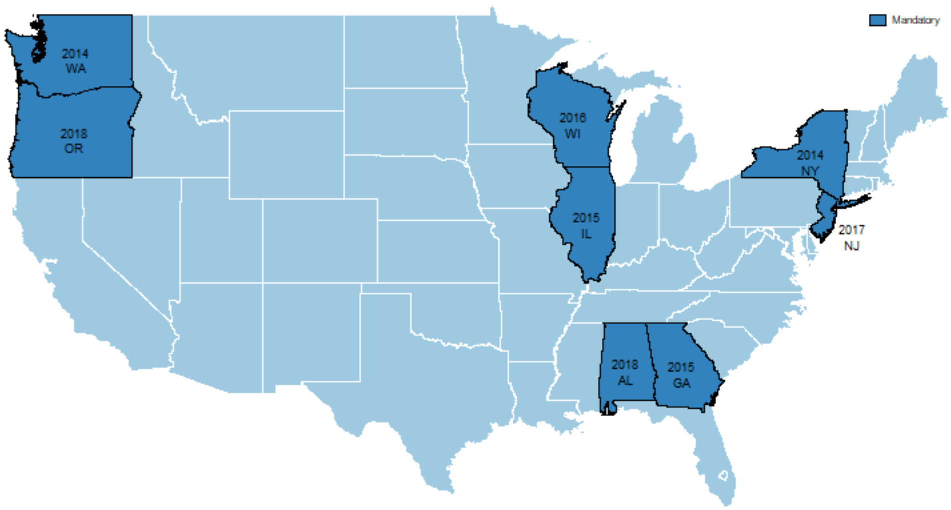
[8] Official document can be found here: `https://secure.aacte.org/apps/rl/res_get.php?fid=1014&ref=edtpa`. We cross-check the mandatory nature in the official websites of state education departments.

[9] The cutoff scores vary by states and subjects. For a typical 15-Rubric criteria with a full score of 75, passing scores range from 35 to 42.

[10] In 2019, Connecticut and Tennessee also mandated edTPA. Since our sample ends in 2019, we treat these two states as the control states in the empirical analysis.

[11] The optional states include Arkansas, California, Delaware, Hawaii, Iowa, Maryland, Minnesota, North Carolina, South Carolina, and West Virginia. Ohio, Texas and Utah also regarded edTPA as an assessment option after 2018.

Figure 1: States mandated edTPA as an program completion and initial licensure requirement, Snapshot in 2018



Note: In 2018, eight states have already introduced edTPA as the only assessment option for program completion and initial teacher licensure.

3 Data

3.1 IPEDS

We measure the teacher supply response to the implementation of edTPA by the number of graduates from teacher preparation programs in post-secondary institutions. The data is obtained from the Integrated Postsecondary Education Data (IPEDS), which contains rich information about the characteristics of post-secondary institutions in the entire US. We exploit the detailed statistics of program completion by majors and identify graduates in teacher preparation programs (both bachelor's and master's degrees) from school year 2010/2011 to 2018/2019.[12] The majors include 'Education, General', 'Bilingual, Multilingual, and Multicultural Education','Curriculum and Instruction', 'Special Education and Teaching', 'Teacher Education & Professional Development, Specific Levels and Methods', 'Teaching English or French as a Second or Foreign Language", and 'Education, Other'.[13] We then aggregate the number of teacher graduates at the institution level. In the sample, we have a panel of 1,243 post-secondary institutions that offer teacher preparation programs.

In Panel A of Table 1, in addition to the outcomes of interest — the number of teacher graduates and the breakdown by white and non-white candidates — we report time-varying institution characteristics to account for concurrent changes in student demographics and the quality of institutions.[14] The variables include the number and percent of minority of graduates in non-education majors, the submission rates and percentile scores of SAT/ACT, first-year full-time enrollment, par-time to full-time faculty ratio, and the amount of and the percent of students receiving federal grants/loans.

[12]To become a licensed public school teacher in the US, a prospective teacher from the traditional route goes through training in a teacher preparation program. Alternatively, a person with a degree from non-education major can opt for the alternative route to complete an approved postgraduate program. EdTPA applies to the candidates in both the traditional and alternative route to teacher certification, and the IPEDS capture both sources.

[13]IPEDS defines the major of a program using CIP codes. We follow the definition of teacher preparation programs recommended by Kraft et al. (2020) in their Appendix C.

[14]In Table A1 of appendix, we present the summary statistics for all states.

Table 1: Summary statistics (IPEDS) - Estimation Sample

	Mean	SD	Min	Max
A. Outcomes:				
education graduates	142.31	188.28	0.00	3041.00
education graduates (white)	107.42	139.71	0.00	1763.00
education graduates (non-white)	34.89	66.76	0.00	1968.00
B. Time-varying controls:				
graduates (non-education majors)	1594.51	2160.49	1.00	16364.00
minority graduates (% of non-education majors)	16.57	17.68	0.00	100.00
SAT submission rate	51.22	34.20	0.00	100.00
ACT submission rate	52.81	32.12	0.00	100.00
SAT 25 percentile score	476.10	65.18	215.00	740.00
SAT 75 percentile score	583.41	63.97	349.00	800.00
ACT 25 percentile score (cumulative)	20.38	3.31	3.00	33.00
ACT 75 percentile score (cumulative)	25.58	3.18	8.00	35.00
first-year FT enrollment	1056.10	1315.98	9.00	9082.00
part-time/full-time faculty ratio	0.03	0.11	0.00	2.32
grant (% student)	76.19	16.74	16.00	100.00
grant (dollar amount, thousands)	44407.21	48785.28	326.33	397711.80
loan (% student)	58.80	16.66	0.00	99.00
loan (dollar amount, thousands)	21099.54	24175.53	0.00	256364.16

Data: IPEDS 2011-2019.
Note: This table shows summary statistics of estimation sample for teacher supply using IPEDS. Optional states are excluded. Summary statistics for all states are presented in the appendix.

3.2 NAEP

To assess the effect of edTPA on student achievement, we analyze the biennial restricted data of the National Assessment of Educational Progress (NAEP) administered by the U.S Department of Education and the Institute of Education Sciences from 2009 to 2017[15]. The assessment is a nationwide test in the US that measures the knowledge of a representative sample of students in various core subjects[16]. The standardized nature of the test enables us to compare student achievement across the country using a common measurement. We standardize the assessment scores by first averaging the composite values of five (or twenty) assessment items within each year-grade-subject and then standardize the averaged assessment scores over the estimation sample to have a zero mean and one standard deviation

[15]NAEP 2017 provides the latest restricted-use data that is available for application.
[16]The subjects include reading, mathematics, science, writing, arts, civics, geography, economics, U.S. history, and technology & engineering literacy.

