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Impact of Monetary Incentives on Teacher Decisions to Leave and Choose Schools: Evidence from a Policy Reform in Sao Paulo

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Abstract

Teacher turnover is a major challenge for human resource management in schools, adversely affecting student learning. We examine the impact of a monetary incentive program introduced in 2022 in the city of Sao Paulo, Brazil, which aims to reduce teacher turnover by allocating wage premiums ranging from 5% to 25% of base salary based on schools' turnover levels. Our results show a significant reduction in turnover: an average decrease of 18% across all schools, with an even more pronounced 30% reduction in schools offering higher incentives. Notably, the program also attracted new teachers to these higher-incentive schools. An analysis of teacher preferences similarly reveals a shift towards schools offering greater wage premiums. Furthermore, we find that schools offering high incentives experienced significant improvements in student test scores, with gains of 0.3-0.6 standard deviations in standardized assessments. The findings demonstrate the effectiveness of monetary incentives in mitigating teacher turnover and improving educational outcomes, providing evidence-based guidance for policymakers developing teacher retention strategies.

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1 Introduction

Teachers are the most essential input in efforts to improve school quality (Araujo et al., 2016; Chetty et al., 2014). However, many countries struggle to achieve effective training, recruitment, and retainment of teachers (OECD, 2005). Teacher turnover is a particularly significant issue around the world (Glassow, 2023). While some attrition can be positive, where underperformers leave schools (Dee and Wyckoff, 2015), teacher departures are not limited to poor instructors. Teachers frequently move between schools, disrupting educational systems and complicating human resource management (Craig, 2017). Research furthermore indicates that teacher turnover negatively affects student learning (Ronfeldt et al., 2013) and disproportionately harms disadvantaged and minority students, thus widening learning gaps (Botelho et al., 2015).

Teacher turnover is primarily driven by individual and school-level factors (Quartz et al., 2005). While individual decisions may be beyond the control of a school system, working conditions remain within its purview (See et al., 2020). Poor working conditions have been shown to substantially affect teacher retention (Bonhomme et al., 2016). Effective policy strategies can support teachers' careers and employment conditions through mentoring and professional development (Kelchtermans, 2017), but their implementation is sometimes difficult. Addressing these issues may involve compensatory measures, such as monetary incentives for teachers in high-turnover schools (See et al., 2020).

In metropolitan areas, implementing human resource policies for teachers can pose unique challenges because they interact with other social, geographic, and economic factors that influence their career choices. Sao Paulo, one of the largest and most dynamic cities in the world, exemplifies the difficulties endemic to rapidly growing urban areas. The city is characterized by vast disparities in wealth and development (Machado and Hill, 2003) and varying degrees of accessibility across its territory, generating different school attractiveness according to geographic area (Elacqua and Rosa, 2023). The presence of different school systems (e.g., private vs public) further increases competition for human resources (Hanushek and Rivkin, 2003; Vedder and Hall, 2000), while the rigidity of public-sector contracts limits flexibility in teacher compensation (Biasi, 2021).

Teacher turnover directly impacts the stability and quality of education in Sao Paulo's public (municipal) schools (Elacqua and Rosa, 2023). Between 2010 and 2018, the city experienced an average annual teacher turnover rate of approximately 10%, even before the disruptions caused by the COVID-19 pandemic. However, this varied considerably across schools, with some establishments experiencing no turnover while others faced rates as high as 30%. School-specific wages were not the cause, as teacher salaries were largely standardized across the city and primarily determined by seniority (Rosa, 2019).

Sao Paulo's Municipal Department of Education serves nearly 400,000 students and employs 30,000 primary and lower-secondary teachers. In an effort to address the problem of high turnover, the Department implemented a new program in 2022 that aims to retain teachers in schools with the highest turnover rates. Specifically, the program offers a salary premium to educators that varies from 5% to 25% of a teacher's regular salary, depending on the school's average turnover rate over the past six years. The overarching objective being to stabilize staffing and enhance the quality of education across the city's diverse school landscape.

We analyze this program using data from the Department of Education's centralized transfer system to reconstruct the turnover rates for each school before and after the program's implementation. We then explore the variation in incentives created by the program to estimate a difference-in-differences model and assess the effects of monetary incentives on turnover.

As a first step, we map Sao Paulo's municipal schools to their respective wage premium schemes and effects on wages. Out of 556 schools, 455 were eligible for the incentive program. We categorized schools as no-incentive, low-incentive, and high-incentive based on the premium. The latter varied from 5% to 25% of the teacher's wages, depending on their seniority. The effects on wages were significant: a teacher with 6-8 years of seniority received a wage premium of approximately 5-10% when in a low-incentive school and 20-25% when in a high-incentive school.

Next, we analyze the effects of these incentives on teacher behavior, focusing on turnover, preferences, and attrition. Given the centralized management of teacher transfers in Sao Paulo, we track requests to change schools, defining "turnover" as the proportion of such requests. We find that incentives decrease turnover by an average of 3 percentage points, or 18%, compared to the baseline rate. The impact was particularly pronounced in high-incentive schools, which saw a 30% reduction in departure rates, compared to a 20% reduction in low-incentive schools.

The introduction of incentives also influenced teacher preferences when searching for schools. Previously less-preferred schools experienced increased desirability with the implementation of the program. This shift in preferences was more pronounced in schools with high incentives, underscoring the effects of different incentive levels on teacher choices.

To address potential concerns about internal validity, we perform several robustness checks. We assess teacher turnover trends from 2010 to 2019 across schools, confirming parallel trends prior to the program's introduction. Additionally, we conduct a placebo difference-in-differences analysis on variables related to teacher attrition, such as school quality, average distance from teachers' homes to schools, and school size. This analysis reveals no significant changes in school characteristics that could influence teacher turnover.

