Subjective versus Objective Incentives and Employee Productivity*

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Abstract

A central challenge facing firms is how to incentivize employees. While objective incentives may be theoretically ideal, in practice they may lead employees to reduce effort on non-incentivized outcomes and may fail in settings where effort is weakly tied to outcomes. Subjective (manager-discretionary) incentives are hence the norm for the vast majority of employees. However whether, manager discretion is able to overcome this noise and distortion problem is unclear and may even perform worse than objective incentives if managers are inaccurate in their evaluations. We study the effect of subjective incentives (manager-discretionary performance evaluation) and objective incentives (test score-based) relative to no incentives for teachers using an RCT in 230 Pakistani schools. First, we show that subjective and objective incentives both increase test scores and have similar magnitude effects. However, objective incentives decrease non-test score student outcomes relative to subjective incentives. Second, we show that teachers' effort response is very different under each scheme, with attendance increasing under subjective and teaching quality decreasing under objective. Finally, we rationalize these effects through the lens of a moral hazard model with multi-tasking. We show teachers believe objective incentives are a noisier function of their effort than subjective incentives, and objective incentives distort effort toward narrow aspects of student learning. Then we use *within-treatment* variation to isolate the causal effect of contract noise and distortion. We show that incentives which are noisier lead to a smaller effort response and negligible effect on student outcomes and similarly for distorted incentives. Combined, the noise and distortion channel explain about two-thirds of the total difference in effect of subjective versus objective incentives.

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1 Introduction

How should firms incentivize employees when effort is non-verifiable or non-contractable? Contract theory provides an answer. The second best is to incentivize on outcomes of the employee's production function. However, this introduces two new problems – distortion (over-incentivizing measurable outcomes while ignoring others) and noise (outcomes are a noisy function of employee effort). How do most firms actually incentivize workers? They use manager-discretionary (subjective) incentives rather than outcome-based (objective) ones. Raises, promotions, and terminations are subject to manager discretion for most employees. In the US, 85% of full-time employees have at least one aspect of their compensation determined by their manager, and 90% of teacher performance evaluations have a subjective component (Engellandt and Riphahn, 2011; National Center for Education Statistics, 2011; Frederiksen et al., 2017). Despite the prevalence of subjective incentives, there is limited causal evidence on the effect of these incentives and whether they could work in the teaching setting (Rockoff and Speroni, 2010).

In this paper, we ask two questions: What is the effect of subjective versus objective incentives versus no incentives on teacher productivity? To what extent, can contract noise and distortion explain the response we see to subjective versus objective incentives? We answer these questions by conducting an 18-month randomized controlled trial with 234 private schools in Pakistan. We randomize schools to provide core teachers with one of three contracts: (i). control: all teachers receive a raise of 5% irrespective of performance, (ii). subjective treatment: teachers receive a raise from 0-10% based on their manager's rating of their performance,[1] or (iii). objective treatment – teachers receive a raise from 0-10% based on their students' mid-year and end of year percentile value-added (Barlevy and Neal, 2012). Both treatments are within-school tournaments and have the same distribution of raise thresholds. These similarities allow us to isolate the effort response from just changing the performance metric (manager rating versus test score) while holding other features of the incentive structure constant.

We use detailed administrative, survey, test, and classroom observation data to understand each contract's effect on teacher effort and student outcomes. Student outcomes are measured along two dimensions: test scores and socio-emotional development. Test score data comes from an endline test conducted by the research team, one month after the end of the contract. Students are tested in core subjects (English, Urdu, math, science, and economics) in grades 4-13. A variety of question types and sources allow us to test whether effects are driven by memorization-type questions. Socio-emotional development is measured along six dimensions: love of learning, ethical decision-making, inquisitiveness, global citizenship, sustained attention and resilience. The first four dimensions are measured using self-report survey items drawn from several psychological indices used for measuring socio-emotional development in children.[2] The latter two dimensions are measured using within

[1] Managers are generally principals or vice-principals and spend about a third of their time on employee management tasks, such as observations, feedback, and professional development.

[2] Items are drawn from the National Student Survey, Learning and Study Strategies Inventory, Big Five (children's

item variation in performance on the academic subject tests.

To better understand the mechanisms behind teachers responses, we construct a model starting from the classic moral hazard model with multi-tasking as presented in Baker (2002). We then restrict to a specific class of incentive contract types and show two key predictions of the model which we test with the experiment: worker productivity is decreasing in incentive contract: noise (lack of correlation between employee action and incentive pay) and distortion (lack of correlation between piece rate for different actions and marginal return to those actions on firm outcomes).

In our first main result, we show that both subjective and objective contracts are equally effective at increasing test scores. Both contracts increase test scores by 0.09 sd, which is very similar to average effects from meta-analyzes of performance pay for teachers (Pham et al., 2020). These results are consistent across subject and grade and are not driven by rote-memorization type questions. However, we find, in contrast to the test score results, objective and subjective incentives have different effects on socio-emotional skills. Objective incentives negatively affect student socio-emotional development, including a significant decrease in love of learning and an increased likelihood students say they want to change schools. Subjective incentives result in a small positive effect on overall socio-emotional skills measured via student surveys. We also find that students in the subjective incentive schools show higher levels of resilience and sustained attention compared to those in objective incentives and control, measured by comparing performance on test items directly after a difficult item or later in the exam, respectively. These combined effects suggest that teachers under objective contracts focused exclusively on improving student academic improvement, at the cost of more well-rounded development for students. Whereas, teachers under the subjective contract were able to prioritize both areas.

To understand teachers' behavioral responses to these incentive contracts, we compile rich data on teacher behavior inside and outside the classroom. We record 6,800 hours of classroom footage and review it using a standard classroom observation rubric (Pianta et al., 2012). The rubric captures teacher behavior along dozens of dimensions, from the use of punitive discipline to the proportion of student versus teacher talk time. The rubric also measures the amount of time spent on test-taking or test-preparation activities. To measure effort outside the classroom, we acquire administrative data on daily clock in and out time and have teachers complete a time use questionnaire. Combined these data sources allow us to understand teacher behavior change under subjective versus objective incentives.

In our second main result, we find both subjective and objective incentives lead to changes in classroom practices. As one might expect, subjective incentives spur actions that managers value, and objective incentives spur actions that most quickly and easily translate into test score gains. Subjective incentives lead to increased targeting of individual student needs and daily attendance. Objective incentive schools see a five-fold increase in class time on test preparation activities,

scale), Eisenberg's Child-Report Sympathy Scale, Bryant's Index of Empathy Measurement, Afrobarometer, World Values Survey, and Epistemic Curiosity Questionnaire.

more lecturing compared to student-centered teaching and a more negative classroom climate (with increases in teacher yelling and use of punitive discipline).

Together these results on student outcomes and teacher behavior suggest that subjective performance incentives increased teacher effort without producing distortionary effects. How are managers able to accomplish this? We use data on teacher beliefs about manager preferences, manager vignette responses and text analysis from the actual written criteria managers used to evaluate teachers. We find, on average, managers tend to value the actions which contribute to both test-score and non-test score outcomes for students. We also do not find evidence that teachers believe subjective incentives are more susceptible to favoritism or gender bias. However, there is heterogeneity in how effectively managers' implement the contract. For the worst 20% of managers, we cannot reject that subjective incentives have no effect on student outcomes relative to the control.

We then return to our model of moral hazard with multi-tasking to explain our three main reduced form results: i). similar, positive effects of subjective and objective incentives on test scores, ii). negative effects of objective incentives on socio-emotional development, iii). significant differences in teacher effort across the two treatments.

To test whether these two mechanisms, noise and distortion, can explain our reduced form results, we take the following approach: First, we show that employees believe the subjective and objective contracts are similar along all dimensions except the extent of noise and distortion. Second, we exploit partially exogenous heterogeneity *within* a given treatment to isolate the causal effect of noise and distortion on student outcomes. Finally, we bring those two estimates together and show that given the difference in perceived noise and distortion across the contracts and the causal effect of noise and distortion on student outcomes, we can explain a large portion of the reduced form effects with these channels. We explain each step in detail below.

The first step is testing whether teachers believe there are differences in the extent of noise and distortion across the two treatments. We do this by asking teachers at endline the extent to working harder will increase their incentive pay. If they believe their effort closely maps into their pay then this is a *less* noisy incentive system. Then we ask what types of actions (lesson planning, improving pedagogy, helping other teachers, etc) are rewarded under each system. This allows us to measure teacher's perception of whether the incentive is distorted toward certain actions at the cost of others.

We find that teachers believe subjective performance incentives are *less* noisy than objective incentives, and, therefore, view subjective incentives as more effective at motivating behavior. They view test-score based incentives as much less within their control because so many other factors beyond their effort affect student scores. We also find that teachers in the objective treatment are more likely to prioritize the type of actions which lead to test score gains, at the cost of other areas of student development. Teachers under subjective contract prioritize actions that lead to academic gains and also prioritize administrative tasks, which are likely to be preferred by their manager. We also show there are no other differences beyond noise and distortion across the two treatment arms.

We show there is similarity in implementation timelines, understanding of the contract treatments, and beliefs about the fairness of each treatment arm.

To determine the causal effect of noise on student outcomes, we ask teachers to rate how accurate their manager is in rating other teachers. However, there may be many other attributes correlated with manager inaccuracy, so we interact this measure of inaccuracy with treatment status giving us the additional effect of manager inaccuracy on subjective vs objective and control schools.

Using this instrument for noise, we find that a 1 SD increase in the perceived noisiness of the contract decreases hours worked by 13 and decreases student test scores by 0.2 SD. These results are robust to a variety of controls. This suggests that employees are very sensitive to the noisiness of the contract, and that this affects the success performance pay has in inducing an effort response from employees. This instrument for noise is robust to controlling for many other features of the contract and school environments.

To understand the effect of distortion on student outcomes, we again exploit variation within treatment status. We use text data on the evaluation criteria managers set for each teacher at the beginning of performance evaluation year and the weight allocated to each criteria, and categorize them into five types of teacher actions: administrative tasks, professional development tasks, improvements in teacher pedagogy, test-score based goals and other. Delineating these criteria and scoring teachers on them at the end of the year takes places in all schools irrespective of treatment status, but in subjective schools teacher's raises are based on these scores. Of course, schools in which managers focus on administrative goals versus those in which managers focus on pedagogy goals are likely different in many ways. Therefore, we interact the weight put on each action category with treatment status. Therefore, we are comparing schools in which principals have delineated the same evaluation criteria but are either randomized to subjective (financial stakes of evaluation criteria) versus objective and control (no financial stakes of evaluation criteria). This allows us to estimate essentially a production function of teacher action on student outcomes. We find that a larger focus on test scores and professional development increases students' endline test scores. However, more focus on test scores results in negative effects on student socio-emotional development. These results are robust to controlling for other features of the contract environment.

Combined, these results help us understand why it is possible to have the same effect on test scores without needing to incentivize test scores directly. Subjective incentives are less noisy, producing a larger overall effort response, and prioritize both test score and non-test score student outcomes, allowing teachers to prioritize multiple areas of student development. We find that the noise and distortion channel are able to explain two-thirds of the reduced form effects we see.

Our paper makes three key contributions. First, it is the first study, to our knowledge, to isolate the causal effect of purely subjective versus objective incentives and the effect of purely subjective versus flat incentives for employees in any sector (Lazear and Oyer, 2012; Oyer and Schaefer, 2011). Existing experimental studies have tested bundled incentives (e.g. combined subjective and objective incentives) versus no incentives on employee behavior (Bandiera et al., 2020; Khan et al., 2019; Fryer,

2013; Leaver et al., 2019). Previous work has also compared the effect of heterogeneity across plants to measure the effect of more or less steep subjective incentives on employee overtime (Engellandt and Riphahn, 2011). There is also evidence that managers, especially in educational settings, may have imperfect information about worker effort or may be biased toward certain groups (Eren, 2023; Gibbs et al., 2004; Jacob and Lefgren, 2008).

Second, we add to a robust literature on the effect of performance pay for teachers by providing two new findings (Biasi, 2021; Fryer, 2013; Goodman and Turner, 2013; Lavy, 2007; Muralidharan and Sundararaman, 2011). We show the first evidence of objective performance pay having detrimental effects on non-academic student outcomes, consistent with multi-tasking models. Next, we show direct evidence that objective incentives result in teachers distorting their effort toward teaching pedagogy that impacts test performance at the cost of other areas of student development. This includes the use of class time doing test prep and the use of punitive discipline. Both of these results have long been suspected, but we provide the first documentation of such effects (Baker, 2002; Deserranno et al., 2025; Leigh, 2013).

Third, we provide, what we believe is, the first evidence on measuring the extent of noise and distortion within an employee's contract and isolating the effects of those mechanisms on firm outcomes. There is a rich theoretical literature on the importance of these mechanisms (Baker, 2002; Yang, 2008) and some empirical work has also investigated the role of noise on employee response (Prendergast, 1999; Prendergast and Topel, 1993; Prendergast, 2007) in non-experimental settings.

The remaining sections are organized as follows. Section 3 details the treatment and control conditions, the data collected, and standard implementation checks. Section 2 gives an overview of the standard moral hazard model with multi-tasking and highlights the two key mechanisms which underpin the reduced form effects we find. Section 4 provides the main results of subjective and objective performance incentives on teacher effort and student outcomes. Section 5 unpacks the mechanisms underlying the main effects in light of the moral hazard model, and section 6 concludes.

2 Conceptual Framework

To understand the potential effects of subjective versus objective incentives, we begin with a simple model of moral hazard with multi-tasking as presented in Baker (2002), which provides a very general framework for how incentives may affect employee behavior. We will then restrict to a subset of performance contract types to further tighten our predictions about the effect of each contract, beyond Baker (2002). At the core of this model is the tension between paying employees for the outcomes the firm cares about while not penalizing employees for things outside of employee's control. This is also the key tension at the heart of the costs and benefits of using subjective versus objective incentives, which we outline in section 2.2.

2.1 Moral Hazard with Multi-tasking

The firm, a school, produces a single outcome – student learning, $V(\mathbf{e}, \epsilon)$ – through a simple linear production function:

$$V(\mathbf{e}, \epsilon) = \mathbf{f} \cdot \mathbf{e} + \epsilon = f_1 e_1 + f_2 e_2 + ... + \epsilon \tag{1}$$

Student learning is a function of an n-dimensional vector of effort teachers can take on different actions, $\mathbf{e}$, and the n-dimensional vector of marginal products of those actions, $\mathbf{f}$. Student learning is also a function of many other things outside the teacher's action set (environment, parental support, peers, etc.), which are captured by the noise term, ϵ, which is mean zero and has a variance of σ^2_ϵ.

Employers cannot perfectly observe effort, but they can observe some components of student learning (for example, test scores) and some actions (for example, teacher attendance). Schools construct a performance contract that pays teachers based on a performance measure, $P(\mathbf{e}, \phi)$, which could be a combination of observable outputs (test scores, student attendance, etc.) and/or actions (teacher attendance, lesson plans, etc.). Teacher's performance measure, and therefore their pay, then is:

$$P(\mathbf{e}, \phi) = \mathbf{g} \cdot \mathbf{e} + \phi = g_1 e_1 + g_2 e_2 + ... + \phi \tag{2}$$

The performance measure, $P(\mathbf{e}, \phi)$, is a function of teacher's effort, $\mathbf{e}$, and the marginal return to those actions on the performance measure, $\mathbf{g}$. In effect, $\mathbf{g}$ translates to a piece-rate for each effort category. ϕ captures everything outside the teacher's effort, which affect the performance measure. It is mean zero and has variance σ^2_ϕ. Two types of noise are captured by ϕ. First is noise coming from features of the performance measure, which are outside the teacher's control. For example, if the performance measure is students' test scores, this could be the students' home environment. Second is the noise coming from mis-measurement of a given action, e_n. For example, if the performance measure is teacher attendance, but principals have error-ridden records of attendance, then this contributes to the noisiness of the performance measure.

Teacher's utility is a function of their pay and a quadratic cost of effort for any effort beyond what they would allocate under no incentives ($\vec{\theta}$).[3] Teachers do not vary in their cost of effort but do vary in the level of effort they exert under no incentives ($\vec{\theta}$).

$$u(\mathbf{e}, \phi) = \mathbf{g} \cdot \mathbf{e} + \phi - \sum_{i=1}^{n} \frac{(e_i - \theta_i)^2}{2} \tag{3}$$

Teachers choose the optimal set of actions that maximizes their utility. Taking the derivative of eq.

[3]Baker (2002) assumes risk-averse agents with a utility function of $u(\mathbf{e}, \phi) = E[P] - rvar[P] - \sum_{i=1}^{n} \frac{e_i^2}{2}$. Because we are not focused on teacher retention, we leave out the risk aversion component, which only enters in determining the nature of the participation constraint and does not affect effort response once an employee has selected the contract.

3, we have that the optimal decision is to set each action amount equal to the piece rate plus the baseline effort exerted under no incentives, $e_1^* = g_1 + \theta_{i1}, e_2^* = g_2 + \theta_{i2}, ...e_n^* = g_n + \theta_{in}$.

Given teacher's optimal action set, the average student learning produced by each teacher relative to no incentives is:

$$E[V(\mathbf{e}^*, \epsilon)] = \mathbf{f} \cdot \mathbf{g} = \|f\|\|g\| cos\theta \tag{4}$$

Average student learning then is a function of the length of the marginal production on student learning vector, $\|f\|$, the length of the piece-rate vector, $\|g\|$, and the alignment between these two vectors, $cos(\theta)$. In other words, student learning is increasing in the steepness of the incentives and how aligned those piece rates are with the student learning production function.

Departing from Baker (2002), we can further re-arrange the expression to show the effect that noise in the performance measure has on average student learning. Taking the variance of eq. 2, we have $var(P) = \|g\|^2 var(\|e\|) + \sigma_\phi^2$. Re-arranging, we can substitute this in for $\|g\|$ into eq. 4. Average student learning then is:

$$E[V^*(\mathbf{e}^*, \epsilon)] = \|f\| \frac{\sqrt{var(P) - \sigma_\phi^2}}{\sqrt{var(\|e\|)}} cos\theta \tag{5}$$

$\|f\|$ is always constant across incentive types. We further assert that $var(\|e\|)$ and $var(P)$ are constant across incentive types. Fixed $var(\|e\|)$ across incentive scheme arises due to our assumption of no heterogeneity in cost of effort and we can test explicitly with our data.[4] Due to the design of our subjective and objective incentives, $var(P)$, is also constant across the two schemes.[5]

2.2 Theoretical Predictions

We are then left with two components of the performance incentive system that affect average student learning. Average student learning is:

- decreasing in performance measure **distortion**, $1 - cos(\theta)$
- decreasing in performance measure **noise**, σ_ϕ^2

Distortion Distortion captures the correlation between the piece rates for different actions and the marginal return to student learning of those actions. In essence, do we pay teachers more for

[4] We test the assumption of a fixed $var(\|e\|)$ in our data by calculate the within-school variance in effort along 25 measured dimensions of teacher effort. Figure A1 plots the distribution of p-values for F-tests of equality within each treatment arm pair. Distribution of p-values is relatively flat from 0-1, providing supporting evidence that $var(\|e\|)$ is constant across treatment.