Table 2: Summary statistics (NAEP)

	Grade 4 Math	Grade 4 Reading	Grade 8 Reading
A. Outcomes:			
Assessment score	234.67 (27.93)	215.25 (34.46)	250.37 (37.41)
B. Student controls:			
White	0.41 (0.49)	0.42 (0.49)	0.45 (0.50)
Black	0.17 (0.38)	0.17 (0.37)	0.17 (0.38)
Hispanic	0.30 (0.46)	0.30 (0.46)	0.26 (0.44)
Female	0.49 (0.50)	0.50 (0.50)	0.50 (0.50)
Individualized Education Program (IEP)	0.13 (0.33)	0.12 (0.32)	0.11 (0.31)
English learner	0.11 (0.31)	0.10 (0.30)	0.06 (0.24)
C. School controls:			
Charter school	0.05 (0.22)	0.05 (0.22)	0.05 (0.22)
Urban area	0.78 (0.41)	0.78 (0.42)	0.75 (0.43)
Share of black student	21.49 (28.92)	20.81 (28.19)	20.24 (28.67)
Lunch program	0.60 (0.49)	0.59 (0.49)	0.55 (0.50)
Student enrollment ($\geq$ 500)	0.49 (0.50)	0.49 (0.50)	0.50 (0.50)
Number of Student	63,610	64,710	52,470

Data: NAEP 2009-2017.
Note: This table shows summary statistics of estimation sample (students with new teachers) for student achievement using NAEP. The mean is shown in the cell while the standard deviation is shown in the parentheses. Each column presents one of the three student assessment samples: Math at Grade 4 , Reading at Grade 4, and Reading at Grade 8. Raw assessment scores are reported in the summary statistics. The number of observations is rounded to the nearest 10 per IES disclosure guidelines.

within the same year-grade-subject level.[17]

NAEP also provides important characteristics of students and schools, which enable more precise estimations by including them as controls. They allow us to conduct balance tests by regressing these predetermined variables on edTPA policy variances in our later analyses. The student controls include student's race and gender, if the student needs an Individualized Education Program (IEP), and if the student is an English-language learner. The school controls include share of black students, indicators for charter school, urban area, eligibility of lunch programs, and whether school enrollment is larger than 500 students[18].

In addition to rich student and school characteristics, the NAEP data links students to

[17] In survey year 2009 and 2011, NAEP uses a five-item scale to measure the composite values of students' math and reading assessment at grade 4 and 8. In survey year 2013, 2015, and 2017, NAEP uses a twenty-item scale for math and reading assessment at grade 4 and 8.

[18] While most control variables employed in this study share consistent measures across the two subjects and grades, one exception is the school enrollment. For students at grade 4, we use enrollment larger than 500 to indicate magnitude of schools. However, for students at grade 8, we use enrollment larger than 600 in year 2009, 2011, 2013, and 2017, as data in these years use a different category for enrollment measure.

characteristics of the corresponding subject teacher. This enables us to narrow down the sample to students whose teachers have less than two years. This criterion is importance since edTPA only applies to new teachers.[19] As far as the data provides, we assess student performances in the mathematics score at grade 4, and the reading scores at grades 4 and 8.[20] To ensure that the teachers have gone through the standard license procedure, we drop students whose subject teachers do not have a teacher license.

Combining the NAEP from different cohorts yields a repeated cross-sectional sample of students. To address the concern that changes in student and school characteristics may affect teacher assignments and contaminate the causal estimates, we control for student and school characteristics presented in Table 2.

[19]The question on years of experience contains continuous measures in survey year 2009 and 2011 and categorical responses in year 2013, 2015, and 2017. The categorical responses are listed as the following: Less than 1 year, 1-2 years, 3-5 years, 6-10 years, 11-20 years, 21 or more years, omitted, and multiple responses.

[20]The restricted data also tracks the mathematics scores at grade 8. However, it does not contain teacher experience in 2017 survey year and cannot identify new teachers.

4 Identification Strategy

4.1 Teacher Supply

We estimate the effects of the mandatory edTPA requirement on teacher and student outcomes using a difference-in-differences framework with the leads and lags of treatment. Formally, for teacher supply analysis, we employ the following specification:

$$Y_{u,s,t} = \sum_{k \neq -1} \beta_k edTPA_{s,t} \mathbb{1}(t = t^* + k) + \mathbf{X}_{u,s,t}\Gamma + \mathbf{Z}_{s,t}\theta + \alpha_u + \alpha_t + \epsilon_{u,s,t} \quad (1)$$

where $Y_{u,s,t}$ refers to the log of the number of teacher graduates from institution u in state s in year t. To differentiate the edTPA effects on teacher supply by race, we run separate regressions on the number of white and non-white candidates. $edTPA$ is a dummy indicator equals 1 after a state mandated edTPA as the initial licensure requirement in the graduation year t^*. In the above non-parametric model, the omitted period is the graduation year right before the policy took effect. For example, the effective date in Illinois is September 2015. Its omitted year is the 2014/2015 school year. Then, $\beta_{(k>-1)}$ measures the edTPA effect on teacher supply in a given post-policy year, whereas $\beta_{(k<-1)}$ detects any deviation in trends in the pre-policy period between the edTPA and non-edTPA states. $X_{u,s,t}$ refers to a vector of time-varying controls at the institution level presented in Table 1. $\mathbf{Z}_{s,t}$ refers to a series of education policy indicators suggested by Kraft et al. (2020) to control for potential confounds on the teacher supply response. The policies include the elimination of teacher tenure, the increase in probationary period, the elimination of mandatory union dues, the adoption of Common Core Standards, and changes in the licensure content.[21] α_u and α_t are institution and year fixed effects, respectively. To account for serial correlation within a state, we cluster the standard errors at the state level.

[21] We code the policy year based on Table A1 of Kraft et al. (2020).

4.2 Student Outcomes

To estimate the impacts of edTPA on student achievement, we exploit the same policy variation in which edTPA becomes consequential in the educator licensing process shown in Figure 1 using the NAEP data. Since the latest available year in NAEP is 2017, we adjust the treatment groups to students in the five earlier edTPA states, namely Washington, New York, Illinois, Georgia, and Wisconsin. Because the mathematics and reading test in NAEP are administered bi-annually, the maximum number of of post-treatment periods is two (2015 and 2017 for Washington and New York; 2017 for Illinois, Georgia, and Wisconsin). We employ the same differences-in-differences framework with a repeated cross-sectional sample of students. Formally, we estimate the following model:

$$\mathrm{Y}_{i,j,s,t} = \sum_{k=-4,k\neq-1}^{k=1} \beta_k edTPA_{s,t} \mathbb{1}\left(t = t^* + k\right) + \mathbf{X}_{i,j,s,t}\Gamma + \mathbf{Z}_{s,t}\theta + \alpha_s + \alpha_t + \epsilon_{i,j,s,t} \qquad (2)$$

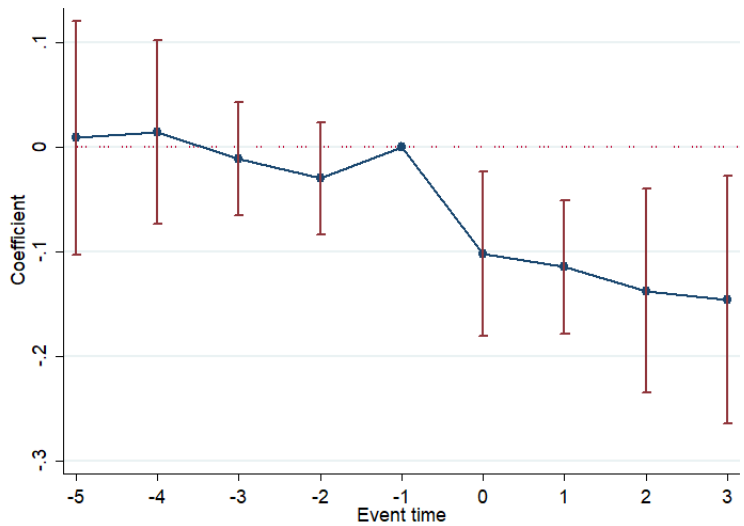
where Y_{ist} is the student i's outcome in school j in state s sampled in period t. We again included the leads and lags of treatment indicators ($edTPA$) to check the parallel-trend assumption and also capture the dynamic effects. t^*_s is the policy implementation year, which varies by states. $\mathrm{X}_{i,j,s,t}$ is a vector of student and school control variables. α_s and α_t are the state fixed effects and year fixed effects, respectively. Stand errors are clustered at state level, which is the level edTPA policies were implemented. While this specification is almost identical to the one for teacher supply above, there is a difference on the time period because of the data structure. NAEP is a biennial assessment and the NAEP data we obtained is from 2009 to 2017, the time period of this specification ranges is from -4 to 1 and each period t represents two years.