Next, we examine the effects of monetary incentives on average school test results. Schools participate in a national exam every two years, providing mathematics and language (Portuguese) scores. We constructed a ten-year panel dataset (2013 to 2023) and combined it with data from the monetary incentive program to analyze the effects using a difference-in-differences approach. We find that the program had a significant positive impact on student test scores, particularly in schools offering high incentives. This suggests that high-incentive schools not only experienced a reduction in teacher turnover but also saw improvements in student performance, highlighting a strong link between teacher retention and better academic outcomes. In contrast, schools with low incentives exhibited smaller and statistically insignificant effects. While these findings support the effectiveness of the high-incentive component of the program, they should be interpreted with caution as the presence of pre-trends raises concerns about potential bias in the estimated treatment effects. Nevertheless, our results provide valuable insights on the potential of monetary incentives to improve school environments and student achievement.

This study contributes to a growing body of research exploring the determinants of teacher turnover, particularly the role of monetary incentives.[1] The literature shows that while wage-premiums reduce teacher turnover (C. Clotfelter et al., 2008), these must be considerable to attract teachers to high-poverty schools (40-50% increase in wages) (C. T. Clotfelter et al., 2011; Elacqua et al., 2022). We distinguish between the effects on turnover and on attractiveness, thus shedding greater light on the differential impacts of wage increases. Furthermore, we explore the trade-offs between monetary and non-monetary job attributes, examining how individual preferences for certain job amenities may shift in response to higher wages. Research demonstrates, in fact, that individuals value certain job attributes and are willing to trade these for higher wages (Eriksson and Kristensen, 2014; Mas and Pallais, 2017). Moreover, preferences for these amenities vary among individuals, depending on their specific characteristics (Wiswall and Zafar, 2018). We explore both school and teacher characteristics to better understand how incentives provide compensation for specific school attributes (e.g., location) and identify which teachers are most influenced by these incentives.

Notably, evidence on the effectiveness of teacher incentives in developing countries is scarce (Evans and Acosta, 2023), making our findings relevant to ongoing discussions in development economics. Our work is closely related to that of Camelo and Ponczek (2021), who analyze a different wage-incentive program implemented in Sao Paulo state schools (as opposed to municipal schools, the focus here) for teachers working in high-poverty establishments. They use a regression discontinuity design to demonstrate that monetary incentives can significantly reduce teacher turnover. While we share the overarching goal of evaluating the impact of monetary incentives, our paper differs in several key aspects. In particular, the program we examine bases wage premiums on observed outcomes over time, rather than immediate external factors. More broadly, the program under study here, and others like it, begs the question of how governmental decisions disrupt established norms and reshape teachers' perceptions and behavior. This investigation helps to elucidate the dynamics of policy implementation and its broader implications for educational systems in developing countries.

The remainder of this paper is organized as follows. Section 2 details the program, providing context and relevant background information. Section 3 outlines our methodology, including data and research design. Section 4 presents the results. Section 5 discusses the implications of our findings and offers concluding reflections.

[1] There is extensive work on this topic, addressing different determinants of teacher turnover: see, among others, Ajzenman et al. (2024), Ajzenman et al. (2021), Bonhomme et al. (2016), Boyd et al. (2013), Cabrera and Webbink (2020), and Elacqua et al. (2022), Falch and Strøm (2005)

2 Institutional Background

2.1 Monetary incentives for hard-to-staff schools

The teacher labor market in Sao Paulo's municipal schools is centrally managed, employing nearly 30,000 teachers across primary and middle schools. Teachers receive uniform wages across schools, determined by seniority (based on both experience and formal education). Pay does not change with working conditions and school principals cannot offer further financial compensation.

To address disparities in working conditions, the Sao Paolo Municipal Department of Education has implemented several reforms. The first was initiated in the 1990s. Specifically, the city compensates public servants, including teachers, who work in remote neighborhoods with a wage premium. However, without inflation adjustments, these payments have become negligible over time (Rosa, 2019). In the first quarter of 2022, teachers working in distant neighborhoods, mainly located in slums (*favelas*), received R$6,600 annually, equivalent to an 8% increase in their annual salary.

To reduce teacher attrition, the Department also implemented another program—the "Job bonus" (*"Gratificação por local de trabalho"*)—, which awards additional pay to teachers in schools with historically higher turnover rates. Schools are classified into seven "turnover groups," ranging from very low to very high. Those in the very low turnover group are not eligible for the new incentive. The incentive amount then varies according to the group. Teachers working in schools with the highest turnover receive an additional R$1,500 monthly, equivalent to a 25% wage increase.

While these two reforms both introduced monetary incentives to compensate teachers for challenging working conditions, the first program is not cumulative with the second one. The final values are displayed in Table 1.

Table 1: Final Values, Official Incentives

	Incentive for neighborhood			
Turnover incentive	Neighborhood low	Neighborhood medium	Neighborhood high	None
Very-low	$ 440	$ 550	$ 660	0
Low	$ 440	$ 550	$ 660	$ 330
Medium-low	$ 690	$ 690	$ 690	$ 690
Medium	$ 860	$ 860	$ 860	$ 860
Medium-high	$ 1,100	$ 1,100	$ 1,100	$ 1,100
High	$ 1,300	$ 1,300	$ 1,300	$ 1,300
Very-high	$ 1,500	$ 1,500	$ 1,500	$ 1,500

*N*ote: This table presents the final value of incentives based on the combination of neighborhood and turnover incentive. Teachers working in schools categorized within neighborhood incentive groups but below low turnover incentives receive the neighborhood incentive. Teachers in schools classified as medium-low or above in terms of turnover receive the turnover incentive.

To enhance analytical clarity and statistical power, we reduce the number of groups and categorize schools as either no-incentive (control) (R$0), low-incentive (less than R$1,000 monthly), or high-incentive (R$1,000 monthly or more). As shown in Table 2, we assigned 103 schools to the control group, 342 schools to the low-incentive group, and 110 schools to the high-incentive group.

Table 2: Intervention Groups

Intervention group	Incentive value	Number of schools
Control	$ 0	103
Low-incentive	$ 440-860	342
High-incentive	$ 1,100-1,500	110
Total	-	555

Note: This figure presents the allocation of schools across different groups in an intervention study, categorized by the incentive value provided. Based on incentive values, we divided schools into three groups: control group, which received no incentives; low-incentive group, receiving incentives between R$440 and R$860 per teacher and month; the high-incentive group, receiving between R$1,100 and R$1,500 per teacher per month.