[5] A large class of incentives, including all tournaments, have a fixed variance, so the predictions of the model, apply in those settings as well.

the actions which are more related to developing student learning? The more distorted a contract is, the more employees focus on actions that are less helpful toward firm outcomes.

Noise Noise captures how much of the performance incentive is unrelated to employee's actions. This could operationalize as other factors outside the employee's control affecting the performance measure (school resources, shocks, etc.) or mis-measurement of employee actions, if the contract attempts to measure teacher actions. It is important to flag that traditionally the way noise enters the optimal contract design is through reducing risk-averse employee's utility. This requires firms to raise the fixed part of an employee's salary to meet employee's participation constraint. Here we are not focused on that consequence of noise as we are not focused on employee entry or exit in this paper.[6]

The effect of noise we focus on here is equivalent to a decrease in the incentive scheme's average piece rate. Since $\sigma_\phi^2 = var(P) - \|g\|^2 var(\|\mathbf{e}\|)$, and $var(P)$ and $\mathbf{a}$ are constant given the tournament nature of each incentive scheme, increasing σ_ϕ^2 directly decreases $\|g\|$. Therefore, increasing noise then reduces the extent of the effort response, $\|\mathbf{e}^*\|$. This effect of noise exists in any incentive scheme with a fixed variance, which includes all tournament or threshold-type incentives.

Subjective vs. Objective Incentives We would expect that both subjective and objective incentives will exhibit some level of noise and distortion. The sources noise and distortion for each incentive can be summarized as the following:

Distortion $1 - cos(\theta)$	Subjective	- Gap between manager's utility function and student learning - Incorrect beliefs about teacher's production function
	Objective	- Gap between objective incentive metric and social welfare function - Incorrect beliefs about own production function
Noise σ_ϕ^2	Subjective	- Mismeasurement of effort - Components of manager's utility function outside teacher's control
	Objective	- Mismeasurement of objective incentive metric (i.e. test scores) - Components of objective incentive metric outside teacher's control

The theoretical framework allows us to understand how the incentive may affect teachers' response and, as a result, the impact on student learning. Ex-ante, it is not clear whether subjective or objective incentives would be more or less distorted in the teaching context. On the one hand, subjective incentives may solve the multi-tasking problem by prioritizing more than just test scores. One of the key critiques of objective incentives is that teachers may focus on actions which enhance test scores (such as test prep skills, memorization, etc.), but have small or zero effects on true human capital (Muralidharan and Sundararaman, 2011). Subjective performance incentives would ideally

[6] A companion paper (Brown and Andrabi, 2025) studies employee selection in response to these contracts.

penalize these types of behaviors and reward more well-rounded teaching. On the other hand, it could be that managers prioritize the wrong actions – because they do not know what the true teacher production function is, because they aspects of student learning differently than the firm, or most nefariously, they weight actions which make their job easier.

It is also uncertain whether subjective or objective would be less noisy. Test scores are notoriously noisy measures of teacher effort (Chetty et al., 2014). One of the most common complaints teachers have against test score-based incentives is that they are mostly unrelated to teacher actions (Podgursky and Springer, 2007). Subjective performance pay could be less noisy than objective performance pay because managers could focus on rewarding actions rather than outcomes. However, this requires managers to observe effort accurately. Subjectivity could even introduce additional noise, if managers introduce bias or favoritism into their evaluations.

3 Experimental Design

3.1 Connecting Framework and Experiment

We first seek to understand the effect of different performance pay schemes on student learning, V, and teacher effort, $\vec{e}$, in section 4. This section will detail the different versions of performance pay, P, and our measurement of V and $\vec{e}$. Then, in section 5, we will test whether we can in fact explain differences in the effect of P through differences in the level of noise, σ^2_ϕ, and distortion, $1 - cos(\theta)$.

3.2 Performance Incentive Treatments

We partnered with a large private school system in Pakistan to implement the research design. Schools are randomized to receive one of three contracts which determine the size of teachers' raises at the end of the calendar year.[7] The three contracts were:

- **Control: Flat Raise** - Teachers receive a flat raise of 5% of their base salary
- **Treatment: Performance Raise** - Teachers receive a raise from 0-10% based on their within-school performance ranking using the percentile thresholds below:

[7] Triplet-wise randomization by baseline test performance was used, which generally performs better than stratification for smaller samples (Bruhn and McKenzie, 2009).

Performance Group	Within-School Percentile	Raise amount
Significantly above-average	91-100th	10%
Above-average	61-90th	7%
Average	16-60th	5%
Below average	3-15th	2%
Significantly below average	0-2nd	0%

There are two treatment arms, which vary what performance metric is used to evaluate teachers. Teachers in a given treatment arm are ranked within their school on one of the following performance measures:

- ***Subjective Treatment Arm:*** Teachers are evaluated by their manager at the end of the calendar year. Managers had complete discretion over how they evaluated teachers and what aspects of performance they would prioritize. To ensure teachers knew what was expected of them, managers delineated between 4-10 evaluation criteria, which would be used to evaluate the teachers at the beginning of the year. These included items such as improving their behavioral management of students, assisting with administrative tasks, helping plan an afterschool event, and improving students' spoken English proficiency.[8]
- ***Objective Treatment Arm:*** Teachers are evaluated based on their average percentile value-added (Barlevy and Neal, 2012) for the spring and fall term. Percentile value-added is constructed by calculating students' baseline percentile within the entire school system and then ranking their endline score relative to all other students who were in the same baseline percentile.[9] We then average across all students the teacher taught during the two terms.

The contract applied to all core teachers (those teaching Math, Science, English, and Urdu) in grades 4-13. Elective teachers and those teaching younger grades received the status quo contract. All three contracts have equivalent budgetary implications for the school. We over-sampled the number of subjective treatment arm schools due to partner requests, so the ratio of schools is 4:1:1 for subjective treatment, objective treatment, and control, respectively.

Both the subjective and objective treatment arms have several features in common, allowing us to isolate the effect of differing the performance metric and nothing else about the incentive structure. Both treatments are within-school tournaments, so this holds the level of competition fixed between the two treatments. In addition, the variance in the distribution of the incentive pay is equivalent across the two treatments. As we showed in section 2, holding the variance constant allows us to

[8] An example set of criteria are provided in Table A2 and a summary of how common different criteria were across our sample is show in Figure A3.

[9] Percentile value-added has several advantageous theoretical properties (Barlevy and Neal, 2012) and is also more straightforward to explain to teachers than more complicated calculations of value-added.

interpret differences in noise levels between the two systems as equivalent to differences in incentive steepness. The performance evaluation timeline also played out the same for all groups. Before the start of the year, managers set performance goals for their teachers irrespective of treatment. Teachers were evaluated based on their performance in January through December, with testing conducted in June and January to capture student learning in each term of the year.[10]

To ensure teachers and managers had full understanding of how each contract would work, we conducted an intensive information campaign with schools. First, the research team had an in-person meeting with each manager, explaining the contract assigned to their school, and, in the case of the subjective treatment, explaining what would be expected of them and when. Second, the school system's HR department conducted in-person presentations once a term at each school to explain the contract. Third, teachers received frequent email contact from school system staff reminding them about the contract and half-way through the year contract teachers were provided midterm information about their rank based on the first 6 months.[11] Control teachers were also provided information about their performance in one of the two metrics, in order to hold the provision of performance feedback constant across all teachers.

3.3 Timeline and Data

Our study was conducted from October 2017 through June 2019. It covered one performance review cycle conducted from January-December 2018 in which the contracts were in place. Figure 1 presents the main treatment implementation (detailed in section 3.2) and data collection activities (detailed below).

Our data allows us to understand how teachers changed their effort under each incentive scheme, why the incentives affected effort in the way they did, and the resulting effect this had on student outcomes. We draw on data from (i). the school system's administrative records, (ii). baseline and endline surveys conducted with teachers and managers (iii). endline student testing and survey and (iv). detailed classroom observation data.

Administrative Data: The administrative data details position, salary, performance review score, attendance, and demographics for all employees. We also have biometric clock in/out data for all schools. The data was provided by the school system for the period of July 2016 to June 2019. It

[10]The school systems' central office designed and administered the June test to all students in a given grade. However, tests are graded locally by the school, often by the students' teacher. Due to concerns of grade manipulation, grading was audited by the research team. 10% of all teacher's exams were regraded. If the teachers' grade and the auditor's grade were off by more than 5%, another 10% of their tests were audited. If the average was still off by more than 5%, all of the teacher's exams were regraded. Overall, grade manipulation was small and was generally driven by cases where teachers bumped up students' grades from just failing to just passing. There was no heterogeneity in grading accuracy by treatment. These tests are *not* used as an outcome measure in this paper. The January test was conducted exclusively by the research team (described in section 3.3 below) and therefore this is the test we use to measure learning effects.

[11]An example midterm information note is provided in Appendix Figure A4.

includes classes and subjects taught for all teachers, and end of term standardized exam scores for all students (linked to teachers). From September through December 2018, we also have data on classroom observations conducted by managers. Managers use a similar rubric to the one used by the research team to conduct classroom observations (detailed below).

Baseline Survey: The baseline survey measured teachers' preferences over different contracts and beliefs about their performance under each contract. 40% of schools were randomly selected to participate in an in-person baseline survey conducted in October 2017. 2,500 teachers and 119 managers were surveyed. These outcomes are primarily used for a companion paper on teacher selection in response to performance pay (Brown and Andrabi, 2025).

Endline Survey: The teacher endline survey measured their understanding of the contract they were assigned, time use, and beliefs about their manager's level of bias in conducting performance evaluations. The manager endline survey measured managers' beliefs about teacher quality and measured management quality using the World Management Survey school questionnaire.[12] The endline survey was conducted online with teachers and managers in spring and summer 2019. 6,080 teachers and 189 managers were surveyed.

Endline Student Testing and Survey: An endline test was conducted with students to measure performance in core subjects and socio-emotional skills after one year of the intervention. The research team conducted the endline test and student survey in January 2019. The test was conducted in Reading (English and Urdu), Math, Science, and Economics. The items were written in partnership with the school system's curriculum and testing department to ensure appropriateness of question items. Grading was conducted by the research team. Items from international standardized tests (PISA, TIMSS, PERL, and LEAPS) and a locally used standardized test (LEAPS) were also included to benchmark student performance.[13]

Students also completed a survey to measure four areas of socio-emotional development: love of learning, ethical decision-making, global citizenship and inquisitiveness. The choice of these four areas came from the school system's priorities. They are the four areas of socio-emotional development they expect their teachers to focus on. These values are posted on the walls in schools, and teachers receive professional development on building these values in students. Some managers also specifically refer to development of these skills in students in teachers' evaluation criteria.

We measure improvement in these areas using student responses to items drawn from the National Student Survey, Learning and Study Strategies Inventory, Eisenberg's Child-Report Sympathy Scale,

[12]Due to budget constraints, we were unable to have the World Management Survey surveyors conduct the survey. Instead, we asked managers to directly rate themselves on the rubric that surveyors use. This approach could result in inflated management scores. As a result, we use additional objective data to corroborate the management scores.

[13]The endline student test data was used both for evaluating the effect of the treatments and used to compute objective treatment teachers' raises.

Bryant's Index of Empathy Measurement, Afrobarometer, World Values Survey, and Epistemic Curiosity Questionnaire, which aim to measure these four skill areas. These items have been shown to correlate with high school graduation, college attendance and civic participation (Amoateng et al., 2014; Kashdan et al., 2018; Pekrun et al., 2002; Tang and Salmela-Aro, 2021; Van Wyk and Mason, 2021). Appendix table A2 lists the survey items used for each area along with their source. We also investigate student resilience and sustained attention by comparing student performance on question items just after difficult ones and over the length of the exam to test for persistence.[14]

Classroom Observation Data: To measure teacher behavior in the classroom, we recorded 6,800 hours of classroom footage and reviewed it using the Classroom Assessment Scoring System, CLASS (Pianta et al., 2012), which measures teacher pedagogy across a dozen dimensions.[15,16] We also recorded whether teachers conducted any sort of test preparation activity and the language fluency of teachers and students.

Performance Evaluation Data: We also draw on data from the school system's existing performance evaluation system. Prior to and during the intervention, the school system maintained a performance management system in which managers would delineate 4-10 evaluation criteria and the weight attached to each criteria. These criteria are open fields for managers decide on for each of their employees. We use the open response text and point weightage to understand manager evaluation criteria. Managers select these criteria in December 2017 before treatment status is announced.

3.4 Sample and Characteristics of the Employee-Manager Relationship

Teachers The study was conducted with a large private school system in Pakistan. Table 1 presents summary statistics of our sample compared to a representative sample of teachers in US (National Center for Education Statistics, 2011). The student body is from an upper middle-class and upper-class background. Teachers are generally younger and less experienced than their counterparts in the US, though they have similar levels of education. Our sample is mostly female (80%), young

[14]These two latter dimensions of socio-emotional development were suggested after data collection based on seminar feedback and therefore were not preregistered.

[15]There are tradeoffs between conducting in-person observations versus recording the classroom and reviewing the footage. Videotaping was chosen based on pilot data which showed that video-taping was less intrusive than human observation (and hence preferred by teachers). Videotaping was also significantly less expensive and allowed for ongoing measurement of inter-rater reliability (IRR).

[16]We did not hire the Teachstone staff to conduct official CLASS observations as it was cost-prohibitive and we required video reviewers to have Urdu fluency. Instead we used the CLASS training manual and videos to conduct an intensive training with a set of local post-graduate enumerators. The training was conducted over three weeks by Christina Brown and a member of the CERP staff. Before enumerators could begin reviewing data, they were required to achieve an IRR of 0.7 with the practice data. 10% of videos were also double reviewed to ensure a high level of ICC throughout the review process. We have a high degree of confidence in the internal reliability of the classroom observation data, but because this was not conducted by the Teachstone staff, we caution against comparing these CLASS scores to CLASS data from other studies.

(35 years on average), and inexperienced (5 years on average, but a quarter of teachers are in their first year teaching). All teachers have a BA and 68% have some post-BA credential or degree.

Managers In order to understand the effects of subjective performance pay, we need to understand who the managers are and what role they play in overseeing teachers. Managers here are either a principal in small schools or a vice principal in larger schools. They are tasked with overseeing the overall operations of the school and managing employees, including teachers and other support staff. Table 2 presents information about managerial duties compared to a US sample of principals. Like in the US, our managers are generally older (45 years old), less likely to be female (61%), and more experienced (9.6 years) than teachers. Most were previously teachers and transitioned into an administrative role.

The distribution of time use is fairly similar to the principals in the US. Managers spend about a 1/3 of their working hours overseeing their staff – observing classes, providing feedback, meeting with teachers and reviewing lesson plans. The rest of their time is spent on other tasks related to the schools functioning. However, managers in our sample spend much more time directly observing teachers. They do about twice the number of classroom observations each year (4.7 versus 2.5 in the US). They also rate themselves higher in most areas of the management survey questions (4.3 versus 2.8 out of 5), including formal evaluation, monitoring and feedback systems for teachers. This is an important difference as these management practices could positively effect the success of the subjective treatment arm, and may help us understand the extent of external validity of these results.

3.5 Intervention Fidelity

In this section, we provide evidence to help assuage any concerns about the implementation of the experiment. First, we show balance in baseline covariates. Then, we present information on the attrition rates. Finally, we show teachers and managers have a strong understanding of the incentive schemes. Combined, this evidence suggests the design "worked".

Schools in the two treatment arms and control appear to be balanced along baseline covariates. Appendix Table A1 compares schools along numerous student and teacher baseline characteristics. Of 27 tests, one is statistically significant at the 10% level and one is statistically significant at the 5% level, no more than we would expect by random chance. Results presented include specifications which control for these few unbalanced variables.

Administrative data is available for all teachers and students who stay employed or enrolled during the year of the intervention. During this time 23% of teachers leave the school system, which is very similar to the historical rate of turnover. 88% of teachers completed the endline survey. While teachers were frequently reminded and encouraged to complete the survey, some chose not to. We do not see differences in these rates by treatment.

Finally, for the endline test, parents were allowed to opt out of having their children tested. Student attrition on the endline test was 13%, with 3 pp of that coming from students absent from school on the day of the test and the remaining 10 pp coming from parents choosing to have students opt out of the exam. On both the endline testing and endline survey, we do not find differences in attrition rate by treatment. We also do not find that lower performing students were more likely to opt out.

Teachers have a decent understanding of their treatment assignment. Six months after the end of the intervention, we ask teachers to explain the key features of their treatment assignment. 60% of teachers could identify the key features of their raise treatment. Finally, most teachers stated that they came to fully understand what was expected of them in their given treatment within four months of the beginning of the information campaign.

4 Results

We now present the main reduced form results of the paper. First, we test the effects of each incentive on student test performance and socio-emotional development, our two measures of student learning, V. Then, we show the effects of the incentives on teacher effort, which helps us to the changes in behavior which brought about these impacts on students. Finally, we discuss how managers actually implemented the subjective performance arm and how that varied across manager.

4.1 Effect of Incentives on Student Outcomes

4.1.1 Specification

Our main specification is:

$$Y_{i1} = \alpha + \beta_1 SubjectiveTreatment_s + \beta_2 ObjectiveTreatment_s + \delta Y_{i0} + \chi_j + \epsilon_i \tag{6}$$

The main dependent variable of interest is student outcome, Y_{i1}, for child, i, at endline, t=1. Student outcomes include test scores in Math, Science, English and Urdu and socio-emotional development. $SubjectiveTreatment_s$ and $ObjectiveTreatment_s$ are a dummy for whether the student's school, s, was assigned to subjective or objective performance raises. The left out group is the control group (flat raise). The coefficients of interest are β_1 and β_2, and their test of equality. For test scores, we control for student's baseline score, Y_{i0}, to improve efficiency as there is high auto-correlation in test scores.[17] We also control for strata fixed effects, subject and grade, χ_j.

[17]For grade 4 students we do not have a baseline because standardized testing in the school system begins in 4th grade. For these students, and any other that are missing a baseline, we denote a score of zero and add a dummy for having the baseline test missing.

Standard errors are clustered at the school level (the unit of randomization), and both standard and randomization inference p-values are provided in each table.

4.1.2 Results

Test Scores We find that both subjective and objective performance incentives have similar effects on test scores, of about 0.09 sd. Figure 2 and table 3 presents the results of each performance incentive on endline test scores. Column (1) shows results for all tests and question items. Effects are similar between the subjective and objective incentives, with an effect of 0.086 sd and 0.092 sd, respectively. In the row titled "F-test p-value (subj=obj)", we present a test for the equality of $\beta_1 = \beta_2$. We cannot reject equality of effects between the two treatments on test scores. All results appear unchanged whether we consider standard p-values (in parentheses) or randomization inference p-values (in brackets).

