Performance Pay at Scale: Evidence from Texas's Statewide Teacher Incentive Program

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Abstract

This paper evaluates the impact of the Teacher Incentive Allotment (TIA), a statewide performance-based pay program introduced in Texas in 2019 to improve the recruitment and retention of effective teachers, particularly in rural and high-poverty schools. Using administrative microdata from the Texas Education Agency (2014–2024) linking personnel, designation, and campus funding records, I examine how teacher retention and mobility respond to the phased roll-out of TIA. The empirical strategy utilizes a dynamic difference-in-differences framework following Callaway and Sant'Anna (2021), exploiting variation in the timing of district entry into the program to identify short run effects. I find that the TIA generated modest but meaningful improvements in staffing stability, increasing district and campus retention rates by roughly one percentage point, driven primarily by reductions in exits from the public school system. A gravity-model analysis of inter-district flows similarly shows no detectable evidence that treated districts attracted teachers away from non-treated districts. These results suggest that the TIA improves retention among incumbent teachers but does not substantially alter mobility patterns across Texas school districts.

1 Introduction

Teacher quality is one of the strongest school-based predictors of student learning (Rockoff, 2004; Rivkin et al., 2005), and evidence shows that effective teachers generate lasting improvements in students' educational attainment and labor market outcomes (Chetty et al., 2014). Yet compensation in most U.S. public school districts is tied almost exclusively to seniority and credentials, with little direct linkage to measured classroom effectiveness. As a result, districts have limited ability to use financial incentives to attract, retain, or motivate highly effective teachers, especially in high-poverty or geographically isolated schools. These challenges are especially acute for retaining highly effective teachers. Under traditional seniority-based salary schedules, teachers are paid identical salaries regardless of their productivity, even though more effective teachers may have stronger outside labor market options. As a result, rigid pay structures can generate selective attrition, when teachers with higher productivity face superior outside options in alternative districts or non-teaching labor markets (Hoxby and Leigh, 2004; Biasi, 2021; Hendricks, 2014). Motivated by these concerns, policymakers have increasingly turned to performance-based compensation as a lever to improve teacher labor market outcomes and strengthen the distribution of effective teachers.

In Texas, the Teacher Incentive Allotment (TIA), enacted under House Bill 3 in 2019, represents the first statewide attempt to incorporate performance-based compensation into the teacher salary structure. The program provides substantial recurring allotments for teachers designated as *Recognized*, *Exemplary*, or *Master*, determined through district evaluation systems combining classroom observations and student growth measures. These allotments translate into sizable salary supplements, often exceeding $10,000 annually and in some cases approaching 50% of base pay. By layering performance-based compensation on top of the existing salary schedule, the TIA increases the marginal financial returns to high performance, particularly in high-need and rural schools.

A large empirical literature examines how short-run financial incentives affect teacher behavior, retention, and productivity. Stand-alone bonus programs in the United States generally find limited effects on student test scores (Springer et al., 2010; Fryer, 2013), though some targeted or group-based programs have produced positive effects on student achievement (Springer et al., 2012; Glazerman et al., 2017; Pham et al., 2021). Evidence is stronger on the labor market side: well-designed incentive systems reliably reduce turnover and improve teacher sorting. For example, the IMPACT evaluation system in Washington D.C. generated large improvements in both selective retention and teacher performance through high-powered bonuses and dismissal threats (Dee and Wyckoff, 2015). Large incentives have also succeeded in attracting highly effective teachers into hard-to-staff schools, as shown in the Talent Transfer Initiative (Glazerman et al., 2013) and in Dallas's ACE initiative, which produced substantial and sustained improvements in student achievement by staffing low-performing schools with top teachers (Morgan et al., 2023). More broadly, research on compensation flexibility shows that when districts can deviate from rigid salary schedules, they attract more effective teachers and improve student outcomes. Biasi (2021) documents that, following Wisconsin's Act 10 reform, districts adopting flexible pay attracted higher-quality teachers and increased student achievement, consistent with competitive sorting toward districts offering stronger performance incentives.

Complementing these findings, a large literature shows that teachers respond systematically to school context and working conditions. Teachers disproportionately leave schools serving low-achieving or disadvantaged students (Hanushek et al., 2004; Lankford et al., 2002), and school working conditions and leadership quality play central roles in predicting teacher mobility (Boyd et al., 2011; Johnson et al., 2012). These contextual factors contribute to persistent staffing differences across schools, with high-poverty and rural campuses experiencing sustained outflows of teachers relative to more advantaged settings. This raises the question of whether sufficiently large medium-horizon compensation differentials can offset these mobility patterns. The TIA's design, which provides larger allotments to teachers working in high-poverty or rural schools, creates a setting in which to examine this possibility.

The structure of the TIA therefore implies several channels through which it may affect teacher labor supply. Larger returns to high performance raise the expected value of remaining in districts that adopt strong designation systems, potentially increasing retention of effective teachers. Payout amounts vary sharply by campus disadvantage, therefore high-need schools may become more financially attractive, potentially altering within-district mobility patterns. Substantial salary differentials may also generate sorting of high-performing teachers across districts, and the prospect of recurring bonuses may influence recruitment into the profession and the distribution of new entrants.

This paper provides the first statewide causal analysis, to my knowledge, of how the Texas TIA program has affected teacher retention, mobility, and recruitment. Using linked administrative data from 2014 to 2024, I examine district-level responses to performance pay. The staggered roll-out of district adoption generates quasi-experimental variation in the exposure of teachers to performance pay, under the assumption that adoption timing is conditionally independent of potential outcomes given district and year fixed effects. I exploit this structure using a district-level staggered difference-in-differences design (Callaway and Sant'Anna, 2021). This method allows for a comprehensive assessment of whether the TIA has reshaped the teacher labor market in line with its policy goals.

This study contributes to several strands of research. First, it expands the performance pay literature by evaluating a legislatively permanent, formula-funded statewide incentive program, rather than the grant-funded pilots that dominate prior evidence. Second, it adds to the compensation design literature by examining how substantial, recurring incentives interact with local discretion in evaluation systems and generate heterogeneous returns across campuses. Third, it contributes to work on teacher labor supply and mobility by analyzing whether high-powered incentives shift retention, cross-district moves, and entry patterns in a broad state labor market. Taken together, these contributions provide new evidence on the labor market effects of large-scale performance-based compensation reforms implemented within an existing pay structure.

