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Evidence from the Philippine Special Hardship Allowance**

by

Jewelle Anne Lalunio

University of the Philippines School of Economics

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Labor supply responses to teacher incentives: Evidence from the Philippine Special Hardship Allowance

Jewelle Anne Lalunio^{*}

UP School of Economics

Abstract

Teacher shortages in schools located in geographically isolated and disadvantaged areas (GIDAs) remain a persistent challenge in the Philippines, constraining learning outcomes in underserved communities despite the long-standing provision of the Special Hardship Allowance (SHA). This paper exploits the Department of Education's adoption of a hardship index-based eligibility criterion in 2021 through a fuzzy regression discontinuity design to examine whether SHA provision affects the net movement of teachers in and out of hardship schools. Pooling 2021 to 2024, schools that are SHA recipients reduced net teacher loss rates by 2.676 percentage points, applying to schools near the cutoff whose SHA receipt changes because of eligibility. A difference-in-differences analysis of newly eligible schools, which relies on a different identifying assumption, points in the same direction. The pooled estimate is stable across a series of robustness checks, including placebo cutoffs, donut hole specifications, and an uncensored outcome measure. The findings of this study suggest that SHA can help staff schools in GIDAs, and that sustained provision grounded in a more accurate and responsive measurement of teacher hardship conditions may be important in addressing teacher shortages in underserved schools.

Keywords: hardship allowance, teacher shortages, geographically isolated and disadvantaged areas, fuzzy regression discontinuity

JEL classification: I28, J38, J45

^{*}Email: jdلالunio@up.edu.ph. The author used generative AI tools for grammar checking and language editing. All content was reviewed by the author, who takes full responsibility for the final paper.

1 Introduction

In the Philippines, the 2025 EDCOM report shows that proficiency in the National Achievement Test among Grade 10 students remains out of reach for nearly all students in schools located in hardship posts – public schools located in geographically disadvantaged areas that are usually inaccessible to transport. These outcomes are not incidental, but reflect deep structural disadvantages that systematically limit the quality of education in the country’s most isolated communities. Among the most persistent of these barriers is the difficulty of attracting and retaining qualified teachers in hardship posts, leaving students in these schools disproportionately exposed to high teacher turnover and instructional discontinuity. Closing these structural gaps demands recognizing the need for equity-weighted school support that does not simply need more of the same resources, but interventions strategically designed to meet the specific barriers these students face.

The geographical remoteness and logistical difficulties characteristic of hardship areas present ongoing challenges to teacher supply. Each school year, retaining and attracting teachers has been a persistent problem of the country, as it serves as the critical step toward recovering learning loss in these areas. As shown in Figure 1, public schools in hardship posts have consistently experienced higher net teacher loss rates than those in non-hardship posts across the 2021 to 2024 period. Both groups follow the same general trajectory, with loss rates declining to their lowest point in 2023, likely reflecting the stabilization of market conditions in the post-pandemic period, before rising again in 2024. Despite this shared trend, the persistent gap between the two groups suggests that hardship designation is associated with structurally higher teacher loss rate, rather than a temporary shock. Left unaddressed, chronic teacher supply shortfalls in these schools risk translating into deteriorating student learning outcomes, a pressing concern for national education policy.

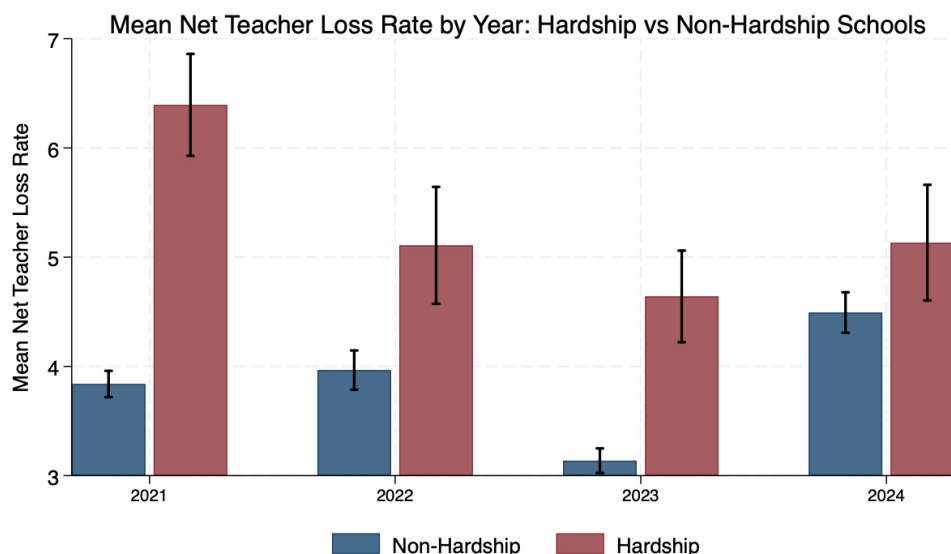


Figure 1: Net teacher loss rate among public schools in the Philippines

Schools classified as hardship posts also exhibit a distinct labor force structure. As shown

in Figure 2 Teachers 2 and 3 dominate the workforce in non-hardship posts, followed by Teacher 1 and then Master Teachers. In hardship posts, however, this pattern is reversed: Teacher 1 dominates the workforce, followed by Teacher 2 and 3, with Master Teachers making up only a small share. Since experienced teachers are defined here as Teacher 2 and above, this composition suggests that hardship schools face a shortage of experienced teachers — precisely the teachers best positioned to help address learning loss in these areas.

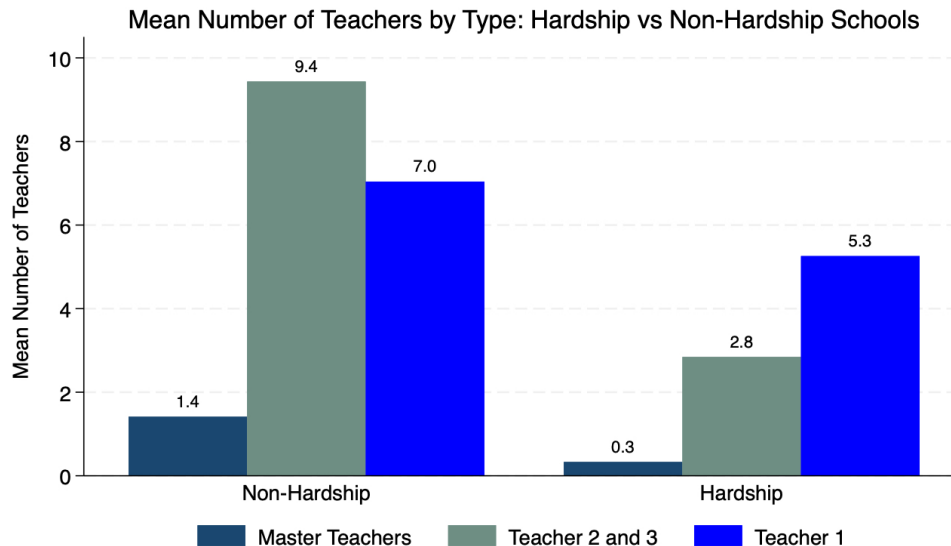


Figure 2: Number of teachers by position

With the high teacher loss rate and the low share of experienced teachers, one of the government’s primary responses has been the Special Hardship Allowance (SHA), a monetary incentive designed to compensate teachers assigned to schools located in hardship posts and encourages their retention. This move is consistent with See et al. (2020) who find that monetary incentives are effective in attracting teachers in hardship areas. The Department of Education has long relied on this policy since its institution in 1966 under RA No. 4670, also known as the Magna Carta for Public School Teachers. The policy has undergone several reforms over the decades, each reflecting the government’s evolving understanding of what constitutes hardship. Most recently, in 2021, the policy adopted a hardship index-based eligibility criterion. The hardship index is a multidimensional measure of the school-level hardship conditions developed jointly by UNICEF and the Department of Education stating that the old eligibility requirement does not consider several hardship considerations.

In the Philippines, this is not the first study to examine how the SHA influences teacher retention. Roa (2025) found that SHA recipients reported a strong intention to stay in their hardship posts. However, Roa (2025) noted that the intention to remain is influenced more by teachers’ place of residence and length of service than by the SHA itself. While Roa (2025) focuses on teachers’ stated intention to stay, this paper evaluates the causal impact of SHA eligibility on actual labor supply response of teachers. Despite the existence of the Special Hardship Allowance for decades, there remains little evidence on whether this policy

effectively meets its goals. To the author’s knowledge, this study is the first to examine the causal relationship between SHA provision and its impact on the teaching labor force. This gap matters beyond the Philippine context as Evans and Acosta (2023) noted that evidence on the effectiveness of monetary incentives for labor supply in education sector in developing countries remains limited. Thus, the findings of this study contribute to ongoing discussions in development economics, both in the Philippines and across developing economies.

This paper examines the causal impact of the Special Hardship Allowance (SHA) on teacher staffing in Philippine public schools, with two primary research questions: (1) What is the impact of SHA eligibility on the net teacher loss rate?; and (2) Does SHA eligibility increase the share of experienced teachers in hardship schools? Using a fuzzy regression discontinuity design, the study finds that the provision of the SHA reduces the net teacher loss rate but there is insufficient evidence that there is the share of experienced teachers increased in SHA-eligible schools. These results are broadly consistent with existing evidence on the impact of financial incentives on teacher supply in hardship areas. The study also conducts a series of robustness checks to validate the estimation strategy.

This paper proceeds as follows. Section 2 provides an overview of the Special Hardship Allowance in the Philippines. Section 3 reviews the relevant literature on teacher incentives and staffing from various international contexts. Section 4 describes the empirical strategy employed throughout the paper. Section 5 presents the results, and Section 6 presents the robustness checks. The last section concludes the paper.

