Making Recognition Matter: A Field Experiment on Recognition Rewards for Bureaucrats

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Abstract

Governments often roll out employer recognition schemes to motivate employees, but there is limited evidence on whether such schemes can work in the public sector or the mechanisms through which they operate. In direct collaboration with the Public Education Department in Punjab, Pakistan, we randomized head teachers attending a mandatory in-service training into different designs of tournament-based recognition incentives tied to training performance, and a control group. The first recognition incentive made peer-esteem in recognition salient, the second made potential career benefits of recognition salient, and the third and fourth treatments combined the first two treatments with a motivational framing to improve the design of the rewards. I find two key results: first, employer recognition that makes potential career benefits salient improves training performance; second, adding a motivational framing bolsters teacher motivation but also makes teachers overconfident reducing their performance in the training. These findings have implications for building upon existing theory regarding how public agents make decisions to exert effort in response to recognition rewards. At the same time, they have policy implications for how to design "soft but sharp" recognition rewards in the public sector.

Keywords: Non-monetary incentives; Peer-esteem; Career benefits; Framing effects; Public school teachers

JEL codes: C93; I28; J3; J45; J53; M52; O15

1 Introduction

A motivated and high-performing bureaucracy is central to improving public service delivery, economic growth, and development. This is especially a challenge in the education sector where low effort of public school teachers remains a critical concern across several developing country contexts (Bold et al., 2017). Public sector organizations have relied on financial incentives to address low effort of teachers with promising results (see Muralidharan and Sundararaman, 2011; Duflo et al., 2012; Mbiti et al., 2019; Leaver et al., 2021). But financial incentives, though effective when designed well, are expensive, and can often be distortionary by creating perverse incentives or crowding out intrinsic motivations (Titmuss, 1970; Holmstrom and Milgrom, 1991; Glewwe et al., 2010; Gneezy et al., 2011). Non-financial incentives such as recognition rewards, on the other hand, are financially more feasible and potentially effective in pro-social settings like education where frontline agents may put a lower weight on financial incentives (Besley and Ghatak, 2005). In this paper, I study the impact of non-financial incentives such as employer recognition on public school head teacher effort.

Employer recognition schemes in governments are not uncommon, but evidence with respect to the mechanisms through which these operate remains limited.[1] First, there is a question pertaining to the different channels of motivation for employer recognition. Two key channels of motivation could be that agents value employer recognition because it generates *peer-esteem* by being recognized in front of peers and colleagues which generates reputational gain and social approval or because agents can use recognition to signal quality to supervisors to reap tangible *career benefits* in the future (Frank, 1985; Benabou and Tirole, 2006; Besley and Ghatak, 2008; Dewatripont et al.;1999). While existing evidence documents the impact of public versus private forms of employer recognition (as in Ashraf et al., 2014a) or the impact of employer versus community recognition (as in Gauri et al., 2018), no existing study tries to unbundle the impact of the peer-esteem and career-benefits channels of employer recognition. This has implications

[1] This is with the exception of a few studies that look at either community recognition or employer recognition in the public sector (but without delving into mechanisms). See Ashraf et al., 2014a; Ashraf et al.; 2014b Gauri et al., 2018;Cotofan; 2021.

both for specifying theory underlying why agents exert effort in response to recognition rewards, as well as how governments can design sharper recognition rewards.

A second question relates to how such incentives are framed. Performance-contingent rewards can often dampen employee morale and beliefs in ability because they are perceived as controlling or as a negative signal of ability (Deci and Ryan, 1985; Bénabou and Tirole, 2003). These negative effects can be especially more pronounced in tournament-based rewards like recognition for low-ability individuals or individuals with low intrinsic motivation at baseline (Connelly et al., 2014; Ashraf et al., 2014a, Mansoor, 2019). This fundamentally implies that equilibrium effort does not only depend on the reward in question but also on the *information* contained in the reward (Gneezy et al., 2011), which makes the framing of rewards important. Despite this evidence, and calls for attention towards how performance-contingent rewards are framed (Frey, 1997), there is limited evidence on how to improve the design of rewards through their framing.

In this paper, I shed light on these gaps and provide experimental evidence on recognition rewards for public school head teachers. I ask the following two questions: First, could employer recognition elicit higher teacher effort? If yes, what is the impact of employer recognition that makes peer-esteem salient versus recognition that makes future tangible career benefits salient? Second, does framing recognition with a motivational framing improve its design and impact? Apart from the theoretical motivation, the research questions are also empirically grounded and build upon a pilot study that I conduct with a smaller sample of public school teachers (Mansoor, 2019).[2]

I study these questions through a direction collaboration with the Education Department in Punjab, Pakistan. Punjab is Pakistan's most populous province, employing a workforce of ap-

[2]The pilot tested the impact of the peer-esteem and career-benefits channels, along with a private self-esteem channel. The results highlighted that the more outward facing "peer" and "career" channels of employer recognition worked (as in Ashraf et al., 2014a; Ariely, Bracha, and Meier, 2009), but only for teachers who reported being intrinsically motivated at baseline. These results implied that the private self-esteem channel is not effective and that motivated individuals are more likely to respond to such rewards. These results support the exclusion of the private self-esteem channel, as well as testing the impact of a motivational framing to improve the design of the incentives. This pilot study is available as an online Appendix to this paper, Mansoor (2019).

proximately 450,000 teachers spread across 52,000 schools.[3] Progress in learning outcomes has remained a challenge in Punjab, and teacher quality and effort is widely seen as one of the main explanations for low student learning outcomes in the province. To address questions around how to improve teacher motivation and effort, the government conducted a Teacher Motivation survey in March 2017 across 8,400 teachers in 3,100 randomly selected schools in Punjab. Descriptive statistics from the survey highlighted that more than 70% of the teachers value non-financial drivers such as employer recognition, community recognition, and professional development opportunities.[4] This contextual setting creates direct relevance to study our questions of interest.

Within the Education department, I design and implement a field experiment in collaboration with the Teacher Training Academy in Punjab, Pakistan called the Quaid-e-Azam Academy for Educational Development (QAED). We embed the experimental design within a mandatory in-service training on school leadership offered to head teachers with the recognition rewards being directly linked to *training performance* as measured through training test scores. This setting has several advantages to study the questions of interest. First, attending the training is mandatory for all head teachers. This is arguably similar to many other non-student facing mandatory tasks that head teachers are required to do such as preparing workplans and budgets. Hence, understanding head teacher response to incentives in these mandatory trainings allows us to understand broader head teacher preferences for these rewards. Second, we are able to learn about teacher preferences for these rewards by incentivizing training test scores which are one-dimensional in effort as opposed to incentivizing teacher performance in the classroom which is multi-faceted and complex. This allows us to avoid the standard issues of multi-tasking (Holmstrom and Milgrom, 1991).Third, the training is offered to head teachers who are critical agents for school performance in their capacity as school leaders (Hallinger and Heck, 1996; Silins and Mulford, 2015). Thus, understanding how to motivate them in trainings has direct implications for school performance. Finally, public in-service training programmes are the primary mechanism for human capital improvements for teachers, and public servants more broadly. Hence, understanding how incentives can increase this human capital acquisition process, and

[3]Annual School Census Data 2017.

[4]Based on author's own analysis of the Teacher Motivation survey data.

whether they encourage application of the acquired skills into mainstream practices on-the-job is non-trivial.

As part of this experiment, the training academy randomly allocated 131 different training sessions (offered to 3,394 head teachers) across 4 different employer recognition schemes and a control group. Treatment 1 (Peer arm) makes peer-esteem salient – trainees are told that those with the top score in the training post-test and the most improved score (over the pre-test) will be provided certificates in a district-level ceremony which will be attended by their peers and colleagues in their district. Treatment 2 (Career arm) offers the same certificate as Treatment 1 but makes career benefits salient instead. Trainees are told that those who qualify will receive the certificates privately but at the same time their name will be added to an 'excellent teacher list' that will be shared with the departmental leadership, that can help them qualify for future career opportunities in their districts or the department. While formal career incentives such as promotions are purely based on seniority in our setting, this treatment leverages the availability of informal career incentives in the system such as postings to preferred schools, transfers to lateral postings that may come with additional benefits, or postings to vacant positions of higher ranks (but with same grade). Treatments 3 and 4 (Peer PLUS and Career PLUS) cross the first two treatments with a motivational framing. The framing aims to improve the information contained in the reward by boosting teacher morale and beliefs about ability to do well in the training and their jobs more broadly.

Our main treatment effects show two key results. First, we find that employer recognition can work when it is linked to tangible career benefits in the future. We find indicative evidence that the Career arm leads to a 0.25σ increase in training test scores as compared to the control group. In comparison, the Peer arm has a coefficient of 0.04 and is insignificant. This implies that head teachers value recognition rewards when they increase the likelihood of accessing informal career incentives in the system. Second, we find that the positive effects of these incentives can backfire depending on how they are framed. The net impact of adding the motivational framing to the Career arm is negative and significant – a reduction of 0.27σ in training test scores. The net impact of adding the motivational framing to the Peer arm is also negative but insignificant.

Overall, the pooled net impact of adding the motivational framing to the recognition treatments is to lower training test scores by 0.22σ.

To understand mechanisms underlying the positive treatment effects in the Career arm, we test whether the treatment effects are primarily coming from the upper tail of the distribution as is often the case in tournament-based rewards (see systematic review by Connelly et al., 2014). Quantile treatment effects show that the Career arm has a positive coefficient in the range of 0.08-0.31 across the distribution. In the upper tail of the distribution, these coefficients are significant and also significantly different from the Peer arm in which the coefficients are in the range of -0.07-0.04. Kolmogorov–Smirnov tests of equality of distribution between the Peer and Career arm confirm that the distributions are significantly different from each other (p-value <0.01). This confirms that the observed treatment effect in the Career arm is not merely coming from the top of the distribution, and that the career-benefits channel is stronger than the peer-esteem channel.

Next, we test whether teachers respond to the Career arm because career-benefits are indeed salient for them. To answer this question, we test whether the Career arm works through individuals who are due for their next promotion sooner or have higher visibility to senior leadership such as Secretary Education and District Education Officers (DEOs). Given teachers have informal career incentives in the system such as through their preferred positions and postings, it is clear how an upcoming promotion can make such career-benefits more salient. Similarly, higher visibility to senior leadership implies greater access to supervisors for accessing informal career benefits in the system. We find that when the Career arm works, it works through individuals who are due for their next promotion sooner or have higher visibility to senior leadership. These results lend further evidence in support of the theory underlying the career-benefits channel of recognition.

