

Effects of the Federal Teacher Loan Forgiveness Program on School-Level Outcomes

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Abstract

Under the U.S. Department of Education's Teacher Loan Forgiveness Program, teachers completing five years of service at a low-income school qualify for up to \$17,500 in federal loan forgiveness. By providing financial incentives for teachers to stay for at least five years, this program has the potential to reduce teacher turnover at low-income schools. Using a regression discontinuity design and data from four large states, I estimate a precise zero for the effect of forgiveness eligibility on schools' teacher retention rates for schools at the margin of qualifying as low-income. Similarly, there are no effects on percent of classes taught by highly qualified teachers or the percent of teachers with more than three years of teaching experience. Finally, I find no robust effects on test-score based measures of student achievement.

JEL Codes: I21, I28.

Keywords: teacher turnover, loan forgiveness, dynamic regression discontinuity.

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1 Introduction

Student loan forgiveness programs offer cancellation of student loans in exchange for service in particular sectors or occupations. Most commonly, loan forgiveness is targeted to teachers, medical personnel, lawyers serving in the public sector, or public and non-profit sector employees more generally. Several loan forgiveness programs operate at the federal level, including the Public Service Loan Forgiveness Program, the Teacher Loan Forgiveness Program, the Perkins Loan Cancellation Program, the NURSE Corps Loan Repayment Program, and the Federal Student Loan Repayment Program, and states and private organizations offer additional loan forgiveness and scholarship programs for nurses and teachers (Tretina, 2020). Despite the popularity of these programs, little is known about their effects, especially on aggregate outcomes they are designed to affect. In this paper, I investigate the effects of the Teacher Loan Forgiveness Program, established in 1998 with the goal of “encouraging individuals to enter and continue in the teaching profession,” particularly at schools serving low-income students (Teacher Loan Forgiveness Program, 34 C.F.R. § 682.216.). This program forgives subsidized and unsubsidized federal loans for qualifying teachers who complete five consecutive years of service at a low-income school. I focus on effects at the school-level since the targeting of this program is designed to affect the educational experience of students at low-income schools.

High rates of teacher turnover are a major problem facing American schools, especially those serving low-income populations. Among new teachers, researchers estimate that anywhere from 17% to nearly half of teachers will leave the profession or their original school within five years (Gray et al., 2015; Phillips, 2015). Some sources indicate that turnover rates are 50% higher for Title I schools compared to non-Title I schools and 70% higher for schools serving the largest concentrations of students of color (Carver-Thomas and Darling-Hammond, 2017). Mathematics, science, special education, ELL, and foreign language teachers have the highest turnover rates. To address shortages in these areas, some states offer scholarships, tuition waivers, and loan forgiveness for teachers in these subject areas, and the federal Teacher Loan Forgiveness Program offers greater levels of forgiveness for science,

math, and special education teachers.

High turnover rates are problematic for several reasons. Teacher turnover is expensive for schools and districts who must continually recruit and hire new teachers. Most estimates place the cost of each teacher who leaves a school district at between \$10,000 and \$20,000 (Barnes et al., 2007). Nationally, attrition costs up to \$2.2 billion annually (National Alliance for Excellent Education, 2014). Furthermore, higher turnover results in less experienced teachers and forces districts to rely on teachers who are not fully qualified or licensed to meet shortages (Carver-Thomas and Darling-Hammond, 2017). Student achievement suffers as students are more likely to have inexperienced teachers.

Much literature documents that teachers improve with experience especially in the first few years (Rockoff, 2004; Clotfelter et al., 2007; Kane et al., 2008; Jackson and Bruegmann, 2009). Ost (2014) finds that both general human capital (total years of teaching experience) and specific human capital (grade-specific years of experience) increase teacher value-added. Clotfelter et al. (2010) shows that teacher licensure and certification, one of the eligibility requirements for the Teacher Loan Forgiveness Program, also have important impacts on student achievement. Ronfedlt et al. (2013) show directly that teacher turnover reduces student achievement; they find that reducing teacher turnover from the highest quartile to the lowest quartile in New York City improves test scores of 4th and 5th graders by at least 2-4% of a standard deviation.

Studies have also shown that financial incentives can encourage teachers to begin working at schools serving disadvantaged populations. Steele et al. (2010) show that a \$20,000 financial fellowship in California attracted talented novice teachers to low-performing schools, and the majority of these teachers stayed for at least four years. Clotfelter et al. (2008) estimate that providing an annual bonus of \$1,800 to certified math, science, and special education teachers working in schools in North Carolina with high-poverty rates or low test scores reduced mean turnover rates of targeted teachers by 17%. An evaluation of the Florida's Critical Teacher Shortage Program (FCTSP) by Feng and Sass (2018) found that the loan forgiveness component of the program reduced mean attrition rates for middle

and high school math and science teachers by 10.4% and 8.9% respectively. A back of the envelope cost-benefit analysis indicated that both the loan forgiveness and bonus incentive pay program were cost-effective. However, Florida's program made teachers in hard to staff subject areas eligible for loan forgiveness after just one year of teaching. They could receive up to \$2,500 in forgiveness for undergraduate loans per year for up to four years. By contrast, the U.S. Department of Education's Teacher Loan Forgiveness Program requires five years of teaching service before teachers become eligible for forgiveness. It is also unclear if this micro-level changes in teachers' decisions aggregate up to affect outcomes measurable at the school level, a question I investigate in this paper.

Evaluations of loan forgiveness programs targeted towards professionals in other fields have also revealed that loan forgiveness can increase occupational retention rates. The National Institute of Health has an Office of Loan Repayment and Scholarship that administers three loan repayment programs: one for researchers studying HIV/AIDS, one for researchers from disadvantaged backgrounds studying clinical topics, and one for general research targeted towards medical doctors and fellows. A Mathematica Policy Research study found that the fellows programs successfully increased yield rates into the medical fellows program by 17 percentage points and increased three year retention rates, also by 17 percentage points. The study was too underpowered to estimate precise effects for the other two programs (Glazerman and Seftor, 2005). Studying the occupational choices of law students at NYU, Field (2009) finds that students are more likely to enroll and later choose public service when offered loan forgiveness or tuition waivers conditional on working in public service. To date, there have been no published studies evaluating the U.S. Department of Education's Teacher Loan Forgiveness Program, though Jacobs, Jones, and Keys (2014) do have a randomized control trial underway which nudges teachers in Michigan towards using Federal Loan Forgiveness benefits. For more information, see <https://www.povertyactionlab.org/evaluation/impact-individualized-information-teacher-loan-forgiveness-uptake-united-states>.

In this paper, I use a regression discontinuity (RD) design and school-level data to assess

the effects of a school becoming eligible for teacher loan forgiveness. This design estimates impacts for schools at the margin of qualifying as a “low-income” school. Since teachers can count years of service at a low-income school towards their five years of service even if the school later falls off the eligibility list, it is necessary to adopt the dynamic RD design of Cellini et al. (2010) which allows for lagged responses to eligibility. Lacking comprehensive data on school-level teacher retention rates for all states, I focus on Massachusetts, New York, North Carolina, and South Carolina - four states for which teacher retention rates and the percentage of low-income students are available for schools from 2007-2014.