Column (2) and (3) provide tests on the effect of the treatment by question item type to understand whether these effects are due to memorization of class content or actual learning. Column (2) only includes questions from the prior grade's content and column (3) only includes questions that were added by the researchers from external standardized test sources including PISA, TIMSS, PERL and LEAPS.[18,19] Both sets of questions provide a useful test because it would not be possible for students to have memorized the answers to the questions. Remedial content (from previous grade levels) and external content had not previously been included on the school system's standardized exam, and so teachers would not have prepared specifically for this material. Given that we find similar if not larger effects on these types of questions, it appears that treatment effects are coming from actual learning as opposed to memorizing curriculum. Again, we do not see a significant difference between the subjective or objective treatment.

Column (4) and (5) present the results by subject, splitting by math and science exams versus the two reading exams (English and Urdu). Magnitudes are similar, around 0.09 sd, for both subjects, though we are less powered to detect overall effects with the smaller sample when we split by subject. Again, we cannot reject equality between the two treatments and the magnitude of the effects is highly similar.

Socio-Emotional Development While the effects on test scores were similar between both treatments, the effects on socio-emotional development paint a different picture. Figure 3 and table 4 presents the results on socio-emotional development overall and broken down socio-emotional area. Pooling across all five components of the index, we find the subjective treatment results in 0.05sd

[18]Not all subject and grade exams had remedial questions or external, so this is reflected in the decrease in sample size.

[19]Question items derived from these international sources were relevant to the curriculum of this school system and were not always matched to corresponding grade from the international exam, if that content was not part of the given year's curriculum.

higher average score compared to the objective incentives, significant at the 10% level.[20]

When we split these results into their sub-areas, we see that the overall negative effect of objective incentives relative to subjective is coming from a differential effect on "love of learning" and whether students like their school or would like to change schools. We can reject equality of the two treatments on these sub-areas at the 10% and 1% levels, respectively. This suggests that while objective incentives led to an increase in test scores, it was at the cost of enjoying school. Whereas, subjective incentives were able to accomplish the same learning gains without these negative consequences. On three other areas, ethical behavior, being a global citizen and inquisitiveness, we cannot reject the equality of the two treatments.

We also find that students under the subjective treatment exhibit stronger resilience and sustained attention than those in the objective incentive or control schools (table A5). Question item order on the exams was randomized allowing us to use variation in performance on specific items or at specific points in the test to isolate these effects. To test for resilience we compare how students perform after an item in the top 30% of difficulty. While students in the control and objective group perform 5 p.p. worse on an item which comes immediately after a difficult question, those in the subjective treatment only perform 3 p.p. worse and we can reject equality of the two treatments at the 10% level.

To test for sustained attention, we compare student performance at the beginning of the test compared to items later in the exam. Figure A6 demonstrates that the pattern over the length of the test is substantially different by treatment status. Students in the objective incentive group perform better than the control in the first half of the exam but perform similarly by the end. In contract, students in subjective incentive schools perform similarly to the control at the beginning but do substantially better in the middle and end of the exam, suffering from less cognitive fatigue compared to the other groups. Table A5, col 2 and 3, compares student performance by question item location in the test. We do not find a statistically significant difference if we assume a simple linear decline in performance over the test (col 2). However, if we allow a more flexible relationship, comparing performance by quintile of the test, we find that the subjective group performs significantly better in quintiles 4-5. These results are consistent with students in the objective group working harder at the beginning of the test, perhaps because their teacher told them to take the exam seriously, but fatiguing as the test goes on. On the other hand, students' in the subjective schools performance is consistent with improved cognitive endurance (Brown et al., 2025).

4.2 Effect of Incentives on Employee Effort

[20] These results come from a small negative effect of objective incentives relative to the control and a small positive effect of the subjective treatment relative to the control (neither of which are statistically significant).

4.2.1 Specification

To understand why we see similar results on test scores but different effects on student's socio-emotional development, we need to understand teacher's behavioral response. To do this, we look at the effect of each treatment on classroom observation ratings and time use. We have a similar main specification, this time at the teacher level:

$$Y_i = \alpha + \beta_1 SubjectiveTreatment_s + \beta_2 ObjectiveTreatment_s + \chi_j + \epsilon_i \tag{7}$$

The main dependent variable of interest is outcome, Y_i, for teacher, i. Teacher outcomes include classroom observation scores and time use. We again control for grade and strata fixed effects, χ_j, and standard errors are clustered at the school level (the unit of randomization).[21]

4.2.2 Results

Classroom Observations The effect of each incentive on classroom behavior sheds light on the student effects we see. Overall, we find teachers under objective incentives using teaching strategies which provide the largest marginal return on test scores but may hamper other areas of human capital development for students. Teachers in the subjective treatment however, do not exhibit any of those distortionary teaching strategies.

Figure 4 and table 5 presents the effects of each incentive on teachers' overall classroom observation score, using the CLASS rubric. On average, objective teachers exhibit worse teaching pedagogy. They score 0.07pts lower on the 7pt CLASS rubric scale. Subjective teachers have no noticeable change in pedagogy quality, and we can reject the equality of the two treatments at the 10% level.

We then break down the 12 CLASS dimensions of pedagogy into three main areas, "class climate", "differentiation", and how "student-centered" the lesson is. "Class climate" captures whether the atmosphere of the classroom is positive, supportive and joyful or negative, punitive and dull. "Differentiation" captures whether the lesson is structured in a way to meet students who are different proficiency levels and/or have different learning styles. Finally, "student-centered" measures how much of the lesson is teacher-directed versus student-involved. Teachers under the objective incentive contract have a more negative class climate and less student-centered lessons. Both see a decrease of around 0.1 pts. We can reject equality of treatments at the 10% level. There is also an increase in level of differentiation in the subjective and objective treatment schools relative to control schools.

We also measure the amount of class time devoted to test preparation activity. This includes practice tests, testing strategies (such as how to approach a multiple-choice test), or lecturing about

[21] We do not control for subject here, unlike in our student specification, because most teachers teach several subjects. In addition, for classroom observations, the observation period often overlapped with several subjects.

the importance of doing well on tests. We find a large increase in the time spent on these activities in objective treatment schools. Relative to a control group mean of 0.14 min out of the 20-minute observation spent on test preparation activities, objective classes see a 5-fold increase, with a total of 0.76 minutes spent on these activities. We can reject equality of treatments at the 5% level along this dimension.

Together with the student outcomes, these classroom observations paint a picture of objective schools as ones that were able to achieve test score gains by taking the path of least resistance for teachers – doing more test preparation and maintaining a stricter, less student-centered classroom. This then results in other negative outcomes on students human capital development, such as love of learning. Subjective classrooms on the other hand are able to accomplish the same academic gains without any negative effects on teacher practices or student socio-emotional development. This suggests that managers are able to prevent these distortionary behaviors, solving, at least to some extent, the multi-tasking problem.

One concern with classroom observation data is that teachers may worry the videos of their classrooms will be provided to their manager, and for subjective teachers that has more a consequence than for the other treatment arms. We do several things to help alleviate these concerns. First, in the consent form and during the camera set up, we communicate to teachers that the videos are confidential and will only be reviewed by the research team. We also let them know that only aggregated data at the school level will be provided to the school system head office. Second, visits were a surprise within a two-month window, so teachers could not adjust their lessons beforehand. Third, we recorded several hours back to back for each teacher. We find teachers are most aware (and responsive) of the camera in the first hour of taping and so restrict analysis to data after the first hour.

Attendance and Time at Work We find that the subjective treatment results in a significant increase in the number of days a teacher is present at work relative to no incentives. Table 6 presents the results of the biometric clock in/out data. Relative to a control group mean of 145 days, subjective teachers are present an additional 6 days. We do not find an effect on hours spent at work for either treatment relative to the control. We cannot reject equality of treatments in either outcome. Columns (2) and (4) restrict to a sample of teachers who were present in the school system both terms and did not take any long leaves (health, maternity, etc.) to ensure the days present result is not driven by these effects. Results are robust to this sample restriction.

4.3 How do Managers Implement the Subjective Incentive?

In the objective treatment schools there is less scope for heterogeneity. The implementation of the contract and employee's response is likely to be similar across schools and comparable to other experiments which used test score-based performance pay. However, the subjective treatment arm

could vary substantially across schools and firms depending on the type of oversight managers have of employees, the oversight firms have on managers and how managers themselves are incentivized.

In this section, we unpack what types of teacher actions managers value, the extent to which managers are biased or show favoritism, and heterogeneity in treatment effects my manager quality. To understand how managers use the subjective treatment arm, we draw on data from the endline teacher and manager survey, measures of teacher effort, and text of the evaluation criteria managers used to evaluate teachers.

What do managers value in rating teachers? We use three approaches to help understand what types of teacher actions' managers reward. In an ideal setting, we would randomize teacher actions to see how this affects managers' performance ratings of teachers. We are unable to do that exact exercise here. Instead use data from teacher beliefs about what actions are valuable, survey vignettes posed to managers and the correlation between teacher actions along different dimensions and evaluation scores. Combined, these three sources of evidence suggest that managers highly value teacher actions which are related to human capital development and are not just focused on administrative tasks or actions unrelated to student development.

Our first piece of evidence on what managers value in teachers, comes from endline survey data from both teachers and managers. We asked both teachers and managers to respond to a hypothetical situation, in which a teacher asks them for advice about how to achieve a higher raise in the following year. They are then asked to rate how much time the teacher should spend on different types of actions. Table A3 presents the data from the survey question. Column 2 shows teachers' responses about which actions would be most highly valued under the subjective contract. Column 3 presents responses to the same question posed to managers. Both subjective teacher and managers agree that improved pedagogy, like making lessons student centered and tailoring lessons to students at different initial levels, would increase their subjective rating. However, managers put additional weight on spending time collaborating with other teachers. Neither subjective teachers nor principals believe more superficial administrative tasks like volunteering at afterschool events or meeting with parents are important drivers of the subjective performance rating.

Our second piece of evidence also comes from the manager endline survey. We provide a vignette describing a hypothetical teacher to managers, and we ask them to provide a performance rating of the hypothetical teacher. The vignette randomizes the hypothetical teacher's name, and rank in terms of value added, classroom behavioral management and attendance.[22] Table A4 presents managers' responses to this survey question. We find that managers highly value all three performance characteristics, but place double the weight on teacher value-added as they do on behavioral management and attendance. On average, moving from the 50th percentile value added

[22]The vignettes stated, "[Female name/Male name] is in the [bottom/middle/top] 10% of teachers in terms of students' test score growth, in the [bottom/middle/top] 10% of teachers in terms of behavioral management, and is in the [bottom/middle/top]10% in terms of attendance and timeliness at work." Managers rated three such vignettes with characteristics randomized across vignettes.

to the 90th percentile value added would increase a teacher's subjective rating by 0.7sd. Columns 1 through 3 of the table test each attribute separately. Columns 5 and 6 add all attributes together, and we see no difference in relative preference for these teacher characteristics. These results are also robust to adding manager fixed effects.

Finally, we can look at what teacher behaviors are correlated with teachers' actual performance rating in the subjective treatment arm. Table A6 shows the relationship between teachers' performance rating and teacher behaviors, as measured from classroom observation data, teacher value-added and biometric clock in/out data. We find that managers value higher value added and teacher attendance.[23] This relationship remains when we control for subject and grade (column 2) and classroom observation scores (column 3). We find mixed evidence on the relationship between pedagogy and subjective rating. Some aspects of good pedagogy are valued (teachers who have a negative class climate have a lower rating) but others are not (teachers who spend more time on analysis/inquiry skills and have more student vs teacher talk time are negatively rated). One important limitation with this approach is that there are certainly omitted variables which we are unable to capture. However, having detailed classroom observation and time use data help us paint a relatively detailed picture of each teacher's behavior. Combined these three pieces of evidence suggest that managers have preferences which are relatively aligned with the preferences of the school system.

Favoritism and bias A primary concern about subjective performance pay is whether managers are biased against certain employees or show favoritism toward preferred individuals. To assess whether this is a significant concern in this setting, we ask teachers at endline whether they felt their manager discriminated against certain groups or played favorites toward certain colleagues.[24] Table A7 presents the results from these survey questions. On average, teachers in the subjective treatment arm are no more likely than teachers in the objective treatment arm to say that the contract unfairly favors certain teachers or that certain groups are discriminated against under this contract. Teachers also state that bias, gaming and favoritism is not a significant concern in either contract.

Though teachers do not say that overt bias is a significant concern, we may be worried that there are more subtle types of bias at play. The primary type of bias we were concerned about in this setting is gender bias. In Pakistan, gender bias in employment is rampant (The World Bank Group, 2018), and managers are more likely to be male then the employees they oversee. Because

[23]There is a negative relationship between subjective rating and hours spent at school. This relationship may be driven by the fact that certain grades and teaching positions have different requirements about the length of the workday, so this could be picking up that variation rather than teacher effort.

[24]One concern with this approach is that teachers may be hesitant to provide honest assessment in a survey. To help minimize this concern teachers' responses are anonymized and we communicate this to teachers at the time of consenting to the survey. We also ask the question several ways, including asking teachers to report such behavior about other schools or about the school system in general. This type of questions phrasing allows teachers to report problematic manager behavior while providing plausible deniability for their own manager.

understanding the existence and conditions necessary for gender bias is a substantial topic on its own, a separate paper, Brown (2025) addresses this in detail. To summarize the findings from that paper, managers no not appear to hold discriminatory views about the productivity or quality of teachers by gender. However, when manager evaluations affect employees' raises, we find male teachers receive 10% higher evaluations controlling for a rich set of teacher actions and student outcomes. When evaluations are only used for feedback, but do not have a financial stake, we see no difference in evaluation score by gender. Finally, we show when we increase the frequency of manager monitoring of teachers this significantly reduces the extent of gender bias for evaluations which are tied to raises. Combined, this suggests subjective evaluations can introduce systematic bias into the performance incentive system but these effects can be minimized when paired with other effective HR policies, like better information about employee productivity.

Heterogeneity in treatment effects by manager characteristics On average the subjective treatment arm appears to have been successful at improving student outcomes and teacher effort, but there may be heterogeneity in how successfully managers implement the contract. We test for heterogeneity in treatment effects along several dimensions. First, table A8 presents heterogeneity in the subjective treatment arm by three manager characteristics: gender, age, and experience. We do not find significant differences in the effectiveness of the subjective treatment by these manager characteristics.

Second, table A8 presents heterogeneity in treatment effects by several dimensions of manager "quality". We find that subjective performance pay is significantly less effective in schools where teachers believe their managers do not have an accurate perception of teacher effort. We measure this by asking teachers to rate how accurate their manager is in rating a fellow teacher.[25] We find there is no effect of subjective performance pay on student test scores for managers who are in the top quintile of this inaccuracy measure. We do not find heterogeneity and treatment effects by world management survey overall manager score (shown in Table A8, column (5)) or personnel management sub-score (column 6). However, as discussed in section 3.3, because this data was collected from manager self-report, we should be cautious about the interpretation, as managers may over rate themselves on these survey questions. This suggests that while subjective performance pay is on average very successful at producing learning games, these contracts may be ineffective in settings where employees do not trust their managers to implement them accurately.

[25]To measure whether a manager has an accurate perception of what their teachers do, we ask teachers to answer the following question about three fellow teachers in their school, "The appraisal score their manager would give them is... [Too high/low by more than one raise category], [Too high/low by about one raise category], [Too high/low by less than one raise category], or [Accurate]". We then construct an average of these ratings per manager;

5 Mechanisms - Noise and Distortion

How can we square our main three reduced form results that we see very different effort responses, similar test score effects and different socio-emotional effects across subjective and objective incentives? We argue that differences in the levels of noise and distortion across the two treatments help explain these outcomes. We structure our argument as follows.

First, in section 5.1, we present the similarities between the two treatments to help eliminate possible channels that could drive the difference in treatment effects. Second, in section 5.2, we highlight the differences between the systems. We show teachers believe subjective incentives to be less noisy and less distorted. Third, we provide evidence that noise and distortion does, in fact, affect outcomes. Section 5.3 shows that noise and distortion are related to student outcomes as predicted in the theoretical framework – more noise reduces the effect of incentives and more distortion diverts employee effort toward those actions. We conduct these tests by exploiting heterogeneity in levels of noise and distortion *within* a given treatment, to isolate the effect of noise or distortion on outcomes. Finally, in section 5.4, we bring together the estimates from section 5.2 and 5.3 to understand how much of the difference in the reduced form student effects can be explained by differences in the level of noise and distortion of the objective versus subjective treatment.

5.1 Similarities between Treatments

In order to isolate the effect of the performance metric (percentile value-added versus manager rating), we hold a number of features constant between the two treatments. Both treatments are within-school tournaments. Both treatments provide a raise from 0-10% and have the same percentile thresholds for each raise category. Both treatments were introduced at the same time in schools and had a similar performance review timing – manager completed midterm feedback in June 2018 and final ratings in December 2018 and the objective score was based on the average of tests in June 2018 and January 2019.

At endline, we survey teachers about their experience with their incentive scheme. We find no difference in teachers reported experience along a number of dimensions. There is no difference in their responses to the following survey questions: i). when teachers said they understood what was expected of them, ii). awareness of contract main features, iii). how frequently they thought about their contract, and iv). whether the system unfairly favors certain types of teachers (age, gender, etc). Figure 5 and table A7 provides results for each of these survey questions, showing no statistical difference between teachers' responses by treatment.

5.2 Differences Across Treatments: Noise and Distortion

In this section through section 5.4, we will focus on two of the remaining differences between the treatments: the perceived noise and distortion. As highlighted in the theoretical framework,

noise captures the extent to which a teacher's actions affect their incentive payment. Distortion captures the extent to which actions which have the largest marginal return to student learning also are actions which have a higher effective piece rate under the given performance measure. First, we will show that the levels of perceived noise and distortion are different across the treatments.

Noise We measure noise using teacher's perceptions of the noisiness of their incentive treatment.[26] To measure perceived noise, we ask teachers to agree or disagree (on a 5pt scale), whether under their contract, "their raise is out of their control", "those who work harder, earn more" and whether "I feel motivated to work harder". Figure 6 presents the average response to each question with 1 being strongly disagree and 5 being strongly agree. We see that teachers in the subjective treatment, feel their raise is more in their control, hard work is rewarded, and they feel more motivated. The average difference is 0.14sd across the three areas, and we can reject equality of treatments for all three questions at the 5% level.