2 Institutional background

In the country’s continuous pursuit of equity among its learners, the Special Hardship Allowance has been in place since 1966, in accordance with Section 19 of Republic Act No. 4670, otherwise known as the Magna Carta for Public School Teachers. The monetary incentive aims to compensate teachers who are assigned to hardship posts in geographically isolated and disadvantaged areas for the logistical and physical burdens of teaching in these locations.

It is not only the schools located in hardship posts that benefit from the allowance, but also the multigrade teachers. As reported in Table 1, from a 29% share of multigrade teachers receiving the hardship allowance it rose to almost half of the population of the SHA recipients. According to Figure 3, most of the SHA recipients classified as ‘Multigrade Teachers’ do not meet the cutoff threshold. With the implementation of the hardship index, there are still schools located in hardship posts which fall below the cutoff but are still considered to receive the hardship allowance.

Table 1: The share of SHA-recipient schools based on their classification

	2019	2020	2021	2022	2023	2024
HARDSHIP POST (HP)	69.44%	57.35%	46.66%	44.42%	50.56%	56.64%
HP/ PMS	1.31%	1.65%	0.24%	0.14%	0.07%	0.14%
PURE MULTIGRADE SCHOOLS (PMS)	29.25%	40.99%	53.10%	55.43%	49.38%	43.22%
Total SHA-recipient schools	7569	10531	7478	7649	8725	4988

The provision and the computation of the SHA incentive have a long history of policy revisions. In 1996, pursuant to DECS Order No. 73, the computation of SHA is as follows:

$$(\text{Salary/mo.} \times 6\%/\text{hr} \times \text{Qualified Travel time}) \times \frac{\text{Days present}}{\text{Class days/mo.}}$$

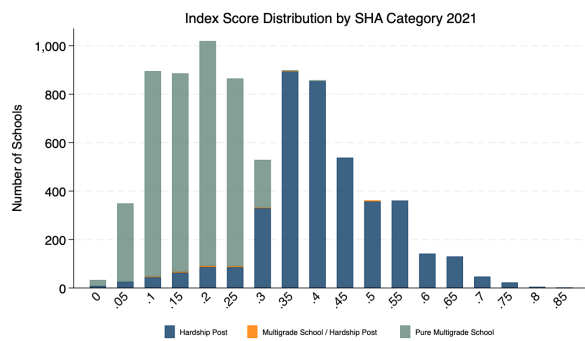
This formula considers the amount of time spent on hiking, banca rides or animal rides of teachers. In 2007, as mandated by the Department of Budget and Management (DBM) National Budget Circular No. 514, s. 2007, “Guidelines on the Grant of Special Hardship Allowance”, the formula changed to

$$(\text{Basic salary} \times \text{rate per distance} \times \frac{\text{no. of days present/mo.}}{\text{no. of working days/mo.}})$$

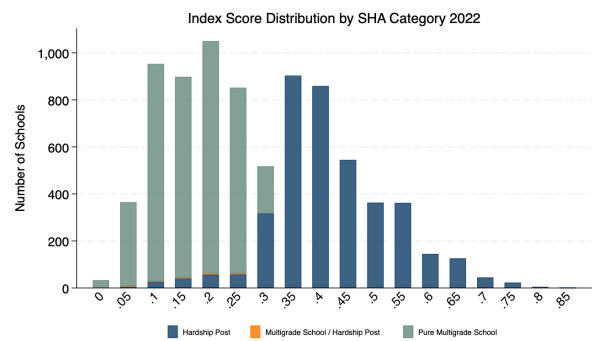
The main difference is that the 2007 amendment measured the distance of the hardship post from the nearest point of available motorized land/water transport rather than the travel time to reach the nearest point of available motorized transport. The rate per distance is presented in Table 2.

In 2019, DepEd’s Bureau of Human Resource and Organizational Development (BHROD-SED), together with UNICEF, argued that the existing SHA policy failed to function as an effective incentive. Key limitations identified included the exclusive reliance on distance as

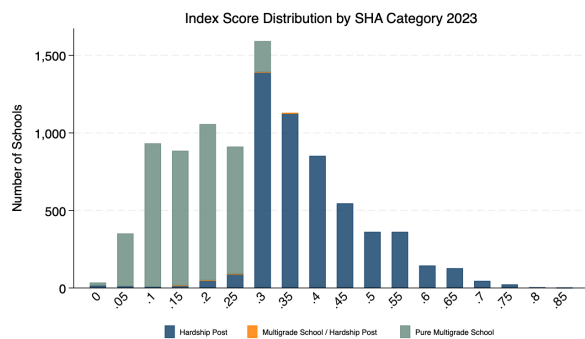
Figure 3: Share of SHA recipients by subclassification from 2021 to 2024, and their corresponding hardship index based on the 2021 HI



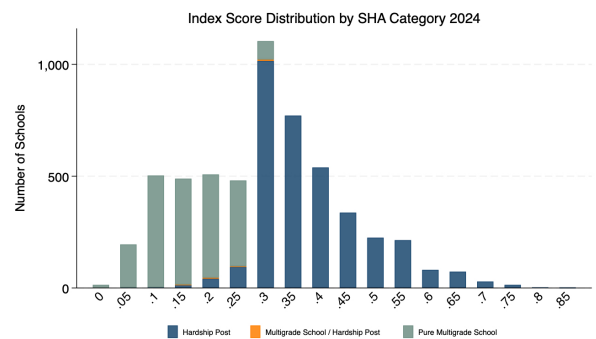
(a) SY 2021-2022



(b) SY 2022-2023



(c) SY 2023-2024



(d) SY 2024-2025

Table 2: Rate per distance under 2007 SHA amendment

Distance*	Rate per distance (% of basic salary)
5-10 km	15%
11-20 km	20%
21 km above	25%

*Distance in km of the hardship post from the nearest point of available regular motorized land/water transport.

a hardship proxy, mismatches between actual hardship conditions and the provision of the same rate regardless of base salary. In response, DepEd and UNICEF jointly developed the hardship index per school as a more standardized, multidimensional proxy for the challenges faced by teachers assigned to difficult school environments.

The hardship index was constructed using an econometric analysis identifying school characteristics associated with lower availability of experienced teachers. The analysis found that travel cost and travel time to the division office, poverty incidence, number of violent acts, and the absence of basic amenities such as electricity, water, and internet were all significantly associated with a lower proportion of experienced teachers in a school. These variables were then weighted according to their relative contribution to the maximum hardship score, with travel time to the division office carrying the highest weight at 35%, followed by poverty incidence at 18%, and travel cost at 16%. Each school is assigned a hardship index score between 0 and 1, where 0 represents a school with no hardship conditions and 1 represents the most extreme hardship conditions observed. Lastly, the hardship index was computed at the national administrative level.

Under DepEd Order no. 039, s. 2021, all teachers assigned to schools with a hardship index of 0.37 or higher are entitled to receive the SHA. The allowance is now computed as 25% of the teachers' basic salary, prorated by days present over 22 working days per month. This entails that higher ranking teachers receive higher hardship allowance. In 2023, by DepEd Order no. 017, s. 2023, DepEd reduced the cutoff to 0.33, citing that schools within the 0.33 to 0.37 band share similar hardship characteristics. The policy change to index-based eligibility criterion is the primary source of variation exploited in this study.

In Figure 4, the two maps illustrate the geographic distribution of SHA recipient schools across the country before and after the 2021 SHA policy reform. This geographic realignment is consistent with the data reported in Section 6.1, wherein 4,684 of the 4,722 schools removed from the recipient list in 2021 were dropped solely because they failed to meet the new cutoff. The contrast between the two periods illustrates how the hardship index reform rationalized SHA provision toward schools in genuinely isolated and disadvantaged areas.

The concentration of recipients in the 2021 to 2024 period is more geographically targeted, with Palawan and parts of Eastern Visayas and Caraga remaining among the areas with the highest number of recipients, suggesting that the index-based system redirected resources toward the most genuinely disadvantaged schools. This transition is central to the identification strategy employed in this paper, as the hardship index and its eligibility thresholds

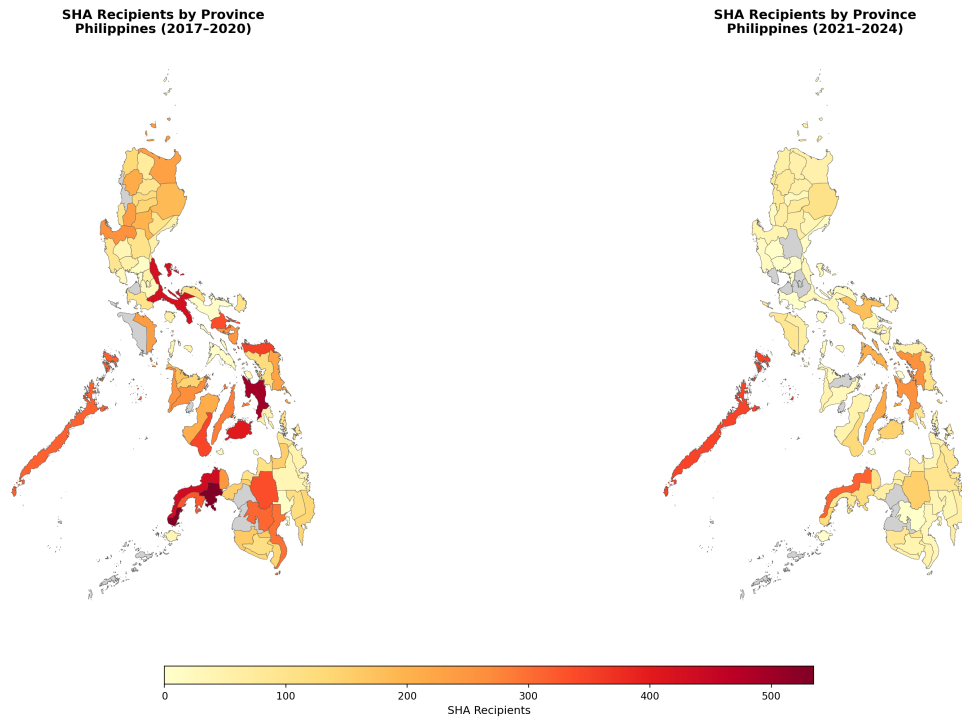


Figure 4: SHA recipients across the Philippines in 2017 to 2024

form the basis of the fuzzy regression discontinuity design.