To understand the negative effects of the motivational framing, we first observe treatment effects on teacher morale, motivation, and beliefs in ability. We measure this through a teacher motivation index which is comprised of validated measures of teacher intrinsic motivation, self-efficacy, and internal locus of control. We find that the net impact of the motivational framing on our

teacher motivation index is positive and significant. This highlights that despite negative effects on training test scores, the framing in the PLUS treatments did bolster teacher motivation as expected. Our main hypothesis for explaining the negative effects of the PLUS treatments investigates if the motivational framing made teachers' over confident in their ability which resulted in lower effort (as argued by Baumeister, 1999; and Swann, 1996). We construct a direct measure of overconfidence as the difference between what teachers' believed they scored on the post-test at endline and what they actually scored. We find that the net impact of the framing is to increase teacher overconfidence by 6 percentage points. Mediation analysis (following guidelines as per Acharya et al., 2016) shows that overconfidence can explain up to 85% of the observed negative effects of the PLUS treatments on training test scores.

Finally, we investigate the impact of our treatments on a set of downstream outcomes at the school level. Application of training knowledge to on-the-job practices can be challenging (Banerjee et al., 2016), but incentives in trainings could create motivational spillovers as well as encourage application of knowledge improvements to on-the-job practices. We test this using government administrative data from monthly school monitoring visits and student examination data, 3-months and 8-months into the programme respectively. We show that the treatment effects on training knowledge do not cascade into any impacts on downstream outcomes such as teacher absenteeism, student examination fail rate, or student exam participation rate. While these results imply that improvements in head teacher knowledge possibly had no impact on these downstream outcomes, they also highlight the following critical points. First, leadership trainings such as the one in our context often aim to impact school performance through changing practices and attitudes of head teachers and teachers (Leithwood and Jantzi, 2000), but there remains limited evidence on these mechanisms making it difficult to elucidate the causal mechanisms. Our paper is unable to report impacts on these intermediary mechanisms due to data limitations, but it remains an open question as to whether there were any improvements in these intermediary outcomes. Second, existing research on the causal relationship between head teacher management trainings and school-level outcomes remains limited with mixed results, where the studies focus on a range of distinct training topics such as leadership, support with data use and monitoring, or instructional leadership (see Fryer, 2017; Muralidharan and Singh, 2020; Romero et al., 2021).

While this highlights the need for careful distinction between types of management trainings, our results also pose the question of whether certain types of management trainings are more effective than others?

This paper provides, to the best of our knowledge, the first empirical evidence that unbundles the peer-esteem and the career-benefits channel of employer recognition. Our results add to the existing empirical literature on non-financial incentives in the public sector (Ashraf et al., 2014a; Gauri et al., 2018; Ashraf et al.; 2014b; Cotofan, 2021) highlighting that linking recognition rewards to career benefits in the future can improve their effectiveness. Our results also contribute to theory underlying recognition rewards. While existing theory argues that agents can have multiple motivations for employer recognition such as individual self-esteem, peer-esteem, or receiving tangible career benefits in the future (Benabou and Tirole, 2006; Dewatripont et al., 1999; Besley and Ghatak, 2008), these motivations are conceptually distinct with implications for how agents assign value to such rewards. Our results highlight that the peer-esteem and career-benefits channels are indeed distinct aspects of agent motivation which can help us better calibrate how agents assign value to such rewards.

We also add to the literature on the framing of rewards. Existing evidence on framing mainly focuses on what happens to employee performance when rewards are framed as losses or gains (Goldsmith and Dhar, 2013; Lagarde and Blaauw, 2021). This experiment studies performance-contingent rewards in combination with a motivational framing. Our study highlights that framing recognition with a motivational framing focused on boosting morale and beliefs about ability can backfire by making teachers overconfident in their ability, implying the need for caution in how such incentives are framed.

These results also directly link to the emerging literature on teacher in-service trainings in particular, and civil service trainings more broadly. Existing evidence on the impact of in-service trainings, though limited, indicates that targeted instruction, provision of learning material alongside training, and linking teacher participation in training to incentives such as promotion or salary implications could be effective ways of improving the impact of in-service trainings (Popova et al., 2016; Cilliers et al., 2020). Given all types of in-service trainings in the public sector are not

promotion-linked, this paper shows that linking performance to informal career incentives could be one possible way of incentivizing performance and engagement of bureaucrats in in-service trainings in cost-effective ways.

Finally, this paper contributes to the broader literature that focuses on improving public sector performance in developing countries. Implementing interventions on the selection margin by tweaking recruitment policies (as in Ashraf et al., 2016; Deserranno, 2019) or on the performance margin by introducing formal pay-for-performance reforms (as in Khan et al., 2016) can often be hard to implement due to regulatory or financial constraints. While formal career incentives in public bureaucracies are negligible given promotions are determined by seniority (Finan et al., 2015), these results indicate that head teachers have career concerns through other informal mechanisms that may be easier to exercise in the system as compared to promotions. Hence, understanding the sources of different agent motivations, informal career concerns in the system being one such source, and designing "soft" non-financial incentives around them could be one way to address the challenge of weak incentive structures.

This paper is organized as follows. Section 2 outlines the experimental setting and Section 3 presents the theory and key hypotheses which the experimental design aims to test. Section 4 describes the experimental design, randomization, and data sources. Section 5 presents the empirical strategy and main results, and Section 6 presents mechanisms for understanding the impact on our main outcome. Section 7 concludes.

2 Setting

2.1 Punjab Education Sector

Punjab, the context for this study, is Pakistan's largest province with 36 districts and a population of 110 million.[5] The public education system employs a workforce of approximately 450,000 teachers responsible for educating nearly 11 million children spread across 52,000 schools.[6] The School Education Department (SED) is the provincial public body which holds the mandate for all policy and implementation pertaining to primary and secondary education.[7]

Improving education outcomes has been one of the top priorities of the Government of Punjab over the last decade. The provincial education budget has doubled in the last 10 years, with a range of reforms such as a School Education 'Reforms Roadmap', an extensive monthly school monitoring programme (including yearly and monthly audits), and a merit-based teacher recruitment strategy (Javed and Naveed, 2018). Despite these efforts, progress in learning outcomes has remained slow. For example, the ASER (2019) report shows that nearly 40% of children in grade 5 have not reached grade 2 levels of learning in literacy and numeracy (this includes English, Math and the national language Urdu).

Low levels of teacher quality and effort is widely perceived as one of the main reasons for low levels of student learning. Anecdotal evidence indicates that while the extensive school monitoring system may have addressed part of the agency problem and reduced teacher absenteeism, it also led to an unbalanced incentive system which relied on too much monitoring and very little rewards. A pilot performance-based pay programme for teachers was launched from 2010 to 2013 but its impact evaluation showed null effects on student test scores (see Barrera-Osorio and Raju, 2017). To address questions around how to improve teacher motivation and effort, the government conducted a Teacher Motivation survey in March 2017 across 8,400 teachers in 3,100 randomly

[5] Pakistan Population Census, 2017 (Pakistan Bureau of Statistics).

[6] Annual School Census Data 2017.

[7] Schools are further divided into primary (grades 1-5), elementary (grades 6-8), secondary (grades 9-10), and higher secondary (grades 11-12) schools.

selected schools in Punjab. Descriptive statistics from the survey highlighted that nearly 70% of teachers value non-financial drivers such as employer recognition, community recognition, and professional development opportunities.[8] However, there are no existing institutionalised recognition schemes.

This contextual setting creates direct relevance to understand whether employer recognition could be effective, as well as how to strengthen its design and impact by unpacking its different channels of motivation. While teachers may value employer recognition because of motivation for peer-esteem and social approval, they may also value recognition because it allows them to signal quality to supervisors to reap tangible career benefits in the future. While formal career incentives for public school teachers in our context are limited since promotions are linked to seniority, three types of informal career incentives might be relevant for how teachers can use the recognition reward to their advantage. First, teachers may want to be posted to better performing schools as opposed to poor performing schools. Second, once teachers become eligible for promotion they may want to be selected for promotion before other competing colleagues.[9] Third, teachers may have preferences to be posted laterally to positions with higher grade (albeit whilst having the same pay and grade). These informal career incentives mostly relate to transfers and postings which can be a sharp incentive as shown in Khan, Khwaja, and Olken. The next subsection explains the specific experimental context in which the recognition schemes are rolled out.

2.2 Quaid-e-Azam Academy for Educational Development (QAED)

The experiment is set-up in collaboration with the Quaid-e-Azam Academy for Educational Development (QAED), an attached department of the Punjab School Education Department, which holds the mandate to provide professional development to all pre-service and in-service public school teachers in Punjab. The academy offers a range of in-service professional development opportunities such as trainings for teachers in subject specific content and pedagogy, as well as

[8] Based on author's own analysis of the administrative data on Teacher Motivation.

[9] Employees who are eligible for promotion have to wait for their turn to get their promotion approved.

leadership and management trainings to head teachers.

I partnered with QAED on a specific training called the 'Student Leadership Development Programme' (SLDP) which was targeted at head teachers of elementary, secondary, and higher secondary schools across Punjab (grades 6 to 12). The employer recognition schemes were embedded within the SLDP training, where the incentives were linked to performance in the SLDP training.

The training was a specialized programme for providing skills in coaching, leadership, and school management over four days.[10] The curriculum was designed by the British Council, following which trainings were provided to a selected pool of 634 master trainers. After the initial training, 500 master trainers were validated by the British Council for cascading the trainings further down to the head teachers.

The training was organized and implemented at the district level at the relevant district training center. Given the high number of head teachers in each district (i.e. between 300-800 in one district), each district had a total of 12-28 different training sessions with a cap of 30 teachers per session. The process of assigning trainees to these sessions was done by the QAED head quarters such that each session had equal representation of rural and urban school head teachers. Given capacity constraints at the district training center, the training was spread over 3 sequential rounds to accommodate all the sessions.[11] Each training session also included a training pre-test and post-test to measure learning gains from the training. These were designed by the project director of the SLDP at QAED and were subsequently validated by their British Council counterparts.[12]

[10]Specific modules included the following: 1) The power of coaching, 2) Co-curricular activities , 3) Protecting children, 4) Student leadership, 5) Staff and distributed leadership, 6) Leave rules, and 7) Pupil voice.