Teachers appear to be relatively correct in their assessment of which contract is noisier. To test the "actual" noise, we compare the R^2, from a "kitchen sink" regression, where we regress the raise they received on everything we can see about the teacher's actions (16 dimensions of classroom observation scores, time use, and attendance). Using a likelihood ratio test, we find that teacher actions are substantially more predictive of subjective performance evaluation scores than objective evaluation scores ($p<0.001$).

Distortion We measure distortion using endline survey data from teachers. We ask teachers to imagine a teacher who really wants to receive a higher raise at the end of the year and commits to work ten additional hours a week to increase their raise. Then we ask teachers how much of those ten hours should the teacher allocate different activities, such as collaborating with other teachers, incorporating higher order thinking skills into lessons, preparing practice tests, helping with extracurricular activities, etc.

We find that teachers in subjective versus objective schools feel that there are some differences in which actions should be prioritized in order to increase their raise. Figure 7 and table A3 presents the differences in stated valuation of each area. Overall, teachers think those under the subjective contract should prioritize making lessens more student-centered and focus less on behavioral management. We will show in the next section that these actions have different implications for student outcomes.

[26] We think this is preferred to using "actual" noise, measured by seeing how predictive teacher's measured behavior is to their raise. Perceived noise is what matters for teacher's behaviors this last year, and there is likely measurement error that is correlated with treatment in measuring "actual" noise.

5.3 Effect of Noise and Distortion on Student Outcomes

Noise We showed that teachers believe there is less noise in the subjective performance measure. However, we do not know if noisier incentives produce a smaller effort response. We showed that theoretically with a fixed variance incentive scheme, a more noisy incentive scheme leads to a lower power incentive, but there is no empirical evidence on this effect.

To test whether noise affects outcomes, we exploit heterogeneity *within* the subjective treatment in noisiness. Managers vary in their accuracy of assessing teacher effort. Some managers observe lessons for each of their teachers every week. Others sit down and review paper lesson plans, and some are more hands off. To measure whether a manager has an accurate perception of what their teachers do, we ask teachers to answer the following question about three fellow teachers in their school, "The appraisal score their manager would give them is... [Too high/low by more than one raise category], [Too high/low by about one raise category], [Too high/low by less than one raise category], or [Accurate]". We then construct an average of these ratings per manager, capturing average *perceived* inaccuracy. On average, teachers believe their managers over or under rate their fellow teachers by 0.8 of an appraisal step (out of the five-step system shown in section 3.2. However, there is considerable heterogeneity. Those most inaccurate quintile of managers are perceived to rate other teachers incorrectly by greater than two steps.

Schools with more inaccurate managers may be different in many ways (experience of manager, student composition, etc). However, manager accuracy should only affect teacher's perceived noisiness of the incentive scheme in subjective treatment schools. In control or objective treatment schools, managers still rate their teachers but have no control over the incentive raise in those schools. Therefore, we use $ManagerAccuracy * SubjectiveTreatment$ as the instrument for $Noise$, controlling for $ManagerAccuracy$ and $SubjectiveTreatment$.

We find that $ManagerRatingInaccuracy_j$ significantly predicts teacher's rating of the noisiness of their appraisal system in subjective but not objective/control schools, as we would expect. A 1 sd increase in manager inaccuracy increases beliefs about the noisiness of the contract by 0.1-0.4 sd in subjective schools. Table 8 presents the results from the first stage for data at the teacher and student level.[27] Columns (2) and (4) add additional controls, including teacher's beliefs about the preference for different actions ("distortion") and teacher beliefs about other non-noise features of the contract (timing, understanding, etc). The coefficient on $ManagerAccuracy * SubjectiveTreatment$ is very robust to the inclusion of these controls, suggesting that this instrument is picking up difference in noise and not other features of the contract environment.

To test for the effect of noise on teacher and student outcomes, we use the following two-stage

[27]The first stage in table 8 columns (1) and (2) is at the level of the teacher used for the hours results in table 9, column (1) and (2). The first stage in columns (3) and (4) is at the level of the student and used for the student test and socio-emotional skills outcomes in table 9, column (3)-(6).

least squares specification:

$$Outcome_{ij} = \alpha_0 + \alpha_1 ManagerRatingInaccuracy_j + \alpha_2 SubjectiveTreat_i + \alpha_3 \widehat{Noise} + \chi_{ij} + \epsilon_{ij} \quad (8)$$

where α_3 is the coefficient of interest, $Noise$ is instrumented using $Manager\ Rating\ Inaccuracy_j * SubjectiveTreat_i$. χ_{ij} are controls, such as school and grade and baseline controls when available for a given outcome.

We find that noise significantly reduces the effectiveness of performance incentives (table 9). A 1 sd increase in noisiness of the incentive scheme reduces teachers' hours worked by 13.2 hours per week and reduces test scores by 0.175 sd. We do not find an effect of noise on socio-emotional scores. Because our effective first stage has an f-stat of less than 10, we present the AR test p-values which are our preferred test, given that they are robust to weak instruments in the just-identified case. Columns (2), (4), and (6) add in the same additional controls as in table 8 for non-noise features of the contract environment. The effect of noise on hours worked and test scores is robust to the addition of those controls.

Distortion Distortion is a measure of how correlated the marginal returns to student learning for different actions are with the effective piece rates for those actions. In order to measure distortion, we therefore need an estimate of marginal returns to different actions. To do this, we again exploit heterogeneity across managers interacted with treatment status.

The idea behind this strategy is that managers have different preferences for actions – some state they want teachers to focus more on improving their lesson plans, others want teachers to help out more with administrative tasks, etc. We are able to measure those preferences for all managers because irrespective of treatment status managers delineate the performance evaluation criteria in which they will rate teachers. However, it is only in the subjective schools in which there is a financial stake of these evaluation criteria. We interact the weight placed on a given teacher action category with subjective treatment status versus objective and control. In effect, we are comparing two teachers whose managers put identical weight certain evaluation criteria but one teacher is in a subjective treatment school and one is in objective or control. Therefore, we expect the one in the subjective school to increase their effort more toward that action, giving us exogenous variation in teacher effort.

To test for the effect of additional effort along one dimension on student outcomes, we estimate:

$$StudentOutcome_i = \alpha_0 + \alpha_1 SubjectiveTreat_i + \sum_{j=1}^{J} \delta_j Points\ on\ Action\ j_i + \sum_{j=1}^{J} \beta_j Points\ on\ Action\ j_i * SubjectiveTreat_i + \chi_{ij} + \epsilon_i \quad (9)$$

Here the coefficient of interest is β_j, which gives the effect having a financial stake of some action on student outcomes. We group our 17 teacher actions into five categories: administrative tasks (grading, helping with extracurriculars, monitoring duty), professional development (collaboration, training, improved English skills and content knowledge), pedagogy (use of student-centered and differentiated lessons), test preparation (achieving certain grade targets) and other. We also add additional controls to capture other features of the contract environment, such as noisiness, understanding of the contract, etc.

We find that several of the action categories are related to student outcomes. Table 10 presents the β_j's for each action category. Professional development and test prep actions are positively related to student test scores. However, test prep is negatively related to student socio-emotional scores. These results are robust to the inclusion of additional controls about the contract environment (table 10, column (2) and (4)).

5.4 Contribution of Noise and Distortion to Reduced Form Effects

Finally, we pull the results together in Figure 8 to understand the extent to which noise and distortion can explain the reduced form results we saw in section 4.1. To do this we decompose the total reduced form effect into the component from noise, distortion and an unexplained component, ϵ:

$$\begin{aligned} dTestScore &= \frac{\partial TestScore}{\partial Noise} * dNoise + \frac{\partial TestScore}{\partial Distortion} * dDistortion + \epsilon \quad (10) \\ -0.006sd &= \quad -0.17 * -0.14sd + \quad -0.03sd \quad + \epsilon \\ \epsilon &= 0.0002sd \end{aligned}$$

The overall effect of subjective relative to objective on test scores was close to zero (-0.006sd, from table 3). The effect of noise on test scores is -0.17 (table 9) and there is 0.14sd less noise in the subjective arm than the objective arm (figure 6). For the distortion component, we repeat the same approach for each of the four action categories (admin, professional development, pedagogy and test prep). We take the difference between subjective and objective for each area (table 7), multiply each category with the return to preference for that action on test scores (table 10) and sum. In

total, $\frac{\partial TestScore}{\partial Distortion} * dDistortion$, then is -0.03. Subjective schools put slightly less focus on test scores. Combined, the positive effect of subjective having less noise and the negative effect of them placing less focus on test scores almost cancel each other out. Overall, the remaining unexplained portion, ϵ, is just 0.0002sd, suggesting noise and distortion are effective at explaining the student results.

We can repeat the same approach for socio-emotional skills.

$$\begin{aligned} dSEScore &= \frac{\partial SEScore}{\partial Noise} * dNoise + \frac{\partial SEScore}{\partial Distortion} * dDistortion + \epsilon \\ 0.0433sd &= \quad -0.06 * -0.14sd + \quad 0.011sd \quad + \epsilon \\ \epsilon &= 0.024sd \end{aligned} \tag{11}$$

The overall effect of subjective relative to objective on socio-emotional development was 0.0433 sd (table 4). The effect of noise on socio-emotional skills is -0.06 and there is -0.14sd less noise in the subjective arm than the objective arm. The subjective teachers focus more on tasks which are related to socio-emotional skills. Overall $\frac{\partial TestScore}{\partial Distortion} * dDistortion$ is 0.011 sd. The remaining unexplained portion is 0.024 sd, or about half of the difference between the subjective and objective treatment. This is perhaps unsurprising given the results throughout this section. Noise and distortion were much less related to socio-emotional skills than test scores. This could be because there is in fact a weak relationship between them. Alternatively, we may not be as successful at measuring socio-emotional skills and certainly have a harder time capturing what aspects of teacher's behavior is related to developing these skills. Better measurement along these areas is an important area for future work.

6 Conclusion

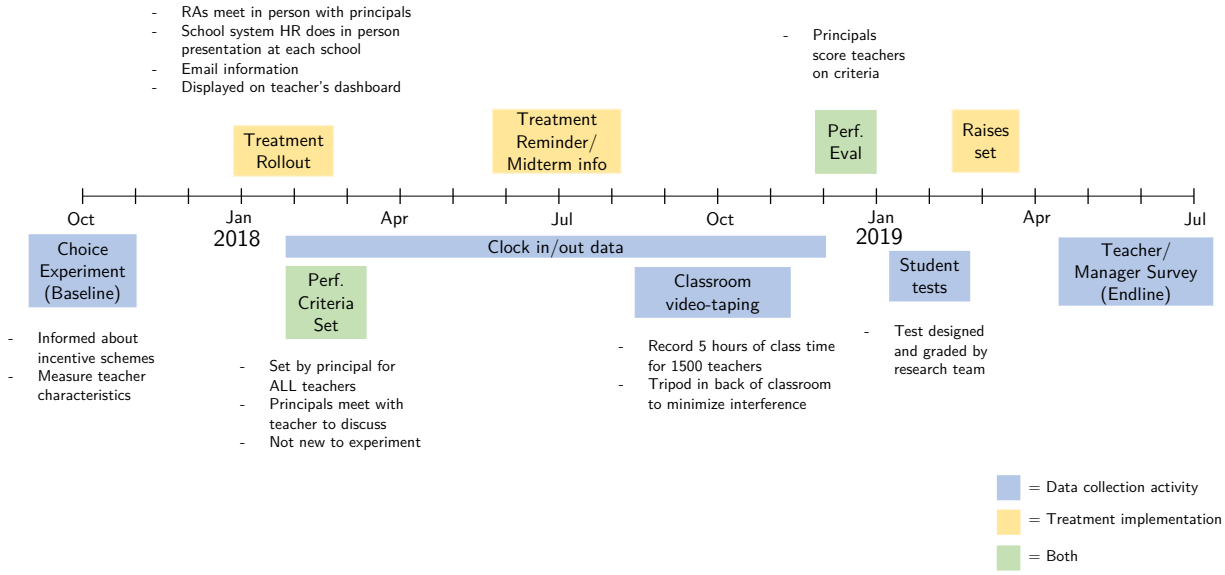
In this paper, we provide evidence on the effect of subjective versus objective incentives for teachers. We find that both subjective and objective incentives increase test scores, but objective incentives result in negative effects on socio-emotional development. These student outcomes make sense given the teacher behaviors we see under each incentive. In subjective treatment schools, teachers make small improvements in pedagogy and are involved in more professional development. In objective treatment schools, teachers distort effort toward test preparation. They spend much more time on practice tests and test strategies and use more punitive discipline. While there is heterogeneity in manager application of the subjective treatment arm, we do not find evidence of widespread favoritism or bias.

We then try to understand the mechanisms underlying the reduced form effects. We show evidence that the two incentive schemes are similar along most dimensions except for two areas: noise and distortion. We show teachers believe that the subjective incentive is less noisy and that it prioritizes both test and non-test student outcomes. Using heterogeneity within treatments we

attempt to isolate the effect of noise and distortion itself on student outcomes. Finally, we show that noise and distortion are able to explain a large portion of the reduced form test score effects but a smaller fraction of the reduced form socio-emotional skill effect.

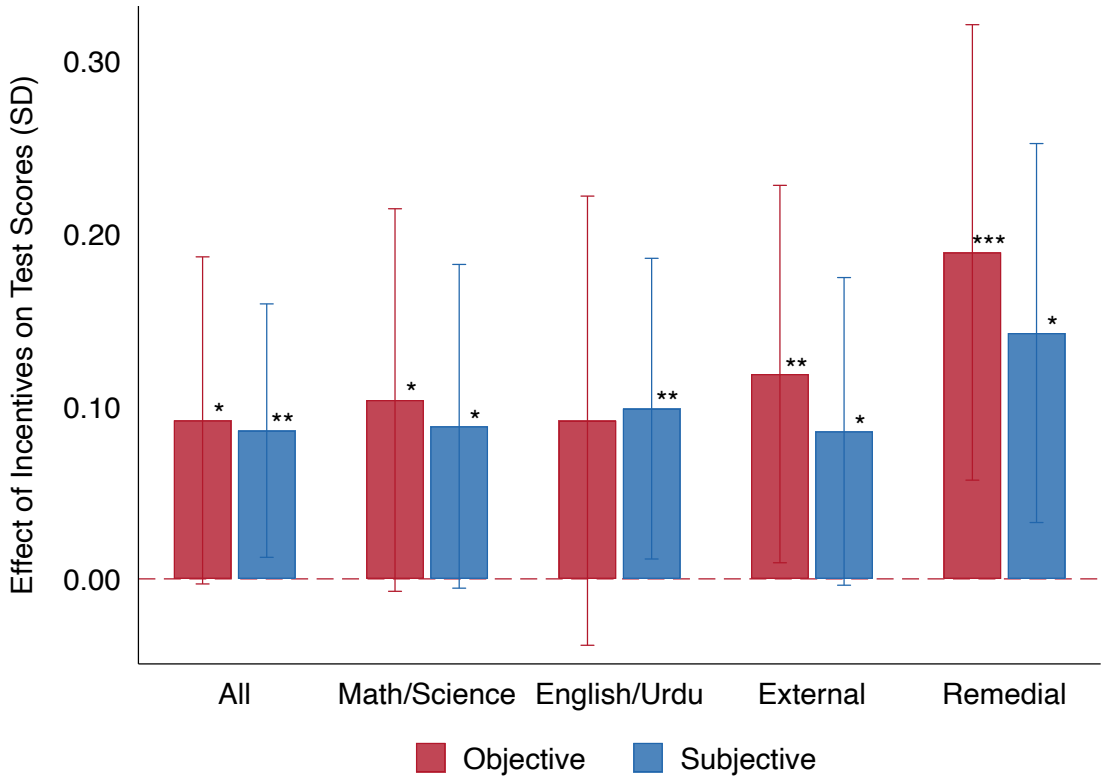
7 Figures

Figure 1: Experimental Timeline



Notes: This figure presents the experimental timeline. It includes data collection activities and treatment implementation activities.

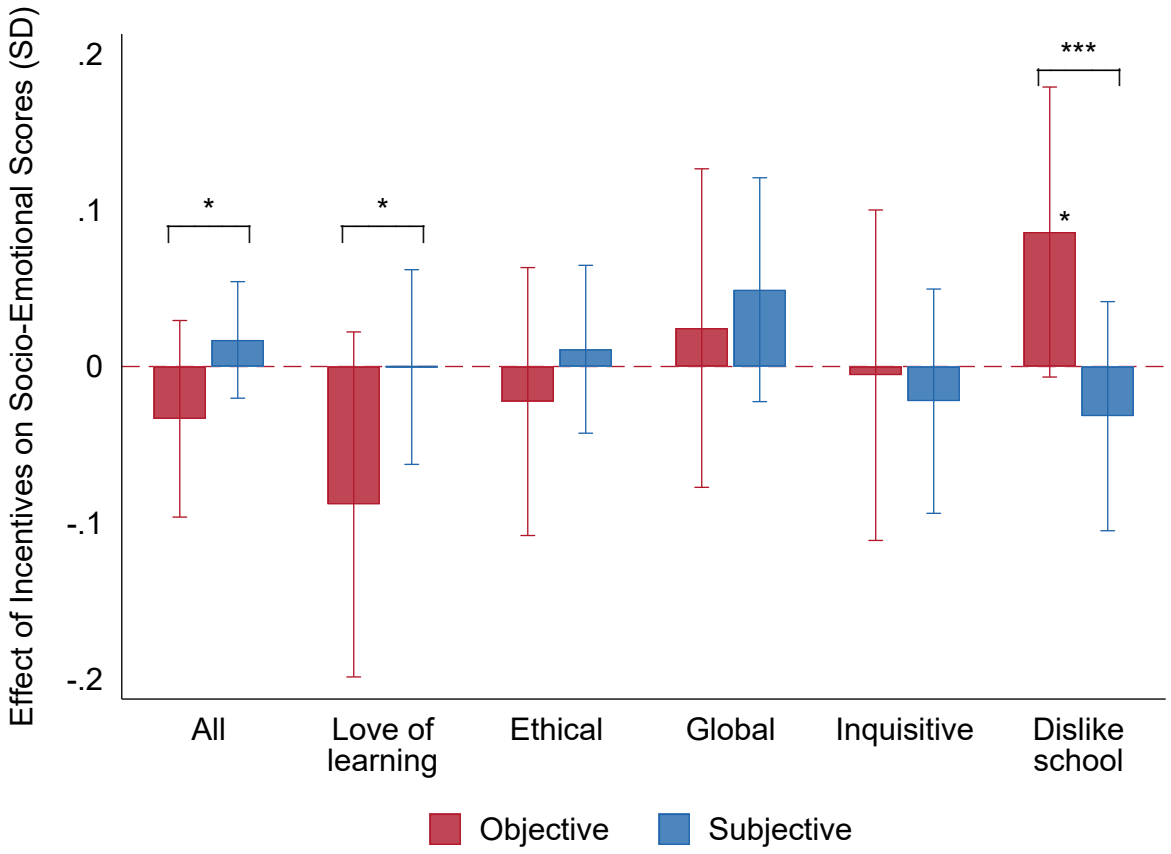
Figure 2: Effect of Incentives on Student Test Scores



Notes: This figure presents the effects of each performance incentive treatment on student endline test scores relative to the control group.