I find that the TIA moderately improves teacher retention. District and campus retention rates rise by about one percentage point relative to a baseline annual retention rate of approximately 79%, driven primarily by reductions in exits from the public school system. Effects on cross-district mobility are small and statistically indistinguishable from zero. Additionally, a gravity-model analysis of origin–destination flows shows no statistically detectable evidence, within the power of the sample, that treated districts attract teachers away from non-treated districts. Taken together, the results indicate that the TIA primarily improves staffing stability by increasing retention among incumbent teachers but does not appear to influence teacher mobility across districts or between campuses within districts.

2 Background

The Teacher Incentive Allotment (TIA) was established in 2019 by Texas House Bill 3 (HB 3) as part of a major school finance reform. Its goal is to create a pathway for effective teachers, particularly in high-need and rural schools, to earn substantial, recurring performance-based pay while remaining in the classroom. Unlike earlier incentive programs funded by short-term grants, TIA is written into the Foundation School Program as a Tier I allotment, meaning it is formula-funded, legislatively permanent, and uncapped. Any teacher in an eligible assignment who earns a state-recognized designation through a validated system generates additional funding for their district (Texas Education Agency, 2024).

Teachers can earn one of three state-recognized designations: Recognized, Exemplary, or Master. Designations are valid for five years and appear on the teacher's state certificate. National Board Certified Teachers (NBCTs) automatically receive the Recognized designation, while all other designations must be earned through a district-designed Local Designation System (LDS). Participation in TIA is voluntary, and districts have discretion over how they evaluate teachers, subject to meeting state requirements. The Texas Education Agency (TEA) maintains a statewide registry of designated teachers, and designations are fully portable across districts. Allotment funding is tied to the campus where the designated teacher works, thus teachers effectively carry their designation-generated revenue with them across employers. Implementing an LDS is a multi-year process involving system design, data collection, and external validation, visualized in Figure 1.

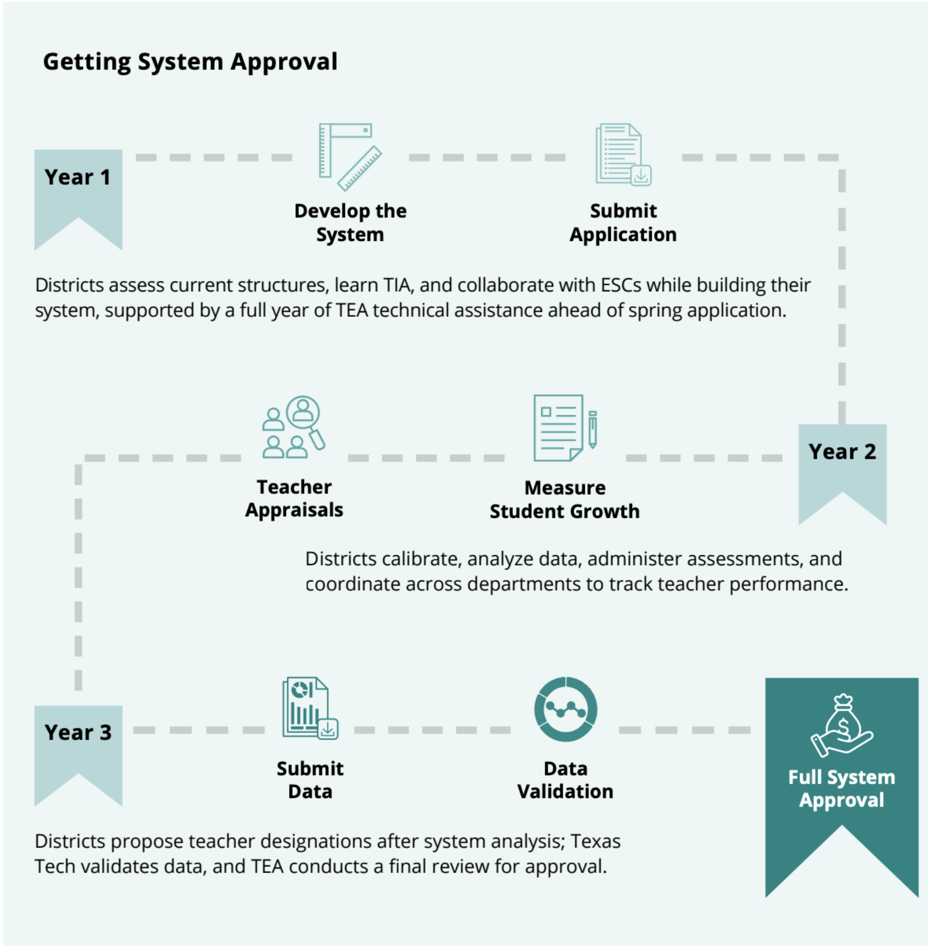


Figure 1: Overview of the TIA System Approval Process. Source: Texas Education Agency, *Teacher Incentive Allotment Annual Report, 2024–2025*.

Districts seeking to participate must design an LDS that includes, at a minimum, (1) classroom observations using a validated rubric such as T-TESS and (2) measures of student growth. Districts have wide discretion over the specific instruments used, how observation and growth are weighted, and what constitutes qualifying performance. Student growth measures vary: some districts use STAAR-based value-added models (VAMs), while others rely on vendor assessments, pre/post-tests, Student Learning Objectives (SLOs), or portfolios for non-tested subjects. TEA provides statewide guidelines, including suggested performance cut scores aligned with the top 33% (Recognized), top 20% (Exemplary), and top 5% (Master) of performers.

Once TEA conditionally approves an LDS, the district enters a Data Capture Year. During this period, all teachers in eligible assignments must receive observations and student growth ratings under the new system. The district submits data to Texas Tech University (TTU) for statistical validation. TTU applies ten analytic checks across five domains, assessing alignment between observations and growth, comparison to statewide value-added benchmarks, and internal consistency in designation patterns. Master teachers should, on average, outperform Recognized teachers in statewide VAMs, imposing a monotonicity constraint on the designation system. TEA uses the validation results to determine whether the district can formally designate teachers. Districts that fail validation must revise their systems and repeat the Data Capture Year, potentially delaying treatment timing in ways correlated with district capacity.

The size of the state allotment is a function of the teacher's designation level and the characteristics of their campus. Each designation level has a base amount and a multiplier, with Recognized teachers generating roughly \$3,000–\$9,000, Exemplary teachers \$6,000–\$18,000, and Master teachers \$12,000–\$32,000, depending on campus socioeconomic tier and rural status. For example, a Master teacher at a low-poverty urban school might generate about \$12,000, while a Master teacher at a high-poverty rural school could generate over \$30,000. These amounts are recalculated annually. Districts must pass through at least 90% of each allotment to the campus where the designated teacher works. Up to 10% may be retained by the district for administrative costs, such as training observers or developing assessments. Uniquely, districts are allowed to allocate the 90% earmarked for teacher compensation between both designated and non-designated teachers, thereby potentially diluting individual-level incentive strength. For instance, a district could opt to give 75% of the generated allotment to the designated teacher and set aside 15% for non-designated teachers. The district must outline the specific percentages in their application.