I estimate a precise zero for the effect of teacher loan forgiveness eligibility on the aggregate teacher retention rate for schools right around the cutoff of qualifying for forgiveness. Two-sided 95% confidence intervals rule out increases in teacher retention rates larger than 0.8 percentage points (6% decrease in teacher turnover for schools in the optimal bandwidth range). I also assess effects on the percent of teachers who are licensed, the percent of teachers with fewer than 3 years of teaching experience, and the percent of classes taught by highly qualified teachers. Highly qualified teachers are those who have obtained a full state certification as a teacher or passed the state teacher licensing examination, hold a minimum of a Bachelor’s degree, and have demonstrated subject matter competency in a manner determined by their state. I find no statistically significant effects on any of these aggregate outcomes nor do I find impacts on test-score based measures of student achievement at the school level.

2 Teacher Debt and the Teacher Loan Forgiveness Program

The majority of education majors leave college with federal student loan debt. Analysis of data in the National Postsecondary Student Aid Study shows that the share of education Bachelor’s graduates with debt increased from 63% in 2000 to 67% in 2012, and the average loan balance increased from \$20,644 to \$26,792 (Delisle and Holt, 2017). By 2012, 67% of Master’s degree recipients had student loan debt with an average balance of \$48,685. Given

the prevalence of student loan debt among graduates planning to go into teaching and those already teaching, benefits from loan forgiveness could be substantial for many teachers.

To qualify for forgiveness under the U.S. Department of Education's Teacher Loan Forgiveness Program, teachers must be employed at a low-income elementary school, secondary school, or local education agency that serves low-income students for at least five consecutive years. All elementary and secondary schools operated by the Bureau of Indian Education or operated on Indian reservations by Indian tribal groups qualify as schools serving low-income students. Other schools are considered low-income if at least 30.01% of enrolled students qualify for the Title I program. Teachers who are unsure of whether their school qualifies as low-income can search the Teacher Cancellation Low-Income Directory online which provides lists of schools by state and year which are eligible for loan forgiveness. If a teacher's school or educational service agency is included in the Low-Income School Directory for at least one year of her teaching service, but is not included during subsequent years, subsequent years of teaching at the school or educational service agency can still be counted toward the required five years of teaching. Teaching service performed at an educational service agency rather than at a school may also be counted toward the required five years of teaching if work at the educational service agency was performed after the 2007-08 academic year.

In addition to the low-income school requirement, teachers must also be full-time, state certified, and have a Bachelor's degree. Whether teachers receive up to \$5,000 or up to \$17,500 in loan forgiveness depends on their subject area and when they began teaching. Secondary school science and mathematics teachers and elementary or secondary special education teachers who began after October 2004 receive up to \$17,500 in loan forgiveness. All other teachers receive up to \$5,000 in loan forgiveness. Teachers can potentially receive loan forgiveness under both the Teacher Loan Forgiveness Program and the Public Service Loan Forgiveness Program, another Federal program that provides forgiveness for direct loans after a period of service at a government agency or non-profit organization, but not for the same period of teaching service. Teachers are not eligible for loan forgiveness if they are in default on student loans unless they have made satisfactory repayment arrangements with

the holder of the defaulted loan. Moreover, the loans must have been originated prior to the five years of service. Receiving loan forgiveness requires teachers to submit a completed two-page “Teacher Loan Forgiveness Application” to their loan servicer at the completion of five years of teaching at a qualified school. If a teacher has multiple loan servicers, a separate application must be submitted to each one.

The total amount of loans discharged annually has increased over time from \$286.4 million (34,989 beneficiaries) in the 2013 Fiscal Year to \$351.4 million (42,297 beneficiaries) in the 2017 Fiscal Year (Congressional Research Service, 2018). A back of the envelope calculation using the total number of teachers and beneficiaries indicates that in any given year, approximately 1% of all teachers receive some federal loan forgiveness through this program.

3 Data

This study uses school-level data from four states: Massachusetts, South Carolina, North Carolina, and New York. These states were chosen because they report teacher retention rates and student test score results at the school-level in state data sources. The percentage of enrolled students who are low-income comes either from these state data sources (North Carolina, South Carolina) or the Common Core of Data (Massachusetts, New York). To merge the state data sources with the Common Core, the state-specific school ID variables as reported to the NCES are used. Teacher retention rates and low-income percentages (the running variable) are available in 2009-2014 for Massachusetts, 2007-2014 for North Carolina, 2010-2013 for New York, and 2008-2014 for South Carolina. Measures of teacher characteristics such as the percent of teachers who are licensed, the percent of classes taught by highly qualified teachers, and the percent of teachers with less than three years of experience are available for a subset of these states and years.

It is worth noting that South Carolina has its own Teacher Loan Forgiveness Program that offers a maximum of \$3,000 in loan forgiveness for each full year of teaching in a public South Carolina school in both a critical subject area and critical geographic area (South

Carolina Student Loan, 2020). However, this program does not have the same school-level eligibility criteria as the Federal Teacher Loan Forgiveness Program where any school with 30.01% or more low-income students is eligible.

Because I do not have access to teacher level microdata, I am unable to undertake an analysis at the teacher level. Thus, I will not be unable to estimate the effect of the federal teacher forgiveness program on the probability that an individual teacher stays in his or her position and contrast teacher-level effects of the Federal Loan Forgiveness Program with previous estimates of the effects of state-level forgiveness programs. Instead, my goal is to estimate whether this program is meaningful enough to impact aggregate outcomes at the school-level. I discuss the possibility of school-level data obfuscating potential micro-level changes in section 6, but the primary goal of this analysis is to investigate whether changes induced by this program are large enough to be reflected in school-level data and student test scores.

As shown in Table 1, there are 9,489 schools with an average enrollment of 598 students across the four states. Schools are slightly larger in South Carolina compared to Massachusetts. In all four states, the average school has a significant number of low-income students. Across schools in Massachusetts an average of 37% of students are low-income compared to 50% in New York, 57% in North Carolina, and 61% in South Carolina. Teacher retention rates are quite similar across the four states. The average school-year in the sample has 85.7% of teachers returning. The most recent data from the National Center for Education Statistics Schools and Staffing Survey indicates that 84.3% of teachers remained in the same school from 2011-12 to 2012-13, so schools in these states have retention rates very close to the national average (U.S. Department of Education, 2016). The vast majority of teachers are licensed (96.6%), and the average school has a very large percentage of classes that are taught by highly qualified teachers (97.5%). The percent of teachers with fewer than three years of experience is available only for North Carolina and New York. Low levels of teacher experience are much more prevalent in North Carolina (21% of teachers on average have fewer than three years of experience) compared to New York (6%).