5 Teacher Supply

5.1 Main Results

In Figure 2, we plot the event study dummies with the corresponding 95% confidence interval, conditional on institution and year fixed effects. the pre-treatment effects show that there is no systematic deviation in pre-trends. This further validates the difference-in-differences model in producing a reliable post-edTPA counterfactual.

Figure 2: No significant deviation of the pre-trend



Note: This figure plots the estimates of the event study dummies and the corresponding 95% confidence interval. The regression in this figure includes year and institution fixed effects. No control variables are added. The endpoints are binned up to show a balanced window.

In Table 3, we present the estimates from the diff-in-diff strategy in various specifications. Panel A of Column 1 shows that edTPA reduced the number of teacher graduates by 14%. In Column 2, we control for regional linear time trends to capture any shocks to local markets. The magnitude of the negative effect drops slightly to 13.4%. In Column 3, we further control for concurrent education policies that may impacted teacher supply. Although the negative effect on teacher supply further decreases to -12.2%, the effect size remains statistically significant. In Column 4 and 5, we include the optional states in the control group and find a similar magnitude. Since New Jersey did not require a cutoff score until September 2019, we exclude it in Column 6 and still find a similar result. In Panel B and C of Table 3, we also find a similar pattern when we breakdown teacher graduate statistics by white and non-white candidates.

Table 3: Diff-in-diff estimates with various specifications

	(1)	(2)	(3)	(4)	(5)	(6)
		All states		Include optional states		Drop NJ
			Panel A: All groups			
edTPA	-0.140***	-0.134***	-0.122***	-0.161***	-0.136***	-0.130***
	(0.0487)	(0.0374)	(0.0353)	(0.0518)	(0.0332)	(0.0367)
Constant	2.117***	2.210***	2.199***	1.997***	2.133***	2.222***
	(0.376)	(0.417)	(0.420)	(0.305)	(0.328)	(0.424)
R-squared	0.190	0.195	0.199	0.171	0.185	0.197
			Panel B: White			
edTPA	-0.130***	-0.122***	-0.112***	-0.148***	-0.119***	-0.114***
	(0.0431)	(0.0339)	(0.0324)	(0.0441)	(0.0280)	(0.0346)
Constant	2.072***	2.192***	2.181***	2.033***	2.166***	2.189***
	(0.337)	(0.363)	(0.369)	(0.271)	(0.287)	(0.375)
R-squared	0.200	0.204	0.207	0.176	0.185	0.205
			Panel C: Non-white			
edTPA	-0.134**	-0.137***	-0.111***	-0.156**	-0.123***	-0.123***
	(0.0569)	(0.0374)	(0.0348)	(0.0611)	(0.0362)	(0.0355)
Constant	0.488	0.447	0.422	0.543	0.531	0.513
	(0.497)	(0.535)	(0.529)	(0.422)	(0.433)	(0.524)
R-squared	0.065	0.071	0.075	0.060	0.071	0.075
Observations	7,281	7,281	7,281	10,598	10,598	7,091
Number of unitid	858	858	858	1,243	1,243	836
Regional trend		X	X		X	X
Policy controls #			X		X	X

Data: IPEDS, 2011-2019

Note: Each column in each panel represents one regression. Dependent variable in each regression is the log of the number of teacher graduates (by race). All regressions include time-varying controls in Panel A of Table 1, year and institution fixed effects. #The policy controls are based on Table A1 of Kraft et al. (2020). Standard errors in the parenthesis are clustered at the state level. ***, **, and * represent 1%, 5%, and 10% significant level, respectively.

In Table 4, we differentiate the effects by program types. We run the analyses using the full specification with all institution controls, regional time trend, and policy controls. Column 1 to 3 show that edTPA reduced the number of teacher graduates in the traditional route and the magnitudes are similar to the results using the full sample in Table 3. By contrast, we do not observe significant changes in the number of teacher graduates in post-graduate programs — one source of the alternative route to certification - as shown from Column 4 to 6. The bigger effect on the traditional route is consistent with the observation that teachers opting for the alternative route are generally more committed (Sass, 2015). The null effect for alternative route is also a useful placebo test since some of the master students may have already been certified.

Table 4: Stronger effects on traditional route programs

	(1)	(2)	(3)	(4)	(5)	(6)
	Bachelor's degree			Post-graduate degree		
	all	white	nonwhite	all	white	nonwhite
edTPA	-0.142***	-0.140***	-0.120**	-0.0377	-0.0394	-0.0203
	(0.0452)	(0.0407)	(0.0474)	(0.0396)	(0.0439)	(0.0294)
Constant	0.799*	0.961**	-0.658	0.317	0.206	-0.122
	(0.460)	(0.429)	(0.624)	(0.587)	(0.503)	(0.705)
Observations	6,680	6,680	6,680	5,756	5,756	5,756
R-squared	0.149	0.175	0.042	0.321	0.290	0.157
Number of unitid	803	803	803	693	693	693

Data: IPEDS, 2011-2019

Note: Each column in each panel represents one regression. Dependent variable in each regression is the log of the number of teacher graduates (by race and program type). All regressions include time-varying controls in Panel A of Table 1, regional time trend, policy controls, year and institution fixed effects. Standard errors in the parenthesis are clustered at the state level. ***, **, and * represent 1%, 5%, and 10% significant level, respectively.

The negative impacts on teacher supply fall disproportionately on candidates with a disadvantaged background, as the education literature suggests. To explore possible heterogeneity by candidate types, we utilize the university-wide SAT and ACT admission scores contained in IPEDS before 2014 to categorize institutions into two groups: more (top 50%) and less (less 50%) selective. In the regression, we interact the two indicators with the treatment dummy to see if there exists heterogeneity by institution selectivity.[22]

IPEDS provides the 25^{th} and 75^{th} percentile scores of an institution. In Table 5, we present the heterogeneity result by ranking institutions based on their 25^{th} percentile scores.

[22] The base indicators for 'top 50%' and 'bottom 50%' are time-invariant and are absorbed by institution fixed effect.

In Column 1 and 4, both the results using SAT and ACT ranking show that the difference in effect size between the two institution types is not significant, though the coefficient for less selective institutions is slightly bigger. When we differentiate the effects by race, we observe a significantly larger impact on minority candidates in less selective universities as shown in Column 3 and 6. The p-values of the difference between coefficients are 0.022 and 0.027, respectively. To check sensitivity, we also find similar patterns in Table A2 of Appendix with the 75^{th} percentile scores.

Table 5: Heterogeneity by the selectivity of university

	(1)	(2)	(3)	(4)	(5)	(6)
	Selectivity by SAT			Selectivity by ACT		
	all	white	nonwhite	all	white	nonwhite
edTPA*(bottom 50%)	-0.129***	-0.0997***	-0.148**	-0.152***	-0.121**	-0.164**
	(0.0387)	(0.0355)	(0.0629)	(0.0451)	(0.0484)	(0.0624)
edTPA*(top 50%)	-0.0865*	-0.108**	-0.0215	-0.0613	-0.0858	-8.89e-05
	(0.0454)	(0.0468)	(0.0430)	(0.0548)	(0.0570)	(0.0536)
Constant	2.121***	2.077***	0.451	2.138***	2.083***	0.481
	(0.397)	(0.361)	(0.507)	(0.397)	(0.360)	(0.505)
Observations	7,204	7,204	7,204	7,204	7,204	7,204
R-squared	0.199	0.207	0.072	0.199	0.207	0.073
Number of unitid	832	832	832	832	832	832

Data: IPEDS, 2011-2019

Note: Dependent variable in each regression is the log of the number of teacher graduates (by race). All regressions include time-varying controls in Panel A of Table 1, policy controls, year and institution fixed effects. We categorise institutions into more (top 50%) and less (bottom 50%) according to their pre-2014 25^{th} percentile SAT/ACT scores. Standard errors in the parenthesis are clustered at the state level. ***, **, and * represent 1%, 5%, and 10% significant level, respectively.