TIA began with 26 pilot districts in 2019, dispersing around \$38 million and increasing in participation and total payouts each subsequent year. By 2024 the TIA had been adopted by over 300 school systems and awarded designations to more than 42,000 teachers, with total payouts exceeding \$481 million for the year and well over \$1 billion total. The scale and structure of the TIA make it a distinctive policy intervention in teacher labor markets, offering sizable, sustained financial incentives linked to measured performance and deployed through a decentralized but state-validated system. Its design generates sharp variation in bonus size across campuses and staggered adoption across districts, providing a rich setting to study how performance-based pay influences teacher retention and mobility.

3 Data

The analysis uses a teacher-level longitudinal panel constructed from the Texas Education Agency's (TEA) Public Education Information Management System (PEIMS) statewide staff files for school years 2014–2024. These files contain individual-level information on all public-school teachers, including demographic characteristics, years of experience, campus and district assignments, and both base and total salary. Teachers are linked across years using a scrambled employee identifier, allowing mobility, retention, and exit measures to be defined consistently over time.

Charter districts are excluded from the analytic sample. Charter systems exhibit idiosyncratic entry and exit patterns, frequent campus reorganizations, and inconsistent reporting practices that generate mechanical fluctuations in mobility rates. Teacher mobility variables are constructed prior to this exclusion so that flows into and out of charters remain observable.

Teachers with simultaneous multi-campus assignments present a fundamental measurement problem for discrete mobility classification. Individuals who work across several campuses and sometimes across multiple districts cannot be cleanly placed into standard retention or movement categories. A teacher who remains on four of five campuses, or who rotates across districts while maintaining the same "primary" assignment, generates ambiguous classifications. Imputing a single campus using a highest-PFTE rule[1] generates artificial campus–district pairings and mechanically inflates misclassification error in mobility outcomes. Although these assignments constitute a small share of the workforce, they generate a disproportionate share of ambiguous transitions; excluding them yields a cleaner estimate for true job mobility.

To capture program rollout and funding exposure, I merge the PEIMS panel with annual campus-level Teacher Incentive Allotment (TIA) files, which report the allotment amount generated for each designation level on each campus and provide information on campus characteristics, including rural status, student demographics, enrollment, and socioeconomic composition. Districts are coded annually as Non-participating, Application Accepted (AA), or Local Designation System (LDS) Approved. I treat the AA year as the district's exposure onset year, rather than the payout year. Districts conduct teacher buy-in surveys, calibrate observation systems, and collect observation and student growth data that determine designations the following year. The LDS approval

[1]Following the highest-PFTE rule would collapse multi-row teachers to a single campus based solely on hours worked, mechanically generating campus transitions that do not correspond to job changes

year marks the first year in which designations are official and allotment funding is distributed. Teacher-level designation records identifying Recognized, Exemplary, and Master teachers, along with the dollar value of generated allotments, are merged to construct continuous measures of treatment intensity within and across campuses. All underlying datasets were obtained through Public Information Requests to TEA or through publicly available Texas Academic Performance Reports (TAPR).

Using the merged dataset, I construct annual mobility outcomes: remaining in the same district or campus, within-district campus moves, cross-district moves, new entrants, re-entrants, and exits from Texas public schools. The initial 2019–2020 pilot cohort is excluded because these districts operated under legacy local incentive systems that were later harmonized into the statewide TIA, making their early exposure non-comparable to post-2021 adopters. After all exclusions, the analytic sample contains approximately 3.3 million teacher-year observations spanning 1,053 independent school districts from 2014–2024.

Defining Treatment and Addressing Data Validation Timing

A district is classified as treated if it ultimately receives LDS approval by 2024. For these districts, treatment begins in the first year TEA records the district as having "Application Accepted" (AA) status. The AA year marks the onset of meaningful exposure to TIA: teachers receive observations and student growth ratings aligned with the forthcoming incentive system, and future compensation is explicitly tied to these data, even though formal designations and payouts occur only after validation.

Districts differ in the time required to move from AA to LDS approval. Some progress in a single year (AA1), while others remain in AA for two years (AA2) or three or more (AA3+). These groups differ systematically. AA2 districts experience an initial year of full exposure followed by a "validation failure" shock; AA3+ districts are extremely small, predominantly rural, lower paying, and exhibit persistently higher baseline exit rates, consistent with administrative capacity constraints rather than incentive uptake. These delays are plausibly driven more by administrative capacity than by short-run changes in teachers' expected returns to incentives. To focus on a more homogeneous set of implementers and avoid conflating program exposure with validation failures, the main analysis restricts the treated sample to AA1 districts to avoid selection on compliance intensity. AA1 districts represent 84% of districts that ultimately receive LDS approval. Pre-treatment comparisons across implementation durations are reported in Table 1.

Table 1: Pre-Treatment Differences Across Implementation Durations

	AA1 vs AA2		AA1 vs AA3+	
Variable	Diff	p-value	Diff	p-value
Teachers (t)	-145.49	0.419	334.88^{***}	< 0.01
Avg total pay	18.84	0.983	5158.53^{***}	< 0.01
Log total pay	0.0013	0.938	0.1028^{***}	< 0.01
Avg experience	0.537	0.098^{*}	0.0934	0.913
Pct. masters	0.317	0.755	2.494	0.560
Pct. Black	-3.056	0.155	-2.523	0.601
Pct. Hispanic	-1.802	0.678	-14.689	0.356
Retention rate	0.0067	0.469	0.0650^{**}	0.033
Exit rate	-0.0011	0.808	-0.0493^{**}	0.025

Notes: Differences are AA1 minus the comparison group. All differences are computed at the district level using pre-AA averages and two-sample t-tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Summary statistics by treatment cohort are shown in Table 2. The earliest adopters, districts whose first AA year occurred in 2020, differ most noticeably from later adopters and never-treated districts. They exhibit somewhat lower baseline district retention (0.765 versus roughly 0.80 for the 2021–2023 cohorts) and higher exit rates (0.139 versus about 0.116). They are also substantially larger, averaging about 467 teachers compared to 235 in never-treated districts. In contrast, the 2021–2023 cohorts closely resemble never-treated districts across retention, mobility, and teacher demographic characteristics. These descriptive differences characterize the composition of early entrants but do not, by themselves, imply differences in pre-treatment trends or causal responses to incentives. Event-study estimates presented below show parallel trends across all cohorts prior to adoption.