There are significant differences between schools classified as low-income (those with a low-income percentage of 30.01% or higher) and those classified as higher income (those with a low-income percentage of 30.00% or lower). Figure 1 shows that schools serving low-income populations are less likely to have teachers with at least three years of experience, are less likely to have a high percentage of classes that are taught by highly qualified teachers, and are less likely to have teachers who are licensed. The starkest difference between the two groups appears for the portion of experienced teachers. For the average high-income school-year in the sample, 93% of teachers have at least three years of experience compared to 86% at lower-income schools. Differences in qualification and licensure of teachers is less dramatic (99% versus 97% and 98% versus 96%), though still statistically significant. Because the federal Teacher Loan Forgiveness Program provides financial incentives for teachers to serve at low-income schools, it may play a role in ameliorating these disparities.

4 Estimating Effects of Loan Forgiveness Eligibility on School-Level Outcomes

To empirically assess the effects of a school becoming eligible for teacher loan forgiveness on its teacher retention rate, I obtained the Teacher Cancellation Low-Income Directory lists from the U.S. Department of Education Federal Student Aid Office. Because these lists do not include the underlying Title I percentages used to construct the lists, I obtained these percentages from the Common Core of Data or state education data sources. My school-level outcome measures, such as the teacher retention, is obtained from state data sources. Not all states tabulate or release data on teacher retention rates. For this study, I use data from four states where such information was available: New York, South Carolina, North Carolina, and Massachusetts.

I match school-level records from state data sources to school listings in the Teacher Loan Cancellation Low-Income (TCLI) Directory using year, state, and school name. School names sometimes differ between state data sources and the TCLI directory. For example,

“ELLERBE JUNIOR HIGH” is listed as “ELLERBE MIDDLE SCHOOL” in the TCLI directory, and “FD JACK KISER INTERM” is listed as “KISER INTERMEDIATE SCHOOL” in the TCLI directory. To account for name discrepancies, I use a fuzzy matching strategy to merge the state datasets with the TCLI directory and manually review non-exact matches. In 98.9% of cases, the school-year level observations match or do not match to the TCLI directory as would be expected based on their low-income student percentages. The remaining 1.1% of records are false positives or false negatives. A false positive case occurs when the school has a low-income percentage 30.01% or higher but does not appear in the TCLI directory in that year. These cases comprise only 0.7% of observations. A false negative case occurs when the school has a low-income percentage of 30.00% or below but does appear in the TCLI directory in that year. These cases comprise only 0.4% of observations.

4.1 Empirical Strategy

Running a cross-sectional regression of a school’s teacher retention rate on an indicator for the school’s cancellation eligibility will give a biased estimate of the effect of the school qualifying. Low-income schools tend to have lower teacher retention rates because these schools serve disadvantaged populations and are challenging work environments for teachers. Because of the endogeneity of qualifying for loan forgiveness, I use a regression discontinuity design which exploits the cutoff point used to construct the lists. Schools that qualify for loan-forgiveness have at least 30.01% of their students who qualify for Title I. Conveniently for the purposes of this research, this cutoff is different from the 40% cutoff used to identify schools qualifying for Title I school-wide programs (U.S. Department of Education, 2015).

States have some discretion on what measure is used to determine Title I eligibility. According to 1113(a) of the Title I Act (ESEA- Elementary and Secondary Education Act of 1965), local education agencies may use the percent of children aged 5-17 that are in poverty as counted in the most recent census data, the percent of children eligible for free and reduced price lunches under the National School Lunch Act, the percent of children in families receiving assistance under Title IV of the Social Security Act, the number of children

eligible to receive medical assistance under the Medicaid program, or a composite of these indicators. In practice, most states, including the four in this study, use as their indicator the percent of children eligible for free and reduced price lunches.

As with any regression discontinuity approach, it is important to consider the possibility that schools may strategically manipulate the running variable determining program eligibility. Though, schools may want to qualify for loan forgiveness because loan forgiveness eligibility may be seen as a perk by potential teachers, it's unlikely that schools would be able to manipulate their Title I eligibility measure. Manipulating this measure would require redrawing enrollment boundaries or otherwise changing the socioeconomic composition of enrolled students.

Though manipulation would be quite difficult, I, nevertheless, check whether there is excess mass to the right of the cutoff which would indicate that significant numbers of schools are able to manipulate their low-income measure to be just over 30.01%. Figure 2 shows that there is no significant excess mass to the right of the cutoff which is consistent with no strategic manipulation around the cutoff. A formal test of excess density using the local polynomial density estimator proposed in Cattaneo et al. (2020) does not reject the null of no excess mass (p-value=0.815).

Another form of selection which would not invalidate the internal validity of the RD approach but could affect external validity is if teachers with large loan debts strategically select into schools that will surely provide eligibility for loan forgiveness (i.e. schools who consistently have a very high Title I percentage). Since I lack teacher level microdata and in particular, teacher-level loan balances and occupational choices, I am unable to investigate this directly. However, given that two-thirds of Education majors graduate with significant student debt, it is unlikely that schools around the eligibility cutoff would have very few or no teachers eligible for forgiveness.

Because the only factor affecting a school's eligibility for teacher loan forgiveness is its Title I percentage, this should be a "sharp" regression discontinuity setting. As previously discussed, there are a few unexplained false negative and false positive cases where schools

that have less than 30.01% of students who are low-income appear on the lists and schools with low-income percents above 30.01% do not. I did inquire about these false positives and false negatives, and unfortunately, the state officials responsible for maintaining these lists have not been able to explain why they exist or have failed to respond to my inquiries.

Figure 3 shows the jump in treatment probability (defined as appearing on the low-income eligibility list). The probability that a school appears on the cancellation list is approximately 0 below the cutoff and jumps to nearly 1 above the cutoff. The treatment probability does not literally jump from 0 to 1 due to the aforementioned false positives and false negatives.

In the analysis that follows, I drop the false negative and false positive schools from the sample. In these cases, it's not clear whether we should consider the schools treated or untreated. On the one hand, false negatives do not appear in the searchable online eligibility directory, so it's unlikely that teachers would be more likely to stay at the school in hopes of receiving forgiveness. On the other hand, if teachers are aware of the program and aware of its requirements, they may be able to argue that their school was accidentally omitted from the list. Implementing a fuzzy RD analysis would require taking a stand on whether these schools are truly treated or not. The effect of appearing on the list when the school should not have qualified based on its Title I percentage is similarly ambiguous. Since this issue affects only a small minority of schools (1.2% of all school-year observations) and because I do not think it is clear whether these schools should be coded as truly treated or not, I focus the analysis on the "perfect compliance" schools. I also drop any schools that do not appear in every year of their respective state panel (2009-2014 for Massachusetts, 2008-2014 for North Carolina, 2010-2013 for New York, and 2008-2014 for South Carolina) so that I can estimate dynamic effects. Some of the dropped schools are new or charter schools, but the majority are schools that simply fail to report data in some years of the panel. This restriction drops about 30% of schools.

