The Value of Student Debt Relief and the Role of Administrative Barriers: Evidence from the Teacher Loan Forgiveness Program*

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Abstract

We explore how much borrowers value student debt relief, in the setting of the federal Teacher Loan Forgiveness (TLF) program, and further document whether information and eligibility for this program affect teacher employment decisions. The program cancels between $5,000 and $17,500 in debt for teachers who remain employed in a high-need school for five consecutive years. Using both quasi-experimental evidence and a randomized control trial, we find that neither eligibility nor a targeted information intervention result in changes in teacher employment decisions, despite the presence of sizable student loan balances in our sample. Information was found, however, to increase application and receipt rates for teachers who had already accrued the five years of eligibility. Additional evidence from contingent valuation surveys suggests that teachers do in general value possible debt relief. Incorporating qualitative evidence from focus groups, we conclude that take-up may be constrained by program complexity and administrative barriers that involve knowing which schools qualify, tracking employment records, having employers sign off, and coordinating with loan servicers.

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1 Introduction

There is currently more than $1.7 trillion in student loan debt held by households in the U.S., which has led many to advocate for federal student loan forgiveness (Friedman, 2022), has raised concerns regarding racial equity and debt accumulation (Addo et al., 2016), and has sparked debates regarding the progressivity of such policies (Perry et al., 2021; Looney, 2022). One possible consequence of rising student debt burdens is debt overhang: borrowers may be constrained in their ability to relocate geographically, pursue better employment arrangements, or start a family (Sieg and Wang, 2018; Di Maggio et al., 2019; Luo and Mongey, 2019). In response to these concerns, the Biden administration proposed a loan forgiveness program that would cancel between $10,000 and $20,000 per borrower, subject to income restrictions, and additional adjustments to repayment rules.

While the most recently proposed student debt forgiveness policy has been blocked by the courts, there already exist more targeted forms of debt forgiveness. One example is the federal Teacher Loan Forgiveness (TLF) program, which offsets between $5,000 and $17,500 in student debt for teachers working in high-need districts for at least five consecutive years. However, as of 2018, only 66 percent of teachers who had graduated with a BA in 2008 were aware of the federal loan assistance program, and fewer than 20 percent had participated (U.S. Department of Education, 2018). The potentially limited take-up of this program is of particular interest against the backdrop of a long-standing challenge of recruiting and retaining teachers, especially in high-need school districts (Rich, 2015; Hackman and Morath, 2018), and, more recently, amid a general teacher shortage that has been exacerbated during the COVID-19 pandemic (Singer, 2021).

The set of facts that have emerged in this setting raises a number of questions. Does debt forgiveness affect major decisions made by borrowers, both in general and relative to equivalent monetary incentives? Is student debt relief in the form of the TLF program an effective recruitment and retention tool? And if so, then why do seemingly eligible teachers forgo the benefit? Is it a matter of awareness, or are there other barriers?

To shed light on these questions, we use a combination of quasi-experimental and experimental evidence on the TLF program, in combination with survey data and qualitative evidence. We first examine whether teachers behave differently upon becoming eligible for TLF. Using the program's rules, which create a discontinuous jump in school-level eligibility, we compare outcomes for similar teachers who do and do not qualify for the program. We confirm, as expected given TLF eligibility rules, that there is a significant and discontinuous increase in school-level eligibility for TLF when more than 30 percent of students qualify for free or reduced-price lunch (FRPL).

We then exploit variation around this discontinuity in eligibility and examine teacher turnover rates depending on whether their school is eligible or not for loan forgiveness during their first year of employment. We find no difference in teacher retention around the threshold, during the subsequent five years of employment. Other attributes of the school and teachers are smooth through the discontinuity, supporting our causal conclusion that loan forgiveness eligibility alone is not sufficient to alter teacher employment patterns. Importantly, we find no evidence of teacher sorting around the eligibility threshold based on observable characteristics, which is itself an indication that teachers either do not value or are unaware of the program. Based on this analysis, we conclude that the TLF program does not have a significant effect on retaining teachers or on attracting them to high-need schools to begin with.

Next, we examine whether informational barriers can explain the lower-than-expected take-up. We implement and evaluate a large-scale randomized controlled trial (RCT) aimed at increasing awareness of, and facilitating enrollment in, the TLF program among public school teachers in the state of Michigan. We sent mailings—electronic and paper—to teachers at a random subset of eligible schools in 2015, informing them of the TLF program and their current or potential eligibility. In 2017, we repeated a similar intervention, with additional phone-based application assistance in addition to paper and electronic communication. In both waves, we tracked subsequent outcomes using follow-up surveys and administrative data on teacher employment patterns.

We find, after two waves of randomized implementation, that the intervention increased teacher awareness of the program, with treated teachers being 7 percentage points more likely to say they have a basic understanding, or are very familiar with, the rules of the TLF program (from a base of 70 percent). Moreover, we find, among teachers who have accrued the minimum number of years to file for TLF, a 5 percentage point increase in the self-reported likelihood of having applied for TLF, a 9 percent increase. Among teachers who have not yet reached the number of years necessary to file, however, we fail to find any differences between the treated and control group in same-school employment retention.

We next examine whether the modest behavioral response that we observe can be explained by a general low value of debt forgiveness programs for teachers. We therefore try to directly measure how much teachers value the TLF as one of many job amenities. Included in our surveys were a series of questions designed to elicit teachers' value of the loan forgiveness program. We administered a contingent valuation exercise, asking teachers to choose from side-by-side comparisons of hypothetical schools, with varying attributes drawn from a pool of actual schools, including TLF eligibility and salary.

Using a discrete choice model, we find that teachers' answers imply a meaningful value of the TLF program. Regarding school-level TLF eligibility status, there is a modest difference in value between TLF-eligible and non-eligible schools when TLF status is not made explicit in the comparison (and therefore must be inferred based on share of FRPL students). The value ranges between \$500 and \$1,000. However, when a TLF school is explicitly noted, teachers' value of that status increases by more than \$3,000, with somewhat larger values for those eligible for larger forgiveness amounts and for those who report having a positive loan balance. The teacher's valuations of other attributes are of the predicted sign, such as requiring more compensation for larger class sizes or working in schools with lower levels of math or reading proficiency.

Taken together, our results suggest a non-trivial value of debt relief. We can benchmark the value of \$5,000 of debt relief from our elicitation exercise. The hypothetical teacher valuation suggests that \$5,000 of forgiveness would break a 50-50 tie between two equivalent schools by 16 percentage points, increasing the probability of selecting the eligible school to 66 percent. Furthermore, in focus group conversations with teachers, many described challenges in making their monthly student loan payments, and some expressed desperation at the prospect of paying their debts in full. There was also a strong desire for options that would have some portion of their debts forgiven.

This value may not translate into take-up of the TLF program due to informational frictions and a variety of administrative barriers. Clear guidelines on how to navigate the enrollment process are difficult to find, and teachers must work with both their school administrators and their student loan servicer to complete the process. Our findings thus have implications for maximizing access to loan forgiveness programs and also suggest that special attention must be paid to applicant-vendor relationships and levels of trust if third-party vendors play a significant role in the enrollment process.

2 Contribution to the Literature

Our paper extends multiple literatures on the effects of student debt and debt forgiveness on student career paths, employment choices, and household financial decisions. First, we explore whether debt forgiveness affects early career decisions. Greater student loan burdens have been found to drive students toward higher-paying private sector jobs (Rothstein and Rouse, 2011; Luo and Mongey, 2019). Other work has shown that an exogenous reduction in debt balances results in greater geographic and employment mobility (Di Maggio et al., 2019). Greater levels of student debt are also associated with lower marriage rates and/or fewer career prospects, especially for women, for both MBA students (Gicheva, 2016) and law students (Sieg and Wang, 2018). In general, it is important to distinguish between shocks to debt levels at the point of origination—where increased access to credit can improve degree attainment and earnings (Black et al., 2020) and college persistence (Card and Solis, 2022), with sometimes heterogeneous returns (Lochner et al., 2021)—and shocks to the balance owed after debt has already been accrued. Although anticipation of the TLF program could affect earlier decisions regarding how much debt to take on, our study largely focuses on the take-up and effects of the TLF program after a loan has been originated.

Second, a few studies examine the idea that student debt forgiveness might serve as a policy lever to incentivize employment in public-service-oriented positions. Pathman et al. (2004) show suggestive evidence that physicians who participate in state-level loan repayment programs are more likely to practice in communities with higher socioeconomic need as compared to non-participants. Field (2009) analyzes an experiment on NYU Law students that randomized financial aid packages of equivalent monetary value, one that provided ex post loan forgiveness if the student chose to work in a low-paying public interest job, and another that offered ex ante tuition subsidies that had to be repaid if the student did not work in public interest law. She finds that students were far more responsive to tuition waivers than the possibility of debt forgiveness despite their equivalent financial value. Cadena and Keys (2013) find further support for debt aversion influencing student decision-making.

In the case of teachers—and closest to our study—Russell (2020) compares schools just above and below the 30 percent threshold for TLF eligibility in Massachusetts, New York, North Carolina, and South Carolina and finds no effect on teacher retention. Relative to that study, we are able to analyze microdata for Michigan teachers and estimate effects specifically among new teachers, which arguably allows for more statistical power. We similarly find null effects of eligibility. In contrast, Feng and Sass (2018) find that a state-level loan forgiveness program in Florida reduced attrition by 8.9 percent for middle school math or science teachers and by 10.4 percent for their high school counterparts. In this latter case, there were differences in the program's design, as compared to the federal TLF program, including incremental loan forgiveness for each year of eligible teaching, up to a maximum amount of $10,000, which is more similar in spirit to the federal Perkins Loan cancellation program for teachers.

Third, our findings suggest non-trivial take-up frictions in the TLF program. Although we were able to encourage a subset of teachers to apply for the program, we were far from exhausting the potential increase in take-up. Prior work has shown behavioral framing and default effects to significantly affect educational financing decisions, both at the point of debt origination (Marx and Turner, 2019; Kramer et al., 2021) and at the stage of enrollment in income-driven repayment (IDR) plans (Abraham et al., 2020; Cox et al., 2020). Aside from behavioral considerations, general take-up frictions may include administrative barriers (see, e.g., Currie, 2006; Bhargava and Manoli, 2015; Finkelstein and Notowidigdo, 2019).

Moreover, in the context of the TLF program there are frictions both at the school level and with the loan servicer that must be overcome in order to obtain the benefits. While we do not completely automate enrollment in this study, we do provide participants with individually tailored information regarding eligibility as well as detailed instructions for applying. The intervention increased awareness and application rates, but the magnitude of the effects suggests that significant barriers may yet remain, including the cost of coordination with the loan servicer. Mueller and Yannelis (2022) show that when enrollment in an IDR plan is facilitated directly by a student loan servicer, via pre-populated applications, enrollment increased by 34 percentage points, or more than double the counterfactual.

Fourth, we provide new estimates of how teachers value different features of their job and how loan forgiveness may or may not factor into their decision-making. Using a technique that is increasingly common to assess employment choices (Eriksson and Kristensen, 2014; Mas and Pallais, 2017; Maestas et al., 2023; Wiswall and Zafar, 2018; Johnston, 2021), we conduct contingent valuation exercises to back out the value of debt forgiveness relative to comparable one-time cash bonuses and other school features. These results tie into a broader literature that looks at the general factors affecting teacher employment decisions, including several studies that find positive effects on the recruitment and retention of teachers from one-time salary bonuses on the order of $20,000 (Steele et al., 2010; Glazerman et al., 2013), annual bonuses of roughly $1,800 (Clotfelter et al., 2010), or a 10 percent wage premium (Falch, 2011). We find, in general, that teachers value loan forgiveness at roughly 90 cents on the dollar relative to a cash bonus, while those who currently have debt value it dollar for dollar. Ultimately, however, we show that the TLF program does not appear to induce behavioral responses in teachers' employment decisions.

Finally, we contribute to the literature on take-up of programs and benefits, which finds that providing information alone often has limited efficacy. Across a range of contexts, studies that randomize information treatments find that potential beneficiaries face additional barriers that prevent take-up (Chetty and Saez, 2013; Bettinger et al., 2012; Beshears et al., 2011; Keys et al., 2016; Bergman et al., 2019). In our setting, going beyond general program information to offer tailored details regarding individual-level eligibility and providing partial assistance with enrollment was sufficient to increase enrollment but perhaps only moderately. Further understanding the frictions faced by potential beneficiaries can increase the effectiveness of public policies and determine the extent of "information plus" interventions needed to improve policy outcomes.

3 Institutional Background

There are several different forgiveness, cancellation, and discharge plans available for federal student loans, including Perkins Loan cancellation options, Public Service Loan Forgiveness (PSLF), and TLF. We focus on the TLF program because its clear target population, straightforward forgiveness amounts, and shorter time horizons for forgiveness make it an ideal test case.

As part of the Higher Education Amendments of 1998, the federal government introduced a loan forgiveness program intended to encourage individuals to work as teachers in high-need schools. Like similar programs for doctors and employees of public service organizations, the TLF program is available for Perkins Loans, Direct Loans, and Stafford Loans. The base amount of forgiveness is \$5,000, with the Taxpayer-Teacher Protection Act (TTPA) of 2004 increasing loan forgiveness to up to \$17,500 for special education teachers or for secondary school math or science teachers. The Teacher Loan Forgiveness Improvement Act of 2022, which was introduced but did not pass, proposes to increase the amounts for TLF to \$15,000 and \$30,000, respectively (U.S. Senate. 117th Congress, 2022).

To qualify for TLF, a teacher must be deemed "highly qualified," which entails having a bachelor's degree and having received full state certification as a teacher. Teachers must teach for five consecutive years in a qualifying school or schools, that is, one serving low-income students. Each year, a list of eligible schools is published in the Teacher Cancellation Low Income (TCLI) Directory (U.S. Department of Education, 2023). Each state is responsible for populating this list, though low-income status for a school is typically defined as having more than 30 percent of students from low-income families. Importantly, the share from the prior year determines eligibility in the current year. In our setting, the state of Michigan uses whether a student receives free or reduced-price lunch (FRPL) to satisfy this criteria. In addition, all schools operated by the Bureau of Indian Education qualify as schools serving low-income students. If a teacher begins at a qualifying school that is later removed from the TCLI directory, the subsequent years still count toward eligibility. In addition, if a teacher switches schools, their subsequent years continue to count toward eligibility if the new school is also TLF-eligible.

The receipt of the benefit depends on a number of inputs under the teacher's control, such as employment in a qualifying school and an understanding of eligibility requirements. Once a teacher decides to apply for loan forgiveness, they must fill out a TLF application, which includes a certification section to be filled out by the chief administrator at the qualifying school. The chief administrator, usually a principal, assistant principal, or district superintendent, must verify that the above qualifications are met for each of the five consecutive years of service.