- The blue bars present the coefficient of the effect of the objective treatment relative to the control (flat raises). The red bars present the coefficient of the effect of the subjective treatment relative to the control.
- The observation is at the student-subject level. The y-axis presents the coefficient from a regression of student's z-score on a given endline exam on treatment dummy variables.
- The sample includes students tested in grades 4-13 in five subjects: Math, Science, English, Urdu, Economics.
- The first two bar graphs includes all test subjects and question items. The next two bars restricts to math and science exams. The next restrict to English, Urdu and Economics exams. The next restrict to question items drawn from external sources, such as PISA and TIMSS. The last two restrict to question items which were from the previous grade.
- All regressions include strata fixed effects and control for baseline student average test score, baseline school average test score, grade and subject. Standard errors are clustered at the school level. 95% confidence intervals are shown on each bar. Stars just above a bar show the significance of the treatment group relative to the control. A bracket above two bars denotes the significance between the two treatments (subjective versus objective). $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

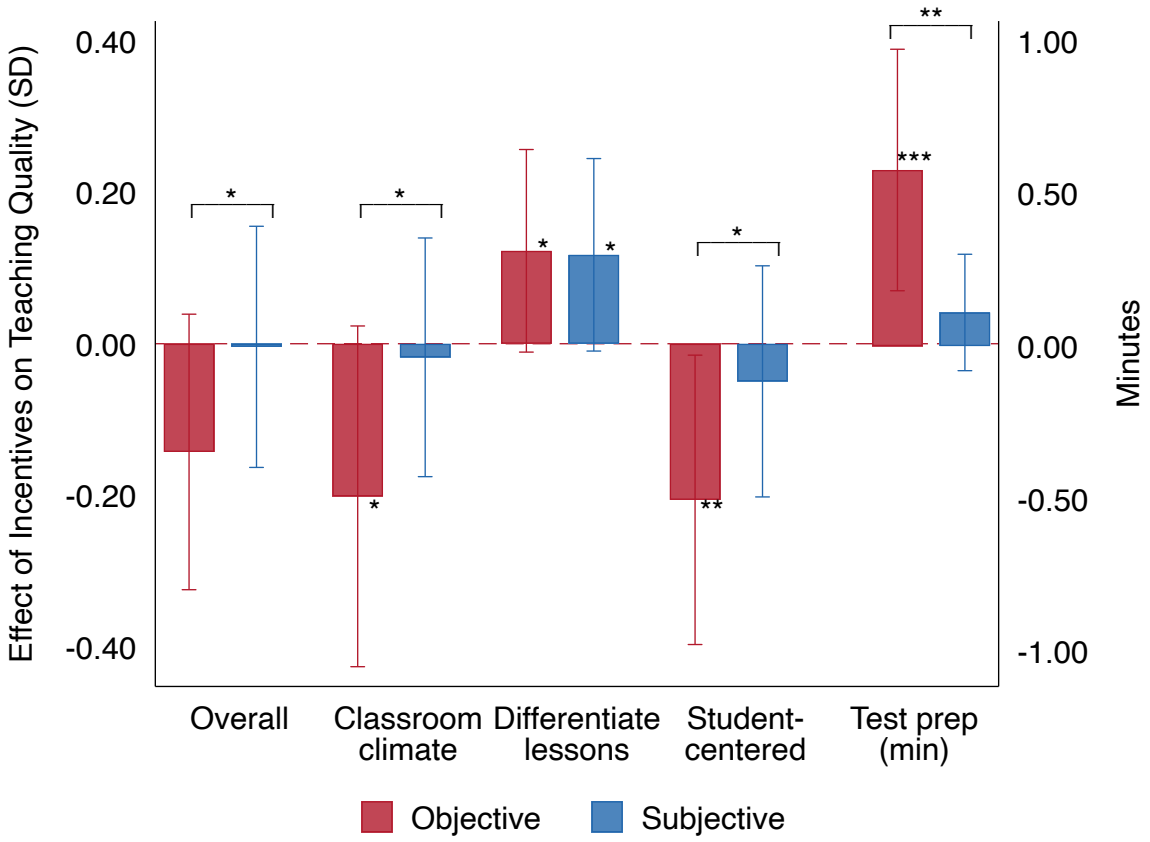
Figure 3: Effect of Incentives on Socio-Emotional Outcomes



Notes: This figure presents the effects of each performance incentive treatment on student socio-emotional outcomes relative to the control group.

- The blue bars present the coefficient of the effect of the objective treatment relative to the control (flat raises). The red bars present the coefficient of the effect of the subjective treatment relative to the control.
- The observation is at the student level. The y-axis presents the coefficient on a regression of student's z-score on a given socio-emotional dimension from an endline survey of students conducted in January 2019.
- The first two bars provides the average across all five dimensions of socio-emotional outcomes. The remaining ten provide effects on each individual dimension.
- All regressions include strata fixed effects and control for student's grade. Standard errors are clustered at the school level. 95% confidence intervals are shown on each bar. Stars just above a bar show the significance of the treatment group relative to the control. A bracket above two bars denotes the significance between the two treatments (subjective versus objective). $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

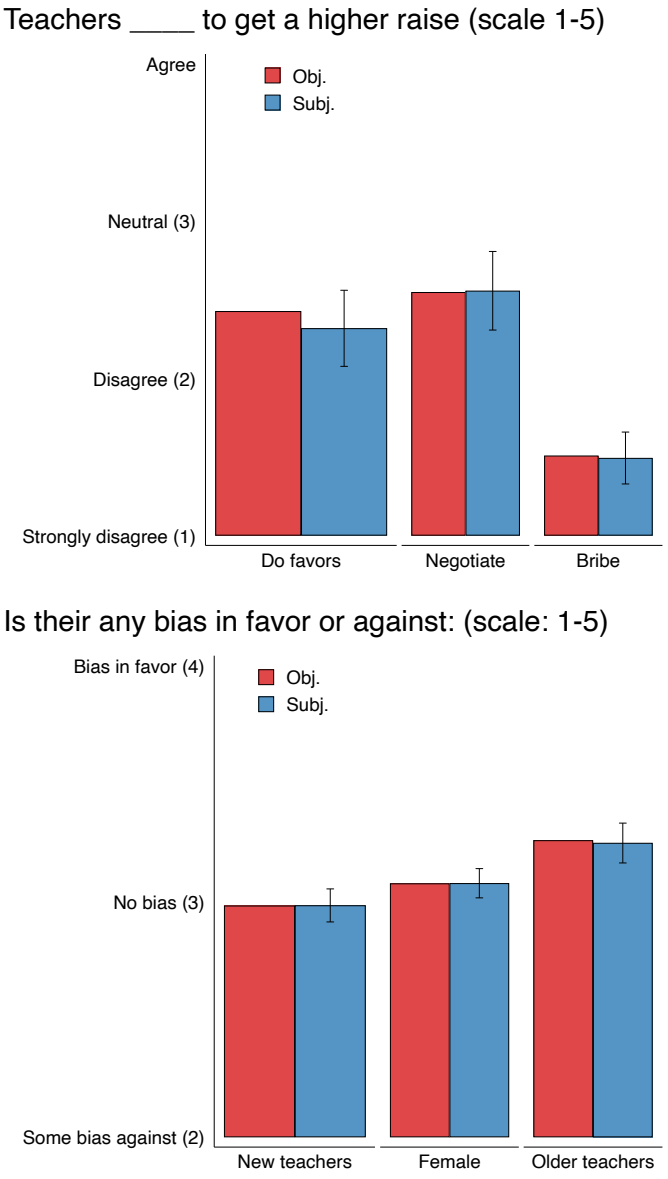
Figure 4: Effect of Incentives on Teacher Pedagogy



Notes: This figure presents the effects of each performance incentive treatment on teacher behavior as rated based on classroom videos relative to the control group.

- The blue bars present the coefficient of the effect of the objective treatment relative to the control (flat raises). The red bars present the coefficient of the effect of the subjective treatment relative to the control.
- The observation is at the classroom observation level. Teachers may be observed multiple times over the course of the intervention. The y-axis presents the coefficient from a regression of classroom observation score in a given dimension on treatment dummy variables.
- The sample includes teachers from grades 4-13 in core academic subjects.
- The first two bars presents the effects on the average score on the CLASS rubric (Pianta et al., 2012), on a 7-pt scale. The next six bars provide effects on scores on sub-areas of the class rubric. The last two bars provide effects on time spent on testing or test-prep activities (in minutes).
- All regressions include strata fixed effects and control for grade and video coder fixed effects. Standard errors are clustered at the school level. 95% confidence intervals are shown on each bar. Stars just above a bar show the significance of the treatment group relative to the control. A bracket above two bars denotes the significance between the two treatments (subjective versus objective). $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

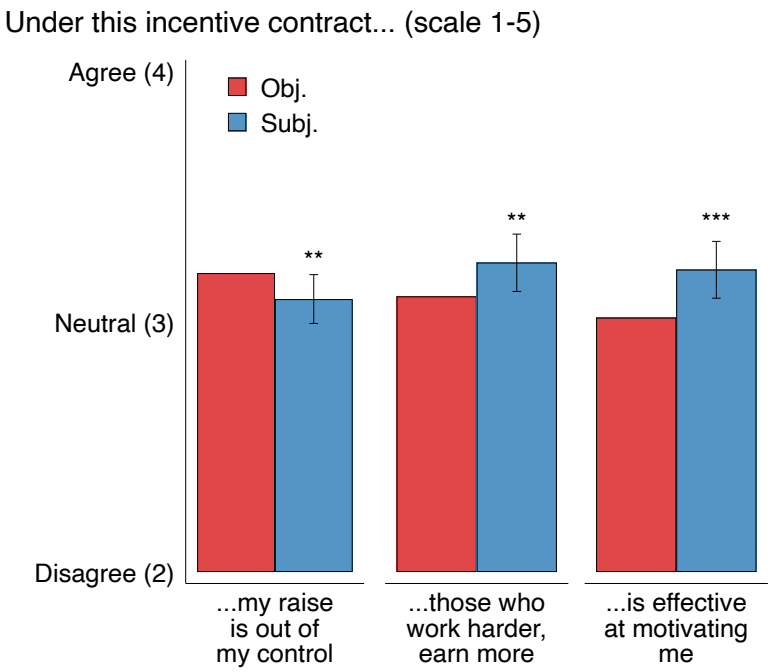
Figure 5: Beliefs about Contracts by Treatment



Notes: This figure presents teacher's responses to questions regarding their incentive contract for the previous year.

- Figure A shows teachers responses to questions about what actions they believe fellow teachers take to increase their raise. Figure B shows their responses to questions about whether certain groups are favored by the incentive scheme.
- The red (blue) bars presents the average response for teachers in the objective (subjective) treatment schools. The observation is at the teacher level and come from the endline survey of teachers.
- In figure A, the outcome is a 5pt scale from Strongly Disagree (1) to Strongly Agree (5). In figure B, the outcome is a 5pt scale (1, lots of bias against, 3, no bias, 5, lots of bias in favor).
- Standard errors are clustered at the school level. 95% confidence intervals are shown on the subjective bar comparing it to the objective treatment. Stars just above the bar show the significance of the subjective group relative to the objective. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

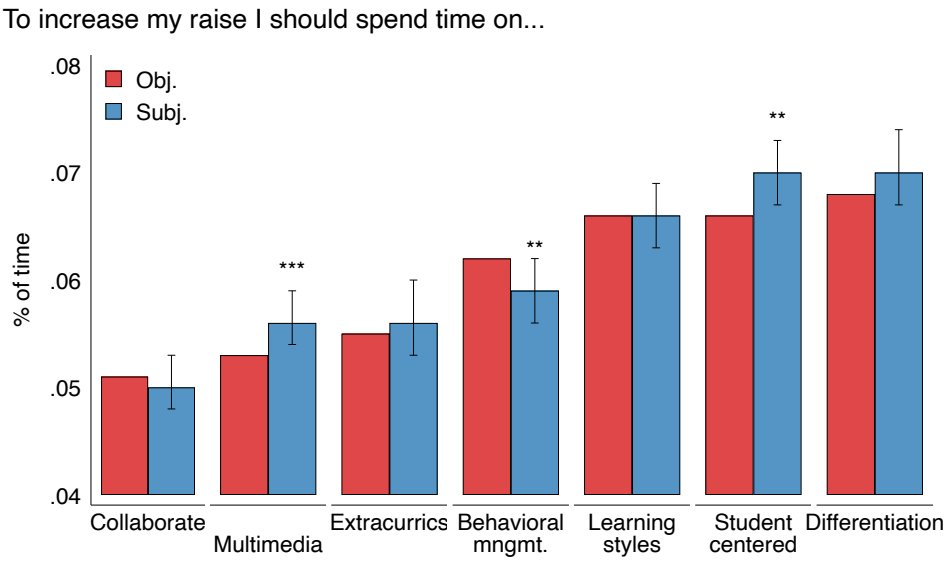
Figure 6: Difference in Noise by Treatment



Notes: This figure presents teacher's responses to a questions about how they respond to their incentive.

- The red (blue) bars presents the average response for teachers in the objective (subjective) treatment schools. The observation is at the teacher level and come from the endline survey of teachers.
- The questions are on a 5pt scale from Strongly Disagree (1) to Strongly Agree (5).
- Standard errors are clustered at the school level. 95% confidence intervals are shown on the subjective bar comparing it to the objective treatment. Stars just above the bar show the significance of the subjective group relative to the objective. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

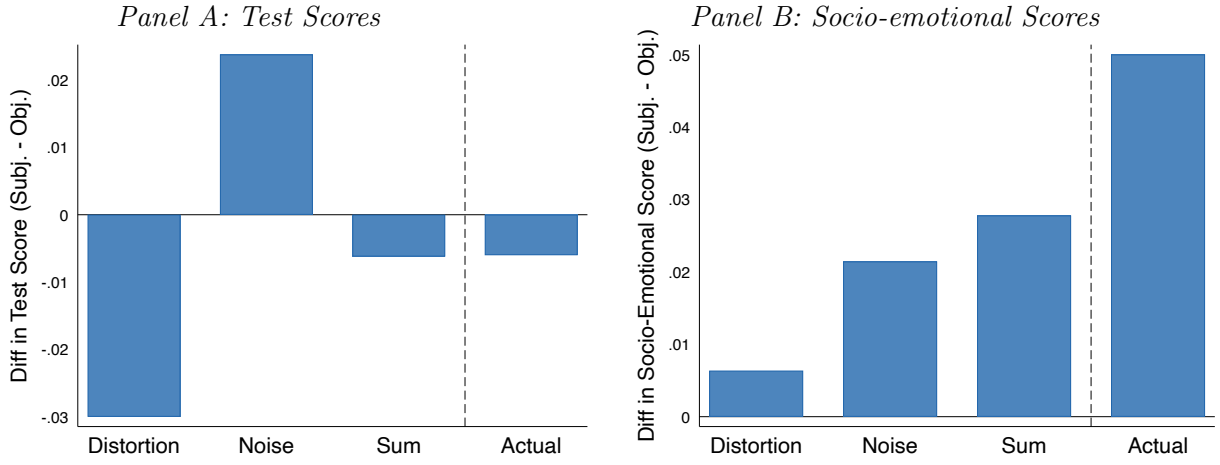
Figure 7: Difference in Value of Teacher Activity by Treatment



Notes: This figure presents teachers' responses to a hypothetical scenario in which they are advising a teacher which actions they should take to increase their raise under a given treatment.

- The red (blue) bars presents the average response for teachers in the objective (subjective) treatment schools. The observation is at the teacher level and come from the endline survey of teachers.
- The questions are on a 5pt scale from Strongly Disagree (1) to Strongly Agree (5).
- Standard errors are clustered at the school level. 95% confidence intervals are shown on the subjective bar comparing it to the objective treatment. Stars just above the bar show the significance of the subjective group relative to the objective. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Figure 8: Decomposing Total Effect into Noise and Distortion Components



Notes: This figure shows the effect from noise and distortion channels compared to the total effect of the subjective contract on test scores (Panel A) and socio-emotional scores (Panel B).

8 Tables

Table 1: Descriptive Statistics about Teachers in Study and Comparison Sample

	Study Sample		US Sample	
	Mean	St. Dev.	Mean	St. Dev.
	(1)	(2)	(3)	(4)
Panel A. Teacher Characteristics				
Age	35.0	8.9	41.8	7.5
Female	0.80	0.40	0.76	0.43
Years of experience	5.1	5.2	13.8	9.6
Has Post BA Education	0.68	0.47	0.54	0.50
Salary, USD(PPP)	17,160	5,700	52,400	18,400
Panel B. Teacher Evaluation				
Number of observations per year	4.7	8.2	2.5	2.9
Use evaluation for compensation	-	-	0.12	0.32
Frequency of evaluation (months)	-	-	13.0	7.0
Performance metric used for evaluation:				
- Principal evaluation	-	-	0.90	0.30
- Test scores	-	-	0.35	0.48
- Peer evaluations	-	-	0.26	0.44
- Student ratings	-	-	0.05	0.22

Notes: This table reports summary statistics on teacher characteristics, monitoring and evaluation for our study sample and a comparison sample of managers in US schools. Data in panel A, columns (1) and (2) comes from administrative data collected from our partner school system. Data in panel B, columns (1) and (2) is from an endline survey conducted with 189 principals and vice principals and 5,698 teachers in our study sample. Data in panel A, B and C, columns (3) and (4) comes from 9,235 principals and 42,020 teachers surveyed in the *School and Staffing Survey* (National Center for Education Statistics, 2011). Most of panel B is not included for our sample as the experiment determined these features.

Table 2: Descriptive Statistics about Mangers in Study and Comparison Sample

	Study Sample		US Sample	
	Mean	St. Dev.	Mean	St. Dev.
	(1)	(2)	(3)	(4)
Panel A. Manager Characteristics				
Age	44.9	9.2	48.8	9.7
Female	0.61	0.49	0.53	0.50
Years of experience	9.6	7.9	13.0	7.5
Salary, USD(PPP)	45,400	34,400	85,400	29,400
Panel B. Manager Time Use				
Total hours worked	47.2	16.3	57.0	13.2
Hours spent on:				
- Administrative tasks	18.5	10.3	18.2	2.3
- Teacher management and teaching	17.5	8.2	15.1	2.0
- Student and parent interactions	6.3	4.4	20.2	2.7
- Other tasks	6.9	12.3	4.0	2.6
Panel C. Management Practice Rating				
Overall Management Score (out of 5)	4.27	0.43	2.76	0.43
People management (out of 5)	4.14	0.53	2.51	0.49
Operations (out of 5)	4.32	0.61	2.89	0.49
Performance monitoring (out of 5)	4.32	0.49	2.81	0.75

Notes: This table reports summary statistics on manager characteristics, time use and management practices for our study sample and a comparison sample of managers in US schools. Data in panel A, columns (1) and (2) comes from administrative data collected from our partner school system. Data in panel B and C, columns (1) and (2) is from an endline survey conducted with 189 principals and vice principals in our study sample. Data in panel A and B, columns (3) and (4) comes from 9235 principals surveyed in the *School and Staffing Survey* (National Center for Education Statistics, 2011). Data in panel C, columns (3) and (4) is from the *World Management Survey* data conducted by the Centre for Economic Performance (Bloom et al., 2015). We restrict to the 270 schools located in the US from that sample.