Assessing the effects of the teacher loan forgiveness program on school-level outcomes using regression discontinuity design requires a dynamic approach for several reasons. First, the annual nature of the Teacher Cancellation Low-Income Directory lists makes it possible

for a school to be eligible for forgiveness in some years but not others. Second, a teacher working at a school that initially qualifies for loan forgiveness but moves below the 30.01% cutoff in later years can still count subsequent years towards the required five years of teaching. Consequently, effects of program eligibility may impact teacher retention rates and school-level outcomes several years after a school appears on the loan forgiveness eligibility list. Finally, teachers frequently make decisions about whether to continue at a school before they know what the school’s Title I percentage will be for the coming academic year. Consequently, if there is an effect of a school’s eligibility for loan forgiveness, we would expect such an effect to be lagged one-year.

To estimate dynamic treatment effects, I adopt the dynamic regression discontinuity design of Cellini et al. (2010) which generalizes a cross-sectional regression discontinuity design to account for panel data and multiple treatments. To understand the efficient pooled regression which takes into account these multiple treatments, school fixed effects, and potentially lagged responses, it is helpful to think about modeling the effect of appearing on the state’s cancellation list in year t . School i ’s outcome τ years later can be written as

$$y_{is,t+\tau} = Q_{it} + P(L_{it}, \gamma_{\tau}) + \varepsilon_{is,t+\tau} \quad (1)$$

where Q_{it} is an indicator that equals 1 if school i in state s qualifies for loan forgiveness in year t , and P is a polynomial in the running variable L for the Title I (low-income) percentage used to construct the list in year t (L_{it}) with coefficients γ_{τ} .

This equation is inefficient because the error term has components fixed within schools over time. As pointed out by Cellini et al. (2010), more precise estimates can be obtained by pooling data from multiple τ . To implement the pooled regression, I select observations from $t - 2$ to $t + 4$ for each list year t . Some observations from the school-year panel are used more than once because these years fall in the $[t - 2, t + 4]$ interval for more than one list year. Then the sample is used to estimate the regression equation

$$y_{ist\tau} = \sum_{\tau=0}^4 Q_{it\tau} \beta_{\tau} + P(L_{it}, \gamma_{\tau}) + \lambda_i + \alpha_{\tau} + \eta_{st} + \epsilon_{ist\tau} \quad (2)$$

Note that α_{τ} are fixed effects for years relative to list release, η_{st} are year by state fixed effects, and λ_i are school fixed effects. $P(L_{it}, \gamma_{\tau})$ is a polynomial in the running variable where coefficients are allowed to vary depending on years relative to list release. The intent-to-treat coefficients β are also allowed to vary with years relative to list release. I constrain β_{τ} and γ_{τ} to be zero for $\tau < 0$. Conceptually, this assumes that teachers do not preemptively respond to their school appearing on the loan cancellation eligibility list in future years. This assumption is plausible since it would be difficult for teachers to predict exactly how the demographics of the school will evolve and translate into the school's exact Title I percentage in future years. I cluster standard errors at the school level.

As a complement to these results, I would have liked to estimate a local linear specification. However, computational restrictions prevent me from estimating a local linear specification with a full set of school fixed effects. Later in the paper I do discuss a robustness check using local linear regressions with state and year fixed effects but not school fixed effects.

Before presenting results of the effect of school qualifications on teacher retention rates using the pooled regression specified above, it is helpful to verify that including a polynomial in the running variable balances the treatment and control groups. Table 2 shows that without a polynomial in the running variable, treatment and control schools are not comparable. Schools appearing on lists for cancellation, which serve large numbers of low-income students, have teacher retention rates that are 3.2-3.3 percentage points lower in years preceding list inclusion. They also have fewer teachers who are licensed (2-2.3 percentage points less), a lower percentage of classes which are taught by highly qualified teachers (1.3 to 1.4 percentage points less), and a greater percentage of inexperienced teachers (3.3-3.5 percentage points more). However, including a cubic polynomial in the running variable that determines list inclusion (the Title I percentage of the student body) shrinks these coefficients to near zero. Columns 3 and 4 show that the differences are no longer statistically significant in the two years preceding list inclusion for schools qualifying and not qualifying for loan forgiveness.

Columns 5 and 6 of Table 2 verify that there are no significant pre-treatment differences in retention rates and other teacher characteristics once school fixed effects are added. These fixed effects are not necessary for identification but may increase statistical power.

5 Results

This paper estimates the effect of a school qualifying for teacher loan forgiveness on school-level outcomes: aggregate teacher retention rates, teacher characteristics, and test-score based measures of student achievement.

5.1 Effects on Teacher Characteristics and Turnover Rates

Table 3 presents the main results from estimating equation 2 on the pooled sample where the dependent variable is the school’s teacher retention rate, the percent of classes taught by highly qualified teachers, the percent of teachers who are licensed, or the percent of teachers with fewer than three years of experience. The estimates indicate that a school’s inclusion on the list for being eligible for loan cancellation has no statistically significant effect on teacher retention rates. The effects on teacher retention rates 0, 1, 2, 3, and 4 years after list inclusion are precisely estimated and 95% confidence intervals rule out increases in teacher retention rates larger than 0.4, 0.8, 0.7, 0.6, and 0.8 percentage points in each of these years respectively.

Local linear regressions that use the MSE-optimal bandwidth selector with a triangular kernel with state and year fixed effects and a static regression discontinuity design also estimate no statistically significant effect on teacher retention rates in the year following list release. The 95% confidence interval from this analysis using cluster-robust nearest neighbor variance estimation is $[-1.95, 0.52]$. It is not possible to estimate this specification with school fixed effects due to computational limitations.

Given a mean teacher turnover rate of 12.5% in the optimal bandwidth range of 22.7% FRL to 33.3% FRL, the main dynamic estimates rule out reductions in yearly teacher

turnover larger than 6%. In particular, the estimates rule out effects as large as those Feng and Sass (2018) find for math and science teachers from the loan forgiveness component of Florida’s Critical Teacher Shortage Program. However, this is to be expected since their study uses teacher-level data and estimates effects on a population of eligible teachers rather than school-level retention rates. The estimates for the effects on other proxies for teacher quality (percent of classes taught by highly qualified teachers, percent of teachers who are licensed, and the percent of teachers with fewer than three years of teaching experience) shown in Table 3 are also precisely estimated and are near zero.

To complement these regression results, Figure 4 shows visual plots of teacher characteristics around the eligibility cutoffs (red line). They plot teacher characteristics in year $t+1$ for a low-income percent in year t . There are no obvious jumps in any of the measured teacher characteristics at the cutoff which is consistent with the dynamic regression discontinuity results. Taken as a whole, the evidence indicates that a school becoming eligible for the federal Teacher Loan Forgiveness Program has no detectable impacts on aggregate teacher retention rates or other aggregate measures of teacher qualifications and characteristics.