3 Review of related literature

Research has examined what types of incentives are most effective in attracting teachers to geographically disadvantaged areas. [Lentini et al. \(2024\)](#); [Bradley et al. \(2006\)](#) both explored this question and, consistent with the theory of compensating wage differentials, found that monetary incentives are more appealing to teachers than non-monetary ones. However, both studies also found that non-monetary incentives best serve as complements to monetary compensation. This suggests that the most effective staffing policies for hard-to-staff areas are likely those that combine financial incentives with meaningful non-monetary support. Indeed, evidence on the effect of monetary incentives alone already points to substantial reductions in teacher turnover across different contexts.

Providing monetary incentives has been shown to significantly reduce teacher turnover rates in high-poverty schools ([Clotfelter et al. \(2008\)](#); [Elacqua et al. \(2025\)](#); [Falch \(2011\)](#); [Allen et al. \(2018\)](#)). [Elacqua et al. \(2025\)](#) found a significant 18% reduction in turnover rates across all schools, with a higher reduction of 30% in turnover rates in schools offering higher incentives. In addition, [Clotfelter et al. \(2008\)](#) and [Camelo and Ponczek \(2021\)](#) found reductions of 17% and 5% in teacher turnover rates, respectively. These studies suggest that teacher supply actively responds not only to the provision of financial incentives, but also to its level. Furthermore, [Castro and Esposito \(2018\)](#) and [Feng and Sass \(2018\)](#) have shown that monetary incentives are an effective means to reduce teacher attrition. While [Springer et al. \(2016\)](#) and [Steele et al. \(2010\)](#) found a causal relationship between retention of teachers and bonuses. Lastly, [Urquiola and Vegas \(2005\)](#) and [Swai \(2013\)](#), similarly found that financial incentives are significant in increasing the number of teachers in hard-to-staff schools. However, these last two studies used matching designs which are considered as less credible than the method used by the studies cited above. In conclusion, the labor supply reacts positively to financial incentives, and the degree of response varies depending on each country's unique demographic feature.

Turnover rates are crucial as it acts as a systemic disruptor that impacts the entire community. In the case of schools, high turnover rates, imply that departing teachers are replaced by new ones unfamiliar with the school community creating disruption to the overall system. The same reason why financial incentives specifically targets a reduction in turnover rates of teachers. [Ronfeldt et al. \(2013\)](#) documented that this frequent cycle of teachers entering and leaving breaks down staff cohesion and school climate suffers. Existing faculty members must spend considerable time onboarding and mentoring new hires, diverting attention and energy away from instruction. Hence, students bear the cost of disruption translating directly into poorer academic outcomes.

Now, the question of whether difficulties in teacher staffing affect students' learning outcomes arises. Studies of [Adnot et al. \(2017\)](#), [Dronkers et al. \(2012\)](#), [Ronfeldt et al. \(2013\)](#), [Sorensen and Ladd \(2020\)](#) all found that teacher supply, specifically teacher turnover, has a significant negative impact on learning outcomes. This underscores the importance of the government's role in ensuring that from urban to rural areas, the stability of teacher supply is not compromised. Hence, the provision of hardship allowances in attracting teachers to hard-to-staff schools is deemed necessary.

Pugatch and Schroeder (2018), Camelo and Ponczek (2021), and Ma and Lei (2025), all found that hardship allowance does not have a significant effect on average test scores of students, their studies have interesting distributional effects on students' achievement distribution beneath the aggregate finding. Ma and Lei (2025) found that in China effects were significant on test scores only in schools with higher incentives, however, it is insignificant in schools with lower monetary incentives. This suggests that in China, teachers respond differently to different levels of allowances. Pugatch and Schroeder (2018) documented the gains concentrated among high-performing students, and on average does not have a significant impact on learning outcomes. On the other hand, Camelo and Ponczek (2021) results showed that despite not having a significant impact on average test scores, it benefited low performing students by improving their math and reading test scores. Together, these studies suggest that the impact of monetary incentives of teachers on students' learning outcomes is highly context- and student-dependent.

One of the many reasons for these inconsistencies may lie in the difference between developed and developing country contexts. Even schools sharing the same hardship classification may face vastly different learning conditions and resource environments, factors that could shape whether and how teachers respond to incentives and translate into student outcomes.

However, Boyd et al. (2008) showed that not all higher attrition rates bring negative impact to schools and to learning outcomes. The authors found that less effective teachers have higher attrition rates than more effective teachers and they suggested that this may actually benefit student achievement. Thus, efforts to staff schools located in hardship areas must come with the goal of increasing the number of qualified teachers in the posts. Similarly, Ronfeldt et al. (2013) also cited that higher turnover rates would have positive impact in the community if less qualified workers leave and Chetty et al. (2014) have noted that replacing low-VA teachers with high-VA teachers would impose a higher average present-value lifetime income to students. Adnot et al. (2017) showed that selective targeting of turnover rates, implying incentivizing less qualified teachers to leave while attracting qualified teachers increases math and reading scores of students significantly. This supports the policy goal of the SHA revision in 2021, to attract and incentivize more experienced teachers to take on hardship postings.

Empirical evidence on whether monetary incentives achieve this goal is mixed. Pugatch and Schroeder (2014) have shown that in Gambia, monetary incentives to teachers assigned to hardship areas have increased the share of qualified teachers. In contrast, Camelo and Ponczek (2021) found that recipient schools get younger teachers on average and Castro and Esposito (2018) found that monetary incentives increase the likelihood that vacancies are filled with non-tenured teachers. Thus, it remains unclear whether the extra compensation incentivizes more experienced teachers to go to hardship posts or the incentives only attract less experienced teachers. Lastly, the impact of monetary incentive is context dependent and relies primarily on whether the application is on a developing or a developed country (Camelo and Ponczek, 2021).

4 Empirical strategy

4.1 Data

The study utilizes datasets from the Department of Education covering SY 2021 –2022 to SY 2024 –2025, which are as follows: (1) School-level datasets on school characteristics and (2) a dataset containing hardship index of all schools and SHA recipient lists from 2016 to 2024. The final estimation sample excludes schools under pure multigrade category, as these schools receive the SHA by virtue of their multigrade nature regardless of their hardship index, which would confound the cutoff-based identification strategy.

Table 3: Descriptive statistics. SHA recipients vs. non-recipients

Variable	Non-recipient		SHA Recipient		Difference	
	<i>N</i>	Mean (SE)	<i>N</i>	Mean (SE)	<i>N</i>	(1) – (0)
Learners	46,691	454.363 (3.268)	5,601	177.770 (2.985)	52,292	–276.592***
Teachers	46,691	17.303 (0.118)	5,601	7.791 (0.123)	52,292	–9.511***
Learner-Teacher Ratio	46,476	25.289 (0.080)	5,585	22.015 (0.167)	52,061	–3.274***
Master Teachers	46,691	1.320 (0.013)	5,601	0.369 (0.012)	52,292	–0.951***
Teachers (T1–T3)	46,691	15.585 (0.099)	5,601	7.298 (0.097)	52,292	–8.287***
Special Science Teachers	46,691	0.077 (0.003)	5,601	0.009 (0.001)	52,292	–0.068***
Water Supply	46,691	0.983 (0.001)	5,601	0.971 (0.002)	52,292	–0.012***
Electricity Supply	46,691	0.992 (0.000)	5,601	0.973 (0.002)	52,292	–0.020***

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes: This reports the mean school-level characteristics of SHA recipients and non-SHA recipients schools. Standard errors in parentheses. Differences based on pairwise t -tests.

Table 3 reports the results of the formal test conducted to show differences between SHA recipients and non recipients. As shown in the table, all covariates differ significantly at the 1% level. Non-recipients are considerably larger, with higher average learner and teacher counts, reflecting the geographic concentration of SHA-eligible schools in remote populated areas. Supported by Figure 5, the distribution of schools in the Philippines is right-skewed, with the majority of schools concentrated at lower hardship index. The learner-teacher ratio gap, while statistically significant, is smaller in magnitude, partly reflecting the prevalence of multigrade arrangements in hardship schools. With lower teacher average in SHA schools, the average of Master Teachers, Teachers 1 to 3, and Special Science Teachers are consistently lower in SHA schools. Lastly, SHA schools have also reported lower access to amenities such

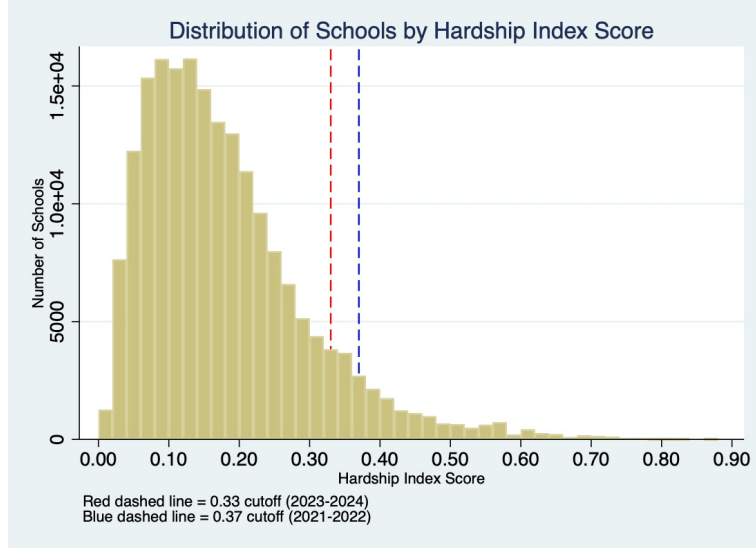


Figure 5: Distribution of schools by hardship index

as water and electricity supply but at very low difference. Taken together, this supports the policy rationale as these descriptive comparisons confirm that SHA schools are systematically disadvantaged from the broader Philippine public school population.