Table 3: Effect of Incentives on Student Test Scores

	Endline Test (z-score)				
	All	Remedial	External	Math/Science	English/Urdu
	(1)	(2)	(3)	(4)	(5)
Objective Treatment	0.0918*	0.189***	0.119**	0.104*	0.0917
	(0.0575)	(0.00518)	(0.0335)	(0.0668)	(0.166)
	[0.0730]	[0.0260]	[0.0200]	[0.194]	[0.144]
Subjective Treatment	0.0859**	0.142**	0.0855*	0.0884*	0.0986**
	(0.0220)	(0.0113)	(0.0601)	(0.0646)	(0.0267)
	[0.0130]	[0.0240]	[0.0170]	[0.121]	[0.0260]
F-test pval (subj=obj)	0.89	0.38	0.43	0.77	0.90
Randomiz infer pval (subj=obj)	0.884	0.453	0.388	0.819	0.873
Control Group Mean	-0.04	-0.09	-0.05	-0.04	-0.04
Clusters	234	204	225	223	225
Observations	141566	31944	100318	72714	68852

Notes: This table presents the effects of each performance incentive treatment on student endline test scores. The outcome is student's z-score on a given endline exam. The sample includes students tested in grades 4-13 in five subjects: Math, Science, English, Urdu, Economics. Column (1) includes all test subjects and question items. The observation is at the student-subject exam level. Column (2) restricts to question items which were from the previous grade. Column (3) restricts to question items drawn from external sources, such as PISA and TIMSS. Column (4) restricts to math and science exams. Column (5) restricts to English, Urdu and Economics exams. All regressions include strata fixed effects and control for baseline student average test score, baseline school average test score, grade and subject. Values in parentheses are standard p-values. Values in brackets are randomization inference p-values. Standard errors are clustered at the school level. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 4: Effect of Incentives on Student Socio-Emotional Outcomes

	Endline Survey Indices (z-score)					
	All	Love of learning	Ethical	Global	Inquisitive	Dislike school
	(1)	(2)	(3)	(4)	(5)	(6)
Objective Treatment	-0.0334	-0.0882	-0.0224	0.0246	-0.00556	0.0860*
	(0.294)	(0.116)	(0.605)	(0.634)	(0.917)	(0.0688)
	[0.395]	[0.0970]	[0.670]	[0.670]	[0.930]	[0.129]
Subjective Treatment	0.0170	-0.000335	0.0110	0.0491	-0.0222	-0.0318
	(0.368)	(0.992)	(0.685)	(0.177)	(0.542)	(0.392)
	[0.560]	[0.993]	[0.762]	[0.228]	[0.629]	[0.451]
F-test pval (subj=obj)	0.09	0.08	0.40	0.58	0.72	0.00
Randomiz infer pval (subj=obj)	0.0940	0.0250	0.511	0.609	0.726	0.00800
Control Group Mean	-0.00	-0.00	-0.00	0.00	-0.01	0.38
Clusters	126	126	126	125	126	124
Observations	15418	15401	14904	14168	14909	11505

Notes: This table presents the effects of each performance incentive treatment on student socio-emotional outcomes. The outcome is student's z-score on a given socio-emotional dimension. Observations are at the student level and come from an endline survey of students in January 2019. Column (1) provides the average across all five dimensions of socio-emotional outcomes. Columns (2)-(6) provide each individual dimension. All regressions include strata fixed effects and control for student's grade. Values in parentheses are standard p-values. Values in brackets are randomization inference p-values. Standard errors are clustered at the school level. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table 5: Effect of Incentives on Teacher Effort

	Classroom Observation Rubric				Test Prep
	All	Class Climate	Differentiation	Student-Centered	Minutes
	(1)	(2)	(3)	(4)	(5)
Objective Treatment	-0.0713	-0.0791*	0.110*	-0.115**	0.577***
	(0.123)	(0.0788)	(0.0719)	(0.0346)	(0.00455)
	[0.171]	[0.101]	[0.149]	[0.0480]	[0.0120]
Subjective Treatment	-0.00206	-0.00704	0.105*	-0.0276	0.110
	(0.959)	(0.822)	(0.0699)	(0.521)	(0.255)
	[0.946]	[0.838]	[0.0690]	[0.559]	[0.649]
F-test pval (subj=obj)	0.10	0.10	0.93	0.09	0.02
Randomiz infer pval (subj=obj)	0.109	0.0830	0.940	0.0940	0.0140
Control Group Mean	4.67	5.64	2.65	4.93	0.14
Clusters	142	142	142	142	142
Observations	6827	6827	6827	6827	6827

Notes: This table presents the effects of each performance incentive treatment on teacher behavior as rated based on classroom videos. The unit of observation is at the classroom observation level. Teachers may be observed multiple times over the course of the intervention. Column (1) presents the average score on the CLASS rubric (Pianta et al., 2012), on a 7-pt scale. Columns (2)-(4) provide scores on sub-areas of the class rubric. Column (5) provides the number of minutes during the observation that were spent on testing or test-prep activities. All regressions include strata fixed effects and control for grade and video coder fixed effects. Values in parentheses are standard p-values. Values in brackets are randomization inference p-values. Standard errors are clustered at the school level. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table 6: Effect of Teacher Time at Work

	Days present at school		Hours worked per day	
	(1)	(2)	(3)	(4)
Objective Treatment	2.426	1.554	0.262	0.293
	(0.570)	(0.339)	(0.195)	(0.282)
	[0.618]	[0.392]	[0.318]	[0.319]
Subjective Treatment	5.927*	3.340***	0.0348	-0.0432
	(0.0719)	(0.00947)	(0.840)	(0.832)
	[0.0960]	[0.0100]	[0.855]	[0.823]
Sample	All	Restricted	All	Restricted
F-test pval (subj=obj)	0.30	0.15	0.13	0.12
Randomiz infer pval (subj=obj)	0.371	0.202	0.295	0.164
Control Group Mean	144.79	182.72	7.90	7.92
Clusters	295	277	295	277
Observations	6394	4363	6394	4363

Notes: This table presents the effects of each performance incentive treatment on teacher attendance and time at work. The outcome is the number of days present at work and the number of hours at work. Data comes from biometric clock in and out data collected at all schools. The restricted sample removes teachers who took long leaves of absence or only worked at the school system for one of the two terms. All regressions include strata fixed effects and control for baseline school average test score, grade and subject. Values in parentheses are standard p-values. Values in brackets are randomization inference p-values. Standard errors are clustered at the school level. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 7: Teachers Perceptions about which Actions to Focus on by Treatment

	Admin (1)	Pedagogy (2)	Prof. Develop. (3)	Test Prep (4)
Subjective Treatment	0.0887*	-0.0175	-0.0513	-0.0623
	(0.0502)	(0.0498)	(0.0495)	(0.0497)
Observations	2887	2887	2887	2887

Notes: This table reports teachers' responses to a hypothetical scenario in which they are advising a teacher which actions they should take to increase their raise under a given treatment. Data was collected as part of the endline survey, and observations are at the unit of the teacher. Actions are categorized into four categories: administrative tasks, pedagogy, professional development, and test preparation. Table A3 provides teacher's weight for the full list of activities by treatment. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 8: Instrumenting Noise with Manager Accuracy - First Stage

	Noise Index (z-score)			
	(1)	(2)	(3)	(4)
Manager rating inaccuracy (z-score)	0.133***	0.123**	-0.316*	-0.219**
	(0.0502)	(0.0502)	(0.165)	(0.106)
Subjective Treatment	-0.326***	-0.116	-0.887***	0.795
	(0.0626)	(0.0867)	(0.180)	(0.528)
Subjective Treatment*Manager rating inaccuracy (z-score)	0.102*	0.103*	0.419**	0.306**
	(0.0537)	(0.0537)	(0.178)	(0.120)
Sample	Teacher	Teacher	Student	Student
Distortion Controls		X		X
Control Group Mean	0.32	0.32	1.23	1.23
Clusters	290	290	245	245
Observations	3356	3356	436740	436740

Notes: This table presents the relationship between manager rating inaccuracy and teacher's rating of how noisy their contract was. The outcome is teacher's rating of how noisy their contract was as measured by an index of their response to the three questions shown in Figure 6. Columns (1) and (2) uses data at the teacher level. Columns (3) and (4) uses data at the teacher-student exam level. Student exam data is matched to all teachers who taught the student in the given exam subject for at least one term from January-December 2018. All regressions control for subject, class and manager inaccuracy squared. Columns (3) and (4) also control for school and student test baseline. Columns (2) and (4) add in additional controls to pick up other non-noise differences across contracts. These controls include weight placed on each of the four activity groups listed in Table 7, those values interacted with the Subjective treatment, when teachers said they learned about the treatment and how often they received information about the treatment. Standard errors are clustered at the school level. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 9: Effect of Noise on Outcomes

	Test Score (SD)		Socio-Emotional Score (SD)	
	(1)	(2)	(3)	(4)
Noise	-0.175**	-0.269**	-0.153	-0.546
	(0.0875)	(0.121)	(0.419)	(1.624)
Controls		X		X
AR test p value	0.05	0.02	0.63	0.37
Montiel-Pflueger effective first stage F stat	5.50	6.46	0.47	0.16
Control Group Mean	-0.02	-0.02	-0.00	-0.00
Clusters	245	245	156	156
Observations	436740	436740	15285	15285

Notes: This table presents the relationship between teacher's rating of the noisiness of their contract, instrumented by manager inaccuracy*Subjective Treatment, on teacher and student outcomes. Columns (1) and (2) use data at the teacher level. Columns (3) and (4) use data at the teacher-student exam level. Student exam data is matched to all teachers who taught the student in the given exam subject for at least one term from January-December 2018. Columns (5) and (6) uses data the student level. All regressions control for subject, class, subjective treatment, manager inaccuracy, and manager inaccuracy squared. Columns (3) and (4) also control for school and student test baseline. Columns (2), (4) and (6) add in additional controls to pick up other non-noise differences across contracts. These controls include weight placed on each of the four activity groups listed in Table 7, those values interacted with the Subjective treatment, when teachers said they learned about the treatment and how often they received information about the treatment. Standard errors are clustered at the school level. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table 10: Effect of Manager Preferences on Student Outcomes

	Test Scores (SD)		Socio-Emotional Score (SD)	
	(1)	(2)	(3)	(4)
% of pts: Admin x Subj Treat	-0.112	-0.0988	0.208	0.264
	(0.0993)	(0.0977)	(0.389)	(0.399)
% of pts: Professional Development x Subj Treat	0.268**	0.271**	0.302	0.309
	(0.105)	(0.104)	(0.520)	(0.524)
% of pts: Pedagogy x Subj Treat	0.0603	0.0734	-0.131	-0.133
	(0.0890)	(0.0862)	(0.405)	(0.400)
% of pts: Testing x Subj Treat	0.209**	0.211**	-1.468*	-1.458*
	(0.0837)	(0.0838)	(0.833)	(0.828)
Controls		X		X
Control Group Mean	-0.02	-0.02	-0.02	-0.02
Observations	2891	2891	2653	2653
Clusters	152	152	100	100

Notes: This table presents the relationship between evaluation criteria interacted with treatment on student outcomes. Data is at the teacher level. All regressions control for the four categories of evaluation criteria and subjective treatment. Columns (2) and (4) add in additional controls to pick up other non-distortion differences across contracts. These controls include noise index, belief about whether the contract affects teacher competition, favors certain teachers, when teachers said they learned about the treatment, how often they received information about the treatment and all of these outcomes interacted with subjective treatment. Standard errors are clustered at the school level. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

9 References

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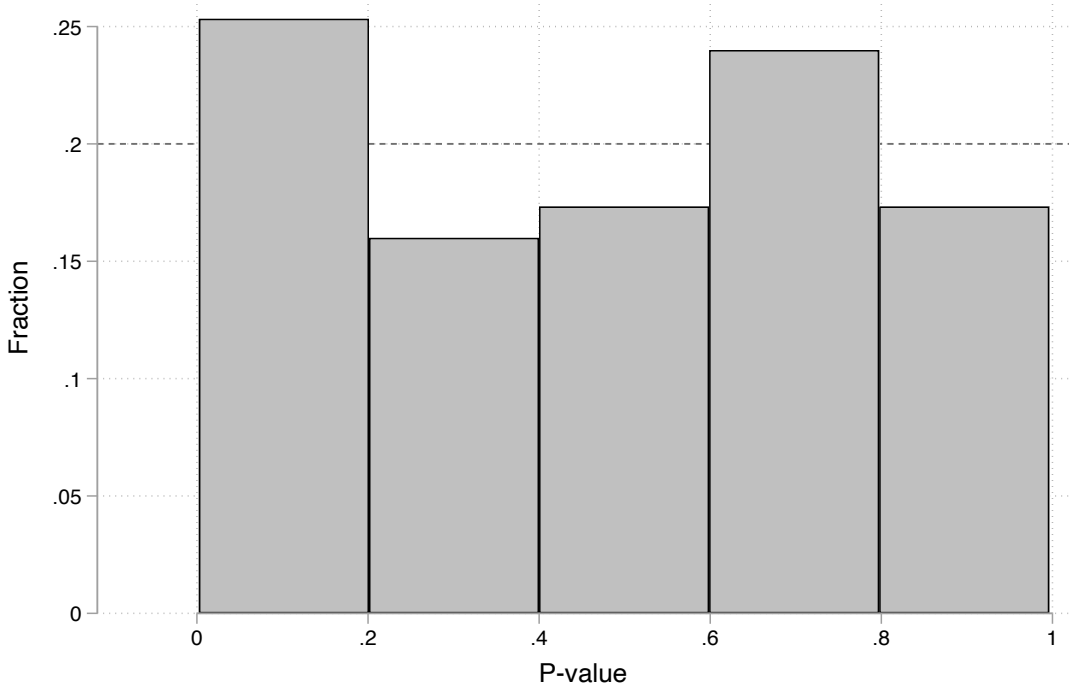
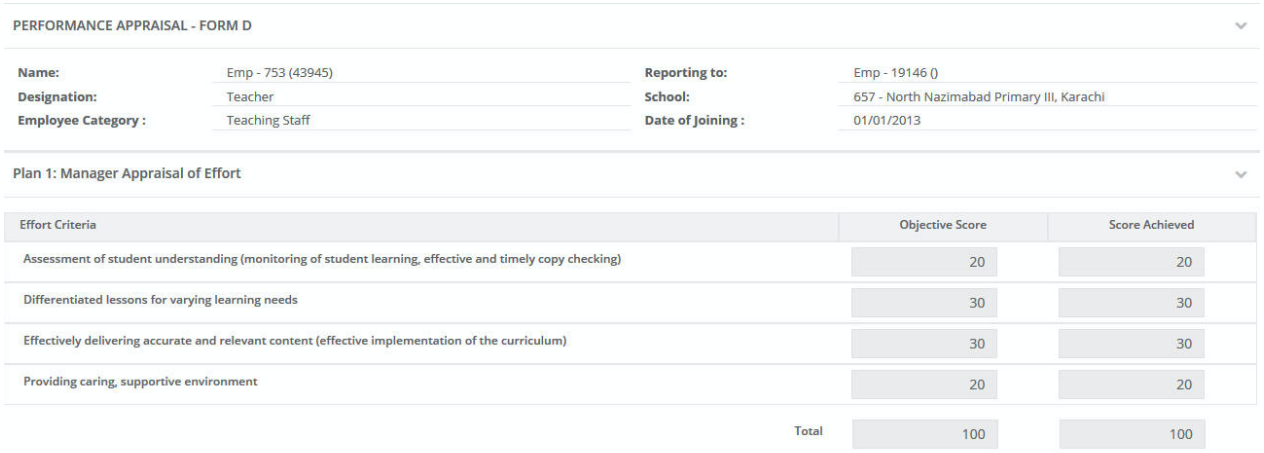
10 Appendix Figures

Figure A1: Distribution of P-Values from F-Test of Equality of Variance in Effort by Treatment



Notes: This figure plots the distribution of p-values for 75 F-tests. For each of our 25 different measures of teacher effort we calculate the within-school variance in effort along that metric and test for equality between each treatment pair (subjective = objective, subjective = control, objective = control). As the number of tests approaches infinity, for a true null of zero, we would expect p-values to be uniform at 0.2 (given 5 bins of the histogram).