5.2 Effects on Student Test Scores

Even if there are no observable changes in teacher retention rates or teacher characteristics, it is possible that loan forgiveness eligibility could still affect measures of student achievement. For example, if loan forgiveness eligibility affected the type of teachers choosing to stay versus leave, without changing overall retention rates, licensure, and average teacher experience, it’s possible that eligibility could still impact student achievement. This is somewhat implausible since it would require higher (or lower) value-added teachers to be more likely to stay after the school begins qualifying for loan forgiveness and lower (or higher) value-added teachers to be more likely to leave in equal proportions so that the overall retention rates are unchanged. Another channel through which loan forgiveness eligibility could impact student achievement is by changing teachers’ perception of their school. For instance, once a school becomes labeled a “low-income” school, teachers may exert more or less effort as their perception

of the school changes. It is also possible that students could respond to this labeling by performing better or worse on standardized tests, if they were made aware of the school's eligibility designation. Unfortunately, these stigma channels cannot be assessed directly. Nevertheless, it is still informative to estimate the effect of loan forgiveness eligibility on test-score based measures of student achievement.

Table 4 presents the results of estimating equation (2) where the dependent variable is a student achievement measure based on standardized test scores. The student achievement measure is standardized to have mean of 0 and standard deviation of 1 within each state and year. Measures chosen were those reported by the state in school accountability and assessment reports. For Massachusetts, the student achievement outcome is the percent of students scoring proficient averaged over math and language arts. For North Carolina, the performance composite percent is used. The student achievement measure for South Carolina is the percent of students scoring C or above on math and English for high school students and the percent of students scoring meets or exceeds standards for elementary and middle school; these measures are averaged across all grades in a school. Finally, the student achievement measure for New York is the secondary level composite performance index for high school, and the elementary-middle level composite index for elementary and middle schools where the measures are averaged over English/language arts and math and over both levels if the school has elementary/middle and high school students.

The point estimates displayed in column 1 of Table 4 correspond to the set of all schools in the analysis sample over the four states. There is a small, positive statistically significant effect for one year after list inclusion, but the coefficients for two and three years after list inclusion suggests that, if anything, teacher loan forgiveness may have a small, negative impact on student achievement two and three years after the school becomes eligible. Columns 2-5 which present results for each state individually indicate that the negative effect in year 2 and year 3 is driven by New York. A similar small, negative effect is not seen in the other states.

Local linear regressions from a static regression discontinuity approach that use the MSE-

optimal bandwidth selector with a triangular kernel with state and year fixed effects to assess the effect of list inclusion on standardized test scores estimates no statistically significant effect on standardized test scores in the year following list release. As was the case with the teacher characteristics local linear regressions, it is not possible to estimate this specification with school fixed effects due to computational limitations. The 95% confidence interval using cluster-robust nearest neighbor variance estimation is $[-0.05, 0.18]$ standard deviations, so the positive statistically significant effect detected one year after the school becomes eligible using the dynamic regression discontinuity approach is not robust to this alternative specification.

Figure 5 presents a visual plot of the lead of student achievement against a school’s low-income percent. There is no obvious discontinuity at the point of eligibility, consistent with the local linear regression results.

6 Discussion

Even though there is no evidence that the federal loan forgiveness program affected aggregate teacher retention in these four states, the results do not preclude the possibility that some number of teachers were induced to continue at a low-income school who would otherwise have left. The numbers of such teachers may have simply been insufficient to affect overall teacher retention rates or rates of classes taught by highly qualified teachers at the school-level. An alternative, though not mutually exclusive explanation for the null finding, is that many teachers at schools on the margin of qualifying as “low-income” may have been ineligible or unaffected by the program, though the large share of Education majors graduating with significant debt suggests that this program could benefit a large number of teachers.

It is also important to note that the data are not well-suited to look at effects separately for teachers in hard to staff areas such as mathematics, science, and special education where loan forgiveness is the most generous. Kramer and Peyton (2017) find that the TEACH Grant program has no effect on increasing overall undergraduate degree production but does shift the distribution of undergraduate education degrees towards hard-to-staff teaching areas, so

there could be important heterogeneity in effects by subject area which cannot be examined with school-level aggregate data. To understand the full impacts of the loan forgiveness program, it would also be necessary to assess whether there are effects on the type of people who enter the teaching profession as a result of the Teacher Loan Forgiveness Program. This is beyond the scope of this paper but could be investigated in future work using teacher-level microdata.

Another limitation of this analysis is that school-level retention rates do not distinguish between teachers who leave the teaching profession altogether versus those who move to another school. It is possible that although loan forgiveness does not increase the percent of teachers returning to a school, teachers who would have otherwise left teaching altogether move to another school due to the possibility of loan forgiveness. However, since teachers who move to another school are unable to develop school-specific human capital, the fact that the loan forgiveness program does not impact the percent of teachers returning to a given school is still noteworthy.

Finally, it is important to keep in mind that even if loan forgiveness does not impact occupational decisions, loan forgiveness may provide personal benefits to teachers by reducing student loan burdens which may increase home ownership and teachers' financial status (Scott-Clayton and Zafar, 2016). That said, if one of the major goals of this federal program is to improve overall teacher retention and qualification/licensure rates at low-income schools, the results indicate that federal loan forgiveness does not have a discernible impact, at least for schools at the margin of qualifying.

The Federal Loan Forgiveness Program has several features which could explain the null effects. For one, most teachers may be unaware of the program. Unlike some state programs, the Federal Loan forgiveness program has not been heavily marketed. Even if teachers are aware that the program exists, the complicated application process may deter teachers from seeking forgiveness. Finally, since teachers in many subject areas (science, math, and special education are exceptions) can only qualify for up to \$5,000; the incentive may not be large enough to affect occupational decisions. A Government Accountability Office report from

2015 noted that less than 1% of eligible teachers participate in Stafford Loan Forgiveness (Nowicki, 2015). An on-going randomized control trial by Jacob et al. (2014) which nudges teachers in Michigan towards using Federal Loan Forgiveness benefits may shed light on whether making teachers aware of the program will increase its use and have meaningful effects on teacher retention.