The application must then be sent to the loan holder or loan servicer, and in the event that there are multiple lenders, an application must be sent to each. The name and address of one's loan guarantor can be obtained from the National Student Loan Data System. Once the servicer receives the application, it must be approved. If approved, the forgiveness amount is applied to outstanding unsubsidized Stafford Loan balances, then to subsidized balances, and finally to any eligible consolidation loan balances. If not approved, the applicant is notified by the servicer, with an explanation of denial.

While forgiveness programs hold out the potential to alleviate the financial stress of indebted graduates, the Consumer Financial Protection Bureau (CFPB) believes they are significantly underused.[1] At present, there are approximately 20 state-level loan forgiveness programs for teachers and an estimated 33 million borrowers eligible for PSLF programs overall, with more eligible jobs being created. In 2020, only 32,700 teachers received federal loan forgiveness, amounting to $320 million.[2]

There are both informational and behavioral barriers to student debt relief program enrollment. Information on forgiveness programs is available online, but it is not often made salient for qualifying borrowers who do not specifically seek it out. Moreover, the behavioral economics literature demonstrates that knowledge often does not translate into action, especially in the face of complex processes (Hilgert et al., 2003). These barriers are compounded by the fact that the entity tasked with collecting debt payments from borrowers, the loan servicers, are also integral to applying for this loan forgiveness. The CFPB has received substantial anecdotal feedback that many borrowers practice avoidance due to the overwhelming nature of large debt burdens, and some even go so far as to not open student debt-related mail, which could impede access to programs like TLF.[3]

Although the TLF program is a federal-level entity, it necessarily involves coordination with state-level educational systems. For example, in our case of the state of Michigan, the Michigan Department of Education determines which schools qualify for TLF on an annual

[1] See, for example, Phillip (2013).
[2] U.S. Department of Education (2021)
[3] Chopra (2014)

basis. In addition, they have an interest in this program insofar as it might aid with the recruitment and retention of qualified teachers in low-income districts. In fact, at the time that our experiment was fielded, state departments of education were required by the U.S. Department of Education to submit equity plans that outlined strategies for ensuring that all students have access to quality instruction. In their 2016 plan, the Michigan Department of Education included their support of this study of the TLF program as an example of their efforts to attract and retain teachers in high-need schools.[4]

4 Does Loan Forgiveness Eligibility Influence Teacher Mobility or Retention?

4.1 Regression Discontinuity Design

The TLF requirement that schools have at least 30 percent of students on FRPL naturally lends itself to a research design exploiting the discontinuity in school eligibility to investigate whether teachers respond to the availability of loan forgiveness in their employment decisions. To implement our regression discontinuity approach, we first group teachers into bins based on the share of students receiving FRPL at their school of employment in the year before their first year of teaching, p_0.[5]

If we believe the TLF program has a direct influence on where teachers sort, then we might expect to observe substantial differences in the types of teachers choosing schools on either side of the eligibility threshold. Teachers who value debt forgiveness and anticipate staying in a high-need school for at least five years might select into precisely those eligible schools. If, on the other hand, there are no differences in the ex ante characteristics of the teachers or schools, then the potential of debt forgiveness may not impact teachers' initial school employment decisions. We therefore first examine patterns of sorting around the 30

[4] Michigan Department of Education (2015)

[5] Recall from Section 3 that the share from the prior year determines eligibility in the current year.

percent FRPL threshold. We formally examine this using the method of Cattaneo et al. (2020), which tests for discontinuities in the density of the running variable.[6]

We then track teachers' likelihood of remaining at the same school or any Michigan school, in their second, third, fourth, or fifth years. Comparing teachers on either side of the threshold, we can establish whether TLF eligibility has a causal effect on teacher retention. In all specifications, when we look at outcomes in years 2 through 5, the running variable remains fixed at the measure observed during the teacher's start at the school, and the sample includes all first-year teachers. In other words, when looking at retention in year 3, we do not condition on having been present in the school during year 2, which is a potentially endogenous outcome.

We first estimate regression discontinuity specifications of the following form:

$$Y_{it} = \alpha + \beta I[p_0 \geq 30] + \gamma_1 f(p_0 | p_0 < 30) + \gamma_2 f(p_0 | p_0 \geq 30) + \epsilon, \tag{1}$$

where $I[p_0 \geq 30]$ is an indicator for whether the share of students receiving FRPL is greater than 30, and $f(\cdot)$ is a smooth function of this share, allowed to vary on either side of the threshold. The outcome, Y_{it}, captures our measures of teacher retention in subsequent years: whether the teacher is in the same school, another TLF-eligible school, or any Michigan school. The parameter β captures any discontinuous changes in the outcome. When the outcome equals TLF eligibility in the first year, we capture the "first stage," that is, how eligibility discontinuously changes at the threshold. In our baseline specification, we use observations within 20 percentage points of the threshold and a linear specification for $f(\cdot)$.

We alternatively estimate the regression discontinuity using a local linear regression and a data-driven selection of the bandwidth, following Calonico et al. (2014b).[7] Under the assumptions that 1) the potential outcomes are a continuous function of the running variable p_0 at the threshold, 2) teachers or schools are not sorting on either side of the threshold,

[6] We implement this using the `rddensity` package (Cattaneo et al., 2018) in `Stata`.

[7] We implement this method using the `rdrobust` package (Calonico et al., 2014a) in `Stata`, with a first-order polynomial.

and 3) no other relevant factors discontinuously change at the threshold, we interpret our estimates as reflective of the casual effect of TLF eligibility.

Following Ganong and Jäger (2018), we use a permutation method to conduct inference and calculate p-values and confidence intervals using a distribution of discontinuity estimates as placebo cutoffs away from the actual threshold. One advantage of this approach to inference is that it is more likely to be robust to the clustered nature of our treatment: teachers who begin in the same year in the same school have the same eligibility status. Our preferred specification uses the local linear regression with data-driven selection of bandwidths. We further assess the research design by testing for discontinuities in baseline teacher and school characteristics at the threshold.

4.2 Regression Discontinuity Sample

Our sample for the regression discontinuity analysis begins with a panel of administrative data on teachers, merged with school-level characteristics. Both databases are maintained by the Michigan Department of Education and are further merged to a school-by-year database of TLF eligibility maintained by the Michigan Department of the Treasury. We focus on teachers whose first year in the data occurs on or after 2007 and follow them as far as 2018. We keep data for up to the first five years of teaching and further restrict to teachers for whom the FRPL share is within 20 percentage points of the 30 percent threshold.[8] This results in 25,717 first-year teachers at 2,529 schools. Relative to the overall distribution of Michigan schools, the sample within 20 percentage points of the threshold contains 53 percent of all schools.

Focusing on mean school-level attributes just below the threshold, we find that the average school enrollment is 700 students, 8 percent of students are Black, 4 percent are Hispanic/Latino, and 3 percent are Asian. The female share of teachers is 76 percent, and

[8] When we produce placebo estimates, we move the threshold to other values but continue to keep the data within 20 percentage points of the new placebo threshold.

95 percent of the teachers are White. The average age of the teacher is 31 years old.[9]

4.3 Effects of TLF Eligibility on Teacher Retention

Our initial analysis uses the fact that a key determinant of whether employment at a school counts toward TLF eligibility is whether 30 percent or more of its students qualify for FRPL in the prior year. Figure 1, panel A collects teachers into bins based on the share of students receiving FRPL in the year before the teachers' first year of employment, which determines whether the school qualifies for TLF. For each bin, we plot the share of teachers in a TLF-eligible school. An approximate 40 percentage point jump in TLF eligibility, from 53 to 93 percent, occurs at the threshold of 30 percent of students receiving FRPL ($p = 0.005$).

This "fuzzy," but large, discontinuity at 30 percent FRPL confirms that while the share of FRPL students is not the only determinant of TLF eligibility, it is a critical determinant that operates through an observable and straightforward school attribute. In what follows, we therefore use this discontinuity to examine the composition of teachers around the threshold to examine sorting and the effect of eligibility of loan forgiveness on employment decisions.

We first find that the substantial increase in TLF eligibility in the threshold is not associated with any differences in the attributes of teachers who start their careers at schools on either side of the discontinuity. Appendix Figure A.1 shows that there is no significant discontinuity in age, gender, race, or the type of school (such as charter school or secondary school) around the eligibility threshold.[10] The final panel of Appendix Figure A.1 shows that the density of schools' lagged share of FRPL is smooth through the 30 percent threshold, addressing concerns regarding manipulation of the running variable (McCrary, 2008; Cattaneo et al., 2020).[11]

With the large difference in TLF eligibility at the threshold, we might expect that this

[9] See Appendix Table A.1 for a summary of these means and their discontinuities at the threshold.

[10] Further, in Appendix Table A.1, we show that there are no discontinuities in school-level average characteristics around the threshold, further supporting the interpretation that teachers are not making either initial or continuing employment decisions on the basis of TLF eligibility.

[11] Formally, we use the `rddensity` package in `Stata` (Cattaneo et al., 2020) and fail to reject the null of no discontinuity in the density.

differential treatment leads to differences in whether teachers stay in the schools that provide loan forgiveness. However, in Figure 1, panel B, we observe no difference in the share of teachers continuing into their second year at the same school ($p = 0.876$). Since TLF receipt requires remaining at an eligible school for five consecutive years, teachers in eligible schools in theory have a higher incentive to remain at the same school.[12] Although the overall rate of retention declines over time due to teacher turnover, we do not find discontinuities in these retention rates at the threshold in the second year, or in the third, fourth, or fifth years either (panels C, D, and E, $p \geq 0.6$ in all cases). We likewise do not find an effect at the threshold on whether teachers who change schools are more likely to choose a TLF-eligible school. [13]

Our first main finding, then, is that eligibility on its own is not sufficient to alter teacher employment patterns. We find neither evidence of teacher or school sorting nor effects on teachers' subsequent retention. One possibility is that teachers are unaware of their eligibility or the various steps required to obtain loan forgiveness. It may also be the case that the magnitude of the debt forgiveness, between \$5,000 and \$17,500, is too small to alter teacher behavior or that teachers do not value debt relief as much as direct cash payments. To explore these potential interpretations, we turn next to the results of our RCT.

[12] Teachers can remain at the same school for five years or can switch schools as long as the new school is also TLF-eligible.

[13] The coefficient estimates associated with these figures are provided in Appendix Table A.2. Appendix Tables A.3 and A.4 further show that teachers are no more likely to stay in teaching positions in a different TLF-eligible school upon moving to a new school, or to stay in the state of Michigan above the FRPL threshold, respectively.

5 Can Informational Frictions Explain the Null Results?

5.1 Informational RCT Design

While the regression discontinuity design allows us to study how a broad set of teachers currently respond to the policy, the approach may be low powered if teachers are unaware of the program. To examine the role of information, we therefore leverage an experimental design that features four components: (1) an informational mailing regarding the TLF program sent in the spring of 2015, (2) a survey mailed in the winter of 2016, (3) an informational mailing and a phone-call-based application assistance regarding the TLF program sent in the spring of 2017, and (4) a survey mailed in the spring of 2018. The set of teachers included in the study were those who were hired during or after 2003, the earliest date for which we could start to calculate employment history and eligibility for TLF. We restricted our attention to schools that qualified for TLF in the year of the study.

The 2015 and 2017 mailings used very similar designs. Both mailed information to about 50 percent of the sample during the spring/summer, based on a stratified school-level randomization. However, due to difficulties in receiving required data (teachers' names) from the Michigan Department of Education, the 2017 mailing was delayed by almost one month compared to the 2015 mailing. All recipients received a cover memo and physical mailer as well as an email. The 2017 call recipients received a cash incentive of $5 and a follow-up mailing to schedule a call if they had not been reached by July of 2017.

The 2016 and 2018 surveys elicited information on student loan debt, TLF program awareness, TLF application status, and measures of financial strain. Although the 2016 and 2018 surveys were also very similar, there were slight differences in their designs. Specifically, the structure of incentives was changed: the 2016 survey featured $5 incentives sent to 10,000 individuals, with only these 10,000 teacher receiving paper mailers. This is in contrast to the 2018 survey, which sent physical mailings to all 25,784 subjects, of which 22,867 received a \$2 bill as an incentive. In addition, a contingent valuation module, that is, a hypothetical choice experiment featuring three school comparisons, was added for the 2018 survey. This method was designed to elicit the dollar value of TLF eligibility and different hypothetical forms of distributing TLF funds (i.e., debt forgiveness versus a one-time signing bonus).

To examine the effects of being assigned to the experimental treatment group, $T_i = 1$, we estimate specifications of the following form:

$$Y_i = \alpha + \beta T_i + \gamma X_i + \epsilon, \tag{2}$$

where the specification includes controls for sample stratification X_i and baseline characteristics: teacher age, gender, and race/ethnicity; year accrued toward TLF eligibility; school size; student race/ethnicity; and school type. We again conduct inference using a randomization inference approach, which accommodates the fact that our treatment is clustered at the school level. We re-randomize treatment 500 times and re-estimate β from equation 2. The distribution of these placebo estimates is used to calculate p-values and confidence intervals.

The outcomes, Y_i, include teacher retention in subsequent years—up to four years following the 2015 intervention and up to two years following the 2017 one. We also estimate effects on TLF program awareness, application, and receipt as measured in follow-up surveys. In our baseline specification, we pool the data across the two waves of the intervention. Given the random assignment of treatment status, we interpret the parameter β as the casual effect of the treatment. To further validate the research design, we test for balance between the treated and control groups in baseline characteristics, also using the specification in equation 2.

5.2 Informational RCT Sample

Our analysis of the RCT relies on a database of school- and teacher-level treatment indicators from our 2015 and 2017 interventions as well as survey data we collected from a subset of study participants in the years following each wave of the intervention, 2016 and 2018. Table 1 summarizes the baseline characteristics of the RCT participants, pooled over the two waves of the experiment in 2015 and 2017. There are 44,362 teachers across the two waves. In this sample, the average school size is between 554 and 575, 62 percent of students receive FRPL, 29 percent of students are Black, 9 percent are Hispanic/Latino, and 2 percent are Asian. Compared to the regression discontinuity sample, which focuses on schools near the 30 percent FRPL threshold, this more general set of schools is smaller, with a higher share of Black students.

The teacher demographics, however, remain similar: 78 percent of the teachers are female, 90 percent are White, 7 percent are Black, and 3 percent are Hispanic/Latino or Asian. The average teacher age is 35. Teachers in this sample have, on average, just more than four years accrued toward TLF eligibility. All teachers in the experimental sample are teaching at eligible schools, and 43 percent have already accrued at least five years of experience, making them eligible for forgiveness at the time of the mailing.

Table 1 also tests for differences in the means of these baseline characteristics between the treated and control groups. We generally find that the observables are balanced. We do find a marginally significant difference if we jointly test all variables ($p = 0.08$), though nearly all the means are identical up to two decimal places.