4.2 Outcome variables

The SHA policy was designed particularly to recruit and retain teaching personnel by compensating them for the challenges faced from working in hardship areas, and to improve teacher staffing conditions in hardship posts by ensuring an adequate supply of teachers each school year. In pursuit of the latter objective, the most recent amendment to the policy’s eligibility criteria sought to address the shortage of experienced teachers in hardship areas. Despite the policy’s long history, there exists no empirical evidence whether it has successfully achieved either objective. This study addresses this gap by estimating the causal effect of SHA provision on the following outcome variables.

The main outcome variables of the study are the net teacher loss rate and the share of experienced teachers. The net teacher loss rate is defined as the proportional reduction in a school’s teacher workforce between two consecutive school years, normalized by the average teacher count across both periods. The denominator is set to the average teacher count across both periods, rather than the previous period’s count alone, to prevent extreme and noisy values, since a previous-period-only denominator is especially sensitive to small bases, and many hardship schools have very few teachers to begin with.

$$NTLR = \frac{T_{i,t-1} - T_{i,t}}{(T_{i,t-1} + T_{i,t})/2} \times 100 \quad (1)$$

$$NTLR(\text{censored at } 0) = \max(0, NTLR_{it}) \quad (2)$$

where T is the number of teachers. Separately, the variable is censored at zero: any negative

computed value, representing a net gain in teachers on the numerator, is recoded to zero. As a result, the measure captures only the intensity of losses among schools that lost teachers, and cannot distinguish a school that gained teachers from one that had no change at all. While the share of experienced teachers measures the amount of experienced teachers in the overall teaching workforce in a school.

A positive net teacher loss rate indicates that a school’s teacher workforce has declined on net between two consecutive school years. Conversely, a lower net teacher loss rate indicates that the provision of SHA is succeeding in its general goal of improving teacher staffing levels in hardship areas, whether through reduced outflows of teachers, increased inflows of teachers, or both. While a positive share of experienced teachers indicates that the pool of experienced teachers in a school has grown on net between two consecutive school years. And a higher share of experienced teachers indicates that SHA is succeeding in its explicit goal of attracting experienced teachers in hardship areas, but not necessarily retaining them. As part of the robustness check, the RD estimates of the net teacher loss rate that is not censored at zero are also computed.

Additionally, the learner-teacher ratio, the share of Teacher 1, the share of Master Teacher, the share of Teacher 2 and Teacher 3 are used as outcome variables to measure the supply of labor force in hardship areas. Note that the share of experienced teachers comprises the share of Master Teacher and the share of Teacher 2 and Teacher 3. The learner-teacher ratio is computed by dividing the number of learners by the number of teachers. Thus, a lower learner-teacher ratio implies either a declining enrollment rate or a rising number of teaching personnel or both. Hence, a lower learner-teacher ratio is consistent with the reduction in the net teacher loss rate.

A shared limitation of these outcome variables, and the study, is that due to absence of teacher-level dataset, it cannot decompose whether a change was driven by departures, arrivals, or both simultaneously. Thus, the outcome variables reflect the net outcome of all teacher movements in and out of the school, including voluntary transfers out, resignations, retirements, and incoming transfers or new hires. An additional limitation specific to the experienced teacher measure is that changes in the stock of Teacher 2 and above may conflate outright separations with Teacher 1 positions vacated through promotion; the study treats all net changes as reflecting attrition or accession.

4.3 Identification strategy

To identify the causal effect of the SHA policy on net teacher loss rate, this study exploits the hardship index eligibility cutoff through a fuzzy regression discontinuity design. A fuzzy design is warranted because SHA receipt is an imperfect function of the cutoff rule: multigrade teachers in pure multigrade schools, mobile teachers, ALS coordinators, and school heads in hardship posts receive the allowance regardless of their hardship index. As noted above, pure multigrade schools are excluded from the estimation sample to preserve identification.

The first stage equation is:

$$SHA_i = \alpha_0 + \alpha_1(C_i - n) + \alpha_2T_i + \alpha_3(C_i - n)T_i + e_i \quad (3)$$

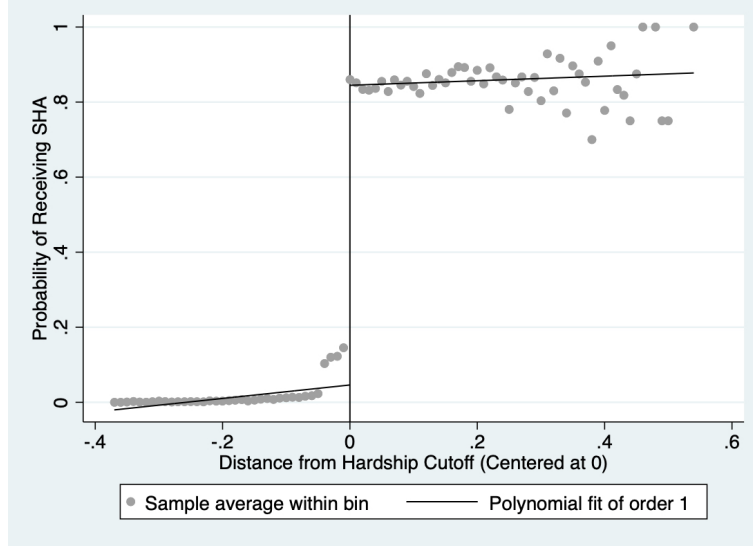


Figure 6: Treatment assignment

where i indexes the schools; SHA_i is the actual receipt, whether they are included in the list of recipients or not. This serves as the treatment status; C_i is the hardship index or the running variable; n is the cutoff, originally it is 0.37 which changed in 2023 to 0.33; T_i is the instrumental variable wherein $T_i = 1$ if $C_i \geq 0.33$ in years 2023 and 2024, and $C_i \geq 0.37$ in years 2021 and 2022.

The second stage equation is:

$$Y_i = \beta_0 + \beta_1(C_i - n) + \beta_2\widehat{SHA}_i + \beta_3(C_i - n)T_i + \mu_i \quad (4)$$

Y_i is the outcome variable; $\widehat{SHA}_i$ is the estimated probability of being able to receive the hardship allowance, using (3) as the first stage. In Eq. (4), β_2 measures the local average treatment effect (LATE). Following Cattaneo et al. (2018), we estimate the fuzzy RDD using a local linear regression (polynomial order $p = 1$) with a triangular kernel and MSE-optimal bandwidth selection on both sides of the cutoff.

4.4 Assumption of the RDD

The key identifying assumption of the RDD is the continuity assumption – potential outcomes must vary smoothly through the cutoff, with no jump of their own – which is plausible only if schools cannot precisely manipulate their position around the cutoff. As seen in Figure 6, where hardship index was centered at 0, it generates a discontinuity at 0. With this, formal manipulation testing was done using the Cattaneo et al. (2018) density test and the resulting p-value for the pooled no multigrade restriction sample is 0.293, which states that the test fails to reject the null hypothesis and concludes that there is no manipulation in the data. However, in our estimation sample, which excludes pure multigrade schools, the same test rejects continuity with p-value = 0.006. The manipulation may come from the restriction in the sample, since for pooled 2021 to 2024, the index shows no discontinuity

before exclusions, and not from manipulation of the hardship index.

Table 4: Manipulation test results

	Including MG	Excluding MG	Excluding Newly-Eligible
<i>Cutoff = 0.37</i>			
2021	$p = 0.823$	$p = 0.007$	–
2022	$p = 0.942$	$p = 0.011$	–
<i>Cutoff = 0.33</i>			
2023	$p = 0.000$	$p = 0.000$	$p = 0.987$
2024	$p = 0.000$	$p = 0.000$	$p = 0.691$
Pooled, All Years	$p = 0.293$	$p = 0.006$	–

Notes: Cells report the p -value from the Cattaneo et al. (2018) density test. MG = multigrade.

The main estimation sample used throughout the paper is the "Excluding MG". "Including MG" is used as robustness check, while "Excluding Newly-Eligible" is discussed in Section 5.1. The significance and magnitude of RD estimates using the "Including MG" sample are close to the RD estimates using the main estimation sample. This suggests that manipulation in years 2021 and 2022 is due to sample restriction. Additionally, excluding newly-eligible schools eliminates evidence of manipulation suggesting that manipulation in 2023 and 2024 came from newly-eligible schools after the cutoff reduction in 2023. In conclusion, the density discontinuity therefore raises a concern about whether schools just above and below the cutoff are comparable, Sections 5 and 6 address this concern.

4.5 Limitations and caveats

Several limitations and caveats of the study should be acknowledged. First, the study lacks data on the timeline of hardship allowance distribution. Payment delays are a documented challenge in implementing hardship allowance programs in low- and middle-income countries (Evans and Acosta, 2023), and the Philippines faces similar administrative frictions: Department of Education, Philippines (2021) acknowledges a long process of availing the Special Hardship Allowance, which the order itself was issued to streamline. Under the permanent income hypothesis (Friedman, 1957), individuals base their decisions on anticipated income rather than on the timing of each payment. Provided that teachers expect the allowance to be paid, delays in disbursement should therefore have limited effect on their decisions. As a result, the study assumes that the impact of the hardship allowance is as if it was distributed in a timely manner and cannot rule out the possibility that the estimated causal impact reflects a lagged effect from eligibility in the prior school year rather than the current one. This is a crucial assumption of the study.