5.2 Robustness

Because we are leveraging different policy timing across states, one concern is that the propensity to adopt edTPA is correlated with the regional teacher market conditions. Although previous licensing studies have pointed out that state variation in licensing policy is largely determined randomly by political forces, we perform balance tests to show there are no systematic differences in observed characteristics between edTPA and non-edTPA states.[23] In all columns of Table 6, we regress an indicator equals 1 if a state adopted edTPA during the sample period on its pre-2014 attributes, including the level/growth of the number of teacher graduates, and average institution characteristics. Across columns, we use different measures of institution quality available in IPEDS to probe the sensitivity of the estimates. In all specifications, we do not find a strong evidence that edTPA adoption was correlated with pre-policy characteristics of post-secondary institution or teacher graduates. This gives us credence about the quasi-random nature of edTPA implementations.

We then perform a couple of placebo tests to show that our identified effect on teacher supply does not capture confounding factors, such as unmeasured shocks of teacher supply and demand. First, in Table 7, we find that the placebo treatment has essentially zero effects on the number of non-education graduates. This alleviates the concern that the drop of teacher graduates simply reflects state-specific shocks in tertiary education.

In Table 8, we run a series of auxiliary fixed-effect models excluding the time-varying controls. As shown in Column 1 to 6, the edTPA treatment does not change institution characteristics, including first-year enrollment (all majors), faculty resource, and the financial background of students. In Column 7 of Table 8, we also find that there is no significant changes in teacher demand measured by public school enrollments.[24]

[23]Relevant studies include Kleiner and Soltas (2019) and Larsen et al. (2020).

[24]We pool the state level statistics (2011-2019) from the National Center for Education Statistics (NCES).

Table 6: Balancing test - Pre-2014 characteristics do not predict edTPA implementation

	(1)	(2)	(3)	(4)
education graduates (level)	0.258*	0.258*	0.266*	0.261*
	(0.138)	(0.138)	(0.138)	(0.138)
education graduates (growth)	0.0393	0.0479	0.0398	0.0406
	(0.161)	(0.161)	(0.164)	(0.161)
first-year FT enrollment (thousands)	-0.122	-0.120	-0.149	-0.141
	(0.261)	(0.260)	(0.255)	(0.255)
part-time/full-time faculty ratio	-0.268	-0.278	-0.254	-0.261
	(0.370)	(0.372)	(0.374)	(0.371)
grant (% student)	-0.00334	-0.00421	-0.00469	-0.00471
	(0.00957)	(0.00905)	(0.00903)	(0.00899)
grant (dollar amount)	-6.43e-05	0.000448	0.00182	0.00139
	(0.00801)	(0.00697)	(0.00756)	(0.00658)
loan (% student)	0.0113	0.0122	0.0114	0.0118
	(0.00864)	(0.00883)	(0.00866)	(0.00880)
loan (dollar amount)	-0.00191	-0.00269	-0.00215	-0.00219
	(0.0141)	(0.0140)	(0.0147)	(0.0141)
SAT 25 percentile score	0.00155			
	(0.00355)			
SAT 75 percentile score		0.00145		
		(0.00298)		
ACT 25 percentile score			0.00790	
			(0.0694)	
ACT 75 percentile score				0.0192
				(0.0625)
Constant	-1.845	-1.950	-1.252	-1.574
	(1.856)	(1.895)	(1.492)	(1.702)
Observations	51	51	51	51
R-squared	0.157	0.158	0.154	0.155

Data: IPEDS, 2011-2014

Note: Dependent variable in all regressions is an indicator equals 1 if a state mandated edTPA after 2014. All regressors are pre-2014 averages.

Table 7: Placebo test on non-education majors

	(1) total	(2) white	(3) non-white
placebo treatment	-0.0181	-0.0329	-0.0296
	(0.0383)	(0.0436)	(0.0347)
Constant	6.739***	6.317***	5.523***
	(0.186)	(0.223)	(0.236)
Observations	7,281	7,281	7,281
R-squared	0.072	0.036	0.188
Number of unitid	858	858	858

Data: IPEDS, 2011-2019

Note: Dependent variable in each regression is the log of the number of non-education graduates (by race). All regressions include time-varying controls in Panel A of Table 1, policy controls, year and institution fixed effects. Standard errors in the parenthesis are clustered at the state level. ***, **, and * represent 1%, 5%, and 10% significant level, respectively.

Table 8: Changes in institution characteristics and teacher demand are not significant confounders

	(1) first-year enrollment	(2) PT/FT faculty ratio	(3) grant (% students)	(4) grant (amount)	(5) loan (% students)	(6) loan (amount)	(7) teacher demand
placebo treatment	0.00730	0.00219	0.670	1.475	-0.348	-0.0247	-0.00972
	(0.0237)	(0.00382)	(0.562)	(1.382)	(0.551)	(0.533)	(0.0116)
Constant	1.028***	0.0346***	75.08***	37.39***	60.88***	22.09***	13.16***
	(0.00786)	(0.00342)	(0.336)	(0.611)	(0.330)	(0.249)	(0.00631)
Observations	7,281	7,281	7,281	7,281	7,281	7,281	351
R-squared	0.025	0.002	0.023	0.219	0.118	0.093	0.172
Number of unitid	858	858	858	858	858	858	
Number of state							39

Data: IPEDS, 2011-2019 (Column 1 to 6); NCES (Column7)

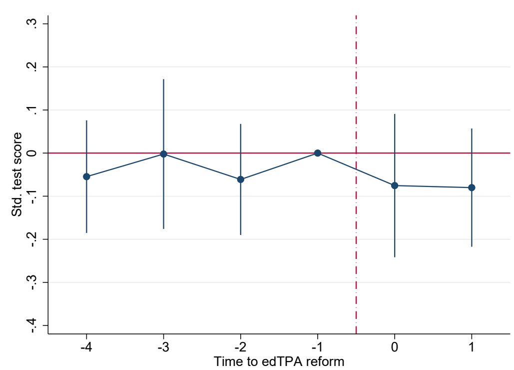
Note: All regressions include year and institution fixed effects. Standard errors in the parenthesis are clustered at the state level. ***, **, and * represent 1%, 5%, and 10% significant level, respectively.

6 Student Achievement

6.1 Main Results

In this section, we test if edTPA benefits student learning. Figure 3 plot the estimates of event study dummies for standardized test scores. We first combine the three subjects - namely mathematics in grade 4, reading in grades 4 and 8 - to show an aggregate picture. In the regression, we do not add time-varying controls to demonstrate the pattern in the raw data, conditional on subject, year, and state fixed effects. There is no significant deviation in pre-treatment trends as shown by the lead indicators, that validates the assumption of the difference-in-differences approach.

Figure 3: Event study figures for standardized test scores



Data Source: NAEP 2009, 2011, 2013, 2015, and 2017.
Note: The dependent variable is the three standardized test scores. Event period -1 is normalized to 0. The underlying regression contains no controls to show raw data patterns, conditional on subject, state, and year fixed effects. The figures show the 95% confidence interval with robust standard errors clustered at the state level.