2.2 The teacher transfer system

The Sao Paulo municipal government manages public schools and their education system operations, including human resources. The Municipal Department of Education oversees the hiring, assigning, and transferring of teachers and other school staff. Specifically, it handles the recruitment process, conducts public hiring exams, and places teachers in schools according to demand. The Department also takes care of teacher transfers between schools, maintaining adequate staffing levels while considering teacher preferences.

Our analysis relies on turnover data from the Department's annual teacher transfer process. This centralized system operates as follows. First, the Department calculates vacancies available at each school based on teacher retirements, departures, and expressions of interest in leaving the current school. It then opens a public application call for in-service teachers wanting to transfer. Teachers use an online platform to rank their preferred schools and can list an unlimited number of vacancies. They are automatically allocated to positions where they are the sole applicant. When multiple teachers apply for the same position, the Department ranks them according to specific criteria, prioritizing those with higher seniority. The matching process continues until all teachers have been reallocated or no more vacancies remain.[2]

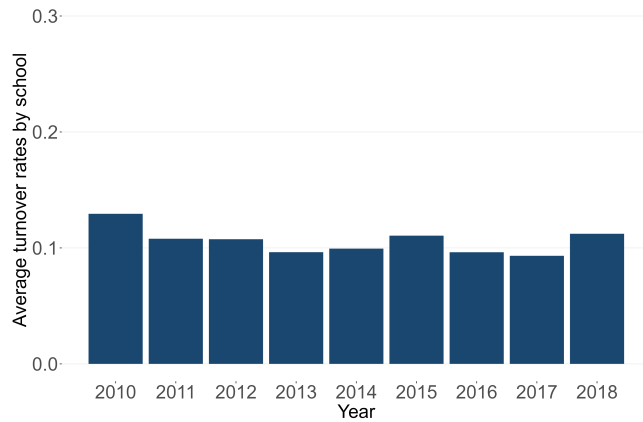
3 Data and Methods

3.1 Data

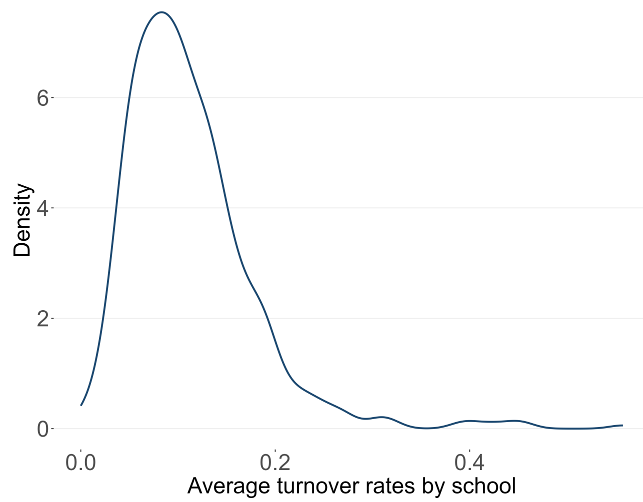
This study examines teacher turnover and departure intentions in elementary and middle schools. Longitudinal data tracking teacher retention from 2010 to 2018 allows us to observe if teachers in service at time t remain at time $t+1$. Figure 1a shows that the average turnover rate by school was around 10% between 2010 and 2018. Though, as illustrated in Figure 1b, there was significant variation among schools, with some reporting turnover rates exceeding 20%.

[2] Further details on the transfer process and the matching algorithm used to allocate teachers are provided in Elacqua and Rosa (2023).

Figure 1: Turnover Rates in Sao Paulo Schools



(a) Historical turnover rates

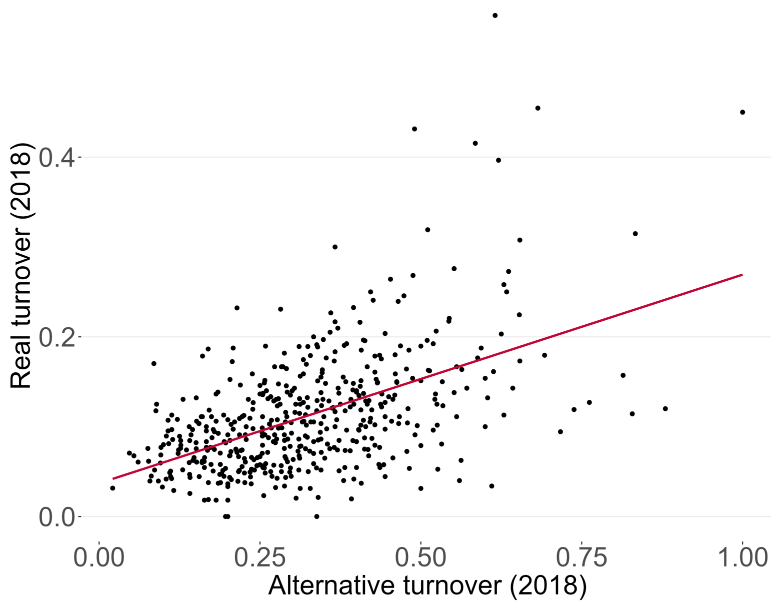


(b) Distribution of turnover rates across schools in 2018

*N*ote: This figure presents descriptive statistics of turnover rates. Panel 1a shows the average turnover rates by year from 2010 to 2018. Panel 1b illustrates the distribution of school turnover rates in 2018.

As actual turnover data is unavailable, we use human resources transfer data – i.e., the willingness to leave a school – as a proxy for potential turnover. As detailed in Section 2, this data indicates a teacher's plans to leave their school by applying for a transfer. We calculate our turnover measure by dividing the number of teachers requesting transfers by the total number of teachers in the school. When we compare our potential turnover measure with the number of teachers who actually left schools in 2018 (based on individual data), we observe that the two measures are highly correlated at the school level (Figure 2).

Figure 2: Correlation of Turnover Measures in 2018



*N*ote: This figure illustrates the real turnover on the y-axis, based on the number of teacher transfers in the transition from year t to $t+1$, and the alternative turnover on the x-axis, based on the number of vacancies, which is used in our baseline estimates. The correlation between the two variables is $\rho = 0.52$.