A second limitation is the exclusion of pure multigrade schools from the sample. This exclusion reduces the external validity of the findings, as the impact of the SHA on pure multigrade schools, which are arguably among the most disadvantaged and isolated schools in the country, remains unexplored. However, the multigrade schools did not utilize its

hardship index to get into the program, thus including them might confuse the results. Future research should consider extending the analysis to this group to provide a more comprehensive assessment of the program's effects. Lastly, since the implementation of the hardship index based eligibility to SHA, analyzing four years worth of the program may not be enough to capture its long-run effects on staffing hard-to-staff location.

5 Results and discussion

The first stage estimates are reported in Table 5. They show that public schools just above the cutoff are 60 to 86 percentage points more likely to receive the hardship allowance than schools just below. This implies that having a hardship index score just above the cutoff substantially increases the probability of receiving the hardship allowance across all years, which can be exploited to identify the causal impact of SHA on the supply of teacher workforce in hardship posts. The first stage coefficients are broadly consistent across annual and pooled specifications, suggesting that the relationship between the cutoff and treatment uptake is stable over time, although notably higher in 2023. The F-statistics range from 301 to 3,841, ruling out any concern of weak instruments. As shown in Figure 6, the sharp discontinuity in the probability of treatment at the cutoff confirms that the hardship index score is a strong predictor of SHA receipt, satisfying the relevance condition required for a valid fuzzy RDD.

Table 5: First stage. Effect of attaining cutoff on SHA program

	(2021)	(2022)	(2023)	(2024)	Pooled	2021–2022	2023–2024
Coefficient	0.619*** (0.032)	0.600*** (0.035)	0.864*** (0.014)	0.631*** (0.018)	0.691*** (0.016)	0.610*** (0.033)	0.744*** (0.013)
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F-statistic	364.174	301.272	3840.776	1268.841	1804.869	344.383	3086.955
Bandwidth	0.056	0.053	0.084	0.105	0.054	0.055	0.092
N (left)	2,239	2,225	5,300	8,147	10,259	4,464	13,170
N (right)	1,466	1,463	3,050	3,338	7,601	2,929	6,404

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Bandwidth selected using MSE-optimal procedure (Calonico et al., 2014).

Pooled estimation includes year fixed effects and clustered SE at school level.

Table 6 presents the estimated impact of SHA on the net teacher loss rate (NTLR), learner-teacher ratio (LTR), share of experienced teachers (SET), share of Master Teachers (SMT), share of Teacher 1 (ST1), share of Teacher 2 and 3 (ST2T3) in SY 2021 – 2022. Note that experienced teachers are composed of Teacher 2, Teacher 3, and Master Teachers. The hardship allowance shows no statistically significant impact on any outcome variable in SY 2021 – 2022.

Similar to the results in SY 2021 – 2022, the hardship allowance shows no significant impact on any outcome variable in SY 2022 – 2023, as presented in Table 7. Table A2 reports RD estimates of the impact of the hardship allowance on the net teacher loss rate using an uncensored measure, wherein net gain in teachers is not recorded as zero. The results remain statistically insignificant, suggesting that censoring at zero is not driving the null result. However, for 2021, the signs changed while in 2022, there is a 3 percentage points change in the magnitude of the RD estimate after not censoring the net teacher loss rate at 0. While Table A1 reports the RD estimates when pure multigrade schools were included, both years remain insignificant and there was a change in the magnitude of the RD estimate in 2022.

Table 6: RD estimates of the impact of SHA in SY 2021 - 2022

	NTLR	LTR	SET	SMT	ST1	ST2T3
RD Estimate	0.645 (1.670)	-3.072 (2.659)	0.011 (0.039)	-0.006 (0.009)	0.009 (0.052)	0.019 (0.035)
Bandwidth (h)	0.098	0.060	0.069	0.069	0.053	0.077
No. of schools left	4,582	2,211	2,725	2,725	2,211	3,280
No. of schools right	2,041	1,451	1,599	1,599	1,451	1,740
Observations	48,234	47,682	47,682	47,682	47,682	47,682

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Bandwidth selected using MSE-optimal procedure (Calonico et al., 2014).

Table 7: RD estimates of the impact of SHA in SY 2022 - 2023

	NTLR	LTR	SET	SMT	ST1	ST2T3
RD Estimate	-3.086 (2.030)	-2.420 (2.194)	0.004 (0.048)	-0.006 (0.009)	-0.031 (0.070)	0.013 (0.046)
Bandwidth (h)	0.091	0.059	0.056	0.067	0.053	0.056
No. of schools left	4,553	2,190	2,190	2,696	2,190	2,190
No. of schools right	2,034	1,441	1,441	1,587	1,441	1,441
Observations	47,975	47,204	47,204	47,204	47,204	47,204

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Bandwidth selected using MSE-optimal procedure (Calonico et al., 2014).

In 2021, the first year of the hardship index-based eligibility criterion, the estimated coefficients are statistically insignificant. This school year falls during the COVID-19 pandemic, in which schools in the Philippines operated predominantly under remote or asynchronous learning modalities. Thus, teachers were not physically present in hardship areas for much of the year, which may have weakened the incentive mechanism of the hardship allowance. The first-stage results remained intact as the index-based classification process was unaffected by school closures. This suggests that the null result reflects a weakened mechanism rather than a loss of identifying variation. In 2022, the estimated coefficients remain statistically insignificant. Schools officially reopened during this year, but the threat of COVID-19 cases kept class suspensions prevalent throughout the school year. It is suspected that there is a confounding factor present in these two years that could help explain the insignificant results.

Beginning in 2023, when Philippine schools returned to full pre-pandemic operations with no mobility restrictions and normalized physical attendance, Table 8 reports a 1.784 percentage point reduction in the net teacher loss rate, significant at the 10% level, and a significant reduction of approximately 2 learners per teacher. The reduction in the learner-teacher ratio is consistent with the reduction in the net teacher loss rate. By excluding the newly eligible schools, schools that were added to the list of SHA recipients after the 2023 cutoff

reduction, from the sample, the effect on the learner-teacher ratio becomes highly significant and greater in magnitude. The share of experienced teachers significantly declined by 10.6 percentage points, driven by a decline in the share of Master Teachers and Teacher 2 and 3, while the share of Teacher 1 increased by 9.7 percentage points. The net teacher loss rate, however, is insignificant in this sample.

Table 8: RD estimates of the impact of SHA in SY 2023 - 2024

Sample	NTLR	LTR	SET	SMT	ST1	ST2T3
<i>Basic - RD Estimate</i>	-1.784*	-2.087**	-0.030	-0.003	0.021	-0.027
	(1.006)	(0.975)	(0.025)	(0.005)	(0.038)	(0.024)
Bandwidth (h)	0.073	0.062	0.062	0.067	0.065	0.061
No. of schools left	4,344	3,471	3,471	3,471	3,471	3,471
No. of schools right	2,844	2,586	2,586	2,586	2,586	2,586
N	47,634	47,211	47,211	47,211	47,211	47,211
<i>Newly excluded - RD Estimate</i>	-0.238	-6.627***	-0.106***	-0.016**	0.097*	-0.089**
	(1.629)	(1.250)	(0.038)	(0.007)	(0.054)	(0.036)
Bandwidth (h)	0.070	0.062	0.059	0.064	0.060	0.058
No. of schools left	3,517	3,471	2,714	3,471	3,471	2,714
No. of schools right	1,367	1,354	1,083	1,354	1,354	1,083
N	46,387	45,979	45,979	45,979	45,979	45,979

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Bandwidth selected using MSE-optimal procedure (Calonico et al., 2014).

'Newly excluded' means that newly eligible schools are excluded from the sample.

Manipulation test p : Basic < 0.001 ; Newly excluded = 0.987.

The effect strengthens further in 2024, with an estimated reduction in the net teacher loss rate of 4.147 percentage points, significant at the level of 1% as reported in Table 9. Excluding the newly eligible schools from the sample increases the magnitude of reduction in the net teacher loss rate to 6.728 percentage points and yields a reduction of roughly 6 to 7 learners per teacher, both significant at the 1% level. As in 2023, there is also a significant 13.5 percentage points decline in the share of experienced teachers, driven primarily by a decline in the share of Teachers 2 and 3. Meanwhile, the share of Teachers 1 increased by the same magnitude as the decline in the share of experienced teachers.

Including pure multigrade schools yields close estimates for 2024 that remained highly significant, while it loses significance in 2023. The same case when the net teacher loss rate is not censored at 0. For both SY 2023 – 2024 and SY 2024 – 2025, the evidence of manipulation was removed after the exclusion of the newly eligible schools. Thus, it appears that the source of manipulation was the schools that were added to the list of SHA recipients after 2023 cutoff reduction. The case of newly eligible schools is explored further in Section 5.1. However, the results from excluding the newly-eligible schools should only serve as a supplementary estimation as it is only a one-sided donut. The resulting estimate should not be interpreted as a local effect at the threshold.