Table 2: Summary Statistics

Outcome	Ever-treated cohorts (first AA year) 2020	2021	2022	2023	Never-Treated
Retention & mobility					
District Retention	.765 (.081)	.800 (.087)	.803 (.082)	.791 (.093)	.793 (.129)
Exit Rate	.139 (.055)	.116 (.054)	.116 (.046)	.117 (.053)	.123 (.085)
Campus Retention	.730 (.093)	.764 (.105)	.771 (.097)	.756 (.105)	.769 (.136)
New Entrant Rate	.107 (.072)	.085 (.068)	.084 (.062)	.088 (.072)	.085 (.085)
Out of District Movement	.096 (.053)	.084 (.060)	.081 (.059)	.092 (.069)	.084 (.080)
Within District Movement	.034 (.045)	.036 (.055)	.032 (.049)	.035 (.050)	.024 (.045)
Teacher characteristics					
Average Age	43.48 (2.78)	43.55 (2.85)	43.44 (2.31)	43.17 (2.83)	44.37 (3.29)
Experience (years)	11.87 (2.78)	12.12 (2.59)	12.22 (2.19)	12.05 (2.53)	12.80 (3.01)
Percent Hispanic	25.08 (29.97)	24.89 (30.63)	18.30 (27.16)	17.75 (22.34)	12.16 (18.52)
Percent Master Degree	20.05 (7.84)	19.54 (8.24)	18.94 (6.52)	19.56 (7.34)	18.82 (9.50)
Staffing & pay					
Average Teacher Total	466.9 (749.5)	431.7 (823.1)	356.4 (731.8)	415.4 (980.6)	235.2 (770.9)
Average Total Pay (thousands)	48.40 (5.11)	50.04 (8.79)	49.58 (5.38)	49.73 (5.19)	48.45 (6.04)
Number of districts					
$N_{\text{districts}}$	34	117	112	79	711

4 Identifying the Effects of State-Wide Performance Pay

The empirical strategy exploits staggered district adoption of the Teacher Incentive Allotment (TIA) to identify the causal effect of performance-based pay on teacher mobility. Identification requires addressing several threats arising from contemporaneous statewide reforms, early pilot participation, non-random adoption, and pandemic-related labor market disruptions.

House Bill 3. — The Teacher Incentive Allotment was created as part of a broad 2019 school-finance reform (House Bill 3), which raises concerns that concurrent policy changes could contaminate estimates of TIA's effects. In addition to authorizing TIA, HB 3 increased the state's Basic Allotment (per-pupil funding) from $5,140 to $6,160 and required districts to use at least 30 percent of the new funds for teacher compensation, along with an update to the statutory minimum salary schedule. These provisions generated a sharp statewide rise in teacher pay: within the analytic sample, mean salaries increased by roughly $3,200 from 2018 to 2019, about three times the typical annual gain in prior years. Fewer than two percent of teachers were paid at or near the statutory minimum, so the direct effect of the schedule change was limited; most of the increase reflected districts' use of the larger Basic Allotment to raise pay scales.

The key implication for identification is that because HB 3 generated a large, statewide, and near-uniform increase in teacher compensation, it enters the empirical design as a common shock absorbed by year fixed effects rather than a source of differential treatment intensity across districts. The per-teacher salary increase was similar in districts that later adopted TIA and in those that never did: the average pay change differs by only about \$200 between these groups, a small and economically negligible gap relative to the \$3,200 statewide increase. HB 3 predates any cross-district variation in TIA adoption timing within the analytic panel and therefore cannot mechanically induce the staggered treatment variation exploited by the design or violate the identifying parallel-trends assumption. Taken together, these features make it unlikely that HB 3's compensation provisions confound the estimated effects of TIA on teacher mobility.

Pilot Districts. — In the 2019–2020 school year, the Texas Education Agency approved Local Designation Systems for twenty-six pilot districts (Cohort A). These districts were required to demonstrate that they already operated strategic compensation systems based on 2018–2019 effectiveness data. Many had been using classroom observations and student growth measures aligned with TIA requirements before the statewide program existed. Dallas ISD was the largest participant; its Teacher Excellence Initiative (TEI) and Accelerating Campus Excellence (ACE) models, launched in 2013 and 2016, were widely cited by policymakers as the blueprint for the TIA.

These districts were effectively pre-treated: the incentive-generating mechanisms later formalized under TIA were already operating prior to statewide rollout. Including them would conflate the effect of the statewide rollout with the effect of pre-existing local reforms. Therefore, I exclude all Cohort A districts from the analytic sample to ensure treatment reflects the introduction of TIA rather than pre-existing local reforms. Accordingly, the causal estimate in this study pertains to the introduction of TIA-style incentives in districts without pre-existing performance-pay systems.

Selection. — A central identification concern in evaluating an optional program such as TIA is non-random district participation. Early adopters in my sample, particularly the 2020 cohort, exhibit somewhat lower baseline retention and larger staffing levels, patterns largely explained by their higher rural composition. Rural districts in Texas consistently experience lower retention, so these differences reflect structural characteristics rather than short-term shocks. While early adopters may have had systematically higher long-run staffing needs, this does not violate the identifying requirement that changes in mobility would have followed parallel trends absent TIA.

Importantly, interest in TIA and the timing of formal participation are not the same. Implementing a Local Designation System requires substantial fixed administrative investments: districts must design or adapt evaluation instruments, collect classroom observations and student-growth measures, and complete a multi-step statistical validation process administered by Texas Tech University. These requirements create long planning horizons and capacity constraints, making the exact year of adoption primarily a function of administrative readiness rather than short-run fluctuations in turnover.

From the perspective of individual teachers, the timing of adoption is plausibly exogenous. Teachers do not control or initiate the district's formal TIA application timing; the application and approval process is set at the district level and subject to multi-stage validation. The empirical specification includes district and year fixed effects, absorbing persistent cross-district differences, including the lower baseline retention levels of early adopters and statewide shocks. As a result, the identifying variation comes from within-district changes in treatment status over time, which are plausibly unrelated to teachers' mobility decisions.

COVID-19 Disruptions. — The onset of the COVID-19 pandemic in spring 2020 disrupted teacher labor markets statewide through remote instruction, school closures, altered testing regimes, and uncertainty around job security. These disruptions raise the possibility that pandemic-related shocks could confound estimates of TIA's effects if they differentially influenced the timing of adoption or early implementation.