Our second dependent variable examines teachers' preferences for schools, derived from the transfer process data where teachers rank their preferred establishments. This measure summarizes school desirability among teachers, and is employed here to determine whether teachers prefer schools with incentives. Using individual data, we conduct a rank-ordered regression analysis. Furthermore, to align with the teacher turnover analysis performed at the school level, we aggregate the individual data at this same level, assessing the likelihood of schools being ranked higher on teachers' preference lists. We identify teachers who rank a wage-premium school as their first choice and those who include this type of establishment among their top three preferences. We then aggregate the preference list at the school level, focusing on the number of teachers who ranked a wage-premium school as their top choice.

Our third dependent variable examines test scores to measure the effects of the program on school quality. We use data from *Prova Brasil*, a national exam administered every two years to students in 5th (elementary) and 9th grade (middle school). These exams assess students' skills in mathematics and language (Portuguese). We analyze school-level data from 2013 to 2023, with 2011 school test scores included as a covariate to account for baseline performance and isolate the effects of monetary incentives on school gains. We also created a composite test score by averaging the mathematics and language scores at the school level. We include establishments offering both elementary and middle school education twice in the dataset, applying school-grade fixed effects to control for systematic differences across grade levels.

We group schools based on municipal listings of school names and their associated incentives. As detailed in

Table 1 and Section 2, we categorized schools as no-incentive, low-incentive, or high-incentive.

Our analysis controls for factors influencing teacher turnover and school preferences, including: average test scores, school size (number of students and number of classrooms), whether the school is located in a *favela*, and socioeconomic level. For teacher-specific decisions, we also include distance from a teacher's home to their school.

3.2 Empirical strategy

We utilize a two-way fixed effects (TWFE) approach combined with a difference-in-differences (DD) methodology to estimate the program's effects on teacher behavior. This accounts for both time-invariant unobserved heterogeneity at the school level and common temporal shocks. We define Y_{jt} as the potential turnover rate of teachers at school j in year t. The variable $Incentive$ captures the presence of the incentive program, and $Post$ is an indicator for whether the year falls after the program's implementation. Year fixed effects, θ_t, control for temporal shocks that affect all schools equally. Our baseline DD model for a single treatment group (those receiving the incentive versus those not receiving it) is specified as:

$$Y_{jt} = \alpha + \beta Incentive_j + \theta_t + \delta(Incentive_j \times Post_t) + \gamma X_j + \varepsilon_{jt}, \tag{1}$$

where δ captures the average treatment effect on the treated (ATT), representing the causal impact of the incentive on teacher turnover rates. The vector X_j includes school-level covariates that may influence turnover, making the differences in differences conditional on controls. Controls include a dummy indicating whether the school is located in a *favela*, school test scores, and number of classrooms in the school. Standard errors are clustered at the neighborhood level.

Given the differences in the incentive structure, we also estimate our models comparing the control group (no incentives) with schools with low incentives, and the control group with schools with high incentives. We follow the same model as above, and multiple treatment indicators investigate heterogeneous treatment effects across different incentive levels.

In light of the potential limitations of the TWFE model, we complement our analysis with the alternative DD estimator proposed by Callaway and Sant'Anna (2021). This estimator accounts for differential timing in the treatment adoption across groups and is robust to issues that often arise in TWFE settings.

To examine teachers' preferences for incentivized schools, we employ a similar empirical approach. Specifically, Y_{jt} represents the proportion of teachers ranking such a school as their first choice, reflecting the desirability of incentivized positions. In the Appendix, we show the results for Y defined as the proportion of teachers ranking wage-premium schools among their top three preferences. Additionally, we estimate a ranked ordered logit model by pooling two cross-sections of teacher preferences. This approach models teacher preferences as a function of various school characteristics, including incentives. The ranked ordered logit fits this context, as it accounts for the ordinal nature of the choice data.

We are particularly interested in the interaction between the year of selection and the incentive category of schools. These interaction terms allow to assess how the desirability of incentivized schools evolves over time, particularly as the program matures. The specification thus captures dynamic changes in teacher behavior and preferences in response to incentives, offering a more nuanced understanding of the program's impact.

4 Results

4.1 Descriptive statistics

We begin by comparing school attributes across the three intervention groups: no-incentive (control), low-incentive, and high-incentive (Table 3). Schools in the two incentive groups have lower test scores, are more likely to be located in a *favela* (i.e., an area characterized by precarious living conditions and poverty), have a larger number of classrooms, lie farther away from the city center, and experience higher rates of teacher turnover. We observe no difference in average class size among these groups.

Considering these differences, we expect a higher incidence of teacher turnover in schools offering incentives. Factors such as student achievement, location in a *favela*, and distance from the city center likely drive teacher preferences, as corroborated by existing research on teacher selection criteria in Sao Paulo (Elacqua & Rosa, 2023; Rosa, 2019).

Table 3: School Characteristics by Intervention Group

	Control	Low-incentive	High-incentive
Avg. test score	0.41	0.01	-0.41
	(0.717)	(0.638)	(0.624)
Favela (%)	0.2	0.46	0.58
	(0.405)	(0.499)	(0.496)
Number classrooms	26.11	31.34	30.92
	(8.059)	(9.683)	(9.265)
Average class size	28.46	29.24	29
	(2.448)	(2.285)	(2.141)
City center dist (km)	9.68	17.56	17.68
	(3.345)	(5.493)	(4.834)
Avg. number of teachers	56.82	59.23	49.83
	(9.905)	(15.876)	(13.99)
Avg. teacher turnover	0.09	0.1	0.15
	(0.027)	(0.041)	(0.071)
Number of schools	103	342	110

*N*ote: This table presents the average characteristics and standard deviations (in parenthesis) of school characteristics. Each column refers to a different group of schools, based on their incentive level, as explained in Section 2.