Table 2 reports additional characteristics for the set of teachers who responded to our follow-up survey. With a response rate of 24 percent, we have 10,713 survey respondents across the two waves. Panel A shows that three-quarters of the respondents have some federal student debt, while 27 percent have private loans. This means that even though all teachers in the RCT sample are at eligible schools, about 25 percent do not have debt that qualifies for TLF. The average monthly payment is between \$644 and \$773 per month. One-third of the respondents report ever having been delinquent, and 80 percent report generally having difficulty paying their bills. Appendix Table A.16 shows that within this subsample that responded to the survey, the treated and control groups remain balanced on baseline observables. Appendix Tables A.17-A.18 further show that the balance between the treated and control group remains intact if we look separately at teachers who have not yet accrued five years of eligibility and those who have.

5.3 Effects of Information on TLF Awareness and Application

Our experimental analysis is designed to sift through competing explanations for the apparent lack of impact of TLF eligibility on teacher employment choices. In the spring of 2015, and again in 2017, we chose a random subset of Michigan public schools to send paper and electronic mail to teachers notifying them of their school's eligibility and their individual progress toward five years of TLF-eligible employment. Using follow-up surveys (see Appendix B), we find that these mailings increased teacher awareness of the program. We have several ways of demonstrating this effect. As an initial check, in Panel B of Table 2, we see that 51 percent of treated group members with less than five years of eligibility recall receiving the treatment correspondence compared to 11 percent of the control group ($p = 0.00$). Panel C shows the equivalent comparison for teachers with five or more years of eligibility: 56 percent of treated teachers recall receiving a treatment call or email compared to 17 percent in the control group.

To further demonstrate the impact of the treatment on program awareness, Figure 2 groups teachers by their actual years of eligibility, using administrative employment records, and then plots their response to a question asking for their self-perceived number of eligible years. We note three patterns. First, there is a correlation between the years of eligibility we calculate using administrative data and self-reported years, for both treated and control teachers, and this correlation strengthens among teachers with more years of eligibility. Second, the correlation is stronger for treated teachers: in each figure, the outlined bars, which indicate a correct answer, are almost always higher for the treated group. Third, treated teachers are less likely to report that they "don't know."

Overall, treated teachers with less than five years of eligibility were 5 percentage points more likely to report the "correct" number of years, from a base of 29 percent, and were 10 percentage points more likely to know their school is TLF-eligible, from a base of 58 percent (Table 2, $p = 0.00$). Looking more closely at specific questions, treated teachers with less than five years of eligibility were 6 percentage points more likely to say they have a basic understanding of, or are very familiar with, the TLF rules, from a base of 65 percent (see Table 2, $p = 0.00$, or Table 3), $p = 0.00$. On the other hand, treated group teachers with under five years of eligibility reported having applied for TLF at a rate similar to that of control group teachers (see Table 2, $p = 0.26$, or Table 4, $p = 0.23$). We find very similar patterns if we focus just on teachers with debt or those who qualify for $17,500 in loan forgiveness (Appendix Tables A.19-A.21).

In contrast, we find that treated teachers with five or more years of eligibility, who are now fully eligible for loan forgiveness, are indeed more likely to have applied than their control counterparts. Panel C of Table 2 shows that 5 percent more treated teachers applied for loan forgiveness than control teachers on a base of 57 percent. Treated teachers who have reached eligibility are more likely to know that their school is eligible, are more likely to know their correct number of years, and know the rules of TLF very well. For those who can immediately apply this information treatment to action, we find that our intervention led to increased application for loan forgiveness. Table 4 shows that these applications are resulting in more treated teachers receiving loan forgiveness, 2 percentage points more likely on a base of 38 percent ($p = 0.02$).

5.4 Effect of Information on Teacher Retention and Mobility

Although we find positive impacts on teacher awareness and application rates among fully eligible teachers, this fails to translate into any differences in teacher retention between treated and control schools, across all years of eligibility. We summarize this finding in Table 5, which estimates the effect of our treatment on the probability of remaining at the same school over the subsequent five years. The results are consistently small and statistically indistinguishable from zero. Thus, the receipt of personalized information regarding the loan forgiveness program and one's eligibility did not meaningfully influence teachers' employment choices. These results are similar if we focus only on teachers with fewer than five years of eligibility, those for whom the incentive to remain at the current school is perhaps most clear.

Appendix Tables A.6 and A.7 further show that there is no difference in the likelihood of remaining in any TLF-eligible school or as a teacher in the state of Michigan.[14] The results are generally unchanged if we focus on specific subgroups, including whether a teacher will qualify for the higher $17,500 forgiveness level or whether the teacher has debt (Appendix Tables A.8-A.13). We therefore conclude that the information intervention was able to influence teachers' awareness and understanding of the loan forgiveness program—and their likelihood of applying and receiving loan forgiveness—but was unable to affect their employment choices.

6 Can Teachers' Lack of Value of TLF Explain the Null Effects on Retention?

6.1 Contingent Valuation Design

While we successfully encouraged higher rates of TLF application and receipt in our experimental intervention, we did not detect any changes in retention, a key goal of the TLF program. To better understand how teachers value the possibility of loan forgiveness, we

[14] In our RD specification, we use as an outcome whether a teacher has moved to a new school that is TLF-eligible, while here we simply use as an outcome whether a teacher remains at any TLF school, including their initial school. In Appendix C, we explain the choice of outcome in each case.

added a series of hypothetical employment choice questions to our second survey of teachers in 2018, presenting the respondents with a contingent valuation exercise based on hypothetical comparisons of employment options. Teachers were asked to consider jobs in two different schools with characteristics drawn from a representative pool of 30 TLF-eligible and 30 non-TLF-eligible schools in Michigan. As shown in the survey materials (see Appendix B), each comparison consisted of a school's total student enrollment, pupil-to-teacher ratio (PTR), percentage of students receiving FRPL, percentage of students proficient in math and reading, and school urbanicity (i.e., urban, suburban, or rural). In addition, half of the surveys included text explicitly indicating the school's eligibility status for the TLF program (see Appendix Figure B.1).

Teachers were asked to choose which school they would hypothetically prefer, assuming they would be paid the same salary at both schools. A pair of follow-up questions asked if the respondent would be willing to work at the school they did not initially choose if they were to receive an additional \$5,000 or \$10,000 in compensation, where compensation was either in the form of a one-time signing bonus or a reduction in student loan debt (the form of compensation varied across respondents as well, see Appendix Figures B.2 and B.3). This exercise required teachers to make a choice that trades off the various attributes of a school, an approach to measuring employment preferences that has been undertaken in several other settings (Eriksson and Kristensen, 2014; Mas and Pallais, 2017; Maestas et al., 2023; Wiswall and Zafar, 2018). Johnston (2021) examines preferences among teachers in an urban Texas school district, using a similar contingent valuation design, but focuses on broader choices made by teachers and not specifically on loan forgiveness opportunities.

In our baseline model, we estimate a logit specification where the teacher chooses between one school (k) or another (j) based on the difference in compensation (if any), $\triangle comp_{kj}$, and its interaction with an indicator for whether or not the salary differential is framed as debt relief, D_{debt}. We also include the difference in the underlying TLF status of the schools, $\triangle TLF_{kj}$, and its interaction with an indicator for whether or not the TLF status is explicitly listed, D_{explicit}. Finally, the model features differences in the remaining school attributes, $\triangle X_{kj}$, described above. For each comparison, we estimate the following model:

$$\begin{aligned} Pr\left[\text{Choose } k \text{ over } j\right] = \Lambda\,(&\beta_0 \triangle comp_{kj} + \beta_{\text{debt}} \triangle comp_{kj} \times D_{\text{debt}} \\ &+ \beta_{\text{TLF}} \triangle TLF_{kj} + \beta_{\text{explicit}} \triangle TLF_{kj} \times D_{\text{explicit}} \\ &+ \beta_X \triangle X_{kj}\,), \end{aligned} \tag{3}$$

where $\Lambda\left(\cdot\right)$ is the logit function.

Once we have estimated the parameters of this model, we can use them to calculate the willingness to pay for marginal changes in the various amenities. That is, we scale the change in the probability of choosing a school due to a change in an amenity a by the change in the choice probability from an increase in the salary differential:

$$WTP_a \equiv \frac{\partial Pr\left[\text{Choose } k \text{ over } j\right] / \partial \triangle \text{Amenity}_a}{\partial Pr\left[\text{Choose } k \text{ over } j\right] / \partial \triangle comp_{kj}} = \frac{\beta_a}{\beta_0}. \tag{4}$$

We interpret this parameter as the dollar value of a marginal change in the amenity. When the amenity in question is discrete in nature, we use the following formula:

$$WTP_a \equiv \frac{\triangle Pr\left[\text{Choose } k \text{ over } j\right] / \triangle\left(\triangle \text{Amenity}_a\right)}{\partial Pr\left[\text{Choose } k \text{ over } j\right] / \partial \triangle comp_{kj}} = \frac{\Lambda\left(\gamma Z_1\right) - \Lambda\left(\gamma Z_0\right)}{\beta_0 \Lambda\left(\gamma Z\right)\left(1 - \Lambda\left(\gamma Z\right)\right)}, \tag{5}$$

where $\gamma = \left(\beta_0, \beta_{\text{debt}}, \beta_{\text{TLF}}, \beta_{\text{explicit}}, \beta_X\right)$ is the vector of coefficients and Z is the vector of regressors from equation (3), while Z_1 and Z_0 force each school to either have or not have the amenity. We average this expression over the set of schools in the sample.

We can also calculate the value of a dollar of potential debt forgiveness relative to a dollar of a cash bonus:

$$WTP_{\text{debt}} \equiv \frac{\partial Pr\left[\text{Choose } k \text{ over } j | D_{\text{debt}} = 1\right] / \partial \triangle comp_{kj}}{\partial Pr\left[\text{Choose } k \text{ over } j | D_{\text{debt}} = 0\right] / \partial \triangle comp_{kj}} = \frac{\beta_0 + \beta_{\text{debt}}}{\beta_0}. \tag{6}$$

Because a cash bonus is fungible, we might expect this ratio to be equal to or less than one, in the case that debt relief includes expected administrative costs. Alternatively, if there is some additional commitment value of being compensated in dollars of debt forgiveness, this could push the value toward one. Finally, we can use the parameters to estimate by how much a \$5,000 cash bonus might increase the chances that a teacher chooses a school.

Each teacher is presented with three comparisons. To minimize survey length, we only ask for up to three choices per comparison, with incremental salary increases designed to get the teacher to change their first decision. This design, however, introduces a mechanical correlation in our sample: a positive $\triangle comp_{kj}$ is only observed when school k was initially rejected. This creates a downward bias on our estimate of β_0. To correct this bias, we add two additional inferred choices for each comparison: if school k is initially chosen with no compensation differential, then we assume it would continue to be chosen when $\triangle comp_{kj} \in \{\$5K, \$10K\}$ and add those choices to our data set. This breaks the mechanical bias in our sample and allows us to recover the value of β_0.

The unit of analysis in this case is each choice made by a respondent. We cluster our standard errors at the respondent-by-comparison level since choices are correlated within a given comparison.

6.2 Revealed Value of TLF from Contingent Valuation Surveys

We have shown that simply becoming eligible for the TLF program does not result in differences in teacher retention. For that matter, increasing awareness about school- or individual-level eligibility and increasing the likelihood of applying does not influence retention either—at least not within the range of information and take-up effects achieved within our intervention. In our final analysis, we attempt to more directly measure teachers' valuations of the TLF program using the discrete choice model presented above. Importantly, we can include in our model an indicator for whether a school was drawn from the TLF-eligible pool. If teachers are sufficiently aware of the types of school that qualify, this may impact their choices. Furthermore, we randomly notify a subset of teachers whether a school indeed qualifies for TLF, which makes the prospect of loan forgiveness explicit.

Table 6, column 1 presents the results of our discrete choice model. The results are presented as willingness to pay, as in equation 4. For example, we find that teachers have a negative valuation for school size as measured by enrollment. The \$0.49 estimate means that every additional 100 students is treated as a one-time \$50 pay deduction. The teachers have a positive valuation of the share of students proficient in math and a slight preference for rural schools relative to suburban ones. They place a negative value on the pupil-to-teacher ratio (PTR) and on average require a \$1,200 compensating bonus to work in an urban school.

Turning to school TLF status, there is a modest and statistically significant difference between TLF-eligible and non-eligible schools when TLF status is not made explicit. Teachers value teaching in a TLF school by \$500 relative to a non-TLF school, all else equal. However, when a TLF school is explicitly noted, teachers value that status at an additional \$3,000, which is a bit more than half the value of debt forgiveness for non-STEM teachers. In this initial column, we do not allow for a separate effect of debt relief or a cash bonus; that is, we assume $\beta_{\text{debt}} = 0$.

The next column of Table 6 examines the heterogeneity of valuation based on whether teachers are eligible for the larger STEM/special education-based amount of \$17,500 (column 2). The value of a TLF school is twice as large, \$1,000 versus \$500, for those teachers eligible for the larger forgiveness amount. In addition, the explicit mention of TLF eligibility is valued more for those who could qualify for \$17,500.

In column 3, we allow the response to vary based on whether the difference in compensation is framed as debt relief. As discussed in equation 6, this allows us to estimate the relative value of debt relief to a cash bonus. The teachers value debt relief at 90 cents on the dollar. A value less than one could reflect the fact that not all teachers currently have student debt or that some teachers may have liquidity constraints that a cash bonus is more effective at solving than a reduction in debt. If the 25 percent of teachers who report not having debt had no value for debt relief, we might expect this ratio to be no more than 75 cents on the dollar. A higher value could signify that even teachers without debt find value in working at a school that is designated as high-need, perhaps for altruistic reasons.

In column 4, we separately look at the teachers who report having a positive federal loan balance. In this case, the value of explicitly mentioning TLF increases, while the implicit value decreases. Not surprisingly, these teachers also have a greater relative value of compensation in the form of debt relief. We cannot reject the null hypothesis that debt relief and a cash bonus are valued equally for this group.

We can also use our estimates in the bottom rows to benchmark the value of $5,000 of debt relief from our contingent value exercise. We find that $5,000 of forgiveness would break a 50-50 tie between two equivalent schools by 16 percentage points, changing the relative probabilities to 66 and 34 percent for the eligible school and comparison school, respectively, or a 32 percent increase.

Can we reconcile these valuations with our empirical results above? Looking at the mean retention rates from one row to the next in Appendix Table A.2 for schools just below the RD thresholds, the share of teachers still at their initial school drops between 9 and 12 percentage points each year.[15] Our contingent valuation estimates suggest that at best, TLF could have averted about 32 percent(= 1 - 34/50) of this attrition, or between 2.9 and 3.8 percentage points. Our preferred point estimates in column 4 are typically smaller than these predictions and of the wrong sign, but our RD confidence intervals cannot rule them out. We therefore deem the RD estimates too imprecise to be conclusive.