In practice, COVID-related disruptions were statewide in scope and not differentially correlated with TIA exposure or adoption timing. All districts, treated and untreated, faced the same instructional mandates, statewide STAAR cancellations, and TEA-issued waivers for observation requirements and validation deadlines. Importantly, districts that entered the Application Accepted (AA) phase in 2020–2021 had submitted their system applications prior to the pandemic[2]. TEA's decisions to validate or extend districts' systems reflected uniform statewide policy responses rather than district-specific labor market conditions.

Year fixed effects absorb the large common mobility shock induced by the pandemic. The staggered timing of TIA adoption in my analytic sample is determined by pre-COVID application

[2]Cohort B applications were due by January 2020, prior to the onset of COVID-related labor market disruptions

submissions and subsequent administrative reviews rather than pandemic-era staffing patterns. Therefore, COVID-19 disruptions do not introduce differential variation that would bias identification.

Under the maintained assumption that, absent TIA, treated and untreated districts would have followed parallel trends in mobility outcomes, the staggered timing of adoption identifies the average causal effect of exposure to performance-based pay. This assumption is evaluated directly using pre-treatment event-study estimates presented below, which show no systematic differential trends prior to adoption across cohorts.

5 Responses in Teacher Mobility to Performance Pay

Performance pay changes the expected returns to remaining in, leaving, or entering a school district and may therefore reshape teacher mobility patterns. By tying compensation partly to measured performance, the Teacher Incentive Allotment (TIA) increases the expected payoff to staying in a participating district, potentially reducing exits, limiting cross-district moves, or shifting teachers toward districts offering stronger incentives. This section estimates how TIA adoption affected teacher retention, mobility, and staffing flows.

To build intuition for the program's effects, I begin with a conventional two-way fixed effects (TWFE) difference-in-differences specification. The primary specification uses the staggered difference-in-differences estimator of Callaway and Sant'Anna (2021) at the district level. This approach credibly identifies treatment effects under heterogeneous timing, using not-yet-treated and never-treated districts as control groups.

Finally, to assess whether TIA generates cross-district spillovers, violations of SUTVA that could bias district-level estimates, I estimate a gravity-style Poisson pseudo-maximum likelihood (PPML) model of teacher flows between districts. The gravity model complements the DiD evidence by testing whether treated districts experience disproportionate inflows relative to untreated districts, which would be consistent with reallocation effects. This provides a complementary test of whether observed retention gains reflect increased teacher attachment rather than increased outward mobility from neighboring districts.

District-Level Empirical Strategy

The district-level analysis is conducted on a panel of independent school districts (ISDs) observed from 2014–2024. The unit of observation is the district–year. Treatment is defined at the district level: a district is coded as treated in year t if it enters the Application Accepted (AA) phase and ultimately obtains Local Designation System approval within a single cycle (AA1). Districts that remain in AA for two or more years (AA2/AA3+) are excluded from the sample, as discussed in the data section. The treatment year is the district's first AA year; all earlier years are coded as pre-treatment, and districts that never enter AA1 by 2024 form the comparison group.

Teacher-level mobility measures are aggregated to district-year means, weighting each teacher equally. District and campus retention rates measure the share of teachers who remain in the same district or campus from year t to $t+1$. Exit rates reflect the share of teachers employed in district i in year t who do not appear anywhere in the statewide staff files in future years. Teachers observed at a different campus within the same district in year $t+1$ are classified as within-district movers, while those appearing in a different district are classified as cross-district movers. These outcomes summarize the main channels through which TIA incentives may affect district staffing patterns.

District-Level Estimation Using Two-Way Fixed Effects

As a starting point, I estimate a standard two-way fixed effects (TWFE) difference-in-differences specification,

$$Y_{dt} = \alpha_d + \lambda_t + \beta D_{dt} + \gamma X_{dt} + \varepsilon_{dt}, \tag{1}$$

where Y_{dt} is a district-level outcome; α_d and λ_t denote district and year fixed effects; and D_{dt} indicates whether district d participates in the Teacher Incentive Allotment (TIA) program in year t. The vector X_{dt} contains student composition controls including socioeconomic disadvantage, racial and ethnic shares, special education, English learner status, and total enrollment. Although TWFE may yield biased estimates when treatment timing is heterogeneous, it provides a useful descriptive benchmark and helps anchor the more robust staggered DiD estimates presented later.

The TWFE estimates suggest modest but meaningful improvements in teacher retention following TIA adoption. District-level retention increases by roughly 1.7 percentage points, while campus-level retention rises by approximately 2.3 percentage points. These improvements correspond to declines in exits from the public school system (-0.86 percentage points) and reductions in out-of-district moves (-0.92 percentage points). Within-district mobility declines slightly, though the estimate is not statistically significant. There is no detectable effect on new entrants or total staffing levels, suggesting that TIA primarily stabilizes the existing workforce rather than expanding it.

Salary outcomes exhibit large and precisely estimated increases, with districts raising total pay by about $735 and base pay by about $727. By contrast, TIA adoption does not meaningfully change the experience or age distribution of teachers, indicating limited short-run shifts in workforce composition.

To complement the static TWFE results, Figure 2 reports a TWFE event-study specification constructed using relative-year indicators. The pre-treatment coefficients are close to zero and statistically indistinguishable from zero, though TWFE pre-trends are not a valid test under heterogeneous treatment effects. Post-treatment coefficients rise gradually over time, consistent with a growing retention response as the program matures and more teachers become eligible for designation-based bonuses.

Taken together, these TWFE patterns should be interpreted descriptively rather than causally. Nonetheless, they offer a clear initial picture: TIA adoption is associated with higher pay and improved retention, driven primarily by reductions in exits and out-of-district moves.