Table 4: Effects of Monetary Incentives on Average Teacher Turnover Rates in Schools

	(1)	(2)	(3)
Post x Incentive	-0.046^{***}	-0.046^{***}	-0.033
	(0.01)	(0.01)	(0.043)
Incentive	0.029^{**}	0.023^{**}	-
	(0.011)	(0.011)	-
# schools	554	554	554
Covariates	NO	YES	YES
Estimator	TWFE	TWFE	CS

*N*ote: This table presents the estimates for the treatment effect on school turnover rates. The first column displays the estimate of the treatment effects with a TWFE model without covariates. The second column displays the estimate of the treatment effects with a TWFE model with covariates. The third column displays the estimate of the treatment effect using the doubly-robust estimator from Callaway and Sant'Anna (2021), with covariates. The included covariates are: baseline presence in slums, test scores, and number of schools. Standard errors are clustered at the district level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

4.2 Effects on teacher turnover

We first examine the effects of monetary incentives on potential teacher turnover or intent to leave a school. We define "intent to leave" as the proportion of teachers requesting a transfer relative to the total number of teachers, as detailed in Section 3. Table 4 presents the Average Treatment Effects (ATT) of receiving any incentive on teacher turnover. Results show a reduction in teacher turnover ranging from 3.3 to 4.6 percentage points (p.p.), depending on the model used. Our preferred specification, in column 3, shows a turnover rate reduction of 3.3 p.p. (non-statistically significant). This point estimate translates to a reduction of nearly 16%, based on the average turnover rate preceding the intervention (2021-22). Consistent with previous research, we interpret this reduction as teachers in incentive groups choosing to stay in their current school rather than those in non-incentive groups seeking transfers to schools offering an incentive (Elacqua et al., 2022).

The variation in incentive size allows for an analysis of the intensive margin of incentives on teacher turnover. Results in Table 5 show that the significant reduction in turnover is predominantly observed in schools receiving high incentives. While the impact on schools with low incentives is approximately 2.5 p.p. and not statistically significant in our preferred specification (equivalent to a 13% reduction from the baseline turnover rates), schools offering high incentives experienced a substantial decrease of 5.6 p.p. (26% relative to the baseline). This differential effect underscores the potential to optimize turnover reduction strategies by directing resources to schools with historically high turnover rates. Schools in the low-incentive groups have turnover rates similar to the control group (no-incentive and very low-turnover), suggesting that the effectiveness of the incentives could be increased by more selectively targeting schools suffering the most from teacher turnover.

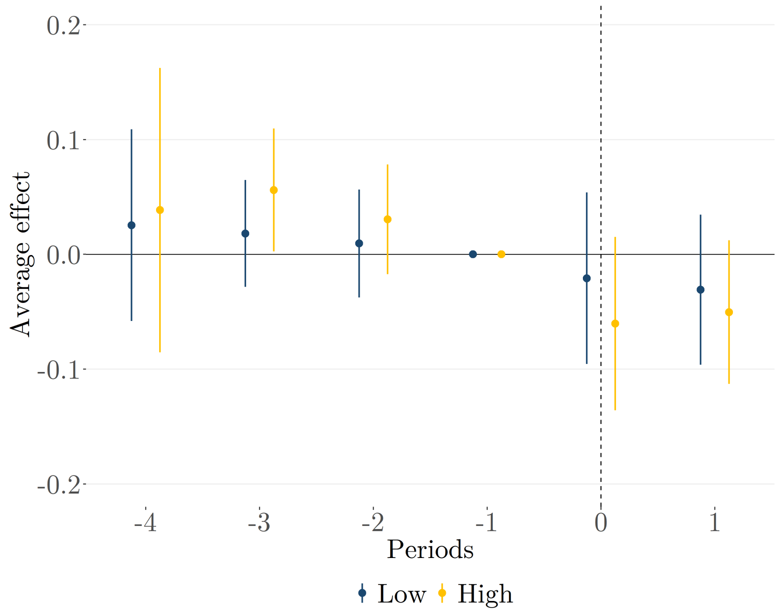
Table 5: Effects of Monetary Incentives on Average Teacher Turnover Rates in Schools, by Incentive Size

	Low			High		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Incentive	-0.034^{***}	-0.034^{***}	-0.025	-0.084^{***}	-0.084^{***}	-0.056^{*}
	(0.010)	(0.010)	(0.031)	(0.015)	(0.015)	(0.029)
Incentive	0.006	0.003	-	0.100^{***}	0.101^{***}	-
	(0.010)	(0.010)	-	(0.019)	(0.020)	-
# schools	445	445	445	212	212	212
Covariates	NO	YES	YES	NO	YES	YES
Estimator	TWFE	TWFE	CS	TWFE	TWFE	CS

Note: This table presents the estimates for the treatment effect on school turnover rates, segmented by incentive size. The first three columns show the results for the treated schools in the low-incentive group. The first column displays the estimate of the treatment effects with a TWFE model without covariates. The second column displays the estimate of the treatment effects with a TWFE model with covariates. The third column displays the estimate of the treatment effect using the doubly-robust estimator from Callaway and Sant'Anna (2021), with covariates. The fourth, fifth, and sixth columns present the same results for the treated schools in the high-incentive group. The included covariates are: baseline presence in slums, test scores, and number of schools. Standard errors are clustered at the district level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Our results are robust to various checks, including adjustments for different covariates and alternative models, as shown in Tables 4 and 5. We also perform a pre-trend analysis, examining turnover rates derived from transfer process statistics before the implementation of the program. Figure 3 shows no significant pre-trends. An event study analysis meanwhile reveals consistent effects in both the first and second years post-intervention. A supplementary pre-trend examination using actual turnover data from 2010 to 2018 corroborates the absence of pre-existing trends, reinforcing the validity of our findings.

Figure 3: Dynamic Treatment Effects on Turnover Rate, by Incentive Size



*N*ote: This figure presents the estimates for dynamic treatment effects on teacher turnover rates, following Callaway and Sant'Anna (2021), and normalizing the estimate of the base period right before the treatment to be equal to zero. The treatment effects are segmented by incentive size. Baseline presence in slums, test scores, and number of schools are included as covariates. The error bars display the 95% confidence intervals.