We present the difference-in-differences estimates by sub-sample in Table 9. In Column 1, 4, and 7 of Panel A, edTPA has both economically and statistically insignificant effects on the three test scores, which is consistent with the flat pattern in Figure 3.

When we add student and school controls, Column 2 and 5 of Panel A show that edTPA decreases mathematics and reading scores of grade 4 students by 8.4% and 8.9% of a standard deviation. Adding the controls for concurrent education policies reduces the magnitude for mathematics score to a decrease of 5.7% in Column 3, while that for reading score remains similar in Column 6. On the contrary, As shown in Column 8 and 9, edTPA has a statistically insignificant effect on reading scores of grade 8 students in all specifications. The stronger impacts on grade 4 students relative to grade 8 students are consistent with the finding by Jackson (2014) that teachers are more influential for younger children.

In Panel B and C of Table 9, we split the analysis by whether the teachers went through traditional route. We utilize one question in the teacher survey of NAEP that asks the subject teacher if he/she went through the alternative route to certification. For the mathematics and reading scores of grade 4 students, Panel B consistently shows that the negative effect of edTPA on grade 4 students primarily occurs on new teachers who went through the traditional route. This coincides the pattern in teacher supply response that edTPA only reduced the number of traditional route graduates. For new teachers who went through the alternative route, there are some signs that edTPA improves the reading scores of grade 8 students in Panel C. However, a caveat is that the magnitude is sensitive to including control variables.

Table 9: Impacts of edTPA reforms on students' achievement

	Std. test score								
Panel A	Grade 4 Math			Grade 4 Reading			Grade 8 Reading		
Full sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
edTPA	-0.071	-0.084**	-0.057*	-0.060	-0.089**	-0.083***	-0.021	0.038	0.052
	(0.059)	(0.032)	(0.029)	(0.047)	(0.036)	(0.031)	(0.034)	(0.040)	(0.041)
R-squared	0.033	0.327	0.329	0.027	0.378	0.379	0.040	0.380	0.381
Observations	63,610	63,610	63,610	64,710	64,710	64,710	52,470	52,470	52,470
Panel B									
Traditional route	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
edTPA	-0.109*	-0.093**	-0.068*	-0.062**	-0.074**	-0.071**	-0.026	0.033	0.042
	(0.061)	(0.036)	(0.033)	(0.028)	(0.030)	(0.027)	(0.030)	(0.029)	(0.032)
R-squared	0.029	0.322	0.323	0.024	0.310	0.371	0.036	0.372	0.372
Observations	52,740	52,740	52,740	54,090	54,090	54,090	39,420	39,420	39,420
Panel C									
Alternative routes	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
edTPA	-0.017	-0.039	0.010	-0.212	-0.188	-0.163*	-0.015	0.183**	0.176**
	(0.093)	(0.073)	(0.071)	(0.197)	(0.114)	(0.081)	(0.110)	(0.084)	(0.083)
R-squared	0.068	0.336	0.339	0.049	0.328	0.389	0.050	0.377	0.378
Observations	10,870	10,870	10,870	10,620	10,620	10,620	13,050	13,050	13,050
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
School controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Policy controls	No	No	Yes	No	No	Yes	No	No	Yes

Data Source: NAEP 2009, 2011, 2013, 2015, and 2017.

Note: Panel A uses full student sample, Panel B uses student samples with teachers obtained the license through a traditional teacher preparation program, and Panel C uses students with teachers obtained the license through alternative routes. The dependent variables in column (1) to (3), (4) to (6), and (7) to (9) are Grade 4 Math, Grade 4 Reading, and Grade 8 Reading, respectively. The test scores are standardized to a zero mean and one standard deviation in the sample. 'edTPA' refers to the treatment indicator. All regressions include state and year fixed effects. Student and school controls are listed in Panel B of Table 1. #The policy controls are based on Table A1 of Kraft et al. (2020). Standard errors in brackets are clustered at the state level. Sample Sizes are rounded to the nearest 10 per IES disclosure guidelines. ***, **, and * represent 1%, 5%, and 10% significant level, respectively.

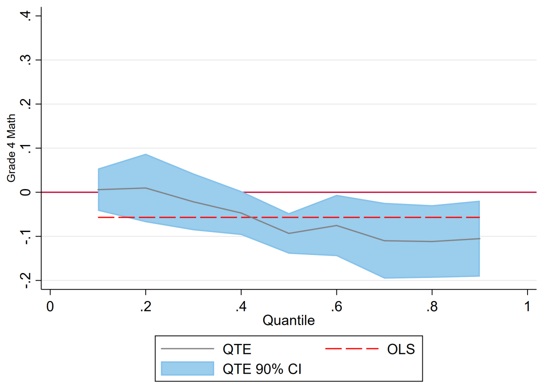
6.2 Heterogenous Effects

We now investigate the heterogeneous effects by student's ability through the quantile regression model (Koenker and Hallock, 2001). The idea is to check if the negative effect on test scores of grade 4 students falls disproportionate on certain types of students.

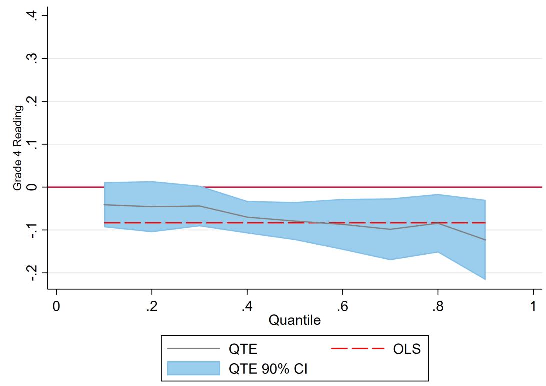
In each sub-figure of Figure 4, the horizontal axis tracks the percentiles and the vertical axis indicates the estimate of the edTPA impacts on achievement at a given percentile. All regressions include the same student, school, and policy controls as in equation 2 using the full sample.[25] The gray dashed line shows the estimate of quantile treatment effects, while the red solid line shows the OLS estimate for comparison. The blue shaded region indicates the corresponding 90% confidence intervals for the quantile regression estimates. The first sub-figure of Figure 4 shows the heterogeneous result for the mathematics score of grade 4 students. We observe that the impacts of edTPA are close to zero for students at the lower achievement percentiles. The negative effect emerges starting from the students at the median and concentrate at the higher score percentiles. In the second sub-figure, we also a similar pattern for the reading scores of grade 4 students that the negative impacts of edTPA concentrates on higher-achievers. For reading scores, the positive effect concentrates on students at the lowest score decile as shown in the third sub-figure. We do not detect apparent heterogeneity by student ability, however. Again, we interpret the positive impact with caution since the estimate is sensitive to different specifications.

[25] In Figure A1 of appendix, we also present the quantile regression graph using only teachers on the traditional route.