However, in the case of our RCT, we have much more precise null results. In Table 5, we see in column 2 that teacher retention drops by 21 percentage points in the second year following the intervention and another 15 percentage points in the third year. Our contingent valuation estimates suggest that TLF might have staved off 6.7 and 4.8 percentage points in

[15]For example, in Table A.2, column 4, the mean retention rate is 88 percent, which means that 12 percent of teachers are gone by year 2. The cumulative retention rate in year 3 is 78 percent, meaning another 10-percentage point reduction, and so forth.

years 2 and 3, respectively. The confidence intervals for our actual estimates rule out such effects. We find similar patterns for years 4 and 5 in column 4: the reductions in attrition implied by the contingent valuation exercise again lie outside of our confidence intervals.

The results from the contingent valuation analysis suggest teachers do in fact value loan forgiveness and that the heterogeneity goes in the expected direction, with those with more incentive to value TLF doing so. Although the valuations may be reconciled with the relatively wide confidence intervals of our RD estimates, we conclude that our null results from our field experiment, which are more precisely estimated, are unlikely to be simply explained by an inherent lack of value of debt forgiveness.

7 Discussion

We have shown that teachers do, in theory, value debt relief and are more likely to take up the program when costs are sufficiently reduced, but in practice the take-up responses are modest, and there are no meaningful changes in teacher retention. These findings suggest that some frictions remain beyond the extent of our previous analysis. To better understand what frictions might remain, we conducted in-person focus groups with Michigan teachers and interviewed student loan servicers by phone.

The focus groups were conducted in spring 2016, consisting of two sessions and eight teachers. The teachers were given $25 gift cards to answer questions about student debt, interactions with their loan servicers, awareness of loan forgiveness options, and whether they had ever pursued loan forgiveness, among other open-ended questions. They frequently noted that the relationship with servicers has had a sometimes adversarial dynamic. They also cited servicers' aggressive collection tactics, such as calling their place of employment when payments are late, and an unwillingness to provide flexibility in repayment schedules through deferral or forbearance. These interactions bred a lack of trust in the servicers and ultimately a skepticism of whether or not a loan forgiveness program would deliver on its intended promises.

The teachers also pointed to broader concerns regarding the accumulation of student loan debt at the point of origination while in college, the trends in teacher salaries not keeping up with rising debt burdens, and wavering trust in an education system that relies so heavily on debt to meet the requirements of being a teacher. Finally, they noted a lack of trust in offers that sound too good to be true, in some cases doubting the promises laid out in the outreach materials our research team developed to increase awareness of the TLF program.

We also reached out to 11 student loan servicers through their publicly listed telephone numbers for customer service. Of these 11, one refused to discuss their practices with us. The 10 servicer representatives we spoke to showed significant variability in answering details about the TLF program, but those with less information on hand said they would ask other representatives about the process if needed. That notwithstanding, the customer service line represents a common first step in the loan forgiveness process for most applicants. As TLF is not a major program for servicers given their large non-teacher borrower populations, this was not a particularly salient program or priority for representatives. We asked a series of specific questions about steps that teachers should take to fulfill the TLF process, but many representatives did not know the exact details of the process and frequently suggested referring the applicant to the Department of Education's website.

The conversations with servicers suggested that it would be easy for TLF applicants to be confused about what steps would be completed individually, the required input from their employer, the required forms from the Department of Education, and ultimately what role the loan servicer plays in the process. The loan servicer representatives we spoke to were in no way discouraging loan forgiveness applications and often shared that if a caller revealed that they were a teacher, the loan servicer would bring up TLF. Nonetheless, our discussions indicate that loan forgiveness programs that rely significantly on the loan servicer may introduce additional barriers to access. In particular, when borrowers have had negative experiences with their servicers or with collections in the past, they may be hesitant to seek out those same entities to apply for loan forgiveness programs.

Another possibility is that the teachers in our sample passed on the TLF program in favor of the Public Service Loan Forgiveness (PSLF) program, which might afford a greater amount of debt reduction. At the time of our study, years of employment could count either toward TLF or PSLF, but not both, a rule that has subsequently been changed. The PSLF program forgives all remaining debt for those who have worked in certain public sector jobs for 10 consecutive years and applies to teachers at any non-profit school, not just high-need ones.[16] However, the PSLF program is not without trade-offs. PSLF program participants are instructed to certify employment each year, rather than upon applying for forgiveness as in TLF. It takes twice as long to qualify for PSLF as compared to TLF, and in order for PSLF to forgive any substantial amount of debt after 10 years, it must be paired with an income-based repayment plan, which, at the time of our study, required additional paperwork for enrollment. At the very least, for people with less than $5,000 in debt, TLF forgives the same amount of debt sooner. While some teachers may have preferred PSLF as a debt forgiveness strategy, this alternative program did not come up in our discussions with teachers, suggesting that similar information barriers may have been present for this alternative option.

8 Conclusion

Our results show that eligibility for TLF alone is unlikely to spur dramatic changes in teacher retention. More targeted information and application assistance did prove effective at substantially increasing teacher awareness and modestly increasing take-up. However, in none of our settings did we see significant changes in teacher retention. The patterns thus suggest that the lack of a retention effect from the TLF program was not simply due to low information or administrative barriers. Our survey evidence further indicates that

[16] For more on the PSLF program and specific challenges with take-up during our period of study, see Briones et al. (2022).

the limited impact on retention is not due to a fundamental low value of the program for teachers, at least in the case of our RCT. At the very least, the hypothetical exercise indicates a non-trivial value for the debt relief. Taken together with our earlier evidence, we find it plausible that debt relief is valuable to teachers in theory—even enough so to potentially alter their decision about where to teach. In practice, however, the process of understanding the requirements, attaining eligibility, enrolling in the program, and working with a financial intermediary, is enough of a barrier to substantially impede those teachers who are not yet eligible from staying at their respective schools in order to qualify for the program.

Our conclusions are corroborated by our own experience in preparing informational materials for potential TLF participants. Our research team, highly motivated to encourage take-up of the program, struggled to find clear guidelines on how to navigate the enrollment process. Public information on the TLF-eligibility status of a school must be found online and confirmed separately for each school year. An administrator at one's school must confirm work history, but it is not always clear who is allowed to do this verification. Finally, a teacher must work through their loan servicer to submit an application, and each servicer may have a varying level of preparedness to facilitate this process. Our results suggest that if any future loan forgiveness program is implemented in the U.S., ease of application and eligibility determination may be key to achieving broad participation.

Ultimately, the intention of teacher loan forgiveness policies is to attract and retain talented teachers. We found no evidence that TLF eligibility increased retention nor did we detect any sorting of teachers on any attributes into marginally eligible schools. While our intervention helped some teachers find relief from their debt burdens, our results suggest that influencing employment choices would require additional information and incentives above and beyond those provided by the current teacher loan forgiveness program.

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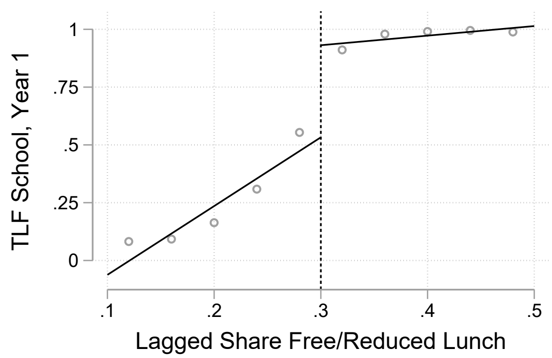
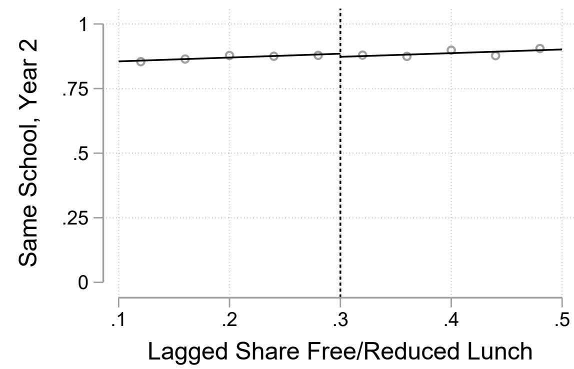
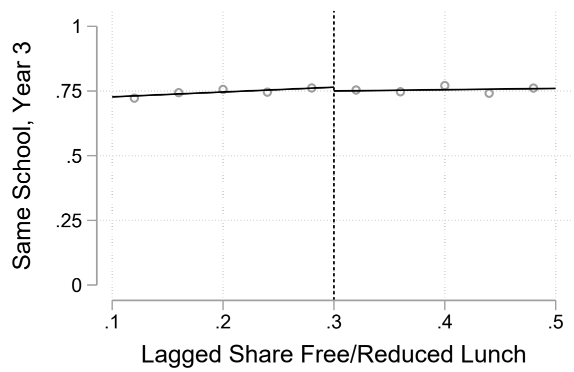
Figure 1: Regression Discontinuity Results: First Stage and School-Level Retention



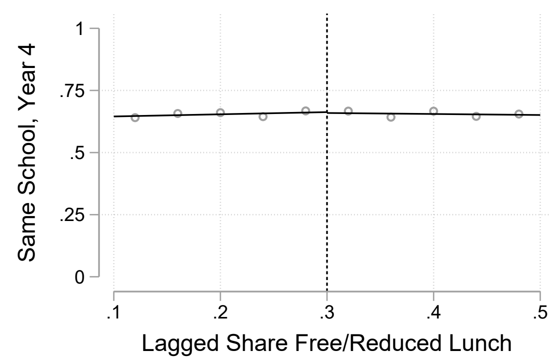
(a) TLF Eligibility by FRPL Share, Year 1



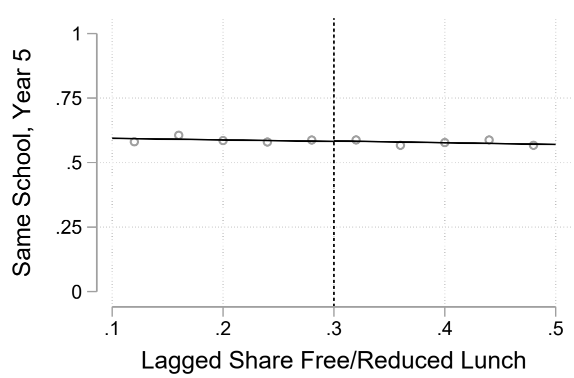
(b) Share in Same School, Year 2

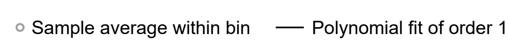


(c) Share in Same School, Year 3



(d) Share in Same School, Year 4

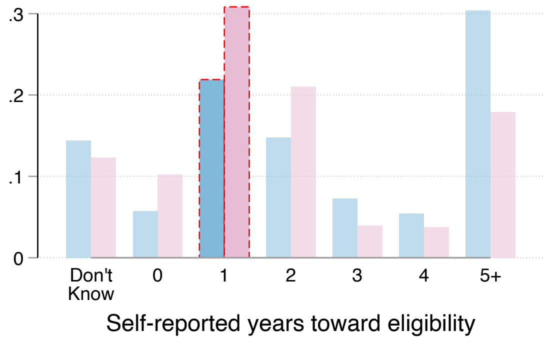




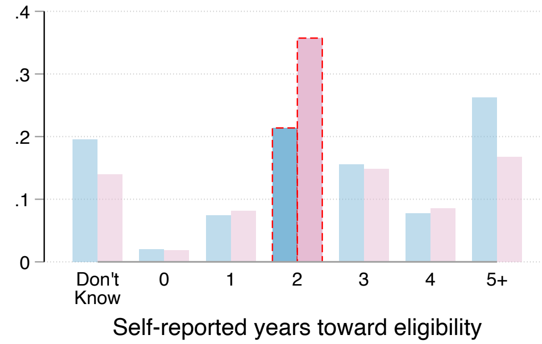
(e) Share in Same School, Year 5

Notes: The figures show teachers grouped by the share of students receiving FRPL in the year before their first year of teaching (x-axis). Plotted on the y-axis in panel (a) is the first stage, i.e. the TLF status of the first-year school, and in panels (b)–(e), retention in the same school in years 2 through 5.

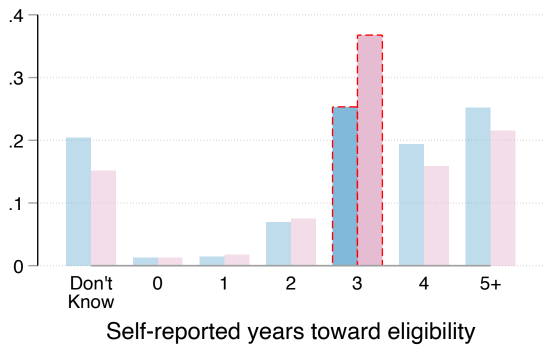
Figure 2: Self-Reported Years of Eligibility versus Administrative Records



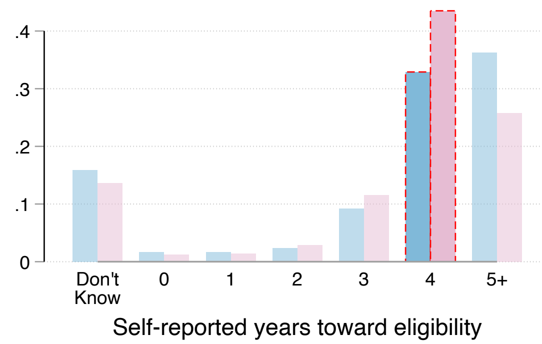
(a) Teachers with 1 Year of Eligibility



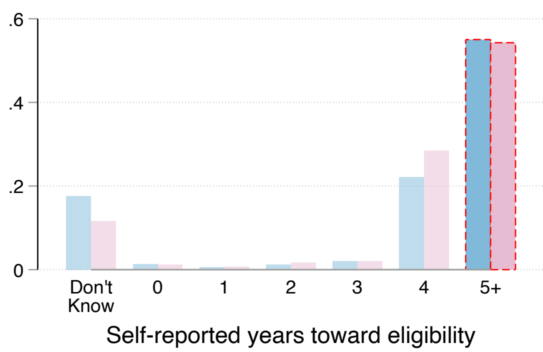
(b) Teachers with 2 Years of Eligibility

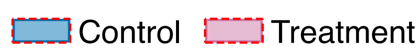


(c) Teachers with 3 Years of Eligibility



(d) Teachers with 4 Years of Eligibility





(e) Teachers with at Least 5 Years of Eligibility

Notes: The figures show the share of teachers who self-reported a given number of years of eligibility (x-axis) in our follow-up surveys, separately for treated and control group members. Each panel features a sample grouped together based on the number of years toward eligibility derived from administrative records. Data are for the 2016 and 2018 surveys, pooled.