[11]For example, if a district had a total of 12 training sessions, these were allocated across 3 sequential rounds such that each round had 4 training sessions operating simultaneously.

[12]we return to the discussion on the design of the tests and nature of question in Section 4.3.1.

3 Conceptual Framework

In this section, we present a simple conceptual framework to fix ideas with respect to how agents decide to exert effort in response to recognition rewards. Two key aspects of our conceptual framework are as follows. First, it distinguishes between two aspects of agent extrinsic utility that could come from either peer-esteem or potential career benefits. This captures existing theory of how agents may value employer recognition because it can generate peer-esteem by being recognized in front of peers and colleagues (Besley and Ghatak, 2008; Frank, 1985) or be used to signal quality to supervisors to reap tangible career benefits in the future (Besley and Ghatak, 2008). Second, it captures the intuition that when agents decide to exert effort, the decision depends on the interaction between the reward and the *information* contained within the reward (Gneezy et al., 2011).

Assume that the principal cares about maximizing the value from the training (i.e. learning gains from training) Y, and employee effort e in the training produces value denoted by:

$$Y = f(e) + \epsilon \tag{1}$$

Agents are risk neutral and care about maximizing expected utility. We assume that agents maximize utility over *extrinsic* payoffs from receiving the recognition reward and *intrinsic* payoffs based on the information contained within the reward. Intrinsic payoffs are effort dependent because of the assumption that rewards contain information. If the information in the reward is perceived as controlling or as a negative signal of ability, it can dampen employee morale and beliefs in ability (Deci and Ryan, 1985; Bénabou and Tirole, 2003). This can decrease intrinsic payoffs to effort. Alternatively, if the information is perceived as motivational, it can increase intrinsic payoffs to effort by giving agents self-esteem and confidence.

Also assume that the agent puts a weight of β_{1i} over his/her extrinsic gain from peer-esteem in recognition, β_{2i} over his/her extrinsic gain from potential career benefits from recognition, and

a weight $1 - \gamma_i$ over the intrinsic payoff based on the information contained within the reward, where $\beta_1 + \beta_2$ equals γ. In addition, there is a cost to effort given by $c(e)$, which is strictly increasing in effort.

The timing is as follows. The principal introduces a recognition scheme with a particular framing through which a worker i with effort e gets a recognition reward R. This is based on the probability $p_i(Pr(e) + Cr(e))$. This captures the intuition that the probability for winning is based on effort that is exerted as a result of motivation for peer-esteem captured by Pr(e), or potential career benefits that is captured by Cr(e). Pr(e) is a reduced form function which captures how effort may be determined based on the peer-esteem channel. This could depend on the number of peers known, respect for peers, or perceived quality of peers. Similarly, Cr(e) captures how effort may be determined by the career-benefits channel. This could depend on factors that increase the likelihood of accessing career benefits in the system such as number of years to upcoming promotion, visibility to senior leadership, or type of contract (permanent versus temporary). The worker chooses his/her effort levels e to maximize utility denoted by:

$$p_i(\beta_1 Pr(e) + \beta_2 Cr(e))R + (1 - \gamma)I(e)R - c(e). \tag{2}$$

We assume that effort is strictly positive and decreasing in the extrinsic payoffs (as is the case in standard utility maximising frameworks with incentives) such that $Pr_e>0$, $Cr_e>0$; $Pr_{ee}<0$, $Cr_{ee}<0$.

Effort based on intrinsic payoffs depends on the way in which the information contained in the reward is perceived by the agent. We assume this to be a function of the signal given by the principal through the framing of the incentive. We capture this through the reduced form information function I(e) given in equation 2.[13] Frey (1997) and Deci et al. (1999) argue that rewards can be administered in a motivational or controlling way, where the former can harness intrinsic motivation but the latter can dampen it. To capture this intuition, we assume

[13]Note that the information contained in the reward could also be based on agent's beliefs about their own ability and beliefs about their peers' ability, we focus here on the signal given by the principal through the framing.

effort is strictly positive and decreasing in intrinsic payoffs if the information is administered in a motivational way, such that I_e>0, I_{ee}<0. This would, for example, be in situations where recognition rewards are framed in a way that bolsters individual self-esteem and confidence, and hence increases intrinsic payoffs to effort. However, if the information is perceived as controlling, we assume effort is decreasing in intrinsic payoffs such that I_e<0, I_{ee}<0. This difference in the functional form of I(e) depending on the framing of the reward captures the theoretical intuition that information could either harness or dampen intrinsic motivation.

The first order condition that characterizes the employee's effort choice is as follows:

$$p_i(\beta_1 \frac{\partial Pr(e)}{\partial e} R + \beta_2 \frac{\partial Cr(e)}{\partial e})R + (1-\gamma)\frac{\partial I(e)}{\partial e} R - \frac{\partial c(e)}{\partial e} = 0 \tag{3}$$

This highlights the following:

- If $\beta_1 > 0$, then agent effort as a result of the peer-esteem channel will be positive. Similarly, if $\beta_2 > 0$, then agent effort as a result of the career-benefits channel will be positive.
- If $1 - \gamma > 0$, then the decision to exert effort in response to the recognition reward will be determined both by the agent's extrinsic payoff as well as the intrinsic payoff.
- The net payoff will always be positive if the information is conveyed in a motivational way since $I_e > 0$. However, if the information is conveyed in a controlling way, the third argument will be negative. In this situation, the overall effect of the reward can be negative if the negative intrinsic payoffs outweigh the positive extrinsic payoffs from peer-esteem and future career benefits.

Our experiment directly relates to the three arguments in equation (3). We design and test the impact of recognition rewards leveraging the peer-esteem or the career-benefits channel to understand whether these two are indeed distinct extrinsic motivations. We also combine these incentives with a motivational framing to understand whether intrinsic payoffs to the agents from

these rewards can be improved by exogenously changing the framing of the rewards, such that $I_e > 0$.

Our hypotheses are as follows:

H1: Employer recognition tools that leverage the peer-esteem channel improve training performance of teachers relative to the control group because agents care about recognition and approval from their peers and colleagues.

H2: Employer recognition tools that leverage the career-benefits channel improve training performance of teachers relative to the control group because agents care about signaling their performance to their supervisors for potential career benefits in the future.

H3: Employer recognition tools that leverage the peer-esteem channel in combination with a motivational framing improve training performance more than the peer-esteem channel only.

H4: Employer recognition tools that leverage the career benefits channel in combination with a motivational framing improve training performance more than the career benefits channel only.

4 Experimental Design

4.1 Treatment Arms

The experimental design includes four alternate treatment arms of employer recognition, and a control group. Two of the recognition arms either make peer-esteem or career benefits of recognition salient. The second two treatments cross the first two recognition arms with a motivational framing to improve the design of the first two arms.

The recognition incentive is a standard tournament-based employer recognition reward. Within a training session, teachers who score the highest in the training post-test score or show the

maximum improvement over the training pre-test score qualify for a prestigious certificate that is authenticated by the QAED head quarters. This encourages teacher effort across the entire distribution of trainees' ability in the training session instead of only high ability teachers (as in Ashraf et al., 2014a).

The sequencing of activities is as follows. On the first day, teachers take the training pre-test which is managed by our team of enumerators. After the pre-test, enumerators administer the relevant recognition incentive following a predetermined script.[14] This is followed by the scheduled training over the next four days. On the fourth and final training day, teachers take a training post-test at the end of the training. The winning teachers receive their recognition rewards nearly two months after the training.

Details of each treatment arm are given below:

Control group: Teachers in this group are administered a neutral script by the enumerator which highlights the broad goals of the SLDP training. All other activities such as the training lectures, pre-test, and post-test operate as in all the other groups.

Peer Recognition (T1): Teachers in this treatment group are informed that if they meet the required qualification conditions, they would be eligible for receiving a prestigious recognition certificate in a district ceremony which would be attended by their peers and district staff. The script for T1 is exactly the same as the control group except for the additional information about the recognition incentive. All other activities such as the training lectures, pre-test, and post-test operate as in all the other groups.

This treatment leverages the motivation for peer-esteem.

Career-based Recognition (T2): Teachers in this treatment group are informed that if they meet the required qualification conditions, they would be eligible for receiving a prestigious recognition

[14]To ensure quality and uniformity in the administration of the recognition incentives across all treatments, standardized delivery of the script across enumerators was essential. To do this, a master version of each script was pre-recorded and shared with the enumerators along with guidelines on necessary pauses and momentum. Each enumerator was given targeted feedback on their delivery prior to being approved for the job.

certificate which would be given to them privately. In addition, they are also told that the names of the winning employees would be included in an 'excellent teacher list' which would be shared with their district's leadership as well as the provincial leadership of the School Education Department, which could make them eligible for future career opportunities in the department. The script for T2 is exactly the same as T1 except for the difference in how career benefits as opposed to peer-esteem is made salient. All other activities such as the training lectures, pre-test, and post-test operate as in all the other groups.

This treatment leverages the motivation for reaping potential career-benefits through recognition, especially informal career benefits such as preferred transfers and postings.

Peer PLUS (T3): Teachers in this group are administered the same script as T1. However, the administration is framed with an additional *motivational framing* to boost individual morale and beliefs in ability to do well in the training and the job more broadly. The motivational framing aims to improve the way information contained in the reward in perceived by the head teachers. More details on the framing are provided below.

Career PLUS (T4): Teachers in this group are administered the same script as T2. However, the administration is framed with an additional motivational framing as in T3.

Motivational Framing: The goal of this framing is to improve the information contained in the reward. This is because performance-contingent rewards can often negatively impact employee morale and beliefs in ability as they can be perceived as controlling and as negative signal of ability(Deci et al., 1989; Bénabou and Tirole, 2003). Moreover, these negative effects can be more pronounced for low-ability or less motivated individuals in tournament-based rewards like recognition (Connelly et al., 2014, Ashraf et al., 2014a, Mansoor, 2019). Hence the framing focuses on information that can bolster teacher morale and beliefs in their capabilities.