As the policy aims to improve the number of experienced teachers in hardship posts, results

Table 9: RD estimates of the impact of SHA in SY 2024 - 2025

Sample	NTLR	LTR	SET	SMT	ST1	ST2T3
<i>Basic - RD Estimate</i>	-4.147*** (1.438)	-1.285 (0.991)	0.004 (0.028)	0.004 (0.005)	-0.003 (0.028)	-0.001 (0.028)
Bandwidth (h)	0.121	0.080	0.073	0.104	0.074	0.071
No. of schools left	10,864	4,681	4,681	7,985	4,681	4,681
No. of schools right	3,610	2,791	2,791	3,296	2,791	2,791
N	49,463	48,774	48,774	48,774	48,774	48,774
<i>Newly excluded - RD Estimate</i>	-6.728*** (2.327)	-6.764*** (2.023)	-0.135** (0.058)	-0.015 (0.010)	0.135** (0.058)	-0.121** (0.055)
Bandwidth (h)	0.117	0.079	0.069	0.095	0.069	0.068
No. of schools left	9,421	4,681	3,796	6,751	3,796	3,796
No. of schools right	2,238	1,574	1,348	1,935	1,348	1,348
N	48,224	47,557	47,557	47,557	47,557	47,557

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Bandwidth selected using MSE-optimal procedure (Calonico et al., 2014).

'Newly excluded' means that newly eligible schools are excluded from the sample.

Manipulation test p : Basic < 0.001 ; Newly excluded = 0.691.

from the sample excluding newly eligible schools suggests that the hardship allowance has not yet materialized to attract experienced teachers in hardship posts. The share of experienced teachers had significantly declined by 13.5 percentage points. On the contrary, the restricted sample has shown a 13.5 percentage point increase in the share of Teacher 1 who may be driving the sustained teaching workforce in these areas. Although it cannot identify whether these are new hires or retained Teacher 1 from the past school year. A full teacher-level data set would be needed to prove this mechanism.

Table 10: Pooled RD estimates of the impact of SHA in 2021 - 2022

	NTLR	LTR	SET	SMT	ST1	ST2T3
RD Estimate	-1.558 (1.533)	-2.887 (2.137)	0.006 (0.041)	-0.006 (0.008)	-0.009 (0.054)	0.016 (0.038)
Bandwidth (h)	0.079	0.055	0.057	0.067	0.052	0.059
No. of schools left	6,621	4,401	4,401	5,421	4,401	4,401
No. of schools right	3,511	2,892	2,892	3,186	2,892	2,892
Observations	96,209	94,886	94,886	94,886	94,886	94,886

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Bandwidth selected using MSE-optimal procedure (Calonico et al., 2014).

The pooled estimates shown in Tables 10 and 11 are consistent with the annual RD estimates reported above. The pooled estimate across all observations, reported in Table 12 likewise yields a highly significant reduction in the net teacher loss rate of 2.676 percentage points and a significant reduction of approximately 2 learners per teacher. Using the uncensored net

Table 11: Pooled RD estimates of the impact of SHA in 2023 - 2024

Sample	NTLR	LTR	SET	SMT	ST1	ST2T3
Basic - RD Estimate	-2.708*** (0.845)	-1.670** (0.847)	-0.016 (0.024)	0.000 (0.004)	0.007 (0.027)	-0.017 (0.024)
Bandwidth (h)	0.104	0.079	0.066	0.089	0.084	0.064
No. of schools left	15,575	8,973	7,267	10,935	10,935	7,267
No. of schools right	6,690	5,604	5,151	6,011	6,011	5,151
N	97,097	95,985	95,985	95,985	95,985	95,985
Newly excluded - RD Estimate	-2.733** (1.337)	-6.645*** (1.430)	-0.119*** (0.042)	-0.014* (0.008)	0.098** (0.041)	-0.105*** (0.040)
Bandwidth (h)	0.097	0.073	0.062	0.070	0.089	0.062
No. of schools left	13,163	8,973	7,267	8,973	10,935	7,267
No. of schools right	3,916	3,155	2,702	3,155	3,562	2,702
N	94,611	93,536	93,536	93,536	93,536	93,536

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Bandwidth selected using MSE-optimal procedure (Calonico et al., 2014).

'Newly excluded' means that newly eligible schools are excluded from the sample.

teacher loss rate, the pooled all-years estimate falls to a 2.227-percentage-point reduction, significant only at the 10% level, compared with 2.676 percentage points at the 1% level under the censored measure.

A simplified projection, applying this local estimate to the 44,403 teachers reported under the SHA program in a 2023 DepEd memo, a 2.676-percentage-point reduction in net teacher loss rate would correspond to approximately 1,188 fewer net teacher losses annually. This calculation assumes the estimated effect near the eligibility cutoff generalizes to the full SHA-recipient population. These results are robust to placebo cutoff tests. Taken together, the pattern across years, insignificant in 2021 and 2022, then increasingly significant in 2023 and 2024, suggests that the hardship allowance's stabilizing effect on teacher staffing materializes as the allowance becomes more established under the expanded eligibility criteria.

Recall from Section 4.4 that the density test shows no evidence of density discontinuity in the pooled full sample, although it rejects continuity in 2023 and 2024. We therefore re-estimate the effect on the net teacher loss rate using the full sample. Table [A1](#) compares these estimates with those from the sample excluding multigrade schools. The results are broadly similar. In the years where SHA has a significant effect, the estimates are close in magnitude and keep their significance: the 2024 estimate is -4.038 compared with -4.147 , and the pooled 2023–2024 estimate is -3.142 compared with -2.708 , all significant at the 1% level. The pre-expansion estimates for 2021, 2022 and the pooled 2021–2022 period remain statistically insignificant in both samples. The only change in significance is in 2023: the estimate is nearly the same, but it is no longer significant at the 10% level. In conclusion, the main findings on pooled estimation do not depend on the exclusion of multigrade schools, and the evidence of manipulation detected earlier may stem from the sample restriction rather than a genuine sorting around the cutoff.

Table 12: Pooled RD estimates of the impact of SHA in ALL YEARS

	NTLR	LTR	SET	SMT	ST1	ST2T3
Robust	-2.676*** (0.842)	-2.223** (0.964)	-0.007 (0.019)	-0.002 (0.004)	0.011 (0.027)	-0.006 (0.018)
Bandwidth (h)	0.075	0.054	0.069	0.073	0.053	0.065
No. of schools left	15,732	10,101	12,688	15,495	10,101	12,688
No. of schools right	9,184	7,503	8,337	9,071	7,503	8,337

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Bandwidth selected using MSE-optimal procedure (Calonico et al., 2014).

Estimates are covariate-adjusted for year fixed effects and corrected for mass points in the running variable.

5.1 The case of newly-eligible schools

Using a different identification strategy that does not depend on the no-manipulation-with-precision assumption of the RD Design, the impact of the SHA for the newly eligible schools is tested after the cutoff reduction in 2023.

The difference-in-difference model for each outcome variable, y , is:

$$Y_{it} = \delta_0 + \delta_1 \text{Newly}_{it} + \alpha_i + \gamma_t + e_{it} \quad (5)$$

Y is any outcome variable, Newly_{it} equals 1 in years $t \in \{2023, 2024\}$ if school i has a hardship index in $[0.33, 0.37)$, that is, it became eligible only after the 2023 cutoff reduction and was not eligible under the 0.37 cutoff, and 0 for school i within $[0.33 - h, 0.33)$ in every year t , where h is the local bandwidth set to 0.05¹; α and γ are school and year fixed effects, respectively, which absorb time-invariant school characteristics and any shock common to all schools within a given year. Standard errors are clustered at the school level. The coefficient δ_1 is the parameter of interest, which measures the average within-school change in the outcome for newly eligible schools after the 2023 cutoff reduction.

Unlike the RD Design, the validity of the DID model rests on the parallel trends assumption. The parallel trend assumption requires that, for newly eligible schools, the outcome variable would have followed the same trend as ineligible schools had the cutoff reduction not occurred.

The results of the parallel trend test assumption are presented in Figure A1. For all outcome variables, the coefficients revealed a statistically insignificant effect of the SHA policy before the cutoff reduction in 2023. However, this evidence rests on a single pre-treatment period and the confidence intervals are wide, so the test has limited power to identify that trends

¹This restriction is not required for DID identification the way a bandwidth is required for RD design. However, the addition of local bandwidth is intended to strengthen the credibility of the parallel trends assumption. Schools far from the hardship threshold are likely to differ systematically from newly eligible schools for reasons unrelated to SHA eligibility and pooling them into the comparison group would risk biasing the estimated effect even in the absence of any true policy impact.

were parallel. In the post-period, only the net teacher loss rate shows a statistically significant effect, at the 5% level in 2024, as shown in Figure [A1a](#). The DD estimates should therefore be interpreted cautiously and as corroborating only to the RD results.

Table 13: DD estimates of the impact of SHA in newly-eligible schools

	NTLR	LTR	SET	SMT	ST1	ST2T3
DD Estimate	-1.692** (0.818)	0.465 (0.755)	0.013 (0.013)	0.005* (0.003)	0.036 (0.026)	0.008 (0.012)
Observations	10,374	10,254	10,254	10,254	10,254	10,254

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Always-eligible schools or the schools that are part of the program since 2021 are excluded from the sample.

As shown in Table [13](#), the newly eligible schools experienced a 1.692 percentage point larger reduction in the net teacher loss rate, significant at the 5% level, relative to the ineligible schools near the cutoff. These results corroborate the significance of the RD estimate above using an entirely different identifying assumption, one that does not rely on the RD's no-manipulation condition. This suggests that the 2023 – 2024 pooled RD estimate is not an artifact of manipulation-driven sorting at the cutoff, since an independent design that sidesteps that assumption points to a similar effect. In conclusion, consistent findings across both identification strategies strengthen confidence that the estimated effect of the hardship allowance on net teacher loss rate reflects a policy impact.

6 Robustness checks

This section reports robustness checks that address the main threats to the validity of the baseline estimates. The first examines whether spurious discontinuities exist elsewhere along the running variable distribution through placebo cutoff tests. The second addresses the concern of sorting or manipulation at the cutoff through a donut hole robustness test. The third assesses whether the baseline results are sensitive to the choice of polynomial order in the local polynomial regression.