Figure A2: Example Performance Criteria



PERFORMANCE APPRAISAL - FORM D

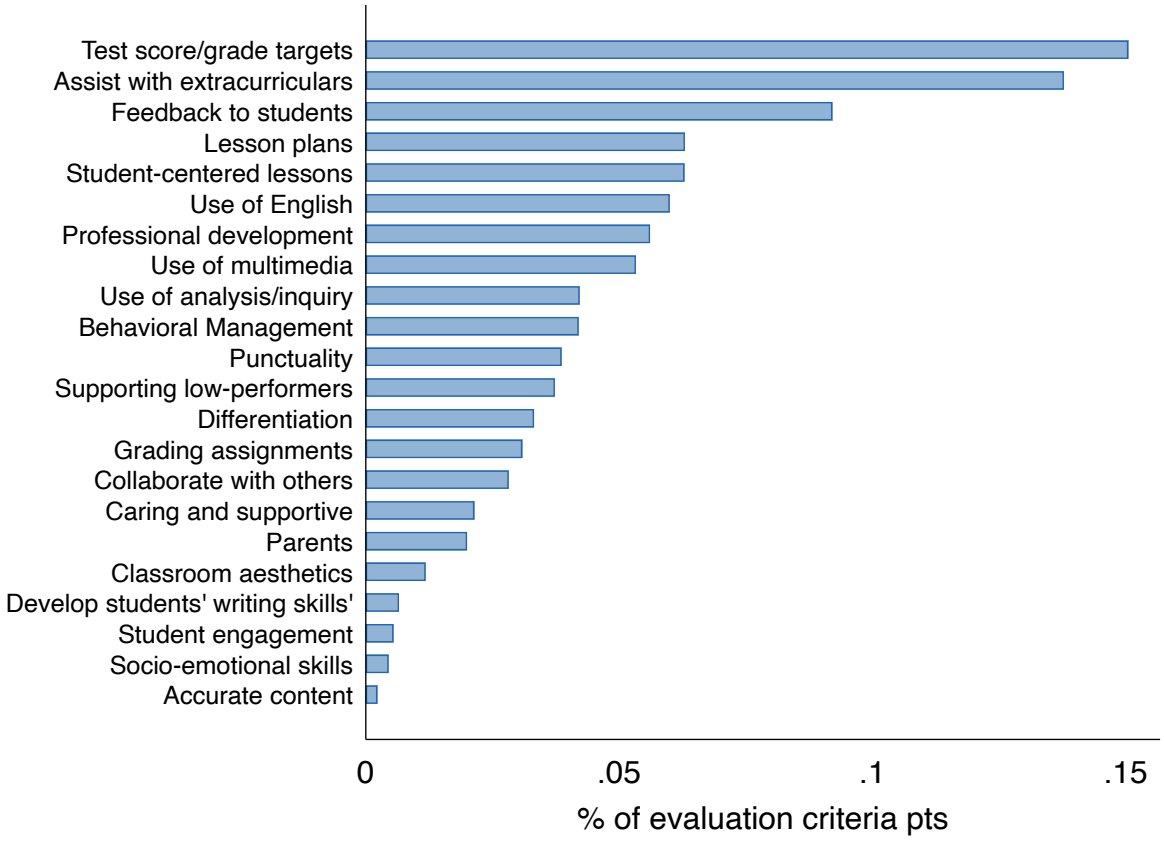
Name:	Emp - 753 (43945)	**Reporting to:**	Emp - 19146 ()
Designation:	Teacher	**School:**	657 - North Nazimabad Primary III, Karachi
Employee Category :	Teaching Staff	**Date of Joining :**	01/01/2013

Plan 1: Manager Appraisal of Effort

Effort Criteria	Objective Score	Score Achieved
Assessment of student understanding (monitoring of student learning, effective and timely copy checking)	20	20
Differentiated lessons for varying learning needs	30	30
Effectively delivering accurate and relevant content (effective implementation of the curriculum)	30	30
Providing caring, supportive environment	20	20
Total	100	100

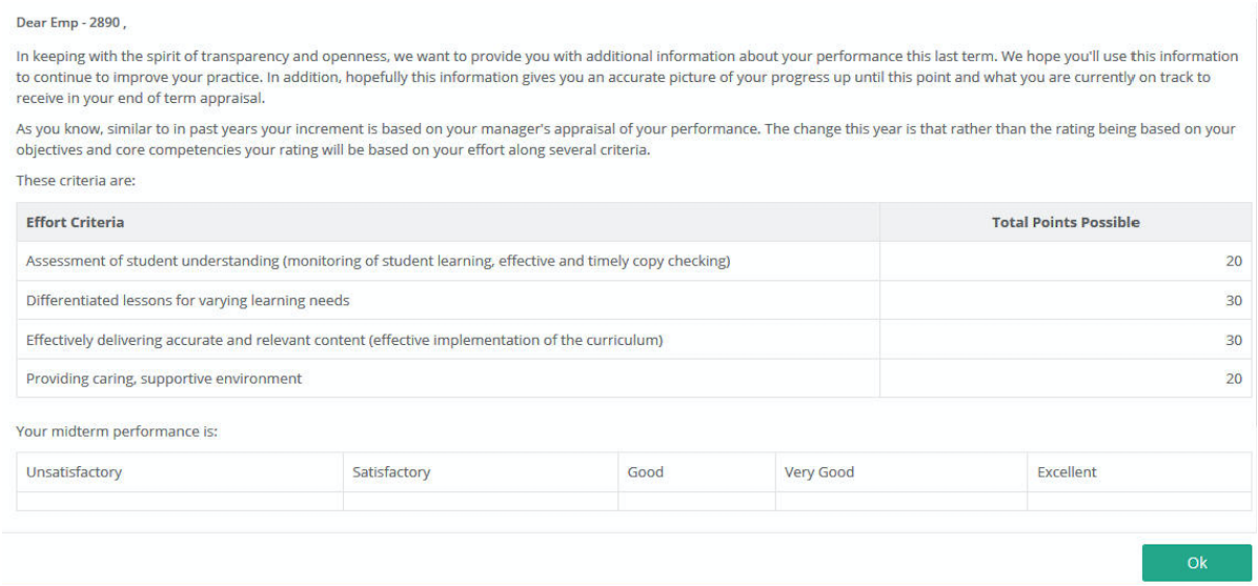
Notes: This figure shows an example set of performance criteria a teacher would have set in collaboration with their manager at the beginning of the year. This list of criteria was located on their employment portal, and available to access throughout the year. Managers could set individual criteria for each of their employees. These ranged from 4 to 10 criteria spanning numerous aspects of the teacher's job descriptions.

Figure A3: Percent of evaluation criteria points allocated to each category



Notes: This figure shows the percent of total points were allocated to evaluation criteria falling into one of 22 categories. Data on the text of the evaluation criteria and corresponding points comes from administrative employment records provided by the school system. The text responses were then categorized into categories by the research team.

Figure A4: Example Midterm Information



Dear Emp - 2890 ,

In keeping with the spirit of transparency and openness, we want to provide you with additional information about your performance this last term. We hope you'll use this information to continue to improve your practice. In addition, hopefully this information gives you an accurate picture of your progress up until this point and what you are currently on track to receive in your end of term appraisal.

As you know, similar to in past years your increment is based on your manager's appraisal of your performance. The change this year is that rather than the rating being based on your objectives and core competencies your rating will be based on your effort along several criteria.

These criteria are:

Effort Criteria	Total Points Possible
Assessment of student understanding (monitoring of student learning, effective and timely copy checking)	20
Differentiated lessons for varying learning needs	30
Effectively delivering accurate and relevant content (effective implementation of the curriculum)	30
Providing caring, supportive environment	20

Your midterm performance is:

Unsatisfactory	Satisfactory	Good	Very Good	Excellent

Ok

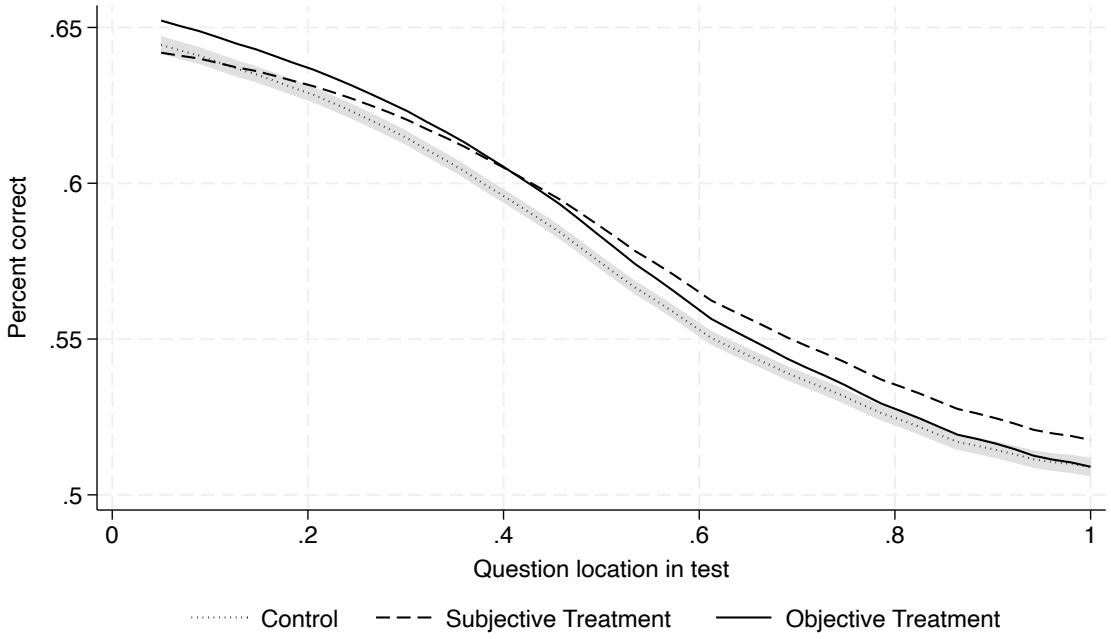
Notes: This figure shows an example notification sent to teachers during the summer between the two school years. The notification gave teachers a preliminary performance rating based on the first term of the experiment. Teachers received this information via email and as a pop-up notification on their employment portal. This example shows the notification that subjective treatment teachers would receive. Teachers in the objective treatment received midterm performance information based on their students percentile value added from the first term. Teachers in the control schools received information about either their performance along the subjective criteria that by their manager or their students' percentile value added.

Figure A5: CLASS Observation, Example Rubric Dimension

Indicator	Behavioral Markers	Low (1, 2)	High (6, 7)
Relationships	- Physical proximity - Peer interactions - Shared positive affect - Social conversation	Teacher and students appear distance and disinterested	Teacher and students share warm and supportive relationship
Positive Affect	- Smiling - Laughter - Enthusiasm	Teacher and student do not appear to enjoy time in class	Frequent displays of positive affect
Positive Communication	- Positive comments - Positive expectations	Teacher and student rarely provide positive comments	Frequent positive communication among teachers and students
Respect	- Respectful language - Use of names - Warm, calm voice - Listening to others - Cooperation	Teacher and students rarely demonstrate respect for one another	Teacher and students consistently demonstrate respect for one another

Notes: This figure shows the classroom observation rubric for one of the 12 dimensions of the CLASS rubric.

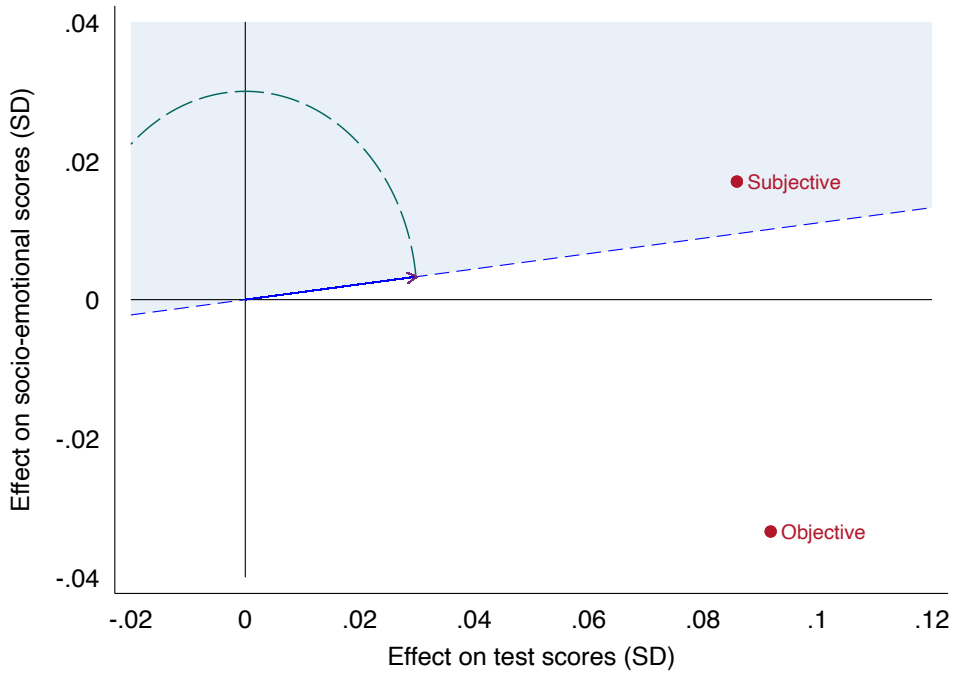
Figure A6: Effect of Incentives on Student Sustained Attention



Notes: This figure plots a kernel weighted local polynomial smoothed function of performance over the over the length of each endline test by treatment group.

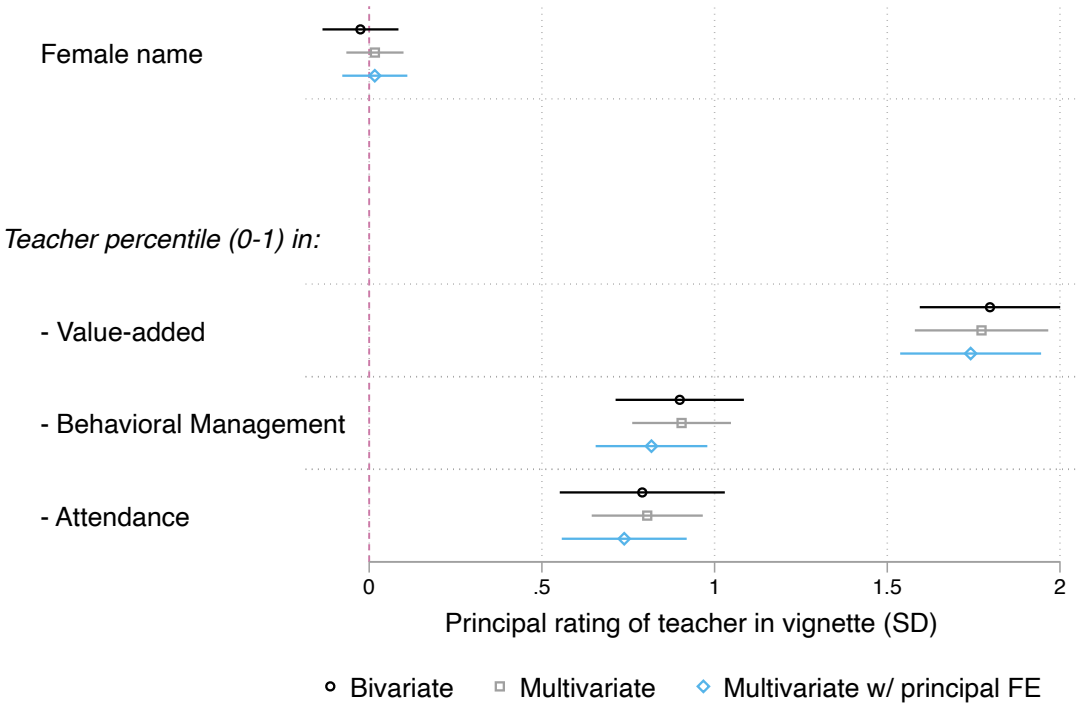
- The observation is at the student-question item level. The y-axis presents the percent of question items correctly answered. The x-axis presents the location of the question item in the test.
- The sample includes students tested in grades 4-13 in five subjects: Math, Science, English, Urdu, Economics.
- The dotted line shows the performance of the control (flat raises) with 95% confidence intervals. The dashed and solid line show the performance for the subjective and objective treatment group, respectively.

Figure A7: Total effect of performance pay on test scores and socio-emotional scores



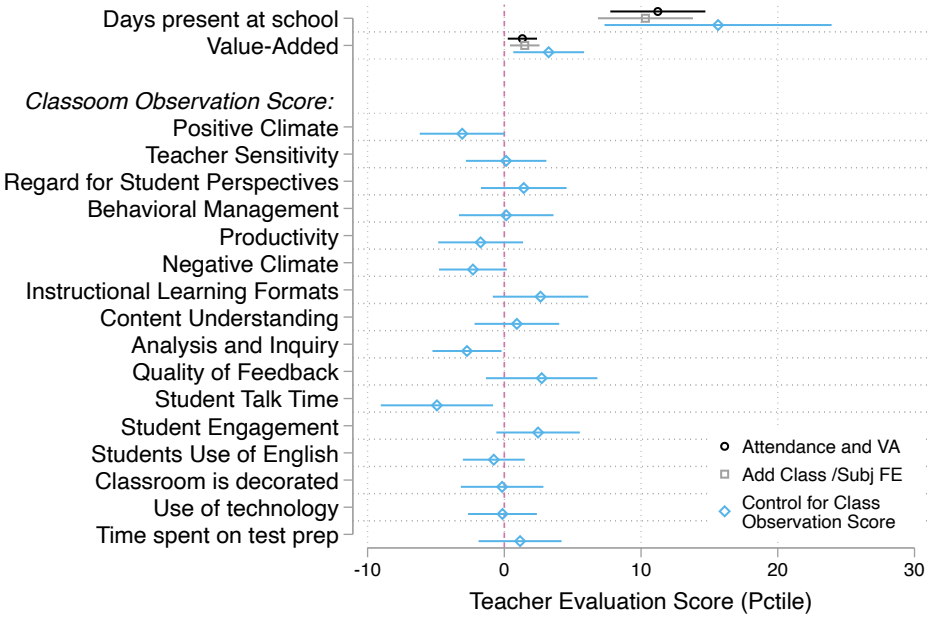
Notes: This figure plots the treatment effect coefficients of the Subjective and Objective treatments (as shown in table 3 and table 4) where the x-axis is the effect on test scores in standard deviations and the y-axis is the effect on socio-emotional scores in standard deviations. The blue dotted line shows the set of preferences (weighting of effect on test scores versus socio-emotional scores) in which a person would be indifferent between the Subjective versus Objective treatments.

Figure A8: Manager Rating by Vignette Characteristics



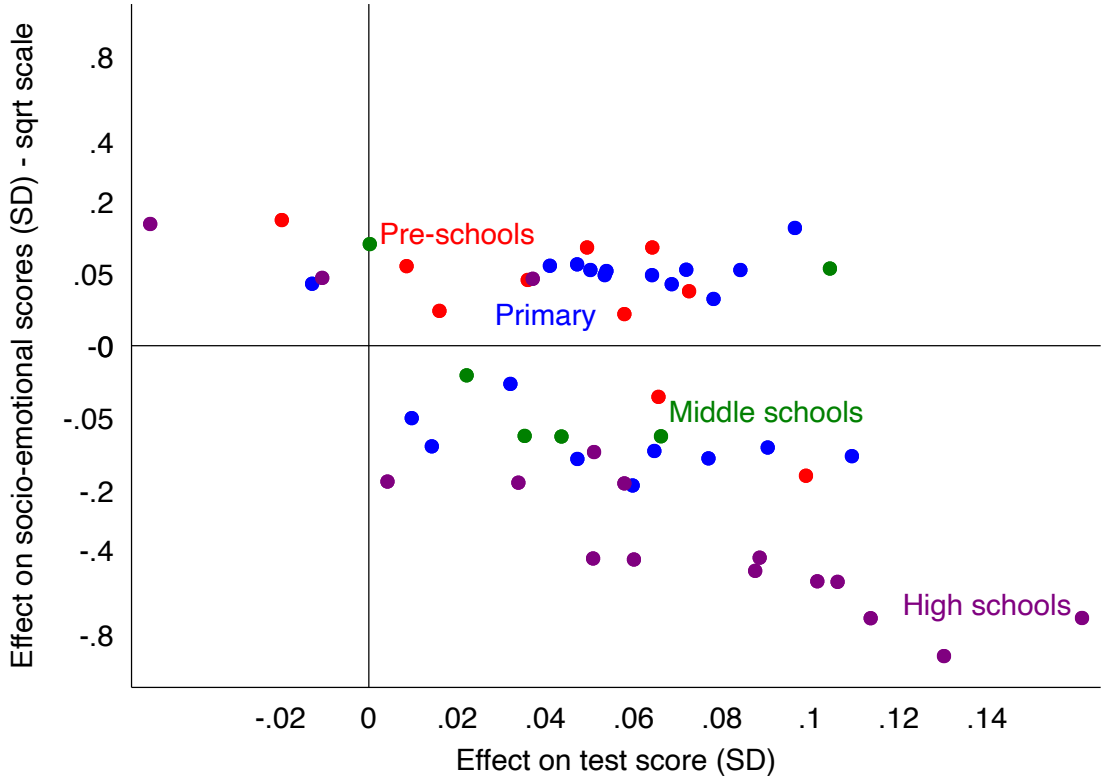
Notes: These figures presents the relationship between vignette characteristics and principal's rating of the teacher in the vignette. Principals received the vignettes stating, "[Female name/Male name] is in the [bottom/middle/top] 10% of teachers in terms of students' test score growth, in the [bottom/middle/top] 10% of teachers in terms of behavioral management, and is in the [bottom/middle/top]10% in terms of attendance and timeliness at work." Managers rated three such vignettes with characteristics randomized across vignettes. *Teacher Value-Added Percentile*, *Teacher Behavioral Management Percentile*, and *Teacher Behavioral Management Percentile* takes values, 10, 50 and 90 to correspond to the bottom, middle and top 10% listed in the vignette. *Principal rating of teacher in vignette (SD)* is the principal's stated rating of the teacher in the vignette in standard deviations.