7 Conclusion

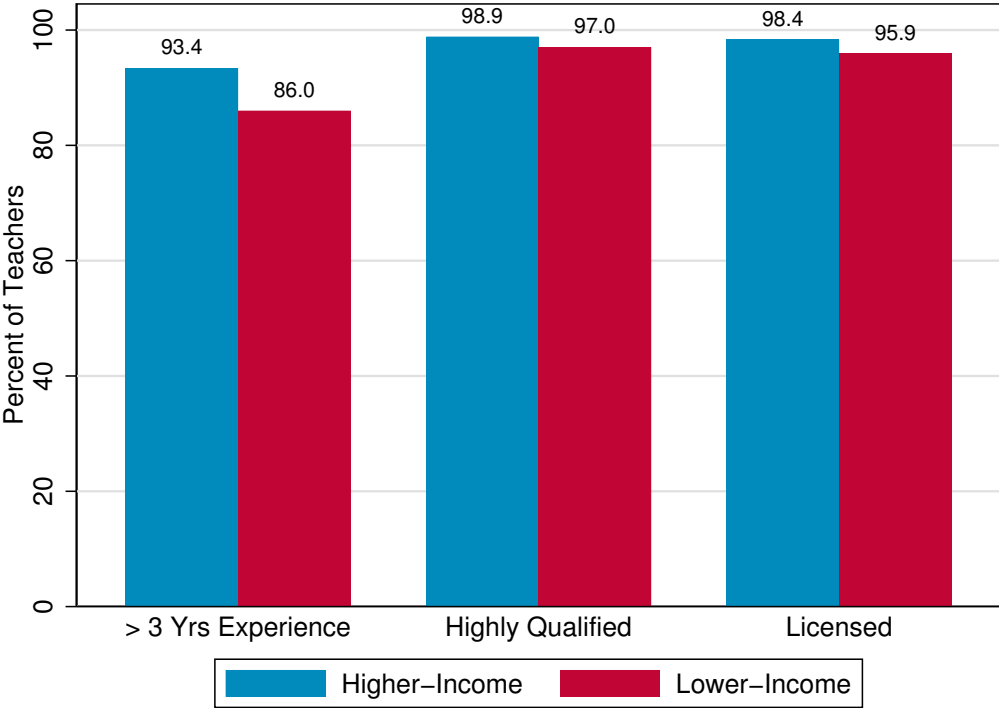
This paper investigates whether offering federal loan forgiveness to teachers at low-income schools increases teacher retention rates at these schools. Using a dynamic regression discontinuity design and data from four states (Massachusetts, North Carolina, South Carolina, and New York), I find that for schools at the margin of qualifying, appearing on the cancellation eligibility list has no effect on a school's teacher retention rates. The effect is a precisely estimated zero. In particular, the 95% confidence intervals rule out increases in retention rates larger than 0.8 percentage points in the four years following eligibility which is equivalent to a 6% decrease in teacher turnover. There are also no statistically significant effects on the percent of classes taught by highly qualified teachers, the percent of teachers licensed, or the percent of teachers with less than 3 years of experience. Given that there are no effects on school-level measures of teacher characteristics or retention, it is unsurprising that the program, similarly, has no strong, consistent impact on measures of student achievement. Taken as a whole, the results suggest that the Federal Teacher Loan Forgiveness Program has not played a significant role in ameliorating differences in teacher retention and qualifications and low versus higher-income schools at the margin of qualifying for this program.

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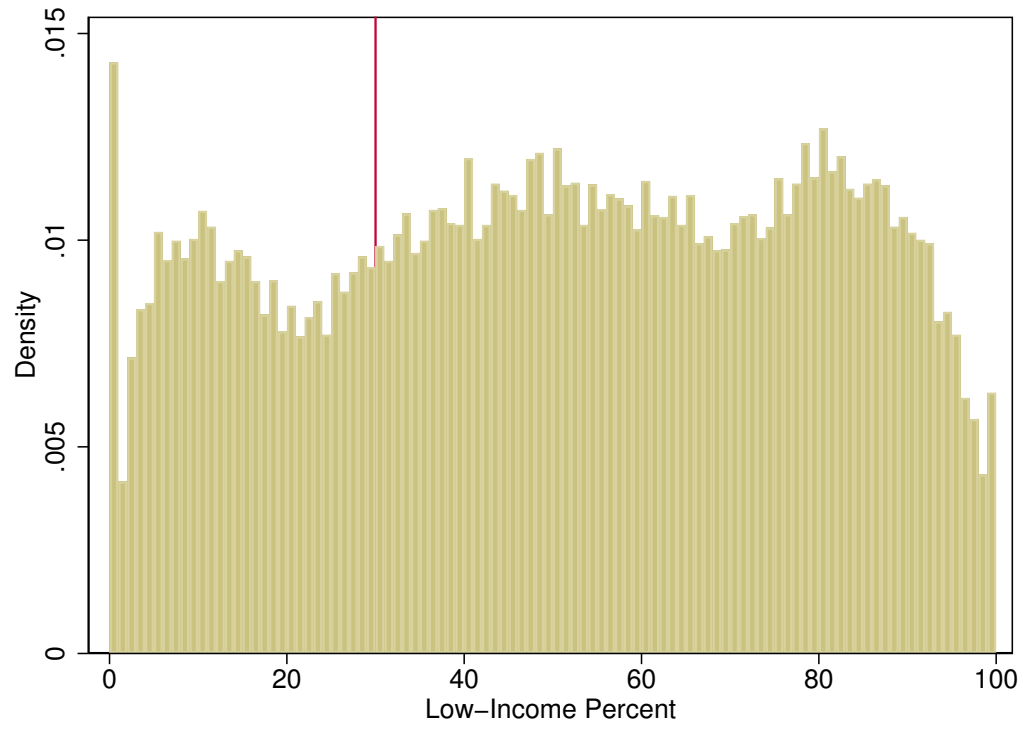
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Figure 1: Comparison of Teacher Characteristics at Lower Versus Higher Income Schools



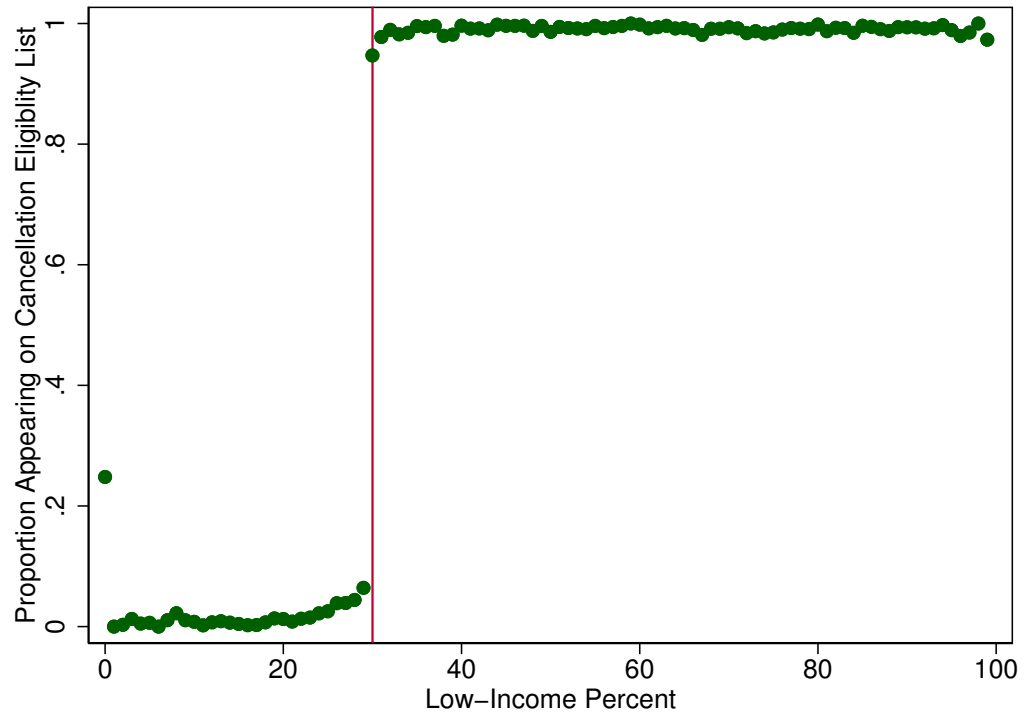
Note: Data are from state data sources in NY, MA, NC, and SC. Share of teachers licensed available only for MA and NC. Share of teachers with more than 3 years of experience available only for NY and NC. Share of teachers who are highly qualified is available for all four states. Higher income schools are those with 30.00% or fewer students qualifying for Title I. Lower income schools are those with 30.01% or more students qualifying for Title I. Differences for all three outcomes are statistically significant.