Table 1: Baseline Covariate Balance - 2015 & 2017, Pooled

	(1)	(2)	(3)	(4)
	Control	Treatment	p-value	N
Enrollment	575	554	0.67	44,309
Percent Free/Reduced Lunch	0.62	0.62	0.88	44,282
Percent Black	0.29	0.27	0.40	44,256
Percent Hispanic/Latino	0.09	0.09	0.97	44,256
Percent Asian	0.02	0.02	0.02	44,256
Magnet School	0.14	0.12	0.54	44,226
Charter School	0.25	0.24	0.90	44,362
Middle/High School	0.33	0.33	0.80	44,362
Special Needs School	0.05	0.04	0.48	44,362
Secondary School	0.42	0.39	0.23	44,362
Female Teacher	0.78	0.78	0.25	44,358
White Teacher	0.90	0.90	0.84	44,362
Black Teacher	0.07	0.07	0.56	44,362
Hispanic/Latino Teacher	0.02	0.02	0.02	44,362
Asian Teacher	0.01	0.01	0.06	44,362
Age	35.1	35.0	0.48	44,358
Cumulative TLF Years: 5K	4.35	4.39	0.79	44,362
Cumulative TLF Years: 17.5K	0.93	0.93	0.94	44,362
Joint Test			0.08	44,173
N	23,050	21,312		44,362

Notes: Balance for experimental intervention, 2015 and 2017 samples, pooled. Columns provide average values for control and treatment groups, p-value of a test of equality, and the sample size for each school or teacher attribute.

Table 2: Survey Responses by Treatment Status

	(1)	(2)	(3)	(4)
Panel A: General Outcomes	Control	Treatment	p-value	N
Has federal student loans	0.75	0.77	0.06	10,654
between \$1 & \$10K	0.05	0.04	0.39	7,972
between \$10K & \$20K	0.11	0.13	0.00	7,972
between \$20K & \$30K	0.19	0.18	0.97	7,972
between \$30K & \$50K	0.29	0.29	0.92	7,972
more than \$50K	0.37	0.35	0.07	7,972
Has private student loans	0.27	0.27	0.75	10,111
Total monthly loan payment	644	773	0.28	7,651
Has ever been delinquent	0.34	0.34	0.87	8,095
Has difficulty paying bills	0.79	0.79	0.60	10,339
Joint Test			0.22	6,860
N	5,530	4,927		10,457
Panel B: Information Outcomes, <5 Years of Eligibility				
Recalls receiving a treatment letter/email	0.11	0.51	0.00	5,787
Knows School is TLF-Eligible	0.58	0.68	0.00	5,764
Knows Correct Years Toward TLF Eligibility	0.29	0.38	0.00	5,755
Knows TLF Rules Very Well or at Basic Level	0.65	0.71	0.00	5,784
Has Applied for TLF	0.24	0.22	0.26	5,762
Joint Test			0.00	5,722
N	3,146	2,806		5,952
Panel C: Information Outcomes, 5+ Years of Eligibility				
Recalls receiving a treatment letter/email	0.17	0.56	0.00	4,624
Knows School is TLF-Eligible	0.68	0.79	0.00	4,620
Knows Correct Years Toward TLF Eligibility	0.52	0.53	0.01	4,600
Knows TLF Rules Very Well or at Basic Level	0.75	0.83	0.00	4,624
Has Applied for TLF	0.57	0.62	0.00	4,610
Joint Test			0.00	4,562
N	2,384	2,121		4,505

Notes: Survey responses 2016 and 2018 follow-up surveys, pooled.

Table 3: Survey - "Are You Familiar with the Federal TLF Program?", by Years of Eligibility

	(1)	(2)	(3)	(4)	(5)	(6)
	<5 Years of Eligibility			5+ Years of Eligibility		
	Control	Treatment	Difference	Control	Treatment	Difference
No, I have no knowledge of such programs.	0.06	0.04	-0.02	0.04	0.02	-0.02
Yes, I have heard of loan forgiveness programs. However, I do not know anything about them.	0.29	0.25	-0.04	0.20	0.15	-0.06
Yes, understand the basic rules, but I do not know the specific details of this program.	0.37	0.45	0.08	0.26	0.28	0.02
Yes, I am very familiar with the rules and details of the program.	0.27	0.26	-0.02	0.49	0.55	0.05
N	3,048	2,736	5,784	2,529	2,095	4,624
Joint Test			0.00			0.00

Notes: Survey answers, 2016 and 2018 follow-up surveys, pooled.

Table 4: Survey - "Have You Applied for and/or Received Loan Forgiveness through TLF?", by Years of Eligibility

	(1)	(2)	(3)	(4)	(5)	(6)
	<5 Years of Eligibility			5+ Years of Eligibility		
	Control	Treatment	Difference	Control	Treatment	Difference
I have applied for and received loan forgiveness.	0.11	0.10	-0.01	0.38	0.40	0.02
I have applied, but have not received loan forgiveness.	0.12	0.12	0.00	0.18	0.22	0.03
No, I have not applied for loan forgiveness.	0.76	0.78	0.01	0.43	0.38	-0.05
N	3,034	2,728	5,762	2,521	2,089	4,610
Joint Test			0.23			0.00

Notes: Survey answers, 2016 and 2018 follow-up surveys, pooled.

Table 5: RCT Results: School-level Retention

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
Same School:						
Year 2	0.004	0.003	-0.000	-0.003	0.008	0.010
	[-0.009, 0.017]	[-0.007, 0.014]	[-0.017, 0.018]	[-0.017, 0.011]	[-0.012, 0.028]	[-0.007, 0.027]
Control Mean:	0.797	0.797	0.806	0.806	0.787	0.787
Year 3	0.006	0.005	0.004	-0.000	0.008	0.011
	[-0.009, 0.021]	[-0.008, 0.018]	[-0.018, 0.025]	[-0.017, 0.017]	[-0.014, 0.030]	[-0.007, 0.029]
Control Mean:	0.648	0.648	0.652	0.652	0.644	0.644
Year 4	-	-	0.017	0.014	-	-
			[-0.005, 0.040]	[-0.003, 0.032]		
Control Mean:			0.533	0.533		
Year 5	-	-	0.006	0.003	-	-
			[-0.017, 0.029]	[-0.015, 0.021]		
Control Mean:			0.453	0.453		
Controls	No	Yes	No	Yes	No	Yes
N	44,362	44,173	23,397	23,263	20,965	20,910

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in the same school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below.

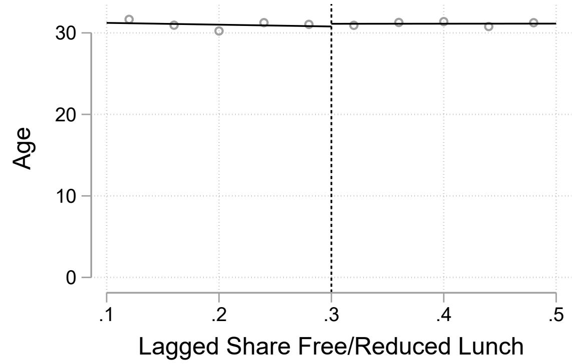
Table 6: Contingent Valuation - Logit Regression Results

	(1)	(2)	(3)	(4)
School Attributes	Baseline	Eligible for $17.5K	Debt Framing	Debt Framing & has Loans
TLF School	$509	$1,051	$484	$263
	[507, 511]	[1,042, 1,060]	[482, 487]	[261, 265]
TLF School x Explicit	$3,081	$3,261	$2,912	$3,965
	[2,647, 3,515]	[2,474, 4,049]	[2,501, 3,324]	[3,461, 4,470]
Enrollment	-$0.49	-$0.86	-$0.46	-$0.36
	[-0.90, -0.08]	[-1.58, -0.15]	[-0.85, -0.07]	[-0.81, 0.09]
Pupil/Teacher Ratio	-$241	-$224	-$229	-$225
	[-268, -214]	[-273, -175]	[-255, -203]	[-255, -196]
Free/Reduced Lunch Share	-$3.84	-$10.35	-$3.61	-$0.10
	[-10.26, 2.57]	[-21.87, 1.17]	[-9.68, 2.47]	[-7.10, 6.89]
Share Proficient in Math/Reading	$91	$73	$86	$82
	[85, 97]	[62, 83]	[81, 92]	[75, 88]
City	-$1,283	-$1,223	-$1,216	-$1,243
	[-1,515, -1,050]	[-1,646, -799]	[-1,436, -996]	[-1,493, -993]
Rural	$211	$397	$201	$59
	[18, 404]	[51, 742]	[18, 384]	[-150, 268]
Average Partial Effect of $5K in Salary	0.18	0.18	0.18	0.18
	[0.18, 0.18]	[0.18, 0.18]	[0.18, 0.18]	[0.18, 0.18]
Relative Value of Debt Relief	-	-	0.90	0.97
			[0.87, 0.92]	[0.94, 1.00]
Number of Respondents	5,561	1,854	5,561	4,132
Number of Choices	83,261	27,893	83,261	61,946

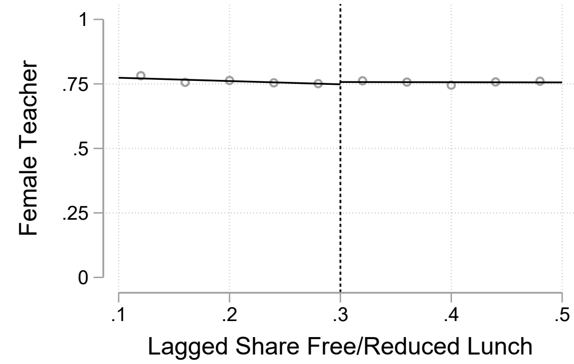
Notes: Results of contingent valuation analysis using sample from experimental intervention, 2018 survey respondents. Column 1 reports valuations from all respondents. Column 2 restricts the sample to those eligible for $17,500 in forgiveness. Column 3 uses the baseline sample and adds information on whether the differences in compensation were framed as an income bonus or debt forgiveness. Column 4 follows the same specification as column 3 but restricts the sample to those with outstanding student loan debt.

Appendix A Additional Figures and Tables

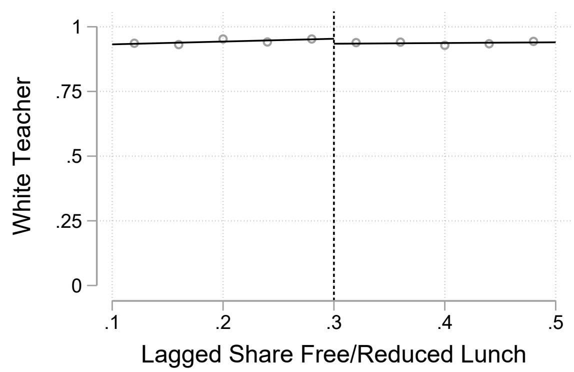
Figure A.1: Regression Discontinuity Results – Covariate Balance and Running Variable Manipulation Test



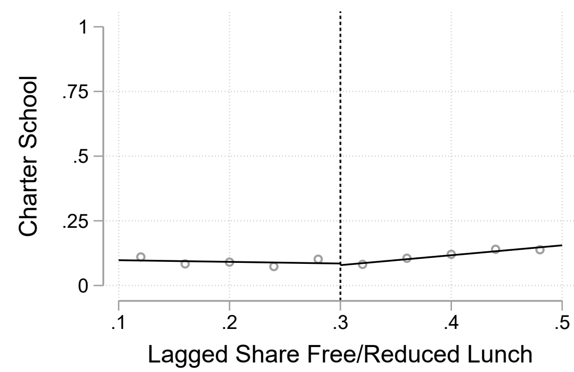
(a) Average Teacher Age



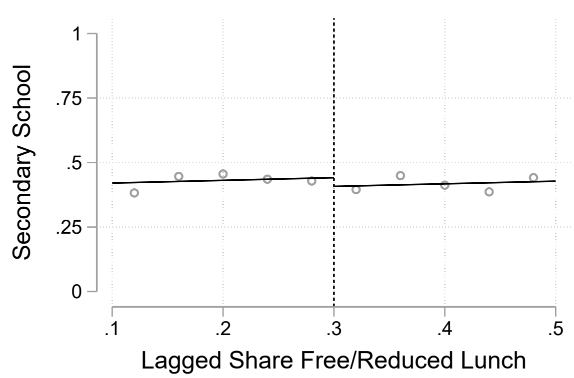
(b) Share Female



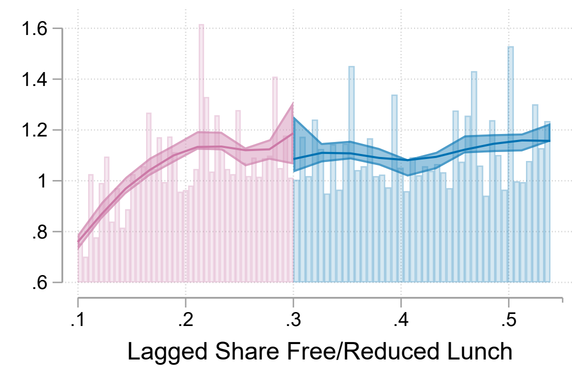
(c) Share White



(d) Share Charter School



(e) Share Secondary School



(f) Density of Running Variable

Density - Left Density - Right
95% CI 95% CI

Sample average within bin Polynomial fit of order 1

Notes: See notes for Figure 1. Running variable figure shows the density of the running variable, used to test for manipulation of the running variable at the threshold.

Table A.1: Baseline Covariate Balance - RD Analysis

	(1)	(2)	(3)	(4)
	Mean Below Cutoff	Discontinuity	p-value	N
Enrollment	701	-128	0.19	6,414
Percent Black	0.08	-0.02	0.53	6,104
Percent Hispanic/Latino	0.04	0.00	0.99	8,561
Percent Asian	0.03	-0.00	0.79	7,830
Magnet School	0.13	-0.01	0.80	6,414
Charter School	0.15	-0.09	0.17	4,940
Middle/High School	0.48	0.01	0.88	12,555
Special Needs School	0.03	-0.00	0.76	11,129
Secondary School	0.44	-0.04	0.57	7,309
Female Teacher	0.76	0.01	0.55	11,993
White Teacher	0.95	-0.02	0.48	10,760
Black Teacher	0.01	0.01	0.36	13,265
Hispanic/Latino Teacher	0.01	0.01	0.15	13,250
Asian Teacher	0.01	-0.00	0.73	11,040
Age	30.9	0.3	0.75	8,125

Notes: Covariate balance test for RD analysis. District eligibility rate is the share of other schools in a teacher's district that are TLF-eligible.