Figure A9: Relationship between Teacher Behavior and Evaluation Score



Notes: This figure shows the relationship between teacher activity and performance evaluation score. Coefficients for a model only using teacher attendance and value-added to predict performance evaluation scores is shown in black circles. A model adding in class and subject fixed effects is shown in gray squares, and a model adding in our measures of classroom behavior from the dimensions of the CLASS rubric is shown with blue diamonds.

Figure A10: Return to Student Outcomes by Selected Evaluation Criteria within School



Notes: This figure presents expected return on student test score and non-test score outcomes based on the average weight allocated to a given evaluation criteria.

- Data is at the manager level (averaging across the evaluation criteria selected for all teachers reporting to a given manager).
- The y-axis shows the expected effect on average socio-emotional scores, and the x-axis shows the expected effect on average test scores.
- Expected effect on student outcome Y = The return to a teacher action category on outcome Y (calculated in 10) x Percent of total evaluation points for a given manager allocated to that action category.
- The text of the evaluation criteria are grouped into the following categories: Administrative tasks, Professional development, Pedagogy, Test prep and Other.
- The color of the marker identifies for a given manager what school level the majority of their teachers teach at.

11 Appendix Tables

Table A1: Baseline Covariates

Variable	(1) Control N/ [Clusters]	(1) Control Mean/ SE	(2) Objective Treatment N/ [Clusters]	(2) Objective Treatment Mean/ SE	(3) Subjective Treatment N/ [Clusters]	(3) Subjective Treatment Mean/ SE	T-test Difference (1)-(2)	T-test Difference (1)-(3)	T-test Difference (2)-(3)
Panel A: Teacher Characteristics									
Performance evaluation score	656 [40]	3.360 (0.030)	384 [32]	3.362 (0.039)	3566 [139]	3.338 (0.010)	-0.002	0.022	0.024
Salary (USD)	920 [40]	5417.984 (313.504)	535 [32]	5125.462 (295.013)	4928 [145]	5329.416 (124.042)	292.523	88.569	-203.954
Age	921 [40]	36.591 (0.738)	539 [32]	36.083 (0.846)	4926 [145]	36.630 (0.298)	0.507	-0.039	-0.546
Years of experience	918 [40]	5.505 (0.277)	534 [32]	5.487 (0.425)	4897 [145]	5.725 (0.156)	0.019	-0.220	-0.238
Panel B: Student Test Scores									
Math Test Z-Score	9959 [40]	0.071 (0.070)	5292 [33]	-0.146 (0.065)	51775 [137]	-0.014 (0.026)	0.217**	0.085	-0.132*
Urdu Test Z-Score	9702 [40]	0.041 (0.072)	5259 [33]	-0.048 (0.063)	50915 [138]	-0.002 (0.028)	0.089	0.043	-0.046
English Test Z-Score	9755 [40]	0.017 (0.056)	5289 [33]	-0.049 (0.050)	51356 [137]	0.002 (0.032)	0.067	0.016	-0.051
Social Studies Test Z-Score	9171 [40]	0.041 (0.046)	5030 [33]	-0.064 (0.056)	49411 [137]	0.007 (0.022)	0.105	0.033	-0.071
Science Test Z-Score	9636 [40]	-0.010 (0.041)	5065 [33]	-0.064 (0.042)	50268 [137]	0.001 (0.024)	0.055	-0.011	-0.066

Notes: This table summarizes teacher and student characteristics before the experiment. The table reports mean values of each variable for each treatment group. The final three columns report mean differences between treatment group. Panel A presents teacher demographics as of September 2017. Panel B presents student test scores from yearly exams conducted in June 2017. Standard errors are clustered at the school level. $^{*}p < 0.10$,** $p < 0.05$,*** $p < 0.01$.

Table A2: Socio-Emotional Outcomes Student Survey

Question	Category	Source
1. I enjoy my math/science/English/Urdu class	Love of learning	National Student Survey
2. When work is difficult, I either give up or study only the easy part (reversed)	Love of learning	Learning and Study Strategies Inventory
3. I get very easily distracted when I am studying or in class (reversed)	Love of learning	Learning and Study Strategies Inventory
4. I can spend hours on a single problem because I just can't rest without knowing the answer	Love of learning	Big Five (childrens)
5. I feel sorry for other kids who don't have toys and clothes	Ethical	Eisenberg's Child-Report Sympathy Scale
6. Seeing a child who is crying makes me feel like crying	Ethical	Bryant's Index of Empathy Measurement
7. It is ok if a student lies to get out a test they are worried about failing (reversed)	Ethical	Bryant's Index of Empathy Measurement
8. The pressure to do well is very high, so it is ok to cheat sometimes (reversed)	Ethical	Bryant's Index of Empathy Measurement
9. I am interested in public affairs	Global	Afrobarometer/World Values Survey
10. This world is run by a few people in power, and there is not much that someone like me can do about it (reversed)	Global	Afrobarometer
11. People who are poor should work harder and not be given charity (reversed)	Global	Afrobarometer
12. It is important to protect the environment even if this means we cannot consume as much today	Global	Afrobarometer
13. People from other places can't really be trusted (reversed)	Global	Afrobarometer
14. I am comfortable asking my math/science/Urdu/English teacher for help or support	Inquisitive	Learning and Study Strategies Inventory
15. I enjoy learning about subjects that are unfamiliar to me.	Inquisitive	Litman and Spielberger, Epistemic Curiosity questionnaire
16. I would like to change to a different school	Dislike school	Learning and Study Strategies Inventory

Notes: This table presents the student survey question items used to assess student socio-emotional skills. Students rated these questions on a 5-pt scale from Strongly disagree to Strongly agree.

Table A3: Percent of Time Individuals Believe Should be Spent on Each Type of Activity

Variable	(1) Objective Teachers N/ [Clusters]	(1) Objective Teachers Mean/ SE	(2) Subjective Teachers N/ [Clusters]	(2) Subjective Teachers Mean/ SE	(3) Subjective Managers N/ [Clusters]	(3) Subjective Managers Mean/ SE	T-test Difference (1)-(2)	T-test Difference (1)-(3)	T-test Difference (2)-(3)
Improving behavioral management	487	0.062	2406	0.059	41	0.054	0.003**	0.009*	0.006
		(0.001)		(0.001)		(0.006)			
Collaborating with other teachers	487	0.051	2406	0.050	41	0.059	0.001	-0.008*	-0.009**
		(0.001)		(0.000)		(0.005)			
Grading student papers	487	0.068	2406	0.071	41	0.069	-0.003	-0.002	0.001
		(0.002)		(0.001)		(0.005)			
Providing differentiated lessons	487	0.068	2406	0.070	41	0.067	-0.003	0.000	0.003
		(0.002)		(0.001)		(0.005)			
Helping with extracurriculars	487	0.055	2406	0.056	41	0.047	-0.001	0.008	0.009
		(0.002)		(0.001)		(0.005)			
Incorporating higher order thinking skills	487	0.067	2406	0.067	41	0.067	0.001	-0.000	-0.001
		(0.002)		(0.001)		(0.005)			
Catering to different learning styles	487	0.066	2406	0.066	41	0.065	0.000	0.001	0.001
		(0.001)		(0.001)		(0.005)			
Incorporating multimedia	487	0.053	2406	0.056	41	0.053	-0.004**	-0.000	0.003
		(0.001)		(0.001)		(0.006)			
Communicating with parents	487	0.042	2406	0.040	41	0.042	0.002	0.001	-0.002
		(0.001)		(0.001)		(0.004)			
Conducting practice tests	487	0.067	2406	0.065	41	0.068	0.002	-0.001	-0.003
		(0.002)		(0.001)		(0.007)			
Making lessons more student centered	487	0.066	2406	0.070	41	0.083	-0.003**	-0.017***	-0.013***
		(0.001)		(0.001)		(0.007)			

Notes: This table reports teachers' responses to a hypothetical scenario in which they are advising a teacher which actions they should take to increase their raise under a given treatment. Data was collected as part of the endline survey, and observations are at the unit of the teacher/manager. $^{*}p < 0.10,^{**}\ p < 0.05,^{***}\ p < 0.01$.

Table A4: Manager Rating by Vignette Teacher Characteristic

	Manager Rating (z-score)					
	(1)	(2)	(3)	(4)	(5)	(6)
Value-Added Percentile	0.0180***				0.0177***	0.0174***
	(0.00103)				(0.000979)	(0.00103)
Behavioral Management Percentile		0.00899***			0.00904***	0.00817***
		(0.000941)			(0.000724)	(0.000819)
Attendance Percentile			0.00791***		0.00805***	0.00738***
			(0.00121)		(0.000815)	(0.000917)
Female name				-0.0253	0.0166	0.0163
				(0.0557)	(0.0420)	(0.0477)
Constant	-0.885***	-0.451***	-0.389***	0.0128	-1.731***	-1.639***
	(0.0738)	(0.0684)	(0.0731)	(0.0634)	(0.106)	(0.0825)
Observations	567	567	567	567	567	567
Manager Fixed Effects						X

Notes: This table presents results from endline survey questions asking managers to rate a hypothetical teacher based on a description of their performance. The vignettes stated, "[Female name/Male name] is in the [bottom/middle/top] 10% of teachers in terms of students' test score growth, in the [bottom/middle/top] 10% of teachers in terms of behavioral management, and is in the [bottom/middle/top]10% in terms of attendance and timeliness at work." Managers rated three such vignettes with characteristics randomized across vignettes. *Teacher Value-Added Percentile*, *Teacher Behavioral Management Percentile*, and *Teacher Attendance Percentile* takes values, 10, 50 and 90 to correspond to the bottom, middle and top 10% listed in the vignette. *Teacher has female name* is a binary variable, which is 1 if the name used in the vignette is a traditionally female Pakistani name (Saadia, Haya, Maira, Anam, Zahra, or Sarah) and 0 if the name used is a traditionally male Pakistani name (Qasim, Tahir, Asim, Zain, Mujahid or Attefaq). Standard errors are clustered at the manager level. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table A5: Effect of Incentives on Student Sustained Attention and Resilience

	Question Correct		
	(1)	(2)	(3)
Subjective Treatment	0.00995	0.00503	-0.00700
	(0.00733)	(0.0131)	(0.0102)
Objective Treatment	0.0164*	0.0237	0.0149
	(0.00967)	(0.0182)	(0.0126)
After difficult item	-0.0519***		
	(0.0102)		
Subjective Treatment* After difficult item	0.0230**		
	(0.0108)		
Objective Treatment* After difficult item	0.00629		
	(0.0127)		
Location (percent of test)		-0.211***	
		(0.0179)	
Subjective Treatment* Location (percent of test)		0.0190	
		(0.0190)	
Objective Treatment* Location (percent of test)		-0.0108	
		(0.0304)	
Location Quintile 2-3			-0.0833***
			(0.0160)
Location Quintile 4-5			-0.171***
			(0.00667)
Subjective Treatment* Location Quintile 2-3			0.0288*
			(0.0164)
Objective Treatment* Location Quintile 2-3			0.00802
			(0.0201)
Subjective Treatment* Location Quintile 4-5			0.0258***
			(0.00771)
Objective Treatment* Location Quintile 4-5			-0.000488
			(0.0144)
P-value (interaction*subj=interaction*obj)	0.051	0.240	0.101
P-value (interaction2*subj=interaction2*obj)			0.050
Control Group Mean	0.573	0.573	0.573
Clusters	234	234	234
Observations	2056337	2056337	2056337
Controls			
Baseline	X	X	X
Grade/Subject	X	X	X

Notes: This table presents the effects of each performance incentive treatment on student endline test items, comparing performance on question items just after a difficult item (Col 1) or at different locations in the test (Col 2 & 3). The outcome is whether a student got a given question correct. The sample includes students tested in grades 4-13 in five subjects: Math, Science, English, Urdu, Economics. The observation is at the student-question item level. All regressions include strata fixed effects and control for baseline student average test score, baseline school average test score, grade and subject. Standard errors are clustered at the school level. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table A6: Teacher Effort and Subjective Performance Rating

	Subjective Performance Rating Percentile (0-100)		
	(1)	(2)	(3)
Hours present at school	-1.793***	-1.550***	-1.979***
	(0.293)	(0.306)	(0.617)
Days present at school	0.167***	0.153***	0.232***
	(0.0263)	(0.0263)	(0.0628)
Value-Added	1.393**	1.574***	3.417**
	(0.575)	(0.581)	(1.388)
CLASS Rubric Dimensions:			
Positive Climate			-7.472*
			(3.836)
Teacher Sensitivity			0.323
			(3.647)
Regard for Student Perspectives			1.650
			(1.847)
Behavioral Management			0.282
			(3.574)
Productivity			-3.829
			(3.492)
Negative Climate			-12.49*
			(6.865)
Instructional Learning Formats			5.060
			(3.396)
Content Understanding			1.780
			(3.051)
Analysis and Inquiry			-4.815**
			(2.268)
Quality of Feedback			3.681
			(2.791)
Student Talk Time			-5.721**
			(2.427)
Student Engagement			5.804
			(3.651)
Other aspects of classroom observation:			
Students Use of English			-0.0498
			(0.0747)
Classroom is decorated			-0.659
			(6.348)
Use of technology			-0.0803
			(0.780)
Time spent on test prep			0.978
			(1.310)
Observations	2778	2628	618
Dependent Variable Mean	49.05	49.05	49.05
Subject and Grade Controls		X	X

Notes: This table presents the relationship between teacher behavior and their subjective performance rating. The dependent variable is subjective performance rating percentile. Column (1) and (2) includes the full sample of teachers and column (3) just includes teachers for whom we conducted a classroom observation. *Hours* and *Days present* are from biometric clock in and out data provided by the school system. Value-added is calculated using administrative test scores and endline test scores. The remaining variables are from classroom observations. The first 12 are the dimensions of the CLASS rubric and the rest are additional elements of teaching not captured by the CLASS rubric. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table A7: Teacher's beliefs about contract features

Variable	(1) Objective Treatment N/[Clusters]	(1) Objective Treatment Mean/SE	(2) Subjective Treatment N/[Clusters]	(2) Subjective Treatment Mean/SE	T-test Difference (1)-(2)
Panel A: Bias and Favoritism					
Is their any bias in favor or against the following groups (in the raises they receive)?					
New teachers	382 [33]	2.982 (0.029)	4237 [237]	2.983 (0.011)	-0.001
Female teachers	382 [33]	3.076 (0.029)	4237 [237]	3.077 (0.012)	-0.001
Older teachers	382 [33]	3.259 (0.054)	4237 [237]	3.248 (0.015)	0.011
Certain teachers are favored regardless of how hard they work	382 [33]	2.754 (0.050)	4237 [237]	2.772 (0.021)	-0.018
Panel B: Gaming					
Teachers do favors for managers to get a higher raise	124 [29]	2.427 (0.102)	2175 [208]	2.318 (0.038)	0.109
Teachers try to negotiate for a higher raise	124 [29]	2.548 (0.198)	2175 [208]	2.557 (0.037)	-0.009
Teachers bribe managers for a higher raise	124 [29]	1.508 (0.090)	2175 [208]	1.493 (0.026)	0.015
Panel C: Other features of the treatment					
How frequently did you think about the appraisal system	382 [33]	3.463 (0.149)	4237 [237]	3.479 (0.046)	-0.016
When did you come to understand what was expected under the contract	380 [33]	4.095 (0.128)	4199 [237]	4.089 (0.053)	0.006

Notes: This table summarizes teacher responses to questions about their contracts from the previous year at endline. The table reports mean values of each variable for objective versus subjective teachers. The final column report mean differences between treatment group and report if any are statistically significant. The three "Is there any bias" questions are on a 5 pt scale (1, lots of bias against, 3, no bias, 5, lots of bias in favor). The remaining questions in panel A and B are on a 5-pt scale from 1 (strongly disagree) to 5 (strongly agree). Questions in panel C were on a scale from 1 to 8. Standard errors are clustered at the school level. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table A8: Heterogeneous Treatment Effects by Manager Characteristics

	Endline Test Scores					
	(1)	(2)	(3)	(4)	(5)	(6)
Subjective Treatment	-0.0156	0.169**	-0.0566	0.249***	0.412	-0.0912
	(0.197)	(0.0688)	(0.117)	(0.0775)	(0.681)	(0.491)
Interaction	0.00111	0.00827	0.0159	0.142*	0.0386	-0.0215
	(0.00274)	(0.00503)	(0.0977)	(0.0763)	(0.0863)	(0.0618)
Interaction*Subjective Treatment	0.00205	-0.00883	0.148	-0.211**	-0.0818	0.0375
	(0.00420)	(0.00648)	(0.127)	(0.0910)	(0.162)	(0.116)
Interaction	Age	Experience (years)	Female	Manager innacuracy (z-score)	Management Rating	Personnel Management Rating
Clusters	255	255	255	255	255	255
Observations	440595	440595	440595	440595	440595	440595

Notes: This table presents the treatment effects by manager characteristics. The row *Interaction* lists which characteristic is used as the interaction variable for a given column. Age, experience and gender are from administrative records. Manager inaccuracy is from teacher endline survey data. Mangement rating and Personnel management rating are from manager endline survey responses to World Management Survey questions. Standard errors are clustered at the school level. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.