Table 3: District-Level TWFE Estimates with Controls

Outcome	TWFE Effect	SE
District retention rate	0.0167***	(0.00466)
Campus retention rate	0.0229***	(0.00590)
Exit rate	-0.00859***	(0.00322)
Out-of-district move rate	-0.00918***	(0.00340)
Within-district move rate	-0.00508	(0.00311)
New entrant rate	-0.00258	(0.00339)
Teachers (count)	1.5168	(4.4749)
Avg total pay	735.14***	(235.30)
Avg base pay	727.07***	(220.19)
Avg experience (years)	-0.0830	(0.1598)
Avg age	-0.1905	(0.1628)

Notes: Standard errors clustered at the district level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

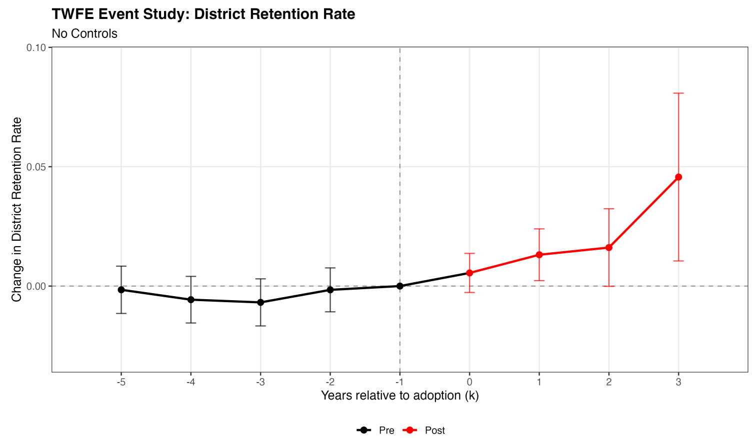


Figure 2: TWFE Event Study for District Retention Rate

District-Level Estimation Using Callaway & Sant'Anna (2021)

The main district-level analysis employs the staggered difference-in-differences estimator of Callaway and Sant'Anna (2021). This approach is well-suited for the TIA setting, where districts enter the Application Accepted phase in different years and treatment effects may vary across cohorts. For each adoption cohort g, defined by a district's first application accepted year (AA1), and each post-adoption year t, the estimator compares districts in cohort g to districts that have not yet entered AA1 by year t. These comparisons yield cohort-by-time average treatment effects, which are then aggregated into overall effects and dynamic event-study profiles.

To ensure that treated and comparison districts are placed on comparable footing, the estimation conditions on district fixed effects, which absorb persistent differences in staffing patterns across districts, and year fixed effects, which capture statewide shocks such as changes in labor supply or state funding. Under this structure, identification relies on the assumption that, absent TIA adoption, districts first entering AA1 in year g would have followed the same underlying trends as districts that remain untreated in year t.

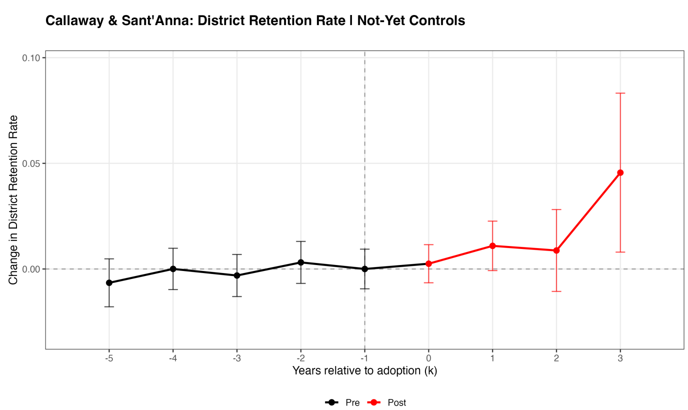
A key advantage of the Callaway & Sant'Anna estimator in this context is that it constructs comparisons only between treated districts and valid control groups, never-treated and not-yet-treated districts, thereby avoiding the negative weighting and inappropriate comparisons that arise in TWFE designs under heterogeneous treatment effects. The resulting estimates provide a transparent and cohort-consistent measure of how district-level retention, mobility, and exit rates respond to the introduction of performance-based compensation.

The estimated treatment effects indicate that TIA participation is associated with modest but precisely estimated improvements in retention. Across specifications, district and campus retention rates rise by roughly 1.1–1.3 percentage points. Importantly, the event-study estimates show flat pre-treatment trends, providing some evidence for the parallel trends assumption. Interestingly, there is no detectable effect in the first "Application Accepted" year (t=0) when districts begin collecting observations and informing teachers about forthcoming designations. The effects emerge only in the subsequent year (t=1), when formal designations are issued and allotment funding is distributed. This timing pattern suggests that teachers might not respond measurably to the prospect of future bonuses but do adjust behavior once the financial returns materialize. The retention gains are driven primarily by reduced exits from the public school system: exit rates fall by about 0.7 percentage points after adoption. Cross-district mobility declines slightly and is close to conventional significance thresholds, while within-district mobility remains essentially unchanged. New-entrant rates decline by roughly 0.5 percentage points, a pattern consistent with reduced vacancy creation following higher retention rather than a contraction in the supply of new teachers. Treated districts experience increases in average teacher pay, as expected under the program's funding formula, and small improvements in average experience levels consistent with reduced exits. Results are similar whether never-treated or not-yet-treated districts serve as controls, and they remain stable when the 2020 cohort is excluded, indicating that findings are not driven by early-adopting districts or control group choice. The C&S estimates are smaller in magnitude than the TWFE estimates, consistent with the attenuation of upward bias that can arise in TWFE designs under heterogeneous treatment effects. Overall, the pattern of results supports a modest but sustained improvement in teacher retention following TIA adoption.

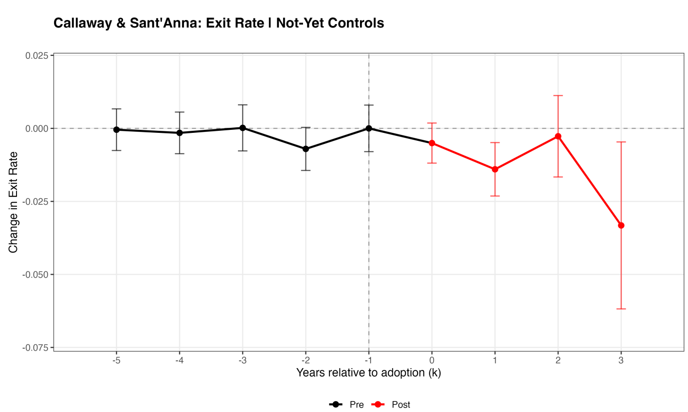
Table 4: District-Level ATT Estimates from Callaway & Sant'Anna (2021)

Outcome	Never-Treated Controls ATT	Never-Treated Controls SE	Not-Yet Controls ATT	Not-Yet Controls SE
District retention rate	0.0115**	(0.00465)	0.0110***	(0.00433)
Campus retention rate	0.0134**	(0.00555)	0.0128**	(0.00591)
Exit rate	-0.00707**	(0.00348)	-0.00702*	(0.00375)
Out-of-district move rate	-0.00443	(0.00303)	-0.00399	(0.00295)
Within-district move rate	-0.00187	(0.00271)	-0.00183	(0.00267)
New entrant rate	-0.00497*	(0.00318)	-0.00498*	(0.00311)
Teachers (count)	2.7866	(5.2070)	3.0720	(5.0187)
Avg total pay	594.98***	(185.12)	587.37***	(177.84)
Avg base pay	633.51***	(181.38)	624.26***	(165.63)
Avg experience (years)	0.1553*	(0.0953)	0.1527*	(0.0975)
Avg age	0.0979	(0.1015)	0.0957	(0.0997)

Notes: Standard errors, clustered at the district level, in parentheses. * p<0.10, ** p<0.05, *** p<0.01.