6.1 Transitional contamination from the pre-hardship index criterion

Recall from Section 2, the policy existed prior to 2021 under a different eligibility criterion. This poses a threat to the validity of the study because the schools below the hardship index cutoff that were SHA recipients under the old system could contaminate the SY 2021 - 2022 control group if they were grandfathered into the new regime. However, based on the data, the transition from the old eligibility SHA criteria to the hardship index, there were 4,722 schools that were removed from the list. Out of 4,722, 4,684 (99.2%) schools were removed specifically because they failed to meet the new hardship cutoff, providing strong evidence that DepEd did not grandfather old recipients. On the other hand, there were 233 schools that were below the cutoff that belonged to 2021 recipients and were also in 2020 SHA recipients. Thus, we hypothesize that it might confound the 2021 estimation. Hence, the impact of the SHA on the net teacher loss rate in 2021 after removing these 233 schools was tested. Robustness checks excluding these schools yield quantitatively similar results, suggesting that transitional contamination due to changes in the said policy does not materially affect the estimates.

6.2 Placebo test

One of the key identifying assumptions of the fuzzy regression discontinuity design is that there should be no statistically significant discontinuities at locations other than the true cutoffs of 0.37 in years 2021 and 2022, and 0.33 in years 2023 and 2024. To assess the validity of the empirical design, one of the robustness checks conducted was the placebo cutoff tests.

Six artificial thresholds were tested: $\pm 0.30, \pm 0.25, \pm 0.15$, these are centered at zero. To prevent contamination from the true treatment effect, all observations ± 0.10 of the original cutoff were excluded from the placebo test. Each placebo was estimated using the sharp RD specification, a local linear regression with a triangular kernel, optimal bandwidth selection, and school-level clustered standard errors.

Figure 7 shows that no spurious discontinuities exist elsewhere along the running variable distribution as all 95% confidence intervals crossed zero. Additionally, of the six placebo cutoffs, five are statistically insignificant and one is marginally significant as shown in Table A3. The placebo coefficients also vary in sign, and none approaches the significance of the estimate at the true cutoff. This supports the interpretation that the discontinuity detected

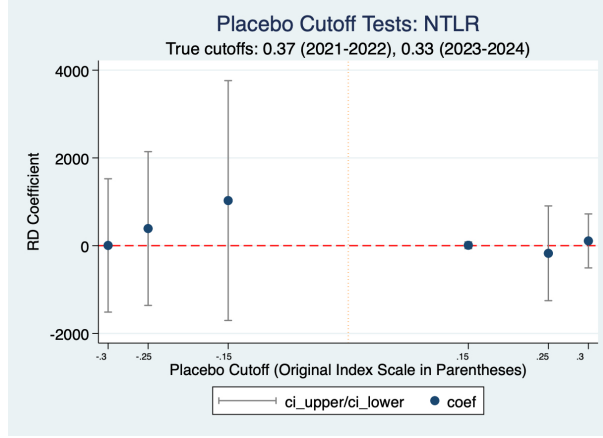
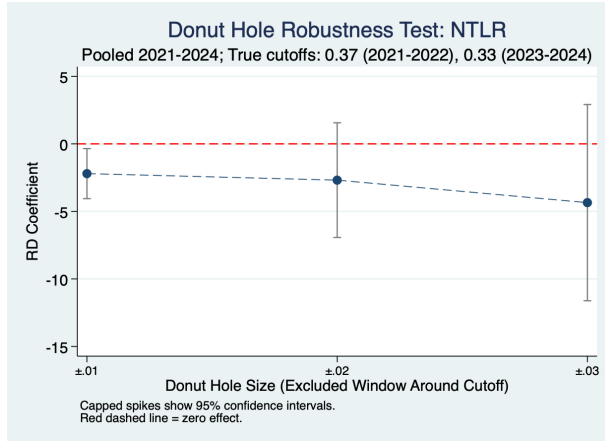


Figure 7: Placebo test: Net teacher loss rate

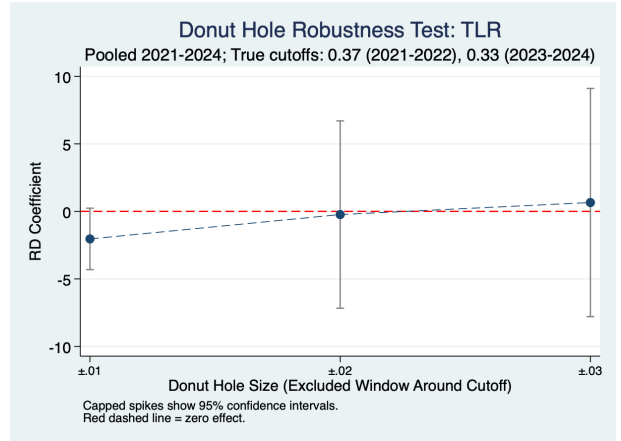
at the true cutoff reflects a genuine effect of SHA on net teacher loss rates rather than a confounding trend.

6.3 Donut hole test

The manipulation test by Cattaneo et al. (2018), done on the main estimation sample, indicates a statistically significant discontinuity in the density of schools at the true hardship index cutoff. It rejects the null hypothesis that there is no manipulation at the cutoff, suggesting the possibility of sorting around the eligibility threshold. However, a failed manipulation test only raises the concern that observations immediately surrounding the cutoff may be driving the results and does not necessarily invalidate the RD design (Barreca et al., 2016). This is consistent with the "donut-hole" approach proposed by Cowan and Goldhaber (2018); Eggers et al. (2015); Almond and Doyle (2011), which treats the exclusion of near-cutoff observations as a robustness check to validate RD estimates despite a failed manipulation test.



(a) Net Teacher Loss Rate



(b) Learner-Teacher Ratio

Figure 8: Donut hole test

Three exclusion windows were tested: $\pm 0.01, \pm 0.02, \pm 0.03$. Figure 8 shows the donut-hole RD estimates excluding the results of the baseline model at the true cutoff. The narrowest exclusion window of ± 0.01 yields a statistically significant estimate, while wider exclusion windows produce statistically insignificant, with confidence intervals crossing the zero effect line, for the net teacher loss rate. For the learner-teacher ratio, similar to the baseline results reported above, wider exclusion windows also produce statistically insignificant results. As reported in Table A4, the case of the insignificant coefficients at wider exclusion windows is consistent with reduced statistical power due to the shrinking sample size as donut holes expand, rather than the absence of a true effect. Schools with lower hardship index are more numerous, and the number of schools retained on the right side of cutoff decreases considerably. The consistent negative coefficient for net teacher loss rate and relatively stable magnitude across all specifications, from -2.203 to -4.351, suggest that the main RD estimate is not driven by observations immediately surrounding the cutoff.

Overall, while the manipulation test flags a density irregularity at the cutoff, the results of the donut hole test support the interpretation of the study that the estimated effect of SHA on teacher labor supply is not driven by the administrative sorting on the hardship index.

6.4 Polynomial order sensitivity

We assess sensitivity to the choice of polynomial order by re-estimating the model using a local quadratic specification ($p = 2$). Results shown in Table 14 are qualitatively similar, confirming that the baseline estimates are not sensitive to the polynomial order used in the local regression.

Table 14: Robustness check: Sensitivity to polynomial order (Pooled ALL YEARS)

	Coefficient	Robust SE
<i>Panel A: Net Teacher Loss Rate</i>		
Baseline: Local Linear ($p = 1$)	-2.676***	(0.842)
Robustness: Local Quadratic ($p = 2$)	-3.120***	(1.042)
<i>Panel B: Learner-Teacher Ratio</i>		
Baseline: Local Linear ($p = 1$)	-2.223**	(0.964)
Robustness: Local Quadratic ($p = 2$)	-2.165**	(1.034)

Bias-corrected coefficients with robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Both specifications include year fixed effects and clustered SE at school level.

The pooled model using a local quadratic specification ($p = 2$) yields a slightly larger estimate than the baseline local linear estimate but remains significant at the 1% level for the net teacher loss rate. For the learner-teacher ratio, the coefficient declined but remains significant at the 5% level. The consistency in sign, significance, and approximate magnitude across polynomial orders confirms that the estimated effect of SHA on net teacher loss rate and learner-teacher ratio is robust to the choice of polynomial order.

7 Conclusion

This paper examined the causal impact of the Special Hardship Allowance (SHA) on teacher supply and workforce quality in geographically isolated and disadvantaged areas (GIDAs) in the Philippines. Using a fuzzy regression discontinuity design and difference-in-difference, the study finds a significant reduction in the net teacher loss rate among schools just above the hardship index cutoff relative to those just below. The smaller reduction in the net teacher loss rate observed among newly eligible schools is consistent with the hardship allowance’s effect on teacher supply in strengthening as the program becomes more established, though it may also reflect that these schools face comparatively less severe staffing shortages to begin with. The initial implementation of the index-based SHA eligibility coincided with the COVID-19 pandemic. The null results in the program’s early years may therefore reflect prolonged class disruptions that kept teachers from being physically present in hardship posts, which could have weakened the allowance’s incentive mechanism. The study also finds insufficient evidence that the share of experienced teachers, who receive proportionally higher hardship allowance, increased. This suggests that the magnitude of the hardship allowance alone may not be sufficient to attract or retain more experienced teachers in hardship posts.

Together, the results are consistent with the findings of [See et al. \(2020\)](#), who show that monetary incentives are effective in attracting teachers to hardship posts. These results also suggest that teachers respond to monetary incentives, and that targeted compensation reforms can be an effective policy instrument for stabilizing teacher supply in hard-to-staff areas. However, without complete teacher-level panel data, the study cannot determine whether the reduction in net teacher loss reflects improved retention of existing teachers or increased inflows through monetary incentives.

Limitations of the analysis should be acknowledged. As with all fuzzy regression discontinuity designs, the estimated treatment effect is a Local Average Treatment Effect (LATE) that is, it applies specifically to schools in the neighborhood of the hardship index cutoff and may not generalize to schools deep within hardship areas where conditions are more extreme.