The framing is structured as follows: teachers are first asked to reflect upon three key limitations and challenges in performing well in the training and their jobs more broadly. This is followed by the distribution of a one-pager with three inspirational stories of head teachers from Punjab that

the trainees are asked to read. The stories are meant to serve as role models to bolster existing levels of belief in one's capability and ability (as in Beaman et al., 2012 and Tanguy et al., 2014 for example).[15] To create a final moment of reflection, after reading the stories trainees are asked to reflect on how they can address their own limitations. [16]

4.2 Randomization

While the SLDP training was spread across all 36 districts of Punjab, our experiment focuses on 7 districts spread across the north, south, and central regions of the province (See Figure 6). Training sessions in each district were assigned a *session number*. Stratifying by district, we randomly allocate a total of 131 training sessions to four different treatments and the control group. This yields a sample of 3,394 head teachers across 131 training sessions in 7 districts of Punjab. Descriptive statistics in Table A.1 show that our sample is 57% female, with an average teacher age of 46 years with around 20 years of experience in the service.

[15] We select these stories from a report on star teachers compiled by the Punjab School Education Department in 2017 to identify and record high performing teachers.

[16] To design this framing, we draw on the seminal work of Bandura (1986), who defines the concept of *self-efficacy* as the "perception of one's capability to accomplish a given level of performance" as central to motivation and performance. He also highlights the ability of vicarious experiences in boosting self-efficacy and thus motivation. Bandura (1986) also highlights a distinction between generalized self-efficacy and domain-specific self-efficacy, which is important since self-efficacy of individuals can vary across different domains. Teacher self-efficacy, for example, measures self-efficacy within the specific domain of the teaching profession. In designing the framing, we focus on how to harness teachers' domain specific self-efficacy.

Figure 1: Districts included in the Sample

4.3 Data and Balance Checks

4.3.1 Data

Teacher Training Performance Data. Our primary outcome of interest is teacher training test scores. Both the pre and post-tests were developed by the SLDP staff at the QAED headquarters. The tests included a total set of 15 MCQ questions that were directly related to the taught content.[17] Given the training in each district had multiple rounds, the pre and post-test questions

[17]See Appendix D for a sample of the training tests.

were different across rounds (although tested the same learning objectives) to reduce chances of gaming. Within each round, the pre and post-tests included the same set of questions with the only difference being in the ordering of the questions in the two tests (and the ordering of options within the questions). Our baseline pre-test score in Table A.1 shows that head teachers scored 34% on average with very few teachers subject to ceiling or floor effects.

To quantify the extent to which teacher effort on the training test is indeed driven by the incentives, we add an additional dimension to the design of the tests. Both the training pre and post-tests include two sections – an *incentivized* and a *non-incentivized* section. When trainees are administered the incentives, they are explicitly told that they will qualify for the recognition certificate based on their performance on the incentivized section only.[18]

Teacher Surveys at endline. To understand mechanisms, we collect data on a selected set of measures of head teacher attitudes and perceptions that the may have been shaped by the treatments. These include teacher intrinsic motivation, self-efficacy, locus of control, and beliefs about performance on the post-test.[19]

Teacher Surveys at baseline. We also capture a range of variables in our baseline survey to study heterogeneous treatment effects. These include basic teacher characteristics such as age, gender, salary, and years of experience; non-cognitive traits and beliefs such as personality type, intrinsic motivation, pro-social motivation, self-efficacy, and locus of control; and training and work-related variables to validate the theory underlying our treatment arms such as number of peers known in training session, time till next expected promotion, contract type, and visibility to senior leadership. [20]

[18]Since effort could be diminishing in the length of the test, we also randomize the order of the two sections in the tests.

[19]We captured intrinsic motivation and self-efficacy using existing validated scales as in Amabile et al. (1995) and Fackler and Malmberg (2016).

[20]The non-cognitive traits are measured using existing validated scales. We measure personality through the short Big Five Inventory (Rammstedt and John, 2007; Soto and John, 2017) and pro-social motivation through the Perry PSM index (Perry, 1996). For personality type, we measure each trait separately and then convert individual scores into z scores. These are then averaged to form one Big Five Index as in Callen et al. (2016) For the PSM index, we calculate the index as an average of all the scale items and then normalize the index.

Master Trainer and Enumerator Data. We also collect data on enumerator characteristics such as age, years of experience, years of education, and communication skills to be able to control for enumerator effects in our estimation. In addition, we also collected on a range of master trainer characteristics such as age, years of experience, and number of trainings received. These are also used as controls in the analysis.

School-level Performance Data. To capture the impact of our treatments on downstream outcomes at the school level, we acquire access to two types of administrative data: 1) school monitoring visits data which gives us access to school performance indicators such as teacher absenteeism and number of school council meetings held from about 3 months after the training; and 2) examination data for grade 8th students based on the provincial exams conducted by the Punjab Examination Commission nearly 8 months after the training. This gives us access to variables such as examination participation rates and passing rates of each school.

Qualitative Data. After completing our analysis, we also held several individual discussions with key stakeholders at QAED to understand our results. This included the SLDP coordinator, the assistant to the SLDP coordinator, the QAED Training and Planning Coordinator, and five different QAED master trainers. The discussions included a presentation of the key results from our analysis to each stakeholder followed by comments and observations from the relevant stakeholder. We explain our results drawing on these discussions with our stakeholders.

4.3.2 Balance Tests and Implementation

Table A.2 shows balance across treatment arms for four different categories of variables: basic teacher characteristics, job characteristics, training baseline test score, and teacher non-cognitive traits. We conduct tests of equality for each variable across all treatment groups. Our training baseline score is balanced at the 5% level of significance. Out of a total of 112 tests, 9 are different from zero at the 5% level. We control for these variables in our analysis.We also conduct joint F tests across all groups. All p-values for the joint test are greater than or equal to 0.14.

Attrition was not a serious concern in our study given the trainings were mandatory for head teachers to attend. However, there is small attrition in our sample (3%) due to teachers being absent on the fourth day of the training when the post-test took place.[21] Table A.3 shows that attrition is not related to any of our treatment groups and Table A.4 shows that the attrited and main sample are balanced across a range of teacher characteristics at baseline.

Where spillovers are concerned, these are unlikely in our setting. The treatment is at the training session level and there is minimal interaction between sessions during the day as trainings are conducted from 8:00 am to 2:00 pm every day within specific training classrooms after which trainees head home. In addition, we only have one head teacher from each school which further minimizes the chances of spillovers after the training is over each day. Spillovers across rounds of trainings are also unlikely given there is no time span across rounds to enable interaction between teachers across schools.

5 Empirical Strategy and Results on Training Performance

5.1 Empirical Strategy

To identify the main treatment effects of our interventions on training test scores, we estimate the following:

$$y_{isd}^{Post} = \beta_0 + \rho . y_{isd}^{Pre} + \beta_1 PR_{isd} + + \beta_2 CR_{isd} + \beta_3 PRplus_{isd} + + \beta_4 CRplus_{isd} + \gamma X_{isd} + \mu_d + \alpha_r + \epsilon_{isd} \quad (4)$$

Where y_{isd}^{Post} is the post-test score for teacher i in session s, and district d; y_{isd}^{Pre} is the pre-test

[21] This occurred either due to personal emergencies or teachers being absent without any officially sought leave.

score that serves as our baseline measure for the ANCOVA estimation. The post-test and pre-test scores are normalized by the mean and standard deviation of the control group. Hence, the treatment effects are observed in standard deviations units. X_{isd} is a vector of teacher, enumerator, and master trainer controls that we include in our estimation for power. These are selected through the LASSO post double selection procedure following Belloni et al. (2014). Since our randomization is stratified by district, we include district fixed effects (as captured by μ_d) to increase the efficiency of our estimate. We also control for training round effects, α_r, by adding round dummies. Finally, errors are clustered at the training session level which is our unit of randomization (as in Abadie et al., 2017). The β coefficients are the coefficients of interest. This specification allows us to test the first and second hypotheses ($\beta_1 > 0$ and $\beta_2 > 0$) as well as the third and the fourth hypotheses ($\beta_3 > \beta_1$ and ($\beta_4 > \beta_2$).

We use Intention to Treat (ITT) to estimate our treatment effects. A small proportion of teachers (6%) refused to participate in the employer recognition scheme.[22] Table A.5 shows that non-consent is not significantly related to any of the treatment groups.[23]

5.2 Main Effects on Training Performance

Treatment effects of Peer (T1) and Career (T2). Table 1 shows the treatment effects on standardized training test scores. We first focus on the treatment effects in the Peer and Career arms as shown in Column 2.[24] We find that teachers in the Career arm score 0.25σ higher training test scores as compared to the control group (significant at the 10% level). In comparison, the Peer arm has a coefficient of 0.04 and is insignificant. Kolmogorov–Smirnov tests of equality of distribution between the Peer and Career arm confirm that the distributions are significantly different from each other at the 1% level.[25]

[22]This included 207 teachers which is roughly 6% of the sample.

[23]Our main treatment estimates remain the same with TOT estimation.

[24]Since we had imbalance on some teachers characteristics, we discuss the results where we include controls in column 2.

[25]The distributions are presented in Appendix B.3.

Given the Career arm made potential career benefits salient, these results point towards the value of informal career benefits in the system that the teachers could have accessed through the recognition certificate (e.g. getting transfers to preferred schools, getting selected for promotions faster once eligible, or getting appointed to higher grade positions on the same salary scale if positions become vacant). Qualitative discussions with selected trainees and our main counterparts at QAED help explain why we observe indicative effects on the Career arm but no effects on the Peer arm. They suggest that the strength of the peer-esteem channel may be weak for head teachers given they have already risen through the ranks and established respect, reputation, and esteem amongst their peers and colleagues. Hence, such a channel may be more effective for primary and secondary school teachers who are younger and looking to establish their reputation amongst their peers (as we observed in the pilot presented in our online appendix Mansoor,2019). However, where the career-benefits channel is concerned, head teachers have strong informal career incentives in the system such as postings to their choice of school or other influential lateral appointments.