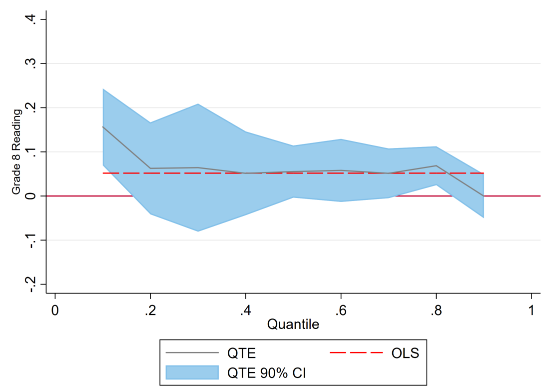
Figure 4: Heterogeneous effects of edTPA reforms on student achievement: Full sample



(a) Grade 4: Math



(b) Grade 4: Reading



(c) Grade 8: Reading

Note. The dependent variables of subfigure (a), (b), and (c) are the standardized grade 4 math score, grade 4 reading score, and grade 8 reading score, respectively. The underlying quantile regression is based on the specification of equation 2. All regressions include state fixed effect, year fixed effects, student and school controls. The gray dashed line shows the estimate of quantile treatment effects, while the red solid line shows the OLS estimate. The blue shaded region shows the 90% confidence interval with robust standard errors clustered at the state level.
Source. NAEP 2009, 2011, 2013, 2015, and 2017.

6.3 Mechanism: Teacher Behaviors

Based on the unintended adversity on students, this section explores possible explanations. We exploit detailed survey questions in NAEP about teacher pedagogy. In all the following regressions, we present the results using the full specification with student, school, and policy controls.

From Column 1 to Column 9 of Panel A and B in Table 10, we investigate potential behavioral changes of grade 4 mathematics teachers. From Column 1 to 4, we first examine whether teachers meet students daily in four aspects, including discussing current performance level, setting goals, discussing progress toward goals, and adjusting teaching strategies that meet needs.[26] Among the four measures, edTPA significantly reduced the likelihood that traditional route teachers meet with students to set goals as shown in Panel A. In the other three measures of teacher-student interaction, we do not observe statistically insignificant changes for both traditional and alternative route teachers. The second set of questions is about pedagogy. Teachers rate with a scale from 1 (not at all) to 4 (large extent) about the likelihood of using a specific teaching method, including setting different standards for some students, using other materials some students, engaging some students in different activity, using different methods for some students, and changing pace for some student.[27] In the ordered choice models from Column 5 to 9, we find weak evidence that edTPA changed teacher pedagogy. Among the five measures, only 'change pace' has a marginally significant coefficient.

The teacher survey for reading class covers a different set of pedagogy questions. In the first subset of questions, teachers in reading subject rate, with a scale from 1 (never) to 4 (always), the regularity of several teaching methods. The methods include students summarizing the passage, interpreting meaning of passage, questioning motives of characters,

[26]The teachers rate the frequency with a scale from 1 to 5: (1) never or hardly ever; (2) a few times a year; (3) once or twice a month; (4) once or twice a week; (5) every day or almost. We define an outcome variable equals 1 if the response is 'every day or almost'.

[27]The scale is: (1) not at all; (2) small extent; (3) moderate extent; (4) large extent.

identifying main theme of passage.[28] In the second subset of questions, teachers in reading subject rate, with a scale from 1 (not at all) to 4 (large extent), the focus of a particular type of literacy work. The type of work includes fiction, literary nonfiction, poetry, exposition, argumentation and persuasion, and procedural texts.[29] From Column 1 to Column 10 of Panel C and D in Table 10, we present the results of the aforementioned pedagogy measures using ordered choice models. Among the ten measures, traditional route teachers in edTPA states are more likely to 'question motives' and focus on 'procedural text'.

The above results regarding changes in pedagogy are not conclusive. One caveat is that statistically significance may not survive the adjustment of multiple hypothesis testing. Another caution is the uncertainty about the relationship between a particular pedagogy and student learning.

Meanwhile, we explore the potential change in class size. It is one possible consequence that could affect the quality of instruction caused by reduced new teacher supply. The five categories in the survey in terms of the number of student in a class: 15 or fewer, 16 to 18, 19 to 20, 21 to 25, and 26 or more. Since the median occurs in the fourth group, we create a dummy variable to indicate the class size is large if there are 26 or more students. In Column 10 of Panel A and Column 11 of Panel C, we observe that both mathematics and reading teachers who went through traditional programs are more likely to teach large classes after the adoption of edTPA. At the same time, there is no class size effect for alternative route teachers. This again is consistent with the teacher supply results that edTPA only reduced tradition route graduates. Relative to the results of pedagogy, we believe the change in class size is more compelling to explain the negative effect on students.

[28] The scale is: (1) never or hardly ever; (2) sometimes; (3) often; (4) always or almost. For 2017, the scale changes to 1 to 5: (1) never or hardly ever; (2) once in a while; (3) sometimes; (4) often; (5) always or almost always. We combine (1) "never or hardly ever" and (2) "once in a while" in 2017 into (1) "never or hardly ever" in pre-2017 surveys to generate consistent measures on the teaching pedagogy.

[29] Specifically, the scale is from 1 to 4: (1) not at all; (2) small extent; (3) moderate extent; (4) large extent.

Table 10: Mechanism: Impacts of edTPA reforms on teacher behaviors

	Meeting with students (daily)				Teaching practices						
	Discuss performance	Set goals	Discuss progress	Adjust teaching	Set diff standards	Use other materials	Engage stud activity	Use diff methods	Change pace	Large class	
Grade4 Math	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Panel A. Traditional route											
edTPA	-0.004	-0.036***	-0.005	-0.006	0.140	0.153	0.008	-0.151	-0.212*	0.067*	
	(0.009)	(0.008)	(0.019)	(0.044)	(0.162)	(0.163)	(0.080)	(0.153)	(0.125)	(0.033)	
R-squared	0.017	0.017	0.015	0.030	0.013	0.017	0.024	0.024	0.019	0.158	
Observations	50,580	50,580	50,580	50,580	50,580	50,580	50,580	50,580	50,580	50,580	
Panel B. Alternative routes											
edTPA	-0.010	-0.031	-0.047	0.077	0.105	-0.120	-0.161	0.254	-0.374	-0.006	
	(0.067)	(0.059)	(0.054)	(0.115)	(0.266)	(0.447)	(0.350)	(0.259)	(0.258)	(0.123)	
R-squared	0.060	0.060	0.056	0.070	0.032	0.035	0.045	0.042	0.039	0.252	
Observations	10,140	10,140	10,140	10,140	10,140	10,140	10,140	10,140	10,140	10,140	
	Pedagogy on reading				Taught about						
	Summarize passage	Interpret meaning	Question motives	Identify theme	Fiction	Literary nonfiction	Poetry activity	Exposition	Argumentation & persuasion	Procedural texts	Large class
Grade4 Reading	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel C. Traditional route											
edTPA	0.018	0.161	0.341**	0.021	0.041	0.035	0.033	-0.232	0.063	0.450***	0.069**
	(0.138)	(0.194)	(0.144)	(0.107)	(0.248)	(0.182)	(0.155)	(0.185)	(0.284)	(0.128)	(0.028)
R-squared	0.012	0.021	0.021	0.024	0.022	0.024	0.028	0.025	0.027	0.022	0.165
Observations	52,240	52,240	52,240	52,240	52,240	52,240	52,240	52,240	52,240	52,240	52,240
Panel D. Alternative routes											
edTPA	1.092**	-0.255	-0.128	0.284	-0.583	0.019	0.669	0.137	0.527	0.405	0.151
	(0.502)	(0.413)	(0.555)	(0.462)	(0.398)	(0.321)	(1.226)	(0.313)	(0.659)	(0.527)	(0.174)
R-squared	0.060	0.058	0.070	0.062	0.045	0.037	0.060	0.096	0.045	0.040	0.274
Observations	10,110	10,110	10,110	10,110	10,110	10,110	10,110	10,110	10,110	10,110	10,110

Data Source: NAEP 2009, 2011, 2013, 2015, and 2017.