The study carries several policy implications. First, the finding that the hardship allowance has a causal impact on staffing conditions in hardship areas sends an important signal to policymakers to continue supporting targeted financial incentives as a policy tool for addressing the geographic maldistribution of teachers. This brings the education system one step closer to resolving teacher supply difficulties in geographically disadvantaged areas.

Second, the Department of Education should ensure the timely disbursement of the hardship allowance to recipient schools. As noted by [Evans and Yuan \(2018\)](#), delays in financial incentive provision may reduce program effectiveness, which in this context could undermine efforts to improve staffing conditions in hardship posts.

Third, alongside timely disbursement, information about the hardship allowance and similar policies must be properly and widely disseminated to teachers. Awareness of available incentives is a prerequisite for those incentives to influence teacher placement decisions.

Fourth, while financial incentives have shown promise in attracting teachers to hardship ar-

eas, the government should not cease efforts to improve non-monetary conditions. Improving learning environments, infrastructure, and road access to hardship schools are equally important. Strengthening non-financial incentives is necessary to complement financial ones in building a sustainable teacher supply in geographically disadvantaged areas.

Fifth, the Department of Education should consider adopting similar index-based targeting criteria for other education programs aimed at addressing equity gaps across schools.

Given that Department of Education policy requires teachers to serve in their home municipality upon entry into the profession, sustained investment in academic quality within GIDAs is essential to cultivating a self-replenishing local teacher pipeline for future generations. Future researchers could examine the long-run effects of the SHA as more post-reform data become available, and explore how financial incentives interact with other education policies such as deployment rules and school-based support programs.

A Appendices

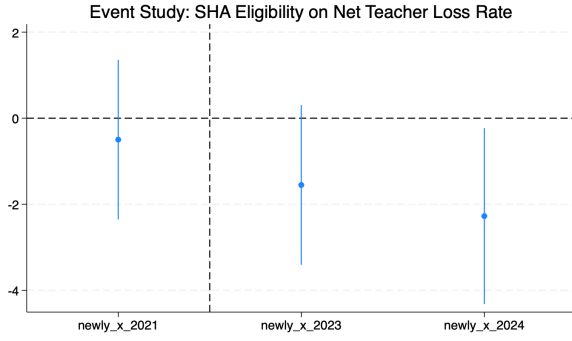
Table A1: RD estimates of the SHA on the net teacher loss rate, with and without pure multigrade schools

	(1) 2021	(2) 2022	(3) 2023	(4) 2024	(5) 21–22	(6) 23–24	(7) All years
<i>Panel A. Including pure multigrade schools</i>							
Net teacher loss rate	0.753 (1.541)	-1.695 (1.452)	-1.742 (1.137)	-4.038*** (1.483)	-0.525 (1.009)	-3.142*** (1.068)	-2.371*** (0.809)
Effective N	9,233	13,160	8,016	18,963	26,357	18,679	35,598
<i>Panel B. Excluding pure multigrade schools</i>							
Net teacher loss rate	0.645 (1.670)	-3.086 (2.030)	-1.784* (1.006)	-4.147*** (1.438)	-1.558 (1.533)	-2.708*** (0.845)	-2.676*** (0.842)
Effective N	6,623	6,587	7,188	14,474	10,132	22,265	24,916

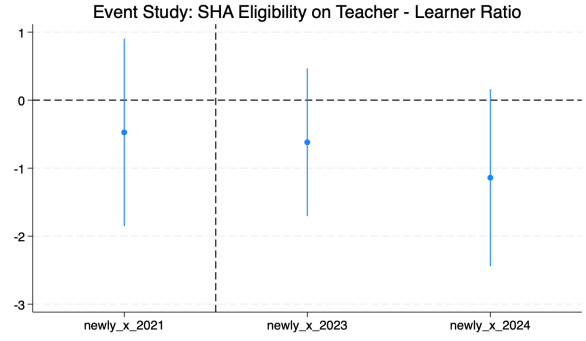
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses

Bandwidth selected using MSE-optimal procedure (Calonico et al., 2014).

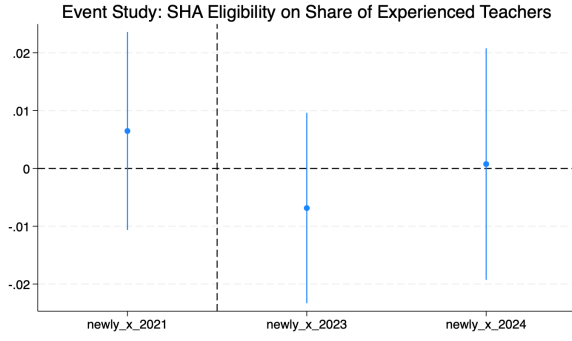
Estimates are covariate-adjusted for year fixed effects and corrected for mass points in the running variable.



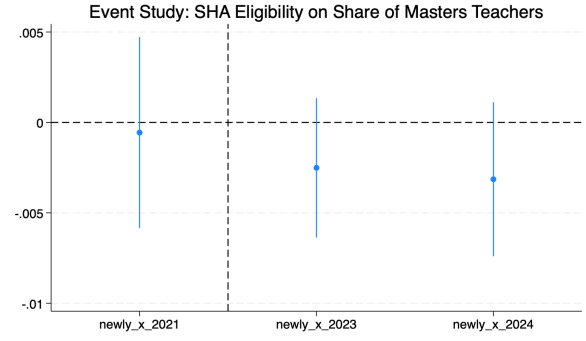
(a) NTL



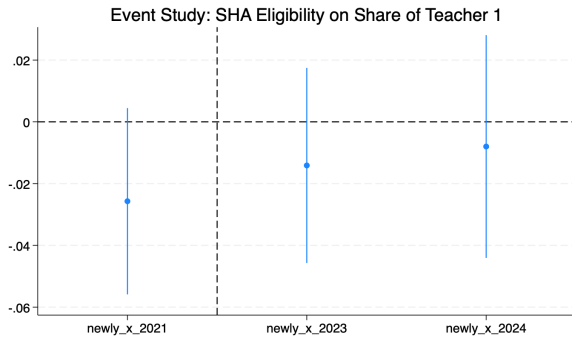
(b) LTR



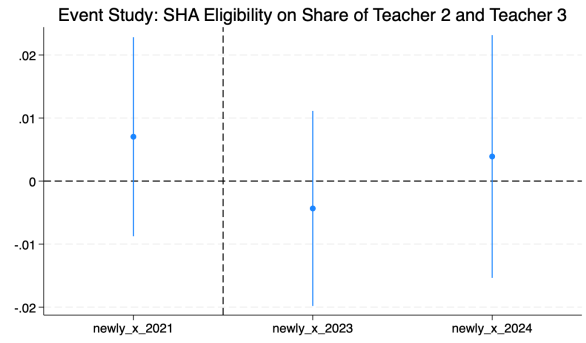
(c) SET



(d) SMT



(e) ST1



(f) ST2T3

Figure A1: Parallel trend test

Table A2: RD estimates of the SHA on the net teacher loss rate, censored and not censored at zero

	(1) 2021	(2) 2022	(3) 2023	(4) 2024	(5) 21–22	(6) 23–24	(7) All years
<i>Panel A. Net teacher loss rate (censored at 0)</i>							
Net teacher loss rate	0.645 (1.670)	-3.086 (2.030)	-1.784* (1.006)	-4.147*** (1.438)	-1.558 (1.533)	-2.708*** (0.845)	-2.676*** (0.842)
Effective N	6,623	6,587	7,188	14,474	10,132	22,265	24,916
<i>Panel B. Net teacher loss rate (not censored at 0)</i>							
Net teacher loss rate	-1.247 (3.206)	-0.067 (2.148)	-0.259 (1.937)	-5.678** (2.402)	-0.500 (1.864)	-2.919** (1.310)	-2.227* (1.213)
Effective N	8,338	10,413	8,274	10,004	18,732	14,667	28,578

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Bandwidth selected using MSE-optimal procedure (Calonico et al., 2014).

Estimates are covariate-adjusted for year fixed effects and corrected for mass points in the running variable.

Table A3: Placebo cutoff RD estimates: pooled (all years)

Cutoff	Index scale	Coefficient	Robust SE	p -value	Bandwidth	N (left)	N (right)
-0.30	0.07	-0.161	0.335	0.631	0.036	14,253	25,777
-0.25	0.12	-0.544	0.586	0.353	0.025	15,542	23,767
-0.15	0.22	0.439	0.385	0.254	0.088	59,713	21,833
0.15	0.52	0.286	1.440	0.842	0.050	1,864	1,305
0.25	0.62	-2.694	2.070	0.193	0.047	1,067	623
0.30	0.67	-4.133*	2.500	0.098	0.066	975	573

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates are from a sharp (reduced-form) RD of the net teacher loss rate at each placebo cutoff, using a local linear regression with a triangular kernel and MSE-optimal bandwidth.

Table A4: Donut hole RD estimates: Pooled (ALL YEARS)

Donut size	Coefficient	Robust SE	Bandwidth	N (Left)	N (Right)
<i>Panel A: Net Teacher Loss Rate</i>					
0.01	−2.203**	0.945	0.089	18,979	8,241
0.02	−2.685	2.166	0.069	11,233	4,456
0.03	−4.351	3.706	0.064	8,306	3,194
<i>Panel B: Learner-Teacher Ratio</i>					
0.01	−2.038*	1.161	0.058	10,101	5,897
0.02	−0.234	3.539	0.046	6,303	2,742
0.03	0.657	4.311	0.073	10,980	3,895

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Note: Bias-corrected coefficients with robust standard errors in parentheses.
fixed effects and clustered SE at school level.

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