Treatment effects of Peer PLUS (T3) and Career PLUS (T4). Next, we focus on the treatment effects of the PLUS interventions with the motivational framing. Column 2 in Table 1 shows that the net impact of adding the motivational framing in Peer PLUS and Career PLUS is negative – a reduction of 0.16σ for Peer PLUS (not significant) and a reduction of 0.27σ for Career PLUS (significant at the 5% level). We also conduct Kolmogorov–Smirnov tests of equality of distribution between the Peer and Career arm and their PLUS counterparts and find that the distributions are significantly different from each other (p-value <0.01 for both tests).[26] Since the net impact of adding the framing moves in a negative direction for both arms, we pool the PLUS treatments (i.e. those receiving the framing) and the non-PLUS treatments (i.e. those not receiving the framing) in Columns 3 and 4. Column 4 shows that the net impact of adding the motivational framing to either of the arms is to lower training test scores by 0.22σ (significant at the 5% level).

The negative effects imply that adding the motivational framing to our recognition incentives

[26]The distributions are presented in Appendix B.4.

resulted in teachers reducing effort in the training, which runs counter to H3 and H4 in Section 3.[27] While our findings are inconsistent with the positive effects of similar motivational interventions (that focus on boosting aspirations and self-efficacy) on a range of outcomes such as job search and health-seeking behaviours (see Eden and Aviram, 1993; Haushofer, John, and Orkin, 2019), they are in line with arguments of skeptics who suggest that creating "positive illusions" of oneself can often have negative effects by leading to overconfidence (Baumeister, 1999; Swann, 1996). They also relate to recent empirical evidence by McKenzie et al. (2021) on how motivational interventions that raise aspirations can backfire if aspirations are unmet. Overall, this suggests caution in the design and administration of motivational interventions as they may interact with individual non-cognitive traits in nontrivial ways.

6 Mechanisms

Our main treatment effects highlight two main sets of results: first, that the career-benefits channel appears to improve training performance. Second, the motivational framing appears to have negative effects on training performance.

In this section, we follow these two sets of results one by one to understand mechanisms underlying these effects.

[27] Our analysis of the net impact of the framing assumes that the PLUS treatments are a linear combination of the incentive scheme and the motivational framing. However, if the two treatments interact together in non-linear ways our point estimates of the net impact of the framing would not be accurate. Irrespective of this assumption, our results highlight that the combination treatment with the framing does worse than the recognition incentive alone. This implies that while this negative effect may not represent the 'true' net impact of the frames, it does capture the substitution effect of including the framing. This interpretation is equally relevant for the implications of these results.

6.1 Mechanisms: Unpacking Treatment Effects in Career arm

Quantile Treatment Effects. While the Career arm appears to work, an important question is whether the effects are driven by the lower or upper tail of the distribution of training test scores. This is especially important in the context of tournament-based rewards (such as our recognition incentive) which often merely elicit effort from agents in the upper tail of the ability distribution (Connelly et al., 2014). To understand the heterogeneity of our treatment across the distribution of training test scores, we estimate quantile treatment effects.

Table 2 shows quantile treatment effects at quantile $\tau \in$ (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9). It shows that the Career arm has a positive coefficient in the range of 0.08 - 0.31 across the entire distribution of the training test scores and that the coefficient is always higher than the Peer arm (see Figure 2). The coefficients on the Career arm are significant at the 5% level in the upper tail of the distribution, where they are also significantly different from the Peer arm. These trends confirm that the career-benefits channel encourages effort across the distribution of training test scores, instead of merely high ability individuals as proxied by training test scores. It also provides further evidence that the career-benefits channel is stronger than the peer-esteem channel in this context.

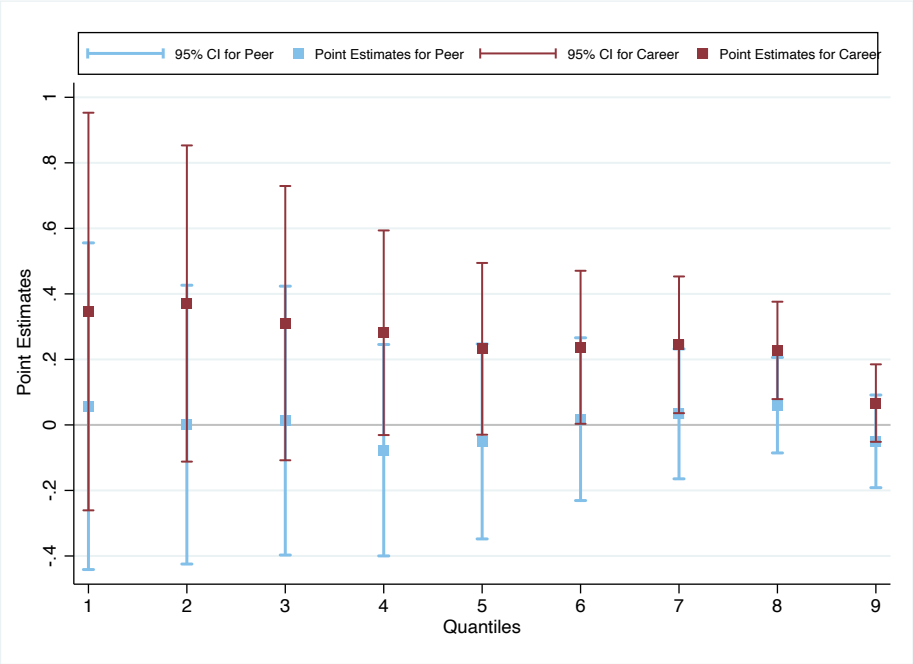

Figure 2: Quantile Treatment Effects

Heterogeneity by Key Moderators. Next, we investigate whether the Career arm works as hypothesized in theory, i.e. whether agents respond to the incentive because they believe it could result in tangible career benefits in the future.

To investigate this, we hypothesize that the Career arm should work better for teachers who have a higher likelihood of being able to use the recognition certificate to reap tangible career benefits in the future. We identify three such categories of teachers: teachers who are expecting a promotion soon, teachers who have higher visibility to senior leadership, and teachers who are permanent employees. These teachers are more likely to use the recognition incentive for career benefits because of the following reasons. First, given teachers in our context have informal career incentives of being posted to their postings of preference (e.g. a school of their liking or other lateral appointments), an upcoming promotion can make these incentives more salient. In our sample, the median time to next promotion is 5 years. We identify teachers as *more promotion eligible* as those who have an upcoming promotion within the next 5 years. Second, higher visibility to senior leadership can increase access to supervisors which can increase opportunities to reap informal career incentives in the system. We identify teachers where frequency of visits by senior leadership (such as Secretary Education and District Education Officers) to the teachers' districts is at least once in 3 months as *more visible to leadership.* Finally, 17% of our sample includes head teachers who are working on a contractual basis and do not have the same career incentives as permanent teachers. We identify teachers who are on permanent contracts as *permanent* employees.

Columns 1, 2, and 3 in Table 3 show that when the Career arm works, the treatment effect comes from individuals who are due for their next promotion sooner, have a higher frequency of visits by the Secretary, or are permanent employees. Of particular note is the fact that the difference in the treatment effect of the Career arm between teachers who have less time to promotion (0.33 σ) versus those who have more time to promotion (0.13 σ), and between permanent (0.28 σ) and temporary employees (0.02 σ) is statistically significant (p-value 0.03 and 0.02 respectively).[28]

[28]We also hypothesize that the Peer arm should work better if teachers know their peers well in the training session. This rests on the assumption that the *peer-esteem* from the Peer arm would be stronger if a teacher knows his/her peers. To operationalize and test this theory, we also explore heterogeneous treatment effects by

Treatment Effects on the Non-Incentivized Dimension. Finally, to confirm if teachers are indeed responding to the incentive in the Career arm, we compare the treatment effects on the non-incentivized and incentivized dimension of the test. To estimate these effects, we use the same specification as (4) but with the non-incentivized test scores as our outcome variable.

Columns 5-8 in Table 4 show the treatment effects on the non-incentivized dimension. We find that the treatment effect of the Career arm on non-incentivized training test scores is insignificant and much smaller as compared to the incentivized dimension (0.022 versus 0.250). This confirms that the Career arm is indeed working as an incentive, and in fact teachers respond to the treatment strategically by exerting more effort on the incentivized dimension to acquire the incentive.[29]

Column 6 in Table 4 also shows that the net impact of the framing on non-incentivized training scores is negative as on incentivized test scores, with the results particularly negative and significant for the Career PLUS arm. These results provide further evidence that teachers who received the motivational framing reduced effort in the training across the board.[30]

6.2 Mechanisms: Unpacking Treatment effects in PLUS arms

Treatment effects on motivation index and beliefs about post-test performance. The main assumption behind the design of the PLUS treatments is that the motivational framing should improve the design of the recognition rewards by addressing potential negative effects on individual morale and beliefs about ability.

the number of peers each trainee knows in their group but find no significant effects (See Columns 4 and 5).

[29]It is possible that this strategic effort is exerted to cheat/game the test instead of exerting more effort on the test. In terms of gaming the test, trainees could have received test questions ahead of the training test or tried to cheat during the test. Our implementation ensured that neither was possible. It might still be possible that trainees who wanted to score better tried to recall questions from the pre-test and memorized those responses ahead of the test. However, we see the latter not as an indication of gaming but as evidence of wanting to exert more effort on the test as a result of the incentive.

[30]One might argue that the negative effects of the framing were specifically due to the interaction effects between the incentive and the framing. This result takes a step towards ruling out this argument.

We investigate the impact of the PLUS treatments on different dimensions of teacher motivation such as intrinsic motivation (Deci and Ryan, 1985), self-efficacy (Bandura, 1986), and locus of control (Rotter, 1966). We measure these using pre-existing validated scales and normalize them by the mean and standard deviation of the control group. To avoid challenges of multiple hypothesis testing, we develop an overall index of teacher motivation as an average of these three measures. We also measure teacher beliefs about post-test performance to capture test specific teacher self-efficacy (i.e. teacher beliefs about their ability to perform well in the test) by asking teachers how much they believed they scored on the post-test on a scale of 1-100. To estimate our treatment effects on the motivation index and teacher beliefs about post-test performance, we run the same specification as (4) but with the teacher motivation index or beliefs about post-test performance as the outcome measure.