Figure 2: Distribution of Low-Income Percents



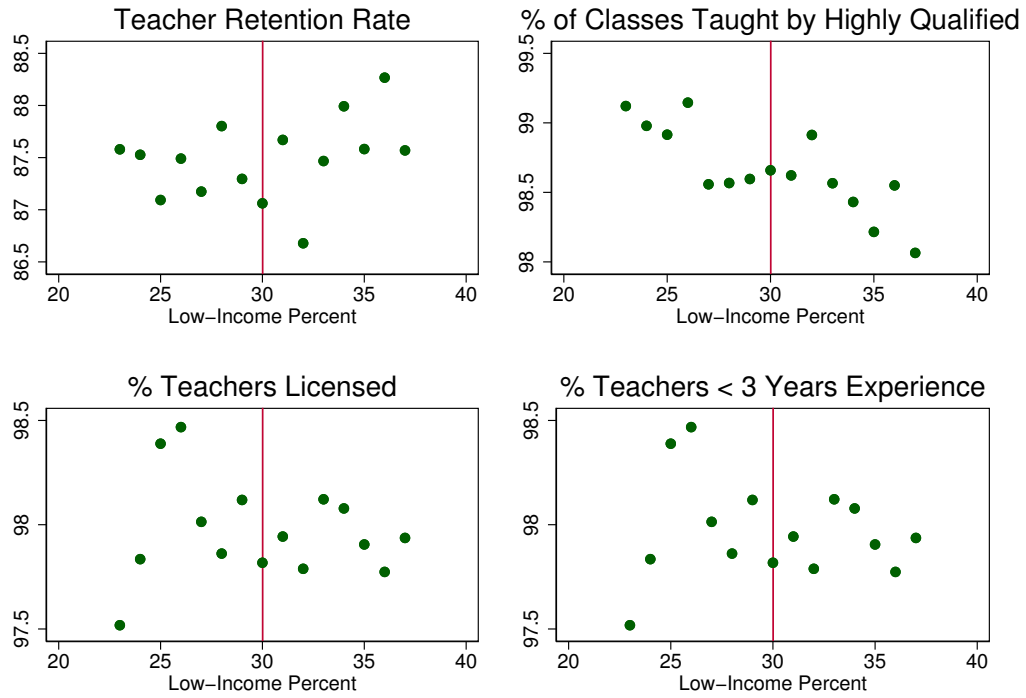
Notes: Density is based on school-year observations.

Figure 3: Discontinuity in Treatment



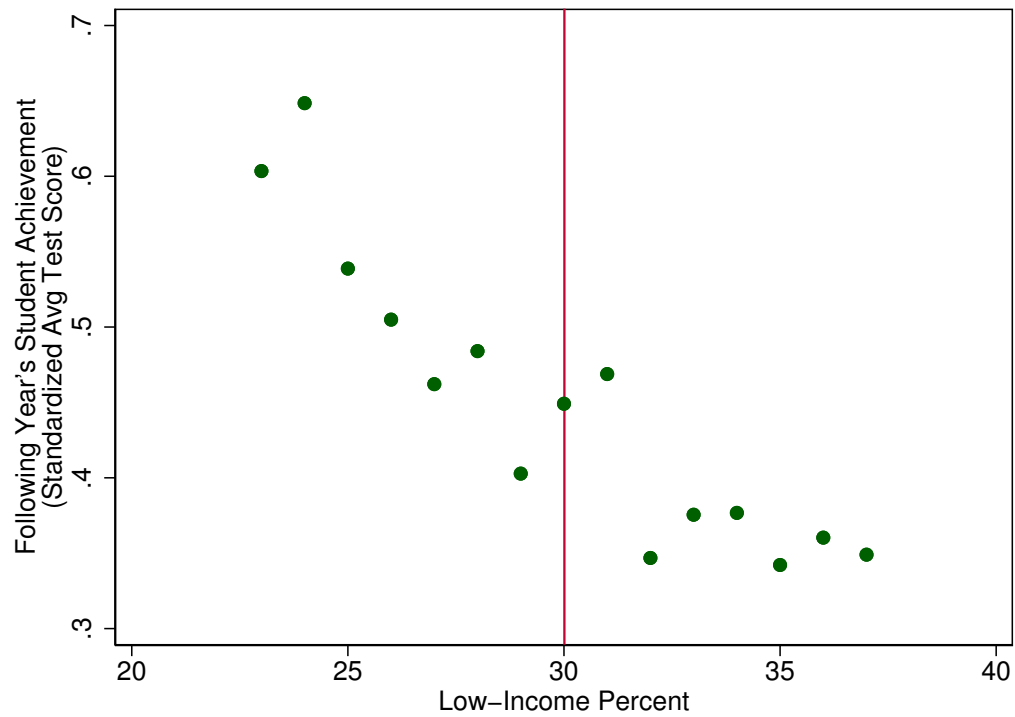
Notes: Data from all four states (NY, MA, NC, and SC) is used. Bin width is one percentage point.

Figure 4: Teacher Characteristics Around the Cutoff



Notes: Data from all four states (NY, MA, NC, and SC) is used for top 2 plots. Licensure plot uses data from MA and NC, and experience plot uses data from NC and NY. Bin width is one percentage point. The y-axis plots teacher characteristics in year $t + 1$ while the x-axis plots low-income percents for year t . Data are shown in the range of 23% to 37% low-income to correspond to the MSE-optimal bandwidth of 7.3 using a triangular kernel for a static RD analysis.