Table A.2: RD Results: School-level Retention

	(1)	(2)
Panel A:	First Stage Effect at 30% Free/Reduced Lunch	
TLF-Eligible School	0.399	0.269
	[0.197, 0.630]	[0.247, 0.304]
Mean below cutoff:	0.533	0.587
N	25,708	4,842
	(3)	(4)
Panel B:	Reduced Form Effect at 30% Free/Reduced Lunch	
Same School:		
Year 2	-0.012	-0.005
	[-0.038, 0.015]	[-0.054, 0.044]
Mean below cutoff:	0.885	0.883
N	22,752	11,042
Year 3	-0.014	-0.018
	[-0.053, 0.026]	[-0.103, 0.063]
Mean below cutoff:	0.764	0.775
N	19,210	7,383
Year 4	-0.002	-0.001
	[-0.034, 0.031]	[-0.091, 0.087]
Mean below cutoff:	0.662	0.687
N	16,233	6,659
Year 5	0.004	0.019
	[-0.040, 0.045]	[-0.077, 0.116]
Mean below cutoff:	0.581	0.584
N	13,890	7,183
Functional Form	Simple Linear	Local Linear
Bandwidth	[.1,.5]	Data driven

Notes: Estimated regression discontinuity effects on probability of remaining in the same school in years 2, 3, 4, and 5. Running variable is percent free/reduced lunch in year prior to first year of teaching.

Table A.3: RD Results: New TLF-Eligible School Transition

	(1)	(2)
Panel A:	First Stage Effect at 30% Free/Reduced Lunch	
TLF-Eligible School	0.399	0.269
	[0.197, 0.630]	[0.247, 0.304]
Mean below cutoff:	0.533	0.587
N	25,708	4,842
	(3)	(4)
Panel B:	Reduced Form Effect at 30% Free/Reduced Lunch	
New TLF-Eligible School:		
Year 2	0.005	-0.003
	[-0.019, 0.029]	[-0.046, 0.040]
Mean below cutoff:	0.082	0.079
N	22,752	9,230
Year 3	0.013	0.036
	[-0.027, 0.052]	[-0.019, 0.098]
Mean below cutoff:	0.163	0.134
N	19,210	5,449
Year 4	0.018	0.031
	[-0.012, 0.048]	[-0.039, 0.106]
Mean below cutoff:	0.230	0.197
N	16,233	6,311
Year 5	0.009	0.021
	[-0.026, 0.045]	[-0.059, 0.105]
Mean below cutoff:	0.293	0.259
N	13,890	6,581
Functional Form	Simple Linear	Local Linear
Bandwidth	[.1,.5]	Data driven

Notes: Estimated regression discontinuity effects on probability of remaining in a new TLF-eligible school in years 2, 3, 4, and 5. Running variable is percent free/reduced lunch in year prior to first year of teaching.

Table A.4: RD Results: State of Michigan Retention

	(1)	(2)
Panel A:	First Stage Effect at 30% Free/Reduced Lunch	
TLF-Eligible School	0.399	0.269
	[0.197, 0.630]	[0.247, 0.304]
Mean below cutoff:	0.533	0.587
N	25,708	4,842

	(3)	(4)
Panel B:	Reduced Form Effect at 30% Free/Reduced Lunch	
Michigan School:		
Year 2	-0.010	-0.014
	[-0.018, -0.000]	[-0.037, 0.006]
Mean below cutoff:	0.948	0.949
N	23,470	10,855
Year 3	-0.012	-0.014
	[-0.028, 0.002]	[-0.050, 0.023]
Mean below cutoff:	0.908	0.903
N	19,979	11,858
Year 4	0.004	0.006
	[-0.015, 0.022]	[-0.031, 0.044]
Mean below cutoff:	0.872	0.869
N	16,936	9,735
Year 5	0.005	0.025
	[-0.016, 0.026]	[-0.014, 0.063]
Mean below cutoff:	0.855	0.836
N	14,481	7,819
Functional Form	Simple Linear	Local Linear
Bandwidth	[.1,.5]	Data driven

Notes: Estimated regression discontinuity effects on probability of remaining in a Michigan school in years 2, 3, 4, and 5. Running variable is percent free/reduced lunch in year prior to first year of teaching.

Table A.5: Baseline Covariate Balance - by Years of Eligibility

	(1)	(2)	(3)	(4)	(5)	(6	(7)	(8)
	<5 Years of Eligibility				5+ Years of Eligibility			
	Control	Treatment	p-value	N	Control	Treatment	p-value	N
Enrollment	572	542	0.75	25,234	579	569	0.67	19,075
Percent Free/Reduced Lunch	0.65	0.65	0.56	25,209	0.60	0.59	0.60	19,073
Percent Black	0.33	0.31	0.44	25,195	0.23	0.22	0.44	19,061
Percent Hispanic/Latino	0.09	0.09	0.85	25,195	0.08	0.09	0.82	19,061
Percent Asian	0.02	0.02	0.02	25,195	0.02	0.02	0.09	19,061
Magnet School	0.14	0.13	0.45	25,174	0.12	0.12	0.76	19,052
Charter School	0.31	0.30	0.85	25,272	0.16	0.16	0.91	19,090
Middle/High School	0.34	0.33	0.46	25,272	0.33	0.34	0.65	19,090
Special Needs School	0.04	0.03	0.40	25,272	0.05	0.05	0.62	19,090
Secondary School	0.44	0.40	0.11	25,272	0.39	0.38	0.68	19,090
Female Teacher	0.78	0.77	0.27	25,270	0.79	0.79	0.51	19,088
White Teacher	0.89	0.89	0.92	25,272	0.92	0.92	0.74	19,090
Black Teacher	0.07	0.07	0.63	25,272	0.07	0.06	0.53	19,090
Hispanic/Latino Teacher	0.02	0.02	0.34	25,272	0.01	0.02	0.00	19,090
Asian Teacher	0.01	0.01	0.08	25,272	0.01	0.01	0.52	19,090
Age	33.4	33.2	0.19	25,270	37.4	37.4	0.66	19,088
Cumulative TLF Years: 5K	1.99	1.95	0.06	25,272	7.50	7.57	0.02	19,090
Cumulative TLF Years: 17.5K	0.44	0.39	0.01	25,272	1.59	1.64	0.51	19,090
Joint Test			0.03	25,141			0.12	19,032
N	13,189	12,083		25,272	9,861	9,229		19,090

Notes: Balance for experimental intervention, 2015 and 2017 samples.

Table A.6: RCT Results: TLF-Eligible School Retention

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
TLF School:						
Year 2	0.004	0.003	0.000	-0.002	0.007	0.009
	[-0.004, 0.011]	[-0.004, 0.010]	[-0.010, 0.011]	[-0.013, 0.008]	[-0.003, 0.018]	[-0.000, 0.019]
Control Mean:	0.896	0.896	0.892	0.892	0.901	0.901
Year 3	0.001	0.000	0.001	-0.003	0.001	0.003
	[-0.009, 0.010]	[-0.008, 0.009]	[-0.013, 0.015]	[-0.016, 0.010]	[-0.012, 0.014]	[-0.009, 0.015]
Control Mean:	0.826	0.826	0.818	0.818	0.835	0.835
Year 4	-	-	0.009	0.006	-	-
			[-0.006, 0.024]	[-0.007, 0.019]		
Control Mean:			0.761	0.761		
Year 5	-	-	0.007	0.004	-	-
			[-0.008, 0.023]	[-0.010, 0.017]		
Control Mean:			0.714	0.714		
Controls	No	Yes	No	Yes	No	Yes
N	44,362	44,173	23,397	23,263	20,965	20,910

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in a TLF school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below.

Table A.7: RCT Results: State of Michigan Retention

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
Michigan School:						
Year 2	0.001	-0.000	-0.002	-0.005	0.004	0.005
	[-0.005, 0.007]	[-0.005, 0.005]	[-0.010, 0.007]	[-0.013, 0.003]	[-0.004, 0.012]	[-0.003, 0.012]
Control Mean:	0.924	0.924	0.921	0.921	0.928	0.928
Year 3	-0.001	-0.002	-0.002	-0.006	0.001	0.001
	[-0.010, 0.008]	[-0.009, 0.006]	[-0.015, 0.010]	[-0.017, 0.006]	[-0.010, 0.012]	[-0.008, 0.011]
Control Mean:	0.867	0.867	0.860	0.860	0.874	0.874
Year 4	-	-	0.005	0.002	-	-
			[-0.008, 0.019]	[-0.010, 0.015]		
Control Mean:			0.812	0.812		
Year 5	-	-	0.002	-0.001	-	-
			[-0.013, 0.017]	[-0.014, 0.012]		
Control Mean:			0.773	0.773		
Controls	No	Yes	No	Yes	No	Yes
N	44,362	44,173	23,397	23,263	20,965	20,910

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in a Michigan school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below.

Table A.8: RCT Results: School-level Retention, Teachers with Debt

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
Same School:						
Year 2	0.003	0.003	-0.001	-0.003	0.008	0.009
	[-0.009, 0.017]	[-0.008, 0.013]	[-0.018, 0.017]	[-0.018, 0.011]	[-0.012, 0.027]	[-0.007, 0.026]
Control Mean:	0.792	0.792	0.801	0.801	0.783	0.783
Year 3	0.006	0.005	0.004	-0.000	0.009	0.012
	[-0.009, 0.022]	[-0.008, 0.018]	[-0.018, 0.025]	[-0.018, 0.017]	[-0.013, 0.031]	[-0.008, 0.030]
Control Mean:	0.639	0.639	0.642	0.642	0.636	0.636
Year 4	-	-	0.017	0.013	-	-
			[-0.007, 0.041]	[-0.005, 0.032]		
Control Mean:			0.525	0.525		
Year 5	-	-	0.006	0.003	-	-
			[-0.017, 0.029]	[-0.015, 0.020]		
Control Mean:			0.445	0.445		
Controls	No	Yes	No	Yes	No	Yes
N	41,876	41,694	21,965	21,837	19,911	19,857

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in the same school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below. Sample includes teachers with debt.

Table A.9: RCT Results: TLF-Eligible School Retention, Teachers with Debt

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
TLF School:						
Year 2	0.003	0.003	-0.001	-0.004	0.008	0.010
	[-0.004, 0.011]	[-0.004, 0.010]	[-0.012, 0.010]	[-0.015, 0.007]	[-0.002, 0.019]	[-0.000, 0.019]
Control Mean:	0.893	0.893	0.889	0.889	0.897	0.897
Year 3	0.000	-0.000	-0.000	-0.004	0.001	0.003
	[-0.009, 0.010]	[-0.009, 0.008]	[-0.015, 0.014]	[-0.017, 0.009]	[-0.012, 0.014]	[-0.008, 0.015]
Control Mean:	0.821	0.821	0.813	0.813	0.830	0.830
Year 4	-	-	0.008	0.005	-	-
			[-0.007, 0.024]	[-0.008, 0.018]		
Control Mean:			0.757	0.757		
Year 5	-	-	0.005	0.002	-	-
			[-0.011, 0.021]	[-0.012, 0.017]		
Control Mean:			0.710	0.710		
Controls	No	Yes	No	Yes	No	Yes
N	41,876	41,694	21,965	21,837	19,911	19,857

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in a TLF school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below. Sample includes teachers with debt.

Table A.10: RCT Results: State of Michigan Retention, Teachers with Debt

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
Michigan School:						
Year 2	0.001	-0.000	-0.003	-0.006	0.005	0.005
	[-0.005, 0.007]	[-0.006, 0.005]	[-0.012, 0.006]	[-0.014, 0.003]	[-0.003, 0.013]	[-0.002, 0.013]
Control Mean:	0.921	0.921	0.919	0.919	0.924	0.924
Year 3	-0.001	-0.003	-0.004	-0.007	0.001	0.002
	[-0.011, 0.008]	[-0.010, 0.005]	[-0.017, 0.009]	[-0.019, 0.005]	[-0.010, 0.012]	[-0.008, 0.011]
Control Mean:	0.862	0.862	0.856	0.856	0.870	0.870
Year 4	-	-	0.004	0.001	-	-
			[-0.010, 0.018]	[-0.011, 0.013]		
Control Mean:			0.808	0.808		
Year 5	-	-	0.000	-0.003	-	-
			[-0.015, 0.015]	[-0.016, 0.010]		
Control Mean:			0.770	0.770		
Controls	No	Yes	No	Yes	No	Yes
N	41,876	41,694	21,965	21,837	19,911	19,857

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in a Michigan school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below. Sample includes teachers with debt.

Table A.11: RCT Results: School-level Retention, Teachers eligible for $17.5K TLF

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
Same School:						
Year 2	-0.001	-0.002	0.004	0.000	-0.006	-0.001
	[-0.018, 0.016]	[-0.017, 0.013]	[-0.018, 0.026]	[-0.019, 0.020]	[-0.032, 0.021]	[-0.027, 0.024]
Control Mean:	0.848	0.848	0.864	0.864	0.831	0.831
Year 3	0.015	0.012	0.016	0.005	0.015	0.023
	[-0.009, 0.040]	[-0.009, 0.033]	[-0.018, 0.050]	[-0.024, 0.034]	[-0.023, 0.054]	[-0.010, 0.057]
Control Mean:	0.674	0.674	0.684	0.684	0.664	0.664
Year 4	-	-	0.030	0.017	-	-
			[-0.009, 0.067]	[-0.014, 0.048]		
Control Mean:			0.559	0.559		
Year 5	-	-	0.008	-0.005	-	-
			[-0.031, 0.046]	[-0.037, 0.027]		
Control Mean:			0.474	0.474		
Controls	No	Yes	No	Yes	No	Yes
N	9,409	9,311	4,936	4,871	4,473	4,440

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in the same school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below. Sample includes teachers eligible for $17,500 in loan forgiveness.

Table A.12: RCT Results: TLF-Eligible School Retention, Teachers eligible for $17.5K TLF

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
TLF School:						
Year 2	-0.002	-0.002	-0.005	-0.005	0.002	0.002
	[-0.012, 0.008]	[-0.012, 0.008]	[-0.020, 0.010]	[-0.019, 0.009]	[-0.012, 0.016]	[-0.012, 0.016]
Control Mean:	0.953	0.953	0.953	0.953	0.953	0.953
Year 3	0.009	0.008	0.009	0.007	0.008	0.010
	[-0.007, 0.025]	[-0.007, 0.024]	[-0.014, 0.031]	[-0.014, 0.029]	[-0.015, 0.031]	[-0.012, 0.033]
Control Mean:	0.862	0.862	0.857	0.857	0.867	0.867
Year 4	-	-	0.014	0.013	-	-
			[-0.012, 0.040]	[-0.012, 0.038]		
Control Mean:			0.797	0.797		
Year 5	-	-	0.015	0.013	-	-
			[-0.013, 0.043]	[-0.016, 0.042]		
Control Mean:			0.735	0.735		
Controls	No	Yes	No	Yes	No	Yes
N	9,409	9,311	4,936	4,871	4,473	4,440

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in a TLF school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below. Sample includes teachers eligible for $17,500 in loan forgiveness.