Column 2 in Table 5 shows that net impact of the framing in the Career PLUS arm is to increase teacher motivation 0.12σ. The net impact of the framing in the Peer PLUS arm is positive but insignificant. Column 4 in Table 5 shows that the net impact of the framing across both the PLUS arms is to increase teacher motivation by 0.08σ.

These results confirm that while the motivational framing reduces training test scores, it does boost teacher motivation. Table A.6 shows these results by each dimension of teacher motivation - intrinsic motivation, self-efficacy, and locus of control - and confirms positive and significant effects of the PLUS arms on teacher self-efficacy, as well as positive coefficients on internal locus of control and intrinsic motivation.

6.3 Why did teachers reduce effort in PLUS arms?

In this subsection we investigate the mechanisms underlying the negative impact of the motivational framing on training test scores. We hypothesize that while the framing improved teacher motivation, they could have simultaneously made teachers overconfident in their ability to do well in the training which could have led to a reduction in teacher effort (and ultimately training

test scores). This explanation is consistent with skeptics who argue that interventions that aim to improve individual self-esteem or efficacy can at times *over-correct* beliefs about ability leading to dangers of overconfidence (Swann, 1996; Baumeister, 1999; Bénabou and Tirole, 2002).

Treatment effects on Overconfidence. In our endline survey, we ask teachers to report how much they believe they scored on the training post-test. This allows us to construct a direct measure of teacher overconfidence as the difference between beliefs about performance and actual performance on the post-test. Typically, measures of overconfidence across economics and psychology are constructed by asking respondents a set of questions, along with their rate of confidence in the answers to each question. Overconfidence is then measured as the *positive bias*, when difference between average confidence level and the proportion of correct answers is greater than zero (Adams, 1957; Michailova, 2010). Since the fundamental idea in measuring overconfidence is to observe individual judgement and/or responses compared to a gold standard of truth (Baumann et al., 1991), our measure of overconfidence is an example of a direct measure of overconfidence and similar to measures used by others such as Glaser et al. (2005).[31]

To investigate treatment effects on overconfidence, we run the same specification as (4) but use teacher overconfidence as our outcome measure. Column 2 in Table 6 show that the net impact of the motivational framing on overconfidence is positive and significant, making teachers 6.8% points more overconfident in Peer PLUS and 5.3% points more overconfident in Career PLUS. Column 4 shows that the net impact of adding the motivational framing across both the PLUS arms is to make teachers 6% points more overconfident. Since our measure of overconfidence is a continuous variable where outliers might drive results, we re-define the measure as above and below median overconfidence and repeat the estimation of our treatment effects in Columns 5-8. We find the same results, with Column 8 showing that the net impact of the motivational framing across both the PLUS arms is to increase the proportion of above-median overconfident

[31]Many studies on ovrconfidence try to measure innate overconfidence in individuals, and hence factors such as task complexity, subject's level of motivation, and skills of subject become important in being able to accurately asses the relationship between overconfidence and accuracy of judgement (Keasey and Watson, 1989). In our case, randomization should ensure that individual level of motivation and skills are balanced between treatment and control groups with the only difference being exposure to different treatments.

trainees by 12.4% points on average.[32]

Mediation Analysis: Overconfidence. We use mediation analysis to quantify the strength of the overconfidence channel in explaining the negative effects of the motivational framing.

We use the procedure of sequential g-estimation as laid out in Acharya et al. (2016) to identify the Average Controlled Direct Effect (ACDE) of the net impact of the motivational framing after accounting for the effects of overconfidence. While ACDE is often calculated by including the post-treatment mediator in the original estimation, this leads to inconsistent estimates due to selection bias. The sequential g-estimation procedure of estimating ACDE, on the other hand, excludes the effect of the mediator (in this case overconfidence) from the observed treatment effect by fixing it at the same level for all units which helps avoid issues of selection bias.[33] The identification of the estimates rests on one central assumption - sequential unconfoundedness - which incorporates two further assumptions: a) there is no omitted variable that is correlated with the error term and the outcome variable; and b) there is no omitted variable that confounds the effect of the mediator on the treatment post controlling for pre-treatment variables and other post-treatment controls. In our setting where treatments are randomly assigned, a) is not violated by design. We assume b) is not violated in our particular setting.[34]

Since overconfidence is measured as the difference between beliefs about training post-test score

[32]Note that an alternate explanation could be that while the frames improved teacher motivation, they simultaneously compromised their cognitive bandwidth (Mullainathan and Shafir, 2013). This could be because the frames provided teachers with additional information which may have caused an information overload that mentally taxed teachers or diverted their attention away from the training. We are limited by the lack of direct observational or survey data that measures distraction, stress, or other aspects of cognitive bandwidth that can allow us to directly rule out this channel. However the strong treatment effects on overconfidence and the upcoming mediation analysis indicates that this is not a likely channel.

[33]We do this in three steps: Step 1 includes regressing the main outcome on treatment, pre-treatment controls, the mediator, interaction between the mediator and treatment, and interaction between the mediator and all other pre-treatment variables, Step 2 involves calculating the de-mediated outcome which is the predicted outcome excluding the magnitude of all coefficients that include the mediator; Step 3 includes regressing the de-mediated outcome on the treatment. The coefficient on the treatment in the final step is the ACDE.

[34]Assumption b) is unlikely to be violated in our setting since individual beliefs of overconfidence are unlikely to have many other confounders (other than a key set of variable such as individual self-efficacy and locus of control) that lead to a reduction in teacher effort and test scores. We control for such potential post-treatment confounders such as self-efficacy and locus of control.

and actual post-test score, including this measure of overconfidence to estimate the de-mediated outcome poses endogeneity concerns due to the high mechanical correlation between overconfidence and the outcome variable – post-test scores. To address these concerns, we predict overconfidence in our sample using baseline variables selected by LASSO as the best predictors of overconfidence. Table A.7 in the appendix shows that the correlation between predicted overconfidence and actual overconfidence is around 0.30. We also estimate treatment effects on our predicted measure of overconfidence and find that the impact of the PLUS treatments on overconfidence remains positive and significant, though the effects are smaller (see Table A.9). This gives us confidence in using our predicted measure of overconfidence in the mediation analysis.

Table 7 shows the original estimation (Column 1) and the revised estimation based on the de-mediated outcome (Column 3). While the net impact of the motivational framing is -0.22σ (significant at the 5% level) in column 1, the ACDE in Column 3 reduces to -0.03 (insignificant). This implies that overconfidence approximately explains up to 86% of the observed negative treatment effects of the PLUS arms (See Figure 7).

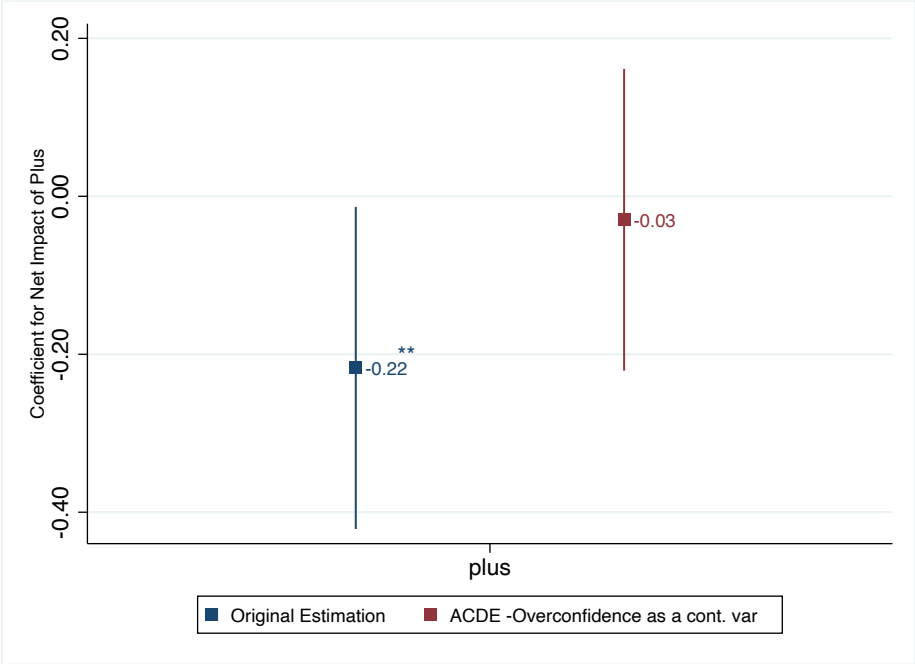

Figure 3: Average Controlled Direct Effect (De-mediated Test Scores)

6.4 Treatment Effects on School Performance

Finally, we investigate the impact of our treatments on a set of downstream outcomes at the school level. Government in-service trainings are the primary platform for improving teacher knowledge and skills for downstream improvements in school performance and student learning outcomes. However, implementation of training knowledge into actual practices can be challenging, especially without top-down monitoring or support structures (Banerjee et al., 2016). Hence, understanding whether incentives in trainings create any motivational spillovers that encourage knowledge translation into on-the-job practices and downstream improvements is important. Moreover, we also aim to investigate whether the positive and negative impacts on training knowledge cascade into improvements in downstream outcomes.

To study the impact of our treatments on downstream outcomes, we use government administra-

tive data from two distinct sources. First, we use administrative data from monthly school-level monitoring visits that are conducted by the Education Department 3 months following the training. This provides us with a set of key school performance indicators that could be impacted by improved head teacher practices - teacher absenteeism (% teachers absent) and performance of school management committees (no. of school council meetings). Second, we web scrape data on exam scores administered by the Punjab Education Commission for 8th grade students nearly 8 months after the training.[35] This gives us two student-focused school performance indicators: exam fail rate (% students who failed exam) and exam participation rate (% students who appeared in exam).

We investigate treatment effects on these school performance indicators through the following specification:

$$S_{isd}^{Post} = \beta_0 + \rho.S_{isd}^{Pre} + \sum_j \beta_j T_{ij} + \mu_d + \epsilon_{isd} \tag{5}$$

Where S_{isd}^{Post} represents the relevant school performance indicator for teacher i in session s and district d, S_{isd}^{Pre} represents the baseline measure for the school-level indicator, and $\sum_j \beta_j$ are the treatment coefficients. As in the other specifications, we use district fixed effects and cluster errors at the training session level.