(a) District Retention Rate



(b) Exit Rate

Figure 3: C&S Event-Study Estimates Using Not-Yet-Treated Controls

Teacher Flows, Local Labor Markets, and SUTVA

A central concern in interpreting the district-level retention estimates is whether the TIA program generates cross-district spillovers that violate the stable unit treatment value assumption (SUTVA). If teachers in non-TIA districts "jump ship" and move into newly treated districts, then retention in treated districts would mechanically rise while retention in untreated districts would mechanically fall. Such mobility-driven reallocation would bias the estimated retention effects upward by attributing to TIA improvements in staffing that instead reflect teacher reshuffling across districts. To diagnose the extent of these potential spillovers, I construct a gravity-style panel of teacher flows and estimate a sequence of Poisson pseudo–maximum-likelihood (PPML) models of origin–destination mobility, a standard approach for modeling multiplicative flow data in trade, migration, and commuting literatures (Santos Silva and Tenreyro, 2006; Beine et al., 2016).

Using the teacher-level panel, I classify each teacher's origin as her district in year t and her destination as her district (or exit) in year $t+1$. I distinguish two mutually exclusive types of flows: (i) cross-district moves $i \to j \neq i$ and (ii) exits and entrants to and from the public school system. Teachers who remain in the same district are not counted as flows; these non-flows correspond to retention. Aggregating to the origin–destination–year level yields, for each ordered pair (i, j) and year t, a count $\text{teacher\_flows}_{ijt}$. Treatment status is merged from the teacher-year panel, and districts are assigned to commuting zones (CZs) using 2020 CZ definitions (USDA, 2020).

I begin with a PPML gravity model of *total flows*, combining cross-district moves, exits, and entrants. The main specification is

$$\begin{aligned}\mathbb{E}[\text{teacher\_flows}_{ijt} \mid \text{TreatDest}_{jt}, \text{TreatOrigin}_{it}, \alpha_i, \delta_j, \lambda_t] = \exp\Big(&\beta_1 \text{TreatDest}_{jt} + \beta_2 \text{TreatOrigin}_{it} \\ &+ \alpha_i + \delta_j + \lambda_t\Big),\end{aligned} \tag{2}$$

where TreatDest_{jt} and TreatOrigin_{it} indicate whether destination and origin districts are treated in year t, and α_i, δ_j, and λ_t denote origin, destination, and year fixed effects. Intuitively, β_2 captures how total outflows from treated origins change after TIA adoption, while β_1 captures how inflows into treated destinations change. Table 5 reports the main estimates. The destination coefficient indicates a statistically significant 5.9 percent decline in inflows to treated districts, consistent with improved retention reducing vacancies. On the other hand the origin coefficient shows a near-zero and statistically insignificant change in total outflows. However, total flows combine conceptually distinct mechanisms such as cross-district mobility, exits, and entrants, therefore the aggregate specification obscures which specific channel drives the observed staffing changes.

Table 5: Total Teacher Flows: PPML Gravity Model

Coefficient	Estimate	SE	p-value
Treated Destination Post	-0.0587	0.0238	0.014
Treated Origin Post	0.0050	0.0478	0.916
Observations		100,486	

To disentangle exits and entrants from mobility, I re-estimate the gravity model separately for (i) cross-district moves and (ii) exits and entrants to and from the public system. As shown in Table 6, cross-district outflows and inflows are small and statistically insignificant. By contrast, the exits-only model finds a statistically significant reduction in exits from treated districts of roughly 6 percent. With an average exit rate of about 12% this equates to about a .72 percentage point reduction. These results align with the staggered DiD estimates and indicate that TIA improves retention primarily by reducing exits rather than altering cross-district mobility.

Table 6: Decomposition of Outflows and Inflows

Model	Estimate	SE	p-value
A. Outflows			
Cross-district outflows	-0.0177	0.0306	0.562
Exits from system	-0.0620	0.0258	0.016
B. Inflows			
Cross-district inflows	-0.0265	0.0237	0.264
Entrants (new teachers)	-0.0371	0.0378	0.326

I next assess whether TIA induces reallocation within local labor markets by restricting the sample to cross-district moves where both the origin and destination lie in the same commuting zone. This restricted-sample approach provides a direct and transparent test for local poaching: if teachers were being pulled from nearby non-TIA districts into treated districts, the effects should appear within CZs. The estimating equation mirrors the baseline gravity model:

$$\mathbb{E}[\text{cross\_flows}_{ijt} \mid \text{TreatDest}_{jt}, \text{TreatOrigin}_{it}, \alpha_i, \delta_j, \lambda_t] = \exp\Big(\beta_1^{\text{within}}\text{TreatDest}_{jt} + \beta_2^{\text{within}}\text{TreatOrigin}_{it} + \alpha_i + \delta_j + \lambda_t\Big). \tag{3}$$

The estimates are near zero and statistically indistinguishable from zero. If TIA induced poaching within local labor markets, within-CZ flows should exhibit detectable changes, yet they do not. The absence of within-CZ movement effects reinforces the conclusion that TIA does not draw teachers away from neighboring districts.

Table 7: Within-Commuting-Zone Gravity Model: Cross-District Flows Only

Coefficient	Estimate	SE	p-value
Treated Destination Post	-0.0385	0.0317	0.225
Treated Origin Post	-0.0394	0.0378	0.297
Observations		36,991	

Finally, I examine whether non-TIA districts exhibit higher outflow rates as the share of treated districts in their commuting zone rises. Let $z(i)$ denote the commuting zone of district i, and define $\text{CZTreatShare}_{z(i)t}$ as the share of districts in CZ $z(i)$ that are treated in year t. For districts that have not yet adopted TIA, I estimate the descriptive fixed-effects regression

$$\text{outflow\_rate}_{it} = \alpha_i + \lambda_t + \rho\, \text{CZTreatShare}_{z(i)t} + u_{it}, \tag{4}$$

with district and year fixed effects. This specification is not designed for causal inference; it provides a diagnostic check for patterns consistent with spillovers.