Figure 5: Student Achievement Around the Cutoff



Notes: Test scores are standardized to have mean 0 and standard deviation 1 within each state and year. Bin width is one percentage point. The y-axis plots student achievement in year $t + 1$ while the x-axis plots low-income percents for year t . Data are shown in the range of 23% to 37% low-income to correspond to the MSE-optimal bandwidth of 7.3 using a triangular kernel for a static RD analysis.

Table 1: Summary Statistics

| | All | MA | NC | NY | SC |
|--|--------|-------|--------|--------|-------|
| Teacher Retention Rate | 85.7% | 84.3% | 86.7% | 85.7% | 85.5% |
| Teachers Highly Qualified | 97.5% | 96.9% | 98.2% | 97.6% | 97.1% |
| Teachers Licensed | 96.6% | 97.7% | 95.9% | N/A | N/A |
| Less than 3 Yrs Experience | 12.3% | N/A | 20.5% | 5.8% | N/A |
| Percent Low-Income Students | 50.8% | 36.5% | 56.9% | 50.1% | 61.4% |
| Total Enrollment | 598 | 536 | 616 | 597 | 658 |
| % of Schools Loan Forgiveness Eligible | 73% | 47% | 88% | 70% | 92% |
| Observations | 46,388 | 9,621 | 13,604 | 16,878 | 6,285 |
| Schools | 9,489 | 1,758 | 2,248 | 4,452 | 1,092 |

Notes: Each cell displays a mean. Averages are across all school-year observations.

Table 2: Treatment and Control Balance

| | (1) | (2) | (3) | (4) | (5) | (6) |
|--|-------------------|-------------------|------------------|-----------------|-----------------|-----------------|
| Year Relative to List: | $t - 2$ | $t - 1$ | $t - 2$ | $t - 1$ | $t - 2$ | $t - 1$ |
| Teacher Retention Rate (%) | -3.09** (0.17) | -3.22** (0.16) | -0.24 (0.31) | 0.05 (0.28) | -0.08 (0.69) | -0.17 (0.48) |
| % Highly Qualified | -1.89** (0.13) | -2.12** (0.12) | -0.03 (0.223) | 0.04 (0.23) | 0.22 (0.39) | -0.51 (0.44) |
| % Licensed | -1.40** (0.27) | -1.53** (0.27) | 0.48 (0.36) | 0.34 (0.34) | 0.25 (0.27) | -0.04 (0.20) |
| % Less 3 Years Experience | 3.47** (0.20) | 3.34** (0.18) | -0.21 (0.41) | -0.60 (0.35) | 0.28 (0.51) | -0.41 (0.39) |
| Student Achievement Index (Mean 0, Std Dev 1) | -1.17** (0.02) | -1.18** (0.02) | -0.02 (0.03) | -0.03 (0.03) | 0.01 (0.03) | 0.012 (0.02) |
| Year by State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cubic in Low-Income Percent | No | No | Yes | Yes | Yes | Yes |
| School FE | No | No | No | No | Yes | Yes |
| Observations | 19,782 | 26,180 | 19,782 | 26,180 | 19,782 | 26,180 |
| Schools | 6,483 | 6,492 | 6,483 | 6,492 | 6,483 | 6,492 |

Notes: Each column and row is a separate regression. Standard errors are clustered at the school level. The sample is limited to schools appearing in all years of their state's panel as described in the text (2009-2014 for Massachusetts, 2008-2014 for North Carolina, 2010-2013 for New York, and 2008-2014 for South Carolina). Significance stars: * indicates $p < 0.05$ and ** indicates $p < 0.01$.

Table 3: Effect of Loan Forgiveness Eligibility on Teacher Characteristics and Retention Rates

| | (1) | (2) | (3) | (4) |
|----------------|--------------------|----------------------|-----------------|---------------------------|
| | Retention Rate (%) | Highly Qualified (%) | Licensed (%) | Less 3 Yrs Experience (%) |
| Directory Year | 0.06 (0.15) | -0.25 (0.13) | 0.04 (0.10) | 0.02 (0.14) |
| 1 Year Later | 0.28 (0.27) | -0.17 (0.15) | 0.07 (0.13) | 0.09 (0.16) |
| 2 Years Later | 0.27 (0.21) | -0.12 (0.14) | 0.01 (0.12) | -0.15 (0.21) |
| 3 Years Later | 0.04 (0.27) | 0.22 (0.19) | -0.16 (0.13) | -0.09 (0.28) |
| 4 Years Later | 0.14 (0.36) | 0.65 (0.47) | -0.13 (0.18) | -0.08 (0.59) |
| States | MA, NC, NY, SC | MA, NC, NY, SC | MA,NC | NC,NY |
| Observations | 151,080 | 144,496 | 74,721 | 96,544 |
| Schools | 6,668 | 6,668 | 2,327 | 4,921 |

Notes: Each column is a separate regression. All specifications include state by year fixed effects and school fixed effects. Standard errors are clustered at the school level. Significance stars: * indicates $p < 0.05$ and ** indicates $p < 0.01$.

Table 4: Effect of Loan Forgiveness Eligibility on Student Achievement

| | (1) | (2) | (3) | (4) | (5) |
|----------------|--------------------|-------------------|-------------------|---------------------|-------------------|
| | All States | MA | NC | NY | SC |
| Directory Year | 0.001 (0.008) | 0.013 (0.013) | -0.016 (0.021) | -0.027* (0.012) | 0.063 (0.025) |
| 1 Year Later | 0.018* (0.009) | 0.008 (0.013) | -0.020 (0.023) | 0.009 (0.014) | 0.038 (0.021) |
| 2 Years Later | -0.024* (0.010) | 0.000 (0.018) | -0.032 (0.023) | -0.074** (0.019) | -0.034 (0.029) |
| 3 Years Later | -0.029* (0.012) | -0.013 (0.023) | -0.008 (0.027) | -0.091** (0.022) | 0.016 (0.035) |
| 4 Years Later | -0.034 (0.019) | -0.009 (0.031) | 0.016 (0.032) | N/A N/A | -0.063 (0.047) |
| Observations | 139,055 | 30,048 | 38,536 | 54,702 | 16,648 |
| Schools | 6,464 | 1,137 | 1,087 | 3,720 | 534 |

Notes: Each column is a separate regression. The outcome variable is standardized to have mean 0 and standard deviation 1 within each state and year. The student achievement measure for Massachusetts is the percent of students scoring proficient averaged over math and language arts. The student achievement measure for North Carolina is the performance composite percent. The student achievement measure for South Carolina is the percent of students scoring C or above on math and English for high school students and the percent of students scoring meets or exceeds standards for elementary and middle school; these measures are averaged across all grades in a school. The student achievement measure for New York is the secondary level composite performance index for high school, and the elementary-middle level composite index for elementary and middle schools where the measures are averaged over English/language arts and math and over both levels if the school has elementary/middle and high school students. All specifications include state by year fixed effects and school fixed effects. Standard errors are clustered at the school level. Significance stars: * indicates $p < 0.05$ and ** indicates $p < 0.01$.