Table A.13: RCT Results: State of Michigan Retention, Teachers eligible for $17.5K TLF

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
Michigan School:						
Year 2	-0.004	-0.005	-0.007	-0.009	-0.000	-0.000
	[-0.012, 0.004]	[-0.012, 0.003]	[-0.019, 0.005]	[-0.020, 0.003]	[-0.011, 0.011]	[-0.011, 0.010]
Control Mean:	0.968	0.968	0.970	0.970	0.965	0.965
Year 3	0.009	0.008	0.007	0.004	0.011	0.012
	[-0.005, 0.023]	[-0.005, 0.022]	[-0.012, 0.026]	[-0.014, 0.023]	[-0.009, 0.031]	[-0.009, 0.033]
Control Mean:	0.897	0.897	0.896	0.896	0.899	0.899
Year 4	-	-	0.015	0.013	-	-
			[-0.007, 0.037]	[-0.009, 0.035]		
Control Mean:			0.848	0.848		
Year 5	-	-	0.013	0.010	-	-
			[-0.013, 0.038]	[-0.017, 0.036]		
Control Mean:			0.799	0.799		
Controls	No	Yes	No	Yes	No	Yes
N	9,409	9,311	4,936	4,871	4,473	4,440

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in a Michigan school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below. Sample includes teachers eligible for $17,500 in loan forgiveness.

Table A.14: RCT Results: School-level Retention, Teachers with <5 Years of Eligibility

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
Same School:						
Year 2	0.004	0.008	-0.009	-0.011	0.021	0.035
	[-0.013, 0.020]	[-0.006, 0.021]	[-0.029, 0.011]	[-0.029, 0.006]	[-0.006, 0.047]	[0.013, 0.058]
Control Mean:	0.735	0.735	0.757	0.757	0.706	0.706
Year 3	0.006	0.010	-0.005	-0.008	0.024	0.039
	[-0.013, 0.026]	[-0.007, 0.026]	[-0.031, 0.021]	[-0.031, 0.014]	[-0.005, 0.054]	[0.013, 0.063]
Control Mean:	0.548	0.548	0.567	0.567	0.520	0.520
Year 4	-	-	0.010	0.004	-	-
			[-0.017, 0.036]	[-0.021, 0.028]		
Control Mean:			0.413	0.413		
Year 5	-	-	-0.010	-0.021	-	-
			[-0.040, 0.020]	[-0.048, 0.007]		
Control Mean:			0.301	0.301		
Controls	No	Yes	No	Yes	No	Yes
N	21,354	21,236	6,237	6,197	8,631	8,606

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in the same school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below. Sample includes teachers with less than 5 years of TLF eligibility.

Table A.15: RCT Results: School-level Retention, Teachers with 5+ Years of Eligibility

	(1)	(2)	(3)	(4)	(5)	(6)
	2015, 2017		2015		2017	
Same School:						
Year 2	0.003	0.002	0.012	0.012	-0.005	-0.006
	[-0.009, 0.016]	[-0.009, 0.014]	[-0.006, 0.030]	[-0.005, 0.029]	[-0.022, 0.013]	[-0.022, 0.010]
Control Mean:	0.880	0.880	0.887	0.887	0.874	0.874
Year 3	0.004	0.002	0.011	0.010	-0.002	-0.005
	[-0.011, 0.020]	[-0.013, 0.017]	[-0.013, 0.035]	[-0.012, 0.032]	[-0.024, 0.020]	[-0.025, 0.016]
Control Mean:	0.755	0.755	0.768	0.768	0.744	0.744
Year 4	-	-	0.022	0.021	-	-
			[-0.006, 0.050]	[-0.003, 0.045]		
Control Mean:			0.659	0.659		
Year 5	-	-	0.005	0.004	-	-
			[-0.025, 0.035]	[-0.021, 0.030]		
Control Mean:			0.580	0.580		
Controls	No	Yes	No	Yes	No	Yes
N	19,090	19,032	9,007	8,971	10,083	10,061

Notes: Results using sample from experimental intervention, 2015 and 2017 samples, reported separately and pooled. Estimated treatment effects on probability of remaining in the same school in years 2, 3, 4, and 5. 95% confidence interval reported in brackets, control means reported below. Sample includes teachers with 5 or more years of TLF eligibility.

Table A.16: Baseline Covariate Balance - Survey Repsondents

	(1)	(2)	(3)	(4)
	Control	Treatment	p-value	N
Enrollment	554	540	0.81	10,447
Percent Free/Reduced Lunch	0.61	0.61	0.88	10,444
Percent Black	0.25	0.24	0.47	10,437
Percent Hispanic/Latino	0.09	0.09	0.79	10,437
Percent Asian	0.02	0.02	0.04	10,437
Magnet School	0.14	0.13	0.94	10,433
Charter School	0.21	0.21	0.63	10,457
Middle/High School	0.35	0.36	0.99	10,457
Special Needs School	0.06	0.05	0.34	10,457
Secondary School	0.43	0.40	0.14	10,457
Female Teacher	0.79	0.79	0.71	10,456
White Teacher	0.91	0.91	0.82	10,457
Black Teacher	0.06	0.06	0.29	10,457
Hispanic/Latino Teacher	0.02	0.02	0.18	10,457
Asian Teacher	0.01	0.01	0.23	10,457
Age	35.1	35.0	0.45	10,456
Cumulative TLF Years: 5K	4.38	4.41	0.41	10,457
Cumulative TLF Years: 17.5K	1.10	1.09	0.93	10,457
Joint Test			0.28	10,422
N	5,530	4,927		10,457

Notes: Balance in baseline characteristics, for survey respondents, 2016 and 2018 follow-up surveys, pooled.

Table A.17: Baseline Covariate Balance - Survey Repsondents, <5 Years of Eligibility

	(1)	(2)	(3)	(4)
	Control	Treatment	p-value	N
Enrollment	556	535	0.93	5,947
Percent Free/Reduced Lunch	0.63	0.63	0.84	5,945
Percent Black	0.28	0.27	0.38	5,941
Percent Hispanic/Latino	0.09	0.09	0.99	5,941
Percent Asian	0.02	0.02	0.03	5,941
Magnet School	0.14	0.14	0.76	5,936
Charter School	0.27	0.25	1.00	5,952
Middle/High School	0.36	0.37	0.95	5,952
Special Needs School	0.05	0.04	0.32	5,952
Secondary School	0.46	0.42	0.08	5,952
Female Teacher	0.79	0.78	0.62	5,952
White Teacher	0.91	0.90	0.50	5,952
Black Teacher	0.06	0.06	0.29	5,952
Hispanic/Latino Teacher	0.02	0.02	0.20	5,952
Asian Teacher	0.01	0.01	0.48	5,952
Age	33.4	33.2	0.20	5,952
Cumulative TLF Years: 5K	2.06	2.13	0.06	5,952
Cumulative TLF Years: 17.5K	0.51	0.51	0.92	5,952
Joint Test			0.12	5,932
N	3,146	2,806		5,952

Notes: Balance in baseline characteristics, for survey respondents, 2016 and 2018 follow-up surveys, pooled. Sample includes teachers with less than five years of eligibility.

Table A.18: Baseline Covariate Balance - Survey Repsondents, 5+ Years of Eligibilty

	(1)	(2)	(3)	(4)
	Control	Treatment	p-value	N
Enrollment	550	545	0.71	4,500
Percent Free/Reduced Lunch	0.59	0.60	0.51	4,499
Percent Black	0.22	0.21	0.79	4,496
Percent Hispanic/Latino	0.08	0.09	0.48	4,496
Percent Asian	0.02	0.02	0.13	4,496
Magnet School	0.12	0.13	0.99	4,497
Charter School	0.14	0.15	0.24	4,505
Middle/High School	0.34	0.35	0.85	4,505
Special Needs School	0.06	0.06	0.46	4,505
Secondary School	0.40	0.38	0.60	4,505
Female Teacher	0.79	0.80	0.91	4,504
White Teacher	0.92	0.93	0.20	4,505
Black Teacher	0.07	0.06	0.49	4,505
Hispanic/Latino Teacher	0.02	0.02	0.42	4,505
Asian Teacher	0.01	0.00	0.25	4,505
Age	37.4	37.3	0.88	4,504
Cumulative TLF Years: 5K	7.43	7.43	0.59	4,505
Cumulative TLF Years: 17.5K	1.88	1.86	1.00	4,505
Joint Test			0.73	4,490
N	2,384	2,121		4,505

Notes: Balance in baseline characteristics, for survey respondents, 2016 and 2018 follow-up surveys, pooled. Sample includes teachers with five or more years of eligibility.

Table A.19: Survey Responses by Treatment Status: Select Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	With Debt				Eligible for $175K TLF			
Panel A: General Outcomes	Control	Treatment	*p*-value	*N*	Control	Treatment	*p*-value	*N*
Has federal student loans	1.00	1.00	1.00	8,110	0.74	0.75	0.86	2,985
between $1 & $10K	0.05	0.04	0.34	7,935	0.04	0.04	0.57	2,195
between $10K & $20K	0.11	0.13	0.00	7,935	0.10	0.14	0.00	2,195
between $20K & $30K	0.18	0.18	0.97	7,935	0.17	0.15	0.13	2,195
between $30K & $50K	0.29	0.29	0.89	7,935	0.28	0.27	0.79	2,195
more than $50K	0.37	0.35	0.08	7,935	0.41	0.39	0.67	2,195
Has private student loans	0.29	0.29	0.81	7,611	0.27	0.25	0.69	2,852
Total monthly loan payment	618	790	0.12	7,423	1,047	827	0.54	2,095
Has ever been delinquent	0.35	0.35	0.70	7,845	0.34	0.30	0.05	2,227
Has difficulty paying bills	0.87	0.86	0.99	7,867	0.78	0.76	0.30	2,898
Joint Test			0.20	6,843			0.26	1,883
Panel B: Information Outcomes								
Recalls receiving a treatment letter/email	0.12	0.53	0.00	7,901	0.14	0.53	0.00	2,927
Knows School is TLF-Eligible	0.66	0.76	0.00	7,883	0.69	0.77	0.00	2,917
Knows Correct Years Toward TLF Eligibility	0.40	0.45	0.00	7,873	0.44	0.45	0.08	2,911
Knows TLF Rules Very Well or at Basic Level	0.73	0.79	0.00	7,903	0.76	0.81	0.00	2,930
Has Applied for TLF	0.40	0.41	0.34	7,872	0.46	0.46	0.98	2,917
Joint Test			0.00	7,822			0.00	2,886
N	4,174	3,797		7,971	1,557	1,342		2,899

Notes: Survey responses 2016 and 2018 follow-up surveys, pooled.

Table A.20: Survey - “Are You Familiar with the Federal TLF Program?”, Select Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)
	With Debt			Eligible for $17.5K TLF		
	Control	Treatment	Difference	Control	Treatment	Difference
No, I have no knowledge of such programs.	0.04	0.02	-0.02	0.04	0.03	-0.01
Yes, I have heard of loan forgiveness programs. However, I do not know anything about them.	0.23	0.19	-0.04	0.20	0.16	-0.04
Yes, understand the basic rules, but I do not know the specific details of this program.	0.35	0.40	0.05	0.30	0.35	0.05
Yes, I am very familiar with the rules and details of the program.	0.38	0.38	0.00	0.46	0.46	0.01
N	4,196	3,707	7,903	1,589	1,341	2,930
Joint Test			0.00			0.00

Notes: Survey answers, 2016 and 2018 follow-up surveys, pooled.

Table A.21: Survey - “Have You Applied for and/or Received Loan Forgiveness through TLF?”, Select Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)
	With Debt			Eligible for $17.5K TLF		
	Control	Treatment	Difference	Control	Treatment	Difference
I have applied for and received loan forgiveness.	0.21	0.21	-0.01	0.29	0.28	-0.01
I have applied, but have not received loan forgiveness.	0.19	0.20	0.01	0.18	0.18	-0.00
No, I have not applied for loan forgiveness.	0.60	0.59	-0.01	0.54	0.54	0.01
N	4,180	3,692	7,872	1,578	1,339	2,917
Joint Test			0.23			0.94

Notes: Survey answers, 2016 and 2018 follow-up surveys, pooled.

Table A.22: Self-Reported TLF Status vs Administrative Records: Select Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Administrative Years of Eligibility									
Self-Reported	Control					Treatment				
Eligibility (Years)	One	Two	Three	Four	Five+	One	Two	Three	Four	Five+
Panel A: With Debt										
Zero	0.06	0.02	0.01	0.01	0.01	0.11	0.02	0.01	0.01	0.01
One	**0.24**	0.08	0.01	0.02	0.01	**0.34**	0.09	0.02	0.01	0.01
Two	0.16	**0.24**	0.08	0.03	0.01	0.22	**0.39**	0.08	0.03	0.02
Three	0.09	0.18	**0.28**	0.10	0.03	0.04	0.15	**0.40**	0.13	0.02
Four	0.05	0.09	0.21	**0.36**	0.25	0.04	0.08	0.18	**0.46**	0.31
Five+	0.29	0.23	0.23	0.33	**0.56**	0.17	0.16	0.19	0.26	**0.54**
Don't Know	0.10	0.15	0.17	0.15	0.13	0.08	0.11	0.13	0.09	0.08
N	468	448	634	452	1,988	399	489	523	415	1,739
Panel B: Eligible for $17.5K TLF										
Zero	0.06	0.03	0.01	0.00	0.01	0.11	0.02	0.01	0.01	0.01
One	**0.29**	0.11	0.02	0.02	0.01	**0.34**	0.10	0.02	0.02	0.01
Two	0.11	**0.23**	0.10	0.05	0.01	0.19	**0.32**	0.08	0.02	0.02
Three	0.09	0.11	**0.25**	0.07	0.02	0.02	0.17	**0.42**	0.13	0.02
Four	0.04	0.11	0.19	**0.37**	0.25	0.04	0.10	0.09	**0.48**	0.33
Five+	0.31	0.22	0.27	0.39	**0.57**	0.17	0.17	0.24	0.27	**0.50**
Don't Know	0.11	0.19	0.16	0.10	0.14	0.13	0.12	0.13	0.07	0.12
N	160	160	231	163	863	118	158	172	125	761

Notes: Respondents' self-reported eligibility status, measured by number of years, as compared to the number of years found in administrative records and sent to treatment gruop members in the prior year, 2016 and 2018 follow-up surveys, pooled.

Table A.23: Balance in Hypothetical School Characteristics - Contingent Valuation Exercise

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Control	Treatment	*p*-value	Schools	First School	Second School	*p*-value	Schools
TLF School	0.50	0.50	1.00	26,724	0.50	0.50	0.89	36,162
TLF School x Explicit	0.25	0.26	0.05	26,724	0.25	0.25	0.42	36,162
Enrollment	498	494	0.16	26,724	497	499	0.29	36,162
Pupil/Teacher Ratio	16.8	16.7	0.02	26,724	16.8	16.8	0.39	36,162
Free/Reduced Lunch Share	0.40	0.40	0.45	26,724	0.40	0.40	0.87	36,162
Share Proficient in Math/Reading	0.45	0.45	0.75	26,724	0.45	0.45	0.94	36,162
City	0.18	0.18	0.76	26,724	0.18	0.18	0.61	36,162
Rural	0.35	0.35	0.83	26,724	0.35	0.35	0.91	36,162
Joint Test			0.08	26,724			0.92	36,162
Schools	15,054	11,670		26,724	18,081	18,081		36,162

Notes: Balance in hypothetical school characteristics used for contingent valuation questions, 2018 survey.