Table 8: Spillover Test: Outflows from Non-TIA Districts

Coefficient	Estimate	SE	p-value
Treated Share	-0.0078	0.0079	0.327
Observations		4,312	

The estimated coefficient is small and statistically insignificant, indicating that non-TIA districts do not experience higher outflows as TIA penetration increases within their commuting zone.

Across the three spillover checks, a consistent picture emerges. The gravity models show little response of cross-district moves to TIA and a modest reduction in exits from treated districts. A separate fixed-effects regression for non-TIA districts finds no relationship between their outflow rates and the extent of TIA penetration in their commuting zone. Together, these patterns suggest that TIA's retention effects operate mainly through reduced exits rather than reallocation from untreated districts. While these exercises cannot fully rule out small spillovers, they provide no indication of large mobility-driven violations of SUTVA that would overturn the difference-in-differences findings.

6 Conclusion

This paper provides early causal evidence on how a large-scale, formula-funded performance pay program shapes teacher labor markets in a statewide public school system. Using a rich administrative panel from Texas covering 2014–2024, I evaluate the Teacher Incentive Allotment (TIA), a legislatively permanent program that layers substantial, recurring performance-based bonuses on top of existing salary schedules. Combining a staggered difference-in-differences estimator with a gravity-model analysis of inter-district flows, I study how TIA affects teacher retention and mobility.

Three main findings emerge. First, TIA produces modest but robust improvements in teacher retention. Across specifications, district and campus retention rates increase by about 1–1.3 percentage points from a baseline retention rate near 79 percent, implying a 1.5–2 percent relative improvement. These gains are driven primarily by reductions in exits from the public school system: district exit rates fall by roughly 0.7–0.8 percentage points. Effects on cross-district mobility are smaller and imprecisely estimated. Out-of-district moves decline slightly, while within-district mobility is largely unchanged. There is no evidence that TIA meaningfully increases the number of teachers employed in treated districts or substantially reshapes the experience or age composition of the workforce in the medium run. Instead, the program appears to stabilize existing staffing levels by making incumbent teachers more likely to remain in their current district and in the teaching profession.

Second, the gravity-model evidence indicates that these retention gains are not primarily driven by teachers "jumping ship" from non-TIA districts into treated districts. In a PPML gravity framework, total flows from treated origins do not increase significantly after adoption, and cross-district outflows and inflows respond weakly, if at all, to treatment. By contrast, origin–exit flows decline by about 6 percent in treated districts, confirming that the primary margin of adjustment is exits from Texas public schools rather than cross-district moves. Commuting-zone interaction models show no detectable increase in within-CZ inflows into treated districts, the margin where displacement of teachers from neighboring districts would be most concerning. A complementary spillover test, which relates outflow rates in non-TIA districts to the share of treated districts in their commuting zone, yields small and statistically insignificant coefficients. Together, these results suggest that TIA's retention effects operate mainly through reduced exits rather than reallocation from untreated districts, alleviating major SUTVA concerns and supporting a direct interpretation of the difference-in-differences estimates.

Third, the pattern of results is consistent with TIA operating as a targeted retention policy rather than a broad recruitment tool or a mechanism for large-scale reshuffling of teachers. Districts that adopt TIA experience sizable increases in average pay, on the order of \$500–\$700 per teacher, which are concentrated in designated teachers but diffuse partially to non-designated staff through district compensation policies. Yet these pay increases do not translate into detectable growth in headcount or systematic shifts in the observable composition of the teaching force over the medium run. Instead, the program primarily slows exits.

Taken together, these findings have several implications for the design and expectations of performance-based pay at scale. First, the results show that a statewide, formula-funded performance pay program can modestly improve retention without triggering large adverse spillovers on untreated districts. This contrasts with concerns that high-powered financial incentives might simply shift teachers from one district to another, generating "winners" and "losers" without increasing the overall supply of effective teachers. In the Texas context, the evidence instead points to a modest but genuine strengthening of teacher attachment to the public system, particularly in more disadvantaged labor markets.

Second, the magnitude of the effects is economically meaningful but not transformative. A one percentage point increase in retention represents a non-trivial improvement for districts facing persistent staffing challenges, but it falls short of the dramatic re-sorting effects documented in some smaller-scale or more targeted interventions (e.g., Dee and Wyckoff, 2015; Glazerman et al., 2013; Morgan et al., 2023). The TIA's design with decentralized evaluation systems, partial pass-through of allotments, and heterogeneity in implementation, may attenuate the behavioral response relative to highly centralized, high-powered schemes. Policymakers considering similar statewide programs should therefore view performance pay as one component of a broader staffing strategy, complementing improvements in working conditions, leadership, and non-monetary aspects of the teaching job.

Third, the Texas experience underscores the importance of administrative capacity and implementation details. Districts must design and operate local designation systems that pass a stringent external validation process, and the timing of adoption reflects these capacity constraints. Future work should examine how variation in local system design, such as the use of value-added measures, the relative weight on observations versus student growth, and the distribution of allotments between designated and non-designated teachers mediates the effectiveness of statewide performance pay.

Several limitations qualify the interpretation of these results and highlight directions for future research. First, the analysis focuses on medium-run effects over roughly a five- to six-year horizon of program expansion. Longer-run impacts on workforce composition, such as changes in the relative supply of highly effective teachers entering the profession or staying into late career stages, remain unknown. Second, while the paper documents retention and mobility responses, it does not directly separate effects by teacher effectiveness; doing so would require value-added measures linked to designations and raises additional concerns about measurement error and sorting. Third, despite robust checks using alternative estimators and gravity models, the identifying assumptions of staggered difference-in-differences remain untestable, and unobserved shocks correlated with adoption timing cannot be fully ruled out. Finally, the analysis focuses primarily on labor market outcomes; a natural next step is to integrate student achievement impacts and assess whether the retention gains documented here translate into improvements in student learning, particularly in high-poverty and rural schools that receive the largest allotments.

Ultimately, the TIA represents a rare case of performance pay implemented at scale through a stable, formula-funded mechanism rather than short-term grant programs. The evidence in this paper provides an early benchmark for what such a reform can achieve in practice: modest but robust improvements in retention, concentrated on the exit margin, with little evidence of harmful reallocation across districts. As more data become available and more cohorts of teachers are exposed to the program, future research can build on these findings to evaluate longer-run effects on teacher quality, student achievement, and the overall efficiency and equity of teacher labor markets.

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