4.3 Effects on school desirability

The program potentially influences both teacher retention and their preferences for schools. To assess teacher preferences, we estimate a rank-order model,[3] pooling two cross-sectional datasets and focusing on the interaction between incentives and year. In this model, a negative coefficient indicates higher desirability (i.e., ranked higher in the individual's preferences), whereas a positive coefficient suggests lower desirability (i.e., ranked lower in the individual's preferences). As shown in Table 6, prior to the program's implementation, the affected schools were less attractive to teachers (column 1). However, after its introduction, we observe an increase in teacher interest in these schools, though this is not statistically significant. An analysis of other variables align with existing research: distance from teacher's home to school, test scores, and location in a vulnerable area remain significant predictors of teacher preferences.

[3] Following the approach of Elacqua and Rosa (2023).

Table 6: Teacher Preferences for Schools with Incentives - Rank Ordered Estimates

	(1) Preference	(2) Preference	(3) Preference
Dist home-sch (log)	0.621***	0.644***	0.676***
	(0.012)	(0.013)	(0.020)
Test scores in 2019 (z-score)	-0.057***	-0.055***	-0.050**
	(0.011)	(0.012)	(0.018)
School in favela	0.040**	0.039**	-0.017
	(0.014)	(0.015)	(0.027)
Any incentive	0.108***		
	(0.020)		
2022 × Any incentive	-0.044		
	(0.037)		
Low-incentive		0.101***	
		(0.020)	
2022 × Low Incentive		-0.042	
		(0.039)	
High-incentive			0.198***
			(0.052)
2022 × High Incentive			-0.250**
			(0.093)
Observations	46621	41477	19842

Note: The table presents the relation between different incentive sizes and teachers' preferences. Negative estimates indicate that the characteristic is associated with teachers' listing wage-premium schools higher in their rankings. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The results reveal significant variation in teacher preferences based on incentive size. In Table 6, columns 2 and 3 show estimates separated by school incentive size (low and high). Before the intervention, schools in the low-incentive group were less desired by teachers, and there is minimal and statistically insignificant change post-implementation. In contrast, schools with high incentives see a notable increase in teacher preference. Specifically, high-incentive schools (column 3) become more desirable than schools without incentives.

Using a difference-in-differences approach at the school level, we observe an increase of almost three teachers applying to these schools as their first choice (Table 7). The TWFE models show statistically significant results. However, in our preferred model (column 3), the estimates have the same size and magnitude but are not statistically significant. When analyzing by incentive size (Table 8), the program's impact on low incentive schools is small. In contrast, high-incentive schools experience a substantial increase, with an average rise of six teacher applications (column 3). Additional analyses (detailed in the Appendix) that consider teachers' top three school choices as the outcome corroborate these findings.

Table 7: Effects of Monetary Incentives on School Desirability (Teacher's First Choice)

	(1)	(2)	(3)
Post x Incentive	3.086***	3.152***	2.680
	(0.965)	(0.963)	(2.453)
Incentive	−6.529***	−6.066***	-
	(1.245)	(1.198)	-
# Schools	555	555	555
Covariates	NO	YES	YES
Estimator	TWFE	TWFE	CS

*N*ote: The table presents the estimates for the treatment effect on school desirability, where desirability is measured as the number of teachers that listed the school as their first option. The first column displays the estimate of the treatment effects using a TWFE model without covariates. The second column displays the estimate of the treatment effects using a TWFE model with covariates. The third column displays the estimate of the treatment effect using the doubly-robust estimator from Callaway and Sant'Anna (2021), with covariates. The included covariates are: baseline presence in slums, test scores, and number of schools. Standard errors are clustered at the district level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 8: Effects of Monetary Incentives on School Desirability (Teacher's First Choice), by Incentive Size

	Low			High		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Incentive	2.057**	2.133**	1.642	6.284***	6.342***	5.770***
	(0.984)	(0.984)	(2.239)	(1.022)	(1.020)	(1.259)
Incentive	−5.484***	−5.284***	-	−9.779***	−8.884***	-
	(1.241)	(1.206)	-	(1.280)	(1.244)	-
# Schools	445	445	445	213	213	213
Covariates	NO	YES	YES	NO	YES	YES
Estimator	TWFE	TWFE	CS	TWFE	TWFE	CS

*N*ote: The table presents the estimates for the treatment effect on school desirability, where desirability is measured as the number of teachers that listed the school as their first option. The results are segmented by incentive size. The first three columns show the results for the treated schools in the low-incentive group. The first column displays the estimate of the treatment effects using a TWFE model without covariates. The second column displays the estimate of the treatment effects using a TWFE model with covariates. The third column displays the estimate of the treatment effect using the doubly-robust estimator from Callaway and Sant'Anna (2021), with covariates. The fourth, fifth, and sixth columns present the same results for the treated schools in the high-incentive group. The included covariates are: baseline presence in slums, test scores, and number of schools. Standard errors are clustered at the district level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

4.4 Effects on school test scores

The program was designed to reduce teacher turnover in schools with high turnover rates. As the existing literature suggests that teacher turnover is detrimental to student test scores, especially in vulnerable schools (Hanushek et al., 2016), we examine the program's effects on student achievement. As outlined above, school test scores are observed every two years. We employ a difference-in-differences (DiD) methodology using test scores before and after the program to estimate the intention-to-treat (ITT) effects on average test scores, combining both math and language scores.

Table 9 suggests that the program improved test scores. For the pooled sample, which combines low- and high-incentive schools and compares them to those without incentives, columns 1 and 2 present results under

Table 9: Effects of Monetary Incentives on School Test Scores

	Pooled		Low		High	
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Incentive	0.193*	0.425	0.165	0.366	0.292**	0.593*
	(0.112)	(0.36)	(0.116)	(0.293)	(0.144)	(0.245)
Incentive	−0.075	-	−0.041	-	−0.23**	-
	(0.057)	-	(0.057)	-	(0.106)	-
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	TWFE	CS	TWFE	CS	TWFE	CS
# Schools	528	528	431	431	199	199
Observations	4054	4054	3356	3356	1498	1498

*N*ote: This table presents estimates of the impact of an incentive program aimed at reducing teacher turnover on school test scores. Columns 1 and 2 show the results for the pooled sample, where the treatment group includes any school offering an incentive, compared to schools with no incentives. Columns 3 and 4 compare schools with low incentives to those with no incentives, while columns 5 and 6 present estimates for schools with high incentives compared to those with no incentives. The covariates in all models include year fixed effects, grade level fixed effects (elementary or middle school), whether the school is located in a slum, number of students per classroom, and the school's baseline test score in 2011. Standard errors are clustered at the district level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

two different specifications. The point estimates are positive, with the two-way fixed effects (TWFE) model showing a statistically significant effect, while the Callaway and Sant'Anna (2021) difference-in-differences (CS DiD) model shows no statistically significant results.