Note: Panel A uses full student sample, Panel B uses student samples with teachers obtained the license through a traditional teacher preparation program, and Panel C uses students with teachers obtained the license through alternative routes. The dependent variables in column (1) to (3), (4) to (6), and (7) to (9) are Grade 4 Math, Grade 4 Reading, and Grade 8 Reading, respectively. The test scores are standardized to a zero mean and one standard deviation in the sample. 'edTPA' refers to the treatment indicator. All regressions include policy controls based on Table A1 of Kraft et al. (2020), state and year fixed effects. Student and school controls are listed in Panel B of Table 1. Standard errors in brackets are clustered at the state level. Pseudo R-squareds are reported for the ordered logistic regression. Sample Sizes are rounded to the nearest 10 per IES disclosure guidelines. ***, **, and * represent 1%, 5%, and 10% significant level, respectively.

6.4 Robustness

Balancing tests - Our student sample is based on the years of experience of teachers. One concern of this sample selection criteria is that the estimation sample changes systematically with the edTPA timing. For example, if new teachers are more/less likely to be assigned to disadvantaged students after edTPA, our negative estimates would falsely be attributed to the causal impact of edTPA.

We test if the edTPA treatment is correlated with student characteristics by performing a number of auxiliary models. We regress student characteristics on the edTPA indicator conditional on state and year fixed effects. As shown in the Table 11, edTPA in general is not related to changes in any of the predetermined student characteristics. This null relationship holds for all the three assessments. Overall, we do not find evidence that there is a sample selection issue in our estimation.

Placebo test - Another concern is that we captured unobservables correlated with both student performance and timing of edTPA. For example, student achievement in edTPA states in general had been experiencing a downward trend. If this is the case, we would falsely attribute the negative estimate to the impacts of edTPA reforms. To confirm the negative impacts on student achievement were not driven by unobserved changes in student or teaching environment, we conduct a placebo test where we implement the same DID analysis on student whose teachers have 3 to 5 years of teaching experiences. We choose teachers with experiences from 3 to 5 years because the NAEP data only contains a dummy variable for teaching experience in survey year 2013, 2015, and 2017. '3 to 5 years' is the nearest category the data has for teacher experience, compared to the '0 to 2 years' category. To the extent that teaching skill grows with years of experience, teachers with experiences from 3 to 5 years are a comparable group for novice teachers.

In Table 12, we conduct the placebo test using student samples whose teachers with 3-5 years experience. As shown in Panel B of Table 12, edTPA does not have impacts on any of the three assessments for students whose teachers went through the traditional route.

Table 11: edTPA is not correlated with changes in student characteristics

Indep Var: edTPA	White	Black	Hispanic	Female	IEP	Eng learner
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
G4 Math	0.024	-0.027	0.012	-0.000	0.004	0.018
	(0.021)	(0.019)	(0.021)	(0.006)	(0.007)	(0.019)
R-squared	0.106	0.128	0.094	0.001	0.008	0.092
Observations	63,610	63,610	63,610	63,610	63,610	63,610
Panel B	(7)	(8)	(9)	(10)	(11)	(12)
G4 Reading	0.023	-0.030	0.011	0.004	-0.002	0.001
	(0.022)	(0.023)	(0.016)	(0.012)	(0.017)	(0.024)
R-squared	0.102	0.123	0.093	0.001	0.011	0.088
Observations	64,710	64,710	64,710	64,710	64,710	64,710
Panel C	(13)	(14)	(15)	(16)	(17)	(18)
G8 Reading	-0.039	0.007	0.026	0.013	0.041	0.018
	(0.038)	(0.028)	(0.018)	(0.019)	(0.016)	(0.020)
R-squared	0.142	0.155	0.153	0.001	0.010	0.060
Observations	52,470	52,470	52,470	52,470	52,470	52,470
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note. The samples in panel A, B, and C are from three NAEP assessments: Grade 4 Math, Grade 4 Reading, and Grade 8 Reading, respectively. The dependent variables are students' predetermined characteristics, while the independent variable 'edTPA' is an indicator where its value equals 1 if state s passes compulsory edTPA policy and 0 otherwise. All regressions include state fixed effects and year fixed effects. Robust standard errors clustered at state level are in brackets. Sample Sizes are rounded to the nearest 10 per IES disclosure guidelines. $***p < 0.01, **p < 0.05, *p < 0.1$.

Source. NAEP 2009, 2011, 2013, 2015, and 2017.

The null effects are consistent across specifications, with or without student, school, and policy controls. In Figure A1 of Appendix, we also show that there is no heterogeneity by performance percentiles. The null effects using alternative student samples give us credence about the adverse impacts caused by edTPA on students of new teachers.

Table 12: Placebo test: Impacts of edTPA on students' achievement using alternative samples

	Std. test score								
Panel A	Grade 4 Math			Grade 4 Reading			Grade 8 Reading		
Full sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
edTPA	0.009	-0.008	0.026	0.051	0.005	0.012	0.053	0.012	0.039
	(0.055)	(0.046)	(0.042)	(0.059)	(0.042)	(0.039)	(0.069)	(0.056)	(0.058)
R-squared	0.023	0.337	0.337	0.026	0.385	0.385	0.032	0369	0.370
Observations	101,070	101,070	101,070	103,240	103,240	103,240	80,530	80,530	80,530
Panel B									
Traditional route	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
edTPA	-0.020	-0.018	0.017	-0.000	-0.020	-0.012	0.040	0.016	0.043
	(0.064)	(0.050)	(0.047)	(0.070)	(0.043)	(0.045)	(0.081)	(0.062)	(0.067)
R-squared	0.022	0.336	0.336	0.021	0.379	0.380	0.032	0362	0.362
Observations	85,420	85,420	85,420	87,880	87,880	87,880	61,710	61,710	61,710
Panel C									
Alternative routes	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
edTPA	0.147	0.065	0.080	0.359***	0.250**	0.239**	0.101	-0.024	-0.014
	(0.116)	(0.044)	(0.062)	(0.105)	(0.101)	(0.101)	(0.141)	(0.065)	(0.068)
R-squared	0.044	0.333	0.333	0.053	0.395	0.396	0.041	0377	0.378
Observations	15,650	15,650	15,650	15,360	15,360	15,360	18,820	18,820	18,820
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Student controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
School controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Policy controls	No	No	Yes	No	No	Yes	No	No	Yes

Note. The estimation sample is student sample whose teachers have 3 to 5 years of teaching experience. Panel A uses full student sample, Panel B uses student samples with teachers obtained the license through a traditional teacher preparation program, and Panel C uses students with teachers obtained the license through alternative routes. The samples in column (1) to (3), (4) to (6), and (7) to (9) are from three NAEP assessments: Grade 4 Math, Grade 4 Reading, and Grade 8 Reading, respectively. The dependent variables are test scores for Grade 4 Math, Grade 4 Reading, and Grade 8 Reading, standardized to a zero mean and one standard deviation over each estimation sample. 'edTPA' is an indicator where its value equals 1 if state s passes compulsory edTPA policy and 0 otherwise. All regressions include state fixed effects and year fixed effects. Student and school controls are listed in Table 1 Panel B. Policy controls include the teacher accountability reforms discussed by Kraft et al. (2020). Robust standard errors clustered at state level are in brackets. Sample Sizes are rounded to the nearest 10 per IES disclosure guidelines. $***p < 0.01, **p < 0.05, *p < 0.1$.

Source. NAEP 2009, 2011, 2013, 2015, and 2017.

7 Conclusion

This paper makes the first attempt to provide causal evidence about the effect of edTPA on teacher supply and student performance, leveraging the quasi-random setting where states integrated edTPA into their licensure systems in different years.