Table 8 shows that that we find no treatment effects on any of our downstream outcomes of interest. These results highlight that the positive and negative impacts that we observe on training knowledge do not cascade into any downstream impacts. We find a negative and marginally significant impact on exam fail rate in the Peer PLUS arm. While this could be because of the increase in the motivation index in the Peer PLUS arm and its related positive spillovers on practices, we do not observe similar impacts in the Career PLUS arm. Hence, there is no conclusive evidence on whether or not the motivational framing actually encouraged knowledge

[35] Matching the school names to our existing data results in a 75% match. We check whether this sub-sample is balanced across treatments and find that the sample is not balanced for Peer PLUS and Career Plus arms. see Table A.10. Hence we add variables that are unbalanced as controls

translation into on-the-job practices and improvements in exam performance.

These null results point to two possible conclusions. First, it is possible that the management training in this context did not have the expected downstream impacts (as in Muralidharan and Singh, 2020). The assumption that improvements in training knowledge of head teachers should have improvements in downstream outcomes assumes a causal relationship between head teacher management trainings and school outcomes. While existing research points to the positive relationship between head teacher management practices and school outcomes (Leaver et al., 2019; Bloom et al., 2015), causal evidence on the impact of head teacher management trainings on school outcomes is sparse and shows mixed results (Fryer, 2017; Muralidharan and Singh, 2020; Romero et al., 2021).[36] Moreover, the trainings appear to focus on a variety of topics ranging from support with instruction, classroom monitoring, use of data, and leadership. This poses the question of how to categorize this range of management trainings, and whether some types of trainings are more effective than others in improving downstream outcomes.

Second, it is possible that the improvements in training knowledge had impacts on intermediary outcomes that are one step down the causal chain such as the head teachers' own practices and attitudes and teachers' practices, beliefs, and attitudes. This could especially be the case since leadership trainings, such as the one in our context, often aim to impact school performance and student outcomes through changing practices and attitudes of head teachers as well as teachers (Leithwood and Jantzi, 2000). This highlights the need for further research that tracks mechanisms for how management and leadership focused trainings cascade into changes in on-the-job practices and attitudes of head teachers and teachers into improving school performance and student learning outcomes.

[36]Romero et al. (2021) show that head teacher training focused on leadership and implementation of classroom observation tools improves head teacher management practices but not training test scores; Muralidharan and Singh (2020) show that head teacher training on use of data has no impact on learning outcomes; Fryer (2017) shows that head teacher training focused on improving classroom pedagogy improves learning outcomes.

7 Concluding Remarks

We present experimental evidence on the impact of employer recognition on teacher training performance in mandatory government in-service trainings held by the Teacher Training Academy in Punjab Pakistan. The study shows that employer recognition can improve teacher performance in trainings if it is linked to tangible career benefits in the future. Despite these positive results, we find that these effects can backfire depending on how such incentives are framed. In particular, we find that adding a motivational framing focused on boosting morale and beliefs about ability to our recognition treatments "over corrects" teacher beliefs about ability to do well in the training leading to overconfidence and reduced effort.

Our results have two key policy implications. First, they open up a discussion on how the public sector can design more effective non-financial incentives for eliciting higher public school teacher effort more specifically, and public sector employee effort more broadly. The career-linked recognition incentive used in this experiment was fairly light touch, yet we find encouraging results which indicates the value of informal career benefits in the system. In our particular context, there are several informal career incentives for teachers such as getting a transfer to a school of liking, getting laterally appointed to an influential position such as Project Director of a large donor-funded program which may be associated with additional pay, or getting appointed to a higher grade position (with the same pay and civil service grade) if a vacancy arises. In the public sector where formal incentive-based reforms are often hard to implement and formal career incentives such as promotions are primarily linked to seniority, designing "soft" non-financial incentives that can leverage informal career incentives can address part of the inefficiency in incentive systems. Second, our results highlight the sensitivity of such incentives to framing effects and how they might interact with individual non-cognitive traits in nontrivial ways. This requires caution in how such incentives are designed across different contexts.

Several additional questions remain open to inquiry. Our experiment was only able to offer the incentive for a single time. Future work could look at the decay rate in the impact of such incentives, and circumstances under which the effects are sustained. Recognition has been of-

ten modelled in standard principal-agent utility maximizing frameworks, but clarity around the weight placed on such incentives in comparison to financial incentives would be useful in calibrating their value and assessing the cost effectiveness of such incentives more explicitly. Given implementation of high quality trainings to public sector employees and achieving their intended downstream effects is generally challenging (see Banerjee et al., 2016), future research on the extent to which incentives in trainings can encourage such downstream implementation, and whether certain types of incentives are more effective than others in achieving this would be useful. Finally, our experiment showed that creating exogenous variation in intrinsic motivation of public sector bureaucrats is possible through the use of our motivational framing. This opens up the possibility of additional research on how to create exogenous variation in intrinsic motivation and/or other non-cognitive traits in the workplace that can shape identities, norms, and culture.

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Table 1: Treatment Effects on Training Performance

	(1)	(2)	(3)	(4)
Peer	0.013	0.036		
	(0.150)	(0.152)		
Career	0.234	0.250*		
	(0.151)	(0.149)		
Net Impact of Framing: Peer PLUS	-0.162	-0.160		
	(0.144)	(0.142)		
Net Impact of Framing: Career PLUS	-0.246*	-0.274**		
	(0.134)	(0.135)		
Peer and Career			0.125	0.144
			(0.134)	(0.133)
Net Impact of Framing : Pooled PLUS			-0.200*	-0.216**
			(0.103)	(0.103)
Peer PLUS*	-0.15	-0.12		
Career PLUS*	-0.01	-0.02		
PLUS*			-0.08	-0.07
Observations	3394	3392	3394	3392
PDS LASSO controls	No	Yes	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes

Notes: Errors clustered at the training session level which is the unit of randomization. All regressions are an ANCOVA estimation with baseline values of the dependent variable and with district FE. Controls include trainee-level teacher controls, master trainer controls, and enumerator controls. Training post test and pre test scores are normalized by the mean and standard deviation of the control group. The PLUS treatments with the asterisks present the overall impact of the treatments (Incentive + the frame). Estimates are significant at the *10%, **5%, and ***1% level

Table 2: Quantile Treatment Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	10th	20th	30th	40th	50th	60th	70th	80th	90th
Peer	0.028	0.016	0.009	-0.068	-0.040	-0.008	0.030	0.042	-0.051
	(0.300)	(0.228)	(0.227)	(0.160)	(0.139)	(0.129)	(0.101)	(0.071)	(0.073)
Career	0.306	0.372	0.333	0.272	0.229*	0.242**	0.242**	0.212***	0.080
	(0.385)	(0.247)	(0.233)	(0.168)	(0.133)	(0.118)	(0.099)	(0.076)	(0.058)
Net Impact of Framing:									
Peer PLUS	-0.163	-0.157	-0.100	-0.082	-0.066	-0.054	-0.079	-0.097	-0.084
	(0.238)	(0.209)	(0.190)	(0.158)	(0.150)	(0.116)	(0.092)	(0.073)	(0.068)
Net Impact of Framing:									
Career PLUS	-0.282	-0.303	-0.312*	-0.287**	-0.250**	-0.266**	-0.198**	-0.155**	-0.124**
	(0.300)	(0.229)	(0.186)	(0.137)	(0.114)	(0.105)	(0.087)	(0.074)	(0.049)
Observations	3392	3392	3392	3392	3392	3392	3392	3392	3392
PDS LASSO controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The regressions report quantile treatment effects. Errors clustered at the training session level which is the unit of randomization. All regressions are an ANCOVA estimation with baseline values of the dependent variable and with district FE. Controls include trainee-level teacher controls, master trainer controls, and enumerator controls. Training post test and pre test scores are normalized by the mean and standard deviation of the control group. Estimates are significant at the *10%, **5%, and ***1% level

Table 3: Heterogeneous Treatment Effects - by Moderators

	Post Test Scores				
	(1)	(2)	(3)	(4)	(5)
Heterogeneous effects by:	Time till next promotion	Secretary visibility	Nature Contract	Peer known in class	Proportion peers known
Below Median (temp contract) x Peer	0.034	-0.031	-0.010	0.097	0.159
	(0.166)	(0.152)	(0.190)	(0.154)	(0.201)
Above Median (perm contract) x Peer	-0.043	0.243	0.031	-0.084	-0.197
	(0.160)	(0.216)	(0.152)	(0.168)	(0.209)
Below Median (temp contract) x Career	0.328**	0.206	0.021	0.214	0.098
	(0.162)	(0.157)	(0.175)	(0.160)	(0.216)
Above Median (perm contract) x Career	0.126	0.391**	0.279*	0.256	0.241
	(0.175)	(0.184)	(0.152)	(0.159)	(0.190)
Below Median (temp contract) x Peer PLUS	-0.225	-0.217	-0.191	-0.214	-0.018
	(0.187)	(0.166)	(0.189)	(0.172)	(0.237)
Above Median (perm contract) x Peer PLUS	-0.104	0.230	-0.134	-0.092	-0.336
	(0.165)	(0.214)	(0.171)	(0.185)	(0.215)
Below Median (temp contract) x Career PLUS	0.030	-0.016	-0.031	0.018	0.180
	(0.161)	(0.143)	(0.151)	(0.148)	(0.166)
Above Median (perm contract) x Career PLUS	-0.051	0.023	-0.013	-0.061	-0.300
	(0.156)	(0.207)	(0.150)	(0.160)	(0.237)
Observations	2181	3394	3394	3394	3394
PDS LASSO controls	No	No	No	No	No
District Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: Errors clustered at the training session level which is the unit of randomization. All regressions include district FE. Each column represents heterogeneous treatment effects by a different moderator. Estimates are significant at the *10%, **5%, and ***1% level