We then split the sample into two groups, where we compare no-incentive schools with low-incentive schools, and no-incentive schools with high-incentive schools. In the no-incentive versus low-incentive comparison (columns 3 and 4), the point estimates remain positive, indicating that student achievement improves in low-incentive schools. However, the point estimates are smaller than the pooled sample and not statistically significant. Results strengthen when comparing no-incentive schools to high-incentive schools (columns 5 and 6). Average school test scores in high-incentive schools increase by 0.3-0.6 standard deviations (school level test scores), statistically significant in both the TWFE and CS DiD models.

These findings are consistent with our earlier results, which show that the program was particularly effective in reducing turnover in high-incentive schools. This suggests that stronger incentives increased these schools' appeal, contributing to greater teacher retention. The corresponding improvement in test scores in high-incentive schools highlights the positive link between reduced turnover and student performance. However, these results should be interpreted with caution due to concerns regarding pre-trends. While not statistically significant, the point estimates suggest that differences between the treatment and control groups may have existed prior to the program's implementation. This underscores the need for careful consideration when drawing conclusions about the program's effectiveness.

5 Conclusion

This study examines the complex interplay between teacher turnover and monetary incentives in Sao Paulo's municipal school system. Our analysis of a wage-premium program designed to curb teacher attrition reveals a substantial reduction in turnover, particularly in schools offering high incentives. Our findings align with the existing literature on the crucial role of monetary incentives in retaining teachers (C. Clotfelter et al., 2008).

An examination of teacher preferences adds further depth to our understanding of monetary incentives. That teachers more frequently choose high-incentive schools suggests that financial rewards help to both retain and attract teachers to specific schools.

Various robustness checks, including an analysis of pre-trends in teacher turnover and a placebo difference-in-differences approach, strengthen the reliability of our findings. Results indicate that the changes we observe are attributable to monetary incentives rather than external factors.

The analysis furthermore demonstrates the positive impact of monetary incentives not only on teacher turnover but also student performance, particularly in schools offering higher incentives. Test score gains at these schools suggest that retaining teachers through financial incentives improves academic outcomes. However, schools with lower incentives showed limited and statistically insignificant effects, indicating that incentive size matters. Despite concerns about potential pre-trends, our findings document that a targeted financial intervention can improve both teacher retention and student achievement.

This study has certain limitations. First, its focus on the city of Sao Paulo may restrict the external validity of our findings. Second, while here we examine the program's short-term effects, further investigation might assess its long-term sustainability and broader systemic impacts.

A notable feature of the incentive program under study is its reliance on historical turnover rates to determine incentives. A negative impact on turnover rates in schools receiving high incentives may mean that these establishments will transition over time to a lower incentive category. A cyclical pattern could thus emerge and revive the initial turnover issue. Policymakers might therefore refine the program's design, considering the dynamic nature of turnover rates and their response to incentives.

Our work contributes to the growing body of knowledge on education policy and teacher behavior, showing the role that well-implemented monetary incentives can play in reducing teacher turnover. These findings are crucial for policymakers and education researchers seeking strategies to retain and attract quality teachers to disadvantaged schools—one of the most pressing challenges in education today. Future research should explore the long-term effects and scalability of incentive programs so as to gain a more comprehensive understanding of their role in shaping the education workforce and student achievement.

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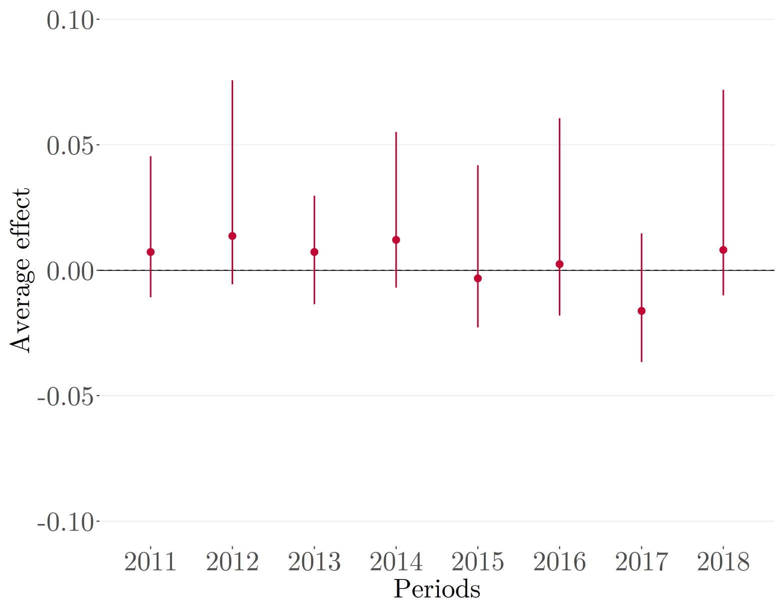
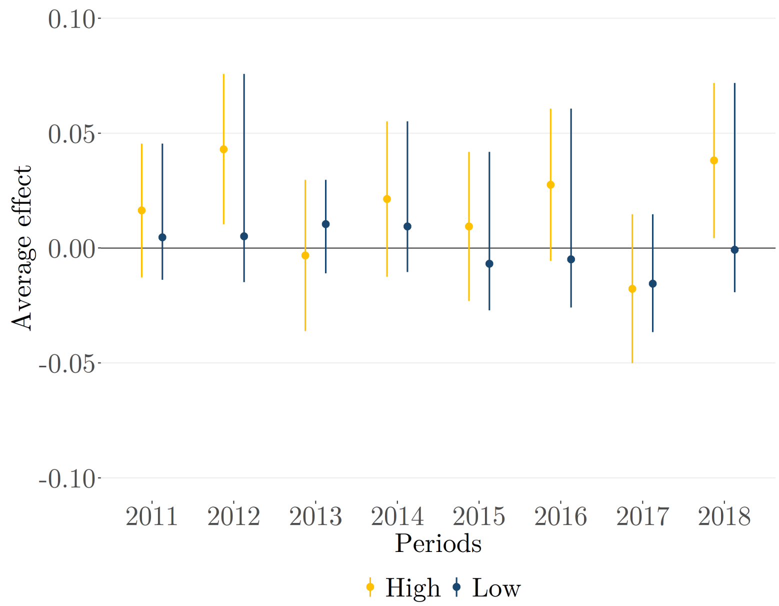
Appendix