In terms of teacher supply, we analyze university-level graduation data from IPEDS which captures the major source of new teachers in the US. We find that edTPA reduced the number of teacher graduates and disproportionately hurt minority candidates in less selective programs. Our results are alarming to the existing shortage and diversity issue in the US public schools. The lost of minority teachers is also worrying given many researchers have found that teachers of the same race bring about a role-modeling effect for minority students.

For student performance, NAEP is a unique dataset that allows us to identify students with new teachers among a national representative sample of students in the US. We do not find strong evidence that edTPA improved student learning. We instead find some evidence that there was a negative impact on the academic performance of higher-achieving students. A potential link we find is larger class size that results in a heavier teaching load. We do not speculate further the underlying mechanisms, but our result on students is consistent with other education research finding that the assessment may not improve teaching effectiveness.

There are two routes to combat teacher shortage and diversity concern brought by the edTPA. An intermediate solution is to provide more supports (financial and mental) and guidelines to help prospective teachers get through the hurdle, which is found to have improved the experience of teacher candidates (Lachuk and Koellner, 2015; Muth et al., 2018). In the recent development, Georgia is among the first state to abolish the edTPA requirement for prospective teachers. Therefore, eliminating the entire assessment is another feasible option.

One final note is that our results do not cast a veto against the entire teacher licensure system. Rather, we focus on a particular component of the licensure system that is hotly debated in the current education community. Our discussion is widely applicable to the educational policymakers nationwide, especially in the states which had integrated or are planning to integrate edTPA as a necessary component for initial teacher licensure.

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Appendix to:
"Teacher licensing, teacher supply, and student outcomes: Evidence from the recent nationwide reform"

Bobby W. Chung & Jian Zou

May, 2021

Table A1: Summary statistics (IPEDS) - Include Optional States

	Mean	SD	Min	Max
A. Outcomes:				
education graduates	138.25	184.57	0.00	3496.00
education graduates (white)	100.85	135.32	0.00	1763.00
education graduates (non-white)	37.40	71.67	0.00	1968.00
B. Time-varying controls:				
graduates (non-education majors)	1623.25	2190.37	1.00	16364.00
minority graduates (% of non-education majors)	18.17	18.72	0.00	100.00
SAT submission rate	51.70	33.25	0.00	100.00
ACT submission rate	54.24	30.44	0.00	100.00
SAT 25 percentile score	474.28	65.21	215.00	745.00
SAT 75 percentile score	581.62	64.95	349.00	800.00
ACT 25 percentile score	20.24	3.33	3.00	33.00
ACT 75 percentile score	25.44	3.27	8.00	35.00
first-year FT enrollment	1101.15	1370.80	6.00	10099.00
part-time/full-time faculty ratio	0.03	0.11	0.00	2.60
grant (% student)	76.63	16.46	16.00	100.00
grant (dollar amount, thousands)	46209.60	51275.09	198.32	488027.59
loan (% student)	58.71	16.50	0.00	100.00
loan (dollar amount, thousands)	21562.41	24967.36	0.00	406393.00

Data: IPEDS 2011-2019.
Note: This table shows summary statistics of estimation sample for teacher supply using IPEDS.The number of observations is 10,586 from 1,243 institutions.

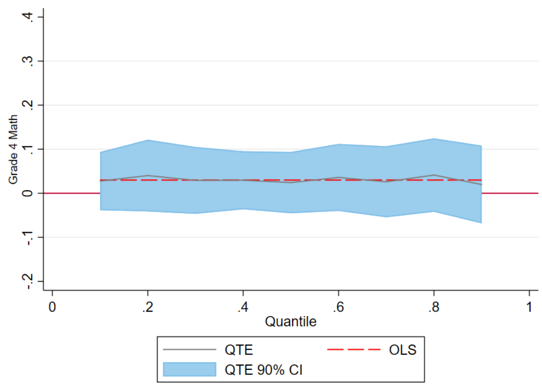
Table A2: Heterogeneity by the selectivity of university - Different measures

	(1)	(2)	(3)	(4)	(5)	(6)
	Selectivity by SAT			Selectivity by ACT		
	all	white	nonwhite	all	white	nonwhite
edTPA*(bottom 50%)	-0.132***	-0.103**	-0.143**	-0.138***	-0.116***	-0.129**
	(0.0382)	(0.0402)	(0.0571)	(0.0381)	(0.0402)	(0.0588)
edTPA*(top 50%)	-0.0830	-0.105*	-0.0253	-0.0760	-0.0906*	-0.0373
	(0.0532)	(0.0530)	(0.0574)	(0.0517)	(0.0534)	(0.0499)
Constant	2.122***	2.077***	0.455	2.121***	2.077***	0.450
	(0.397)	(0.360)	(0.507)	(0.397)	(0.360)	(0.508)
Observations	7,204	7,204	7,204	7,204	7,204	7,204
R-squared	0.199	0.207	0.072	0.199	0.207	0.071
Number of unitid	832	832	832	832	832	832

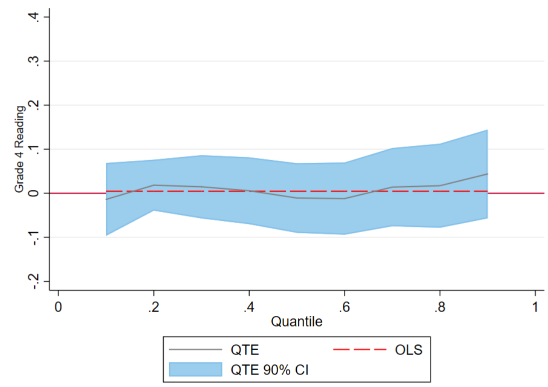
Data: IPEDS, 2011-2019

Note: Dependent variable in each regression is the log of the number of teacher graduates (by race). All regressions include time-varying controls in Panel A of Table 1, policy controls, year and institution fixed effects. We categorise institutions into more (top 50%) and less (bottom 50%) according to their pre-2014 75^{th} percentile SAT/ACT scores. Standard errors in the parenthesis are clustered at the state level. ***, **, and * represent 1%, 5%, and 10% significant level, respectively.

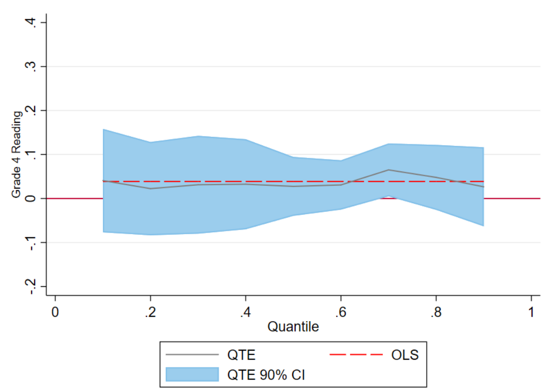
Figure A1: Placebo test: Heterogeneous effects of edTPA reforms on student achievement using alternative samples



(a) Grade 4: Math



(b) Grade 4: Reading



(c) Grade 8: Reading

Data: NAEP 2009, 2011, 2013, 2015, and 2017.
Note: The estimation sample is student sample whose teachers have 3 to 5 years of teaching experience. The dependent variables of subfigure (a), (b), and (c) are the standardized grade 4 math score, grade 4 reading score, and grade 8 reading score, respectively. The underlying quantile regression is based on the specification of equation 2. All regressions include state fixed effect, year fixed effects, student and school controls. The gray dashed line shows the estimate of quantile treatment effects, while the red solid line shows the OLS estimate. The blue shaded region shows the 90% confidence interval with robust standard errors clustered at the state level.