Appendix B 2018 Sample Survey

«surveyid_18»

This survey is designed to gain a better understanding of teachers' level of student debt and what they know about student loan forgiveness options. The survey is part of a research partnership between the Michigan Department of Education and researchers at the University of Michigan and University of Chicago. All responses will be kept confidential and results of the survey will only be disseminated in aggregate form. There are 22 questions and the survey should take you less than 10 minutes. Please return the survey and the consent form in the enclosed, stamped envelope. Thank you!

1. Do you currently have any federal student loans? (These loans are often called Federal Perkins, Direct Stafford loans, either unsubsidized or subsidized, or PLUS loans.)

☐ Yes
☐ No → **Skip to Question 3**

2. Approximately how much have you borrowed through federal student loans?

$___________________

If you don't know the exact amount or would prefer to specify a range [check only one]:
☐ $1 - $10,000
☐ $10,001 - $20,000
☐ $20,001 - $30,000
☐ $30,001 - $50,000
☐ $50,001 - $75,000
☐ Over $75,000

3. Do you have private student loans or other forms of borrowing from when you were in school? (These loans are nonfederal loans, made by a lender such as a bank, credit union, state agency or school.)

☐ Yes:
If yes, explain the type of loans (e.g. loan from a credit union or Wells Fargo): _____________________
If yes, estimate the amount of loans while in school: ___________________________
☐ No
☐ I don't know

IF YOU DO NOT HAVE ANY STUDENT LOANS OF ANY KIND, **SKIP TO QUESTION 7**

4. About how much is your monthly payment of federal and private student loans combined?

$___________________

5. Have you ever been delinquent or behind on your federal or private student loans?

☐ Yes
☐ No

6. Do your student loan payments get in the way of making other financial-related life choices? [check all that apply]

☐ No, my student loan payments do not affect my life choices
☐ Yes, I have been unable to buy a car
☐ Yes, I have been unable to buy a house
☐ Yes, I have lived in a smaller house
☐ Yes, I have lived in a less desirable neighborhood
☐ Yes, other life choices (please specify: ___________________________)

7. Are you familiar with the federal Teacher Loan Forgiveness program, which offers partial forgiveness of federal student loans after five years of teaching in a qualified (low-income) school? [check only one]

☐ No, I have no knowledge of such program
☐ Yes, I have heard of loan forgiveness programs. However, I do not know anything about them
☐ Yes, I understand the basic rules, but I do not know the specific details of this program
☐ Yes, I am very familiar with the rules and details of the program

PLEASE TURN OVER AND COMPLETE OTHER SIDE

«surveyid_18»

8. Do you recall receiving a letter or email from the University of Michigan in May of last year with personalized information regarding Teacher Loan Forgiveness?
[check only one]

☐ Yes, I received a letter
☐ Yes, I received an email
☐ Yes, I received both a letter and an email
☐ No, I do not recall receiving a letter or an email from the University of Michigan in May of last year

9. Do you know if service at your current (or most recent) school counts towards Teacher Loan Forgiveness? [check only one]

☐ Yes, it counts
☐ No, it does not count
☐ I don't know

10. Have you applied for and/or received loan forgiveness through the federal Teacher Loan Forgiveness program? [check only one]

☐ I have applied and received loan forgiveness
☐ I have applied and been rejected for loan forgiveness
☐ I have applied but not yet received a response
☐ No, I have not applied for loan forgiveness

11. How many years of your teaching experience count towards Teacher Loan Forgiveness? [check only one]

☐ 0
☐ 1
☐ 2
☐ 3
☐ 4
☐ 5 or more
☐ I don't know

12. In a typical month, how difficult is it for you to cover your expenses and pay all your bills? [check only one]

☐ Very difficult
☐ Somewhat difficult
☐ Not at all difficult

13. Please indicate, on a scale from 1 to 5, how much the various factors influenced your choice of what school to work in this year (or most recently). 1 is not at all important, 5 is very important.

__ Personal connection (e.g., worked there previously)
__ Geographic location
__ Grades/subject offered to teach
__ Salary/benefits
__ School leadership
__ District policies (e.g., teacher evaluation)
__ Instructional support (e.g., Professional Development, Coaching, Peer Collaboration)
__ Counts toward Teacher Loan Forgiveness eligibility
__ Assigned by district

PLEASE COMPLETE THE FOLLOWING PAGE

«surveyid_18»

For the next questions, pretend you are deciding on which school to work at:

14. Which school would you prefer to work at if you were paid the same salary at each school?

☐ School A
«s1_cv_enr» students enrolled
«s1_cv_ptr» pupil/teacher ratio
«s1_cv_frl» receive free or reduced-price lunch
«s1_cv_mstep» were proficient in math and reading
«s1_cv_urb»
«s1_cv_tlf»

☐ School B
«s2_cv_enr» students enrolled
«s2_cv_ptr» pupil/teacher ratio
«s2_cv_frl» receive free or reduced-price lunch
«s2_cv_mstep» were proficient in math and reading
«s2_cv_urb»
«s2_cv_tlf»

15. Think about the school you didn't choose. Would you choose that school if you received a one-time $5,000 «cvu_fill»?

☐ Yes → **Skip to Question 17**
☐ No

16. If you said no to question 15, would you choose that school if you received a one-time $10,000 «cvu_fill»?

☐ Yes
☐ No

---

17. Which school would you prefer to work at if you were paid the same salary at each school?

☐ School D
«s3_cv_enr» students enrolled
«s3_cv_ptr» pupil/teacher ratio
«s3_cv_frl» receive free or reduced-price lunch
«s3_cv_mstep» were proficient in math and reading
«s3_cv_urb»
«s3_cv_tlf»

☐ School E
«s4_cv_enr» students enrolled
«s4_cv_ptr» pupil/teacher ratio
«s4_cv_frl» receive free or reduced-price lunch
«s4_cv_mstep» were proficient in math and reading
«s4_cv_urb»
«s4_cv_tlf»

18. Think about the school you didn't choose. Would you choose that school if you received a one-time $5,000 «cvu_fill»?

☐ Yes → **Skip to Question 20**
☐ No

19. If you said no to question 18, would you choose that school if you received a one-time $10,000 «cvu_fill»?

☐ Yes
☐ No

---

20. Which school would you prefer to work at if you were paid the same salary at each school?

☐ School G
«s5_cv_enr» students enrolled
«s5_cv_ptr» pupil/teacher ratio
«s5_cv_frl» receive free or reduced-price lunch
«s5_cv_mstep» were proficient in math and reading
«s5_cv_urb»
«s5_cv_tlf»

☐ School H
«s6_cv_enr» students enrolled
«s6_cv_ptr» pupil/teacher ratio
«s6_cv_frl» receive free or reduced-price lunch
«s6_cv_mstep» were proficient in math and reading
«s6_cv_urb»
«s6_cv_tlf»

21. Think about the school you didn't choose. Would you choose that school if you received a one-time $5,000 «cvu_fill»?

☐ Yes
☐ No

22. If you said no to question 21, would you choose that school if you received a one-time $10,000 «cvu_fill»?

☐ Yes
☐ No

Appendix B.1 Alternative Contingent Valuation Question Examples

Figure B.1: Contingent Valuation Question: Explicit TLF Designation

For the next questions, pretend you are deciding on which school to work at:

14. Which school would you prefer to work at if you were paid the same salary at each school?

☐ School A
267 students enrolled
13.8 pupil/teacher ratio
43% receive free or reduced-price lunch
28% were proficient in math and reading
Rural
Eligible for federal teacher loan forgiveness

☐ School B
454 students enrolled
18.6 pupil/teacher ratio
18% receive free or reduced-price lunch
53% were proficient in math and reading
Suburban

15. Think about the school you didn't choose. Would you choose that school if you received a one-time $5,000 **signing bonus**?

☐ Yes → **Skip to Question 17**
☐ No

16. If you said no to question 15, would you choose that school if you received a one-time $10,000 **signing bonus**?

☐ Yes
☐ No

Figure B.2: Contingent Valuation Question: Baseline Signing Bonus

For the next questions, pretend you are deciding on which school to work at:

14. Which school would you prefer to work at if you were paid the same salary at each school?

☐ School A
267 students enrolled
13.8 pupil/teacher ratio
43% receive free or reduced-price lunch
28% were proficient in math and reading
Rural

☐ School B
454 students enrolled
18.6 pupil/teacher ratio
18% receive free or reduced-price lunch
53% were proficient in math and reading
Suburban

15. Think about the school you didn't choose. Would you choose that school if you received a one-time $5,000 **signing bonus**?

☐ Yes → **Skip to Question 17**
☐ No

16. If you said no to question 15, would you choose that school if you received a one-time $10,000 **signing bonus**?

☐ Yes
☐ No

Figure B.3: Contingent Valuation Question: Debt Framing

For the next questions, pretend you are deciding on which school to work at:

14. Which school would you prefer to work at if you were paid the same salary at each school?

☐ School A
267 students enrolled
13.8 pupil/teacher ratio
43% receive free or reduced-price lunch
28% were proficient in math and reading
Rural

☐ School B
454 students enrolled
18.6 pupil/teacher ratio
18% receive free or reduced-price lunch
53% were proficient in math and reading
Suburban

15. Think about the school you didn't choose. Would you choose that school if you received a one-time $5,000 **reduction in student loan debt**?

☐ Yes → **Skip to Question 17**
☐ No

16. If you said no to question 15, would you choose that school if you received a one-time $10,000 **reduction in student loan debt**?

☐ Yes
☐ No

Appendix C Estimating Retention in any TLF School

In addition to keeping teachers at their current, TLF-eligible school, greater awareness of the TLF program may make a teacher more likely to choose a TLF-eligible school when moving to a new school. Suppose we measure the TLF status of a teacher's school in period $t > 0$, regardless of whether they are still at their initial school. We can write this binary outcome for teacher i as:

$$TLF_{i,t} = Stay_{i,t} \times TLF_{i,0} + (1 - Stay_{i,t}) \times TLF^{New}_{i,t}, \tag{C.1}$$

where $Stay_{i,t}$ is an indicator for remaining at one's period 0 school, and $TLF^{New}_{i,t}$ is the counterfactual school a teacher would move to in period t if they were to move.

Now, consider the comparison between a "treatment" and "control" group, indicated by $D_i \in \{0, 1\}$. This could be those above or below the eligibility threshold in our RD design, or the treatment and control groups in our RCT. The expected current TLF status for a teacher, conditional on D_i is then:

$$\begin{aligned} \mathbb{E}\left[TLF_{i,t} \middle| D_i\right] &= \mathbb{E}\left[Stay_{i,t} \times TLF_{i,0} \middle| D_i\right] + \mathbb{E}\left[(1 - Stay_{i,t}) \times TLF^{New}_{i,t} \middle| D_i\right] \\ &= \mathbb{E}\left[Stay_{i,t} \middle| TLF_{i,0} = 1, D_i\right] \times \mathbb{E}\left[TLF_{i,0} \middle| D_i\right] \\ &\quad + \mathbb{E}\left[(1 - Stay_{i,t}) \times TLF^{New}_{i,t} \middle| D_i\right] \end{aligned} \tag{C.2}$$

Define $\triangle\mathbb{E}[X] \equiv \mathbb{E}[X| D = 1] - \mathbb{E}[X| D = 0]$ as the treatment effect of D on X. The treatment effect of D_i on current current TLF status, then, will be:

$$\begin{aligned} \triangle\mathbb{E}\left[TLF_{i,t}\right] &\equiv \mathbb{E}\left[TLF_{i,t} \middle| D_i = 1\right] - \mathbb{E}\left[TLF_{i,t} \middle| D_i = 0\right] \\ &= \mathbb{E}\left[Stay_{i,t} \middle| TLF_{i,0} = 1, D_i = 1\right] \times \mathbb{E}\left[TLF_{i,0} \middle| D_i = 1\right] \\ &\quad - \mathbb{E}\left[Stay_{i,t} \middle| TLF_{i,0} = 1, D_i = 0\right] \times \mathbb{E}\left[TLF_{i,0} \middle| D_i = 0\right] \\ &\quad + \triangle\mathbb{E}\left[(1 - Stay_{i,t}) \times TLF^{New}_{i,t}\right] \\ &= \mathbb{E}\left[Stay_{i,t} \middle| TLF_{i,0} = 1\right] \times \triangle\mathbb{E}\left[TLF_{i,0}\right] \\ &\quad + \triangle\mathbb{E}\left[(1 - Stay_{i,t}) \times TLF^{New}_{i,t}\right], \end{aligned} \tag{C.3}$$

where in the last line, we have used the assumption that:

$$\mathbb{E}\left[Stay_{i,t} \middle| TLF_{i,0} = 1, D_i = 0\right] = \mathbb{E}\left[Stay_{i,t} \middle| TLF_{i,0} = 1, D_i = 1\right] = \mathbb{E}\left[Stay_{i,t} \middle| TLF_{i,0} = 1\right] \tag{C.4}$$

In the case of our RCT, this is satisfied due to randomization of D_i. In the case of our RD design, this holds under an exclusion restriction: that D_i only affects mobility through it's affect on $TLF_{i,t}$. This will hold in general under the assumption that unobservable determinants of mobility are the same for teachers in schools just above and just below the TLF-eligibility threshold.

In the case of our RD design, if we look at equation (C.3), we can see that if we use current TLF status as an outcome variable, we will be picking up two forces. The first component depends on $\triangle\mathbb{E}\left[TLF_{i,0}\right]$, the difference in baseline TLF-eligibility, which, by design within the RD, is nonzero. Intuitively, even if teachers never leave their original school, there will be a discontinuity in current TLF-status. For this reason, we directly focus on the second part of equation (C.3) when using an RD: the effect of being on either side of the discontinuity on the joint outcome of relocating to a new school and choosing one that is TLF-eligible.

In the case of our RCT, the first term in equation (C.3) vanishes, since, due to randomization, $\triangle\mathbb{E}\left[TLF_{i,0}\right] = 0$. In fact, since all teachers start at a TLF-eligible school, there is not even variation in this attribute. Intuitively, if teachers remain at the same school, all teachers in our RCT will be at TLF-eligible schools, and there will be no difference in current TLF status. Thus, we can simply use current TLF status as an outcome when analyzing our RCT, regardless of whether a teacher has moved or not, to capture the second term in equation (C.3). This captures the impact of treatment on the joint outcome of choosing a new school, and the choice of TLF status of the new school.