Figure A1: Estimated Pre-Trends for the Turnover Rate



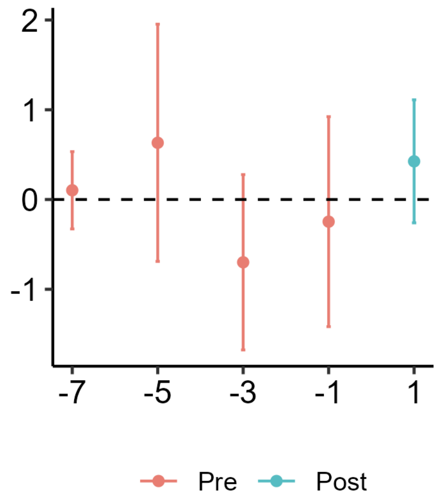
*N*ote: This figure presents the estimates for pre-trends in turnover rate following a TWFE specification without covariates, using as outcome the real turnover. The error bars display the 95% confidence intervals.

Figure A2: Estimated Pre-Trends for the Turnover Rate, by Incentive Size

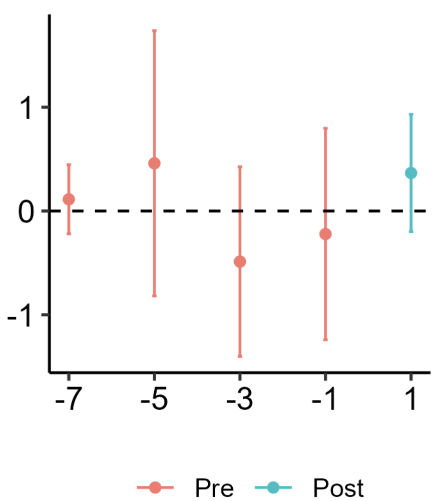


Note: This figure presents the estimates for pre-trends in turnover rate following a TWFE specification without covariates, using as outcome the real turnover. The results are segmented by incentive size. The error bars display the 95% confidence intervals.

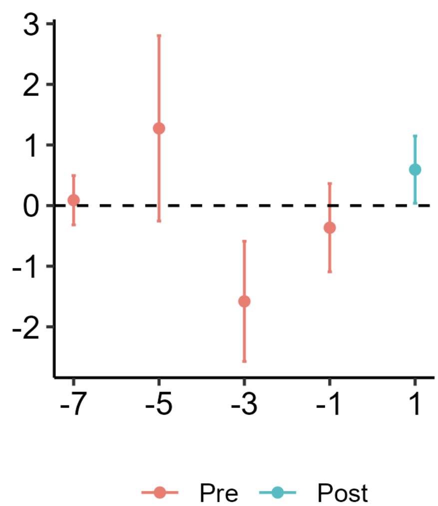
Figure A3: Event Studies - Monetary Incentives and Test Scores



(a) Event study - incentive vs no-incentive schools



(b) Event study - low- vs no-incentive schools



(c) Event study - high- vs no-incentive schools

Table A1: Effects of Monetary Incentives on School Desirability (Teachers' First Three Choices)

	(1)	(2)	(3)
Post x Incentive	8.403***	8.542***	2.680
	(2.073)	(2.069)	(2.459)
Incentive	−17.471***	−15.972***	-
	(3.023)	(2.924)	-
# Schools	555	555	555
Covariates	NO	YES	YES
Estimator	TWFE	TWFE	CS

Note: This table presents the estimates for the treatment effect on school desirability, where desirability is measured as the number of teachers that listed the schools as their first choices. The first column displays the estimate of the treatment effects with a TWFE model without covariates. The second column displays the estimate of the treatment effects with a TWFE model with covariates. The third column displays the estimate of the treatment effect using the doubly-robust estimator from Callaway and Sant'Anna (2021), with covariates. The included covariates are: baseline presence in slums, test scores, and number of schools. Standard errors are clustered at the district level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A2: Effects of Monetary Incentives on School Desirability (Teachers' First Three Choices), by Incentive Size

	Low			High		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Incentive	6.113***	6.269***	4.636	15.523***	15.638***	12.473***
	(2.083)	(2.080)	(3.810)	(2.080)	(2.084)	(2.315)
Incentive	−14.792***	−13.753***	-	−25.800***	−23.681***	-
	(2.997)	(2.916)	-	(3.028)	(3.038)	-
# Schools	445	445	445	213	213	213
Covariates	NO	YES	YES	NO	YES	YES
Estimator	TWFE	TWFE	CS	TWFE	TWFE	CS

Note: This table presents the estimates for the treatment effect on school desirability, where desirability is measured as the number of teachers that listed the schools among their first three options. The results are segmented by incentive size. The first three columns show the results for the treated schools in the low incentive group. The first column displays the estimate of the treatment effects with a TWFE model without covariates. The second column displays the estimate of the treatment effects with a TWFE model with covariates. The third column displays the estimate of the treatment effect using the doubly-robust estimator from Callaway and Sant'Anna (2021), with covariates. The fourth, fifth, and sixth columns present the same results for the treated schools in the high incentive group. The included covariates are: baseline presence in slums, test scores, and number of schools. Standard errors are clustered at the district level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.