Table 4: Treatment Effects on Non-Incentivised Training Scores

	Incentivised				Non Incentivised			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer	0.013	0.036			-0.094	-0.097		
	(0.150)	(0.152)			(0.106)	(0.107)		
Career	0.234	0.250*			0.045	0.022		
	(0.151)	(0.149)			(0.082)	(0.089)		
Net Impact of Framing:								
Peer PLUS	-0.162	-0.160			-0.017	-0.021		
	(0.144)	(0.142)			(0.125)	(0.116)		
Net Impact of Framing:								
Career PLUS	-0.246*	-0.274**			-0.171*	-0.185**		
	(0.134)	(0.135)			(0.095)	(0.091)		
Peer and Career			0.125	0.144			-0.023	-0.036
			(0.134)	(0.133)			(0.082)	(0.088)
Net Impact of Framing:								
Pooled PLUS			-0.200*	-0.216**			-0.095	-0.106
			(0.103)	(0.103)			(0.080)	(0.076)
Peer PLUS*	-0.15	-0.12			-0.11	-0.12		
Career PLUS*	-0.01	-0.02			-0.13	-0.16		
PLUS*			-0.08	-0.07			-0.12	-0.14
Observations	3394	3392	3394	3392	3394	3392	3394	3392
PDS LASSO controls	No	Yes	No	Yes	No	Yes	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Errors clustered at the training session level which is the unit of randomization. All regressions are an ANCOVA estimation with baseline values of the dependent variable and with district FE. Controls include trainee-level teacher controls, master trainer controls, and enumerator controls. Training post test and pre test scores are normalized by the mean and standard deviation of the control group. The PLUS treatments with the asterisks present the overall impact of the treatments (Incentive + the frame). Estimates are significant at the *10%, **5%, and ***1% level

Table 5: Treatment Effects on Motivation Index and Beliefs about Post Test Performance

	Motivation Index				Beliefs about Test Performance (out of 100)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
Peer	0.031	0.051			-0.806	-0.574		
	(0.034)	(0.034)			(1.046)	(1.108)		
Career	-0.011	0.003			1.481	1.521		
	(0.037)	(0.034)			(1.232)	(1.214)		
Net Impact of Framing: Peer PLUS	0.034	0.042			2.376**	2.328**		
	(0.040)	(0.037)			(0.987)	(0.990)		
Net Impact of Framing: Career PLUS	0.120***	0.116***			-0.824	-1.130		
	(0.040)	(0.040)			(1.397)	(1.401)		
Peer and Career			0.009	0.026			0.372	0.515
			(0.032)	(0.029)			(1.002)	(1.029)
Net Impact of Framing: Pooled PLUS			0.079***	0.081***			0.732	0.528
			(0.030)	(0.029)			(0.906)	(0.957)
Panel B								
Peer PLUS*	0.07	0.09			1.57	1.74		
Career PLUS*	0.11***	0.12***			0.66	0.39		
PLUS*			0.09**	0.11***			0.73	1.03
Observations	3375	3373	3375	3373	3072	3072	3072	3072
PDS LASSO controls	No	Yes	No	Yes	No	Yes	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Errors clustered at the training session level which is the unit of randomization. All regressions are an ANCOVA estimation with baseline values of the dependent variable and with district FE. Controls include trainee-level teacher controls, master trainer controls, and enumerator controls. Self-efficacy at baseline and endline is normalised by the mean and standard deviation of the control group. The PLUS treatments with the asterisks present the overall impact of the treatments (Incentive + the frame). Estimates are significant at the *10%, **5%, and ***1% level.

Table 6: Treatment Effects on Overconfidence

	Overconfidence (beliefs about performance - actual performance)				Overconfidence (=1 if above median overconfidence)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer	0.687	0.710			0.033	0.028		
	(2.822)	(2.878)			(0.067)	(0.063)		
Career	-2.216	-2.581			-0.066	-0.076		
	(2.900)	(2.891)			(0.073)	(0.067)		
Net Impact of Framing: Peer PLUS	6.162**	6.819**			0.124**	0.129**		
	(2.721)	(2.829)			(0.058)	(0.058)		
Net Impact of Framing: Career PLUS	5.296**	5.329**			0.115*	0.122**		
	(2.345)	(2.239)			(0.061)	(0.058)		
Peer and Career			-0.745	-0.899			-0.016	-0.023
			(2.579)	(2.601)			(0.063)	(0.058)
Net Impact of Framing: Pooled PLUS			5.618***	5.982***			0.117***	0.124***
			(1.877)	(1.901)			(0.044)	(0.044)
Peer PLUS*	6.85**	7.53**			0.16**	0.16**		
Career PLUS*	3.10	2.75			0.05	0.05		
PLUS*			4.88*	5.08*			0.10*	0.10*
Observations	3072	3072	3072	3072	3072	3072	3072	3072
PDS LASSO controls	No	Yes	No	Yes	No	Yes	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Errors clustered at the training session level which is the unit of randomization. The dependent variable is overconfidence. In the first four columns, its is constructed as a continuous variable that is the difference between teacher beliefs of how well they scored on the test and actual test score at endline. In the last four columns, we construct a dummy variable of above median overconfidence based on the continuous variable. All regressions include district FE. Controls include trainee-level teacher controls, master trainer controls, and enumerator controls. The PLUS treatments with the asterisks present the overall impact of the treatments (Incentive + the frame). Estimates are significant at the *10%, **5%, and ***1% level.

Table 7: Mediation Analysis: Average Controlled Direct Effects

	(1)	(2)	(3)
	Post Test Scores	Post Test Scores (with mediator)	Post Test Scores (de-mediated)
Peer and Career	0.144	0.134	0.134
	(0.133)	(0.137)	(0.132)
Net Impact of Framing:			
Pooled PLUS	-0.216**	-0.030	-0.027
	(0.103)	(0.117)	(0.096)
Observations	3392	3212	3212
PDS LASSO controls	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes

Notes: Errors are clustered at the training session level which is the unit of randomization. Both regressions are an ANCOVA estimation with the baseline value of the dependent variable and district FE. In column 1, the dependent variable is the post-test score. In column 2, the dependent variable is the de-mediated post-test score which is calculated by: 1) regressing the main outcome on treatment, pre-treatment controls, the mediator, interaction between the mediator and treatment, and interaction between the mediator and all other pre-treatment variables; 2) calculating the de-mediated post-test scores which is the predicted outcome excluding all coefficients that include the mediator fixed at a specific value. Controls include trainee-level teacher controls, master trainer controls, and enumerator controls. Estimates are significant at the *10%, **5%, and ***1% level.

Table 8: Treatment Effects on School-level Outcomes

	%. Teachers Absent		No. of SCMs		% Failed PEC Exams		% Absent PEC Exams	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer	0.016		-0.007		0.010		0.002	
	(0.080)		(0.041)		(0.014)		(0.003)	
Career	-0.041		0.036		0.014		0.002	
	(0.080)		(0.041)		(0.012)		(0.003)	
Net Impact of Framing: Peer PLUS	-0.034		-0.017		-0.023*		-0.001	
	(0.068)		(0.035)		(0.012)		(0.002)	
Net Impact of Framing: Career PLUS	-0.069		-0.073		0.003		-0.001	
	(0.071)		(0.047)		(0.013)		(0.002)	
Peer and Career		-0.011		0.016		0.012		0.002
		(0.073)		(0.037)		(0.011)		(0.003)
Net Impact of Framing: Pooled PLUS		-0.058		-0.046		-0.008		-0.000
		(0.050)		(0.031)		(0.010)		(0.002)
Observations	2279	2279	2279	2279	2275	2275	2279	2279
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Errors are clustered at the training session level which is the unit of randomization. Columns 1-4 are an ANCOVA estimation with the baseline value of the dependent variable and district FE. In columns 3-4 SCM refers to 'school council meetings'. The regressions in this table are based on a sub-sample of five districts where we have availability of school examination data. We add controls in this sub-sample that are not balanced in this sub-sample as shown in Table A.10. Estimates are significant at the *10%, **5%, and ***1% level.

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Appendix

Appendix A: Tables

A. 1: Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)
	Mean	Sd	p0.25	p0.50	p0.75
Basic teacher characteristics					
Age	45.54	10.31	37	49	54
Gender (=1 if male)	0.43				
Salary	77604.47	31779.54	51000	71000	97328
Years of experience	19.99	10.94	10	22	30
Years of education	15.72	0.83	16	16	16
Married (=1 if married)	0.90				
Total teachers in a session	27.38	6.48	23	26	31
Basic job characteristics					
Job Grade	15.53	2.58	15	16	17
Time till next promotion (in yrs)	6.06	4.83	2	5	10
HT's school's enrollment capacity	467.05	480.86	189	317	555
Baseline Performance					
normalised					
Pre Test Scores (Incentivized)	-0.15	1.01	-0.78	-0.23	0.32
Non-cognitive traits					
Personality traits & Self-efficacy					
BFI Index	0.01	0.55	-0.32	0.02	0.35
Openness	0.01	1.00	-0.63	0.02	0.68
Extraversion	0.01	1.00	-0.71	-0.13	1.04
Conscientiousness	0.01	1.10	-0.07	-0.07	0.27
Agreeableness	-0.00	1.00	-0.77	0.00	0.76
Neuroticism	-0.00	0.99	-0.93	0.31	0.93
Self-Efficacy	-0.01	0.99	-0.68	-0.12	0.92
Primary Motivational Orientation					
Extrinsic Motivation	0.25				
Intrinsic Motivation	0.41				
Pro-social Motivation	0.31				
Other intrinsic measures					
PSM Index	0.00	0.38	-0.26	-0.01	0.25
Donation in hypothetical game (total PKR 10,000)	4052	2876	2000	4000	5000
Observations	3394				

Notes: Pretest scores, overall personality index, each individual personality trait, and self-efficacy are normalized against the control group.

A. 2: Randomization Balance - All Treatments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Control	Peer	Career	Peer +	Career +	C-Peer	C-Career	C-Peer +	C-Career +	Peer- Career	Peer-Peer +	Career-Car +
Age	44.79	46.70	46.65	46.16	45.39	0.03**	0.03**	0.15	0.53	0.96	0.58	0.18
	(0.90)	(0.88)	(0.83)	(0.97)	(0.97)							
Gender (=1 if male)	0.42	0.57	0.50	0.56	0.45	0.01***	0.18	0.03**	0.67	0.26	0.94	0.39
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)							
Salary	69009	74779	77471	74336	70669	0.06	0.02**	0.11	0.61	0.45	0.89	0.07
	(3578)	(3408)	(3671)	(3404)	(3404)							
Years of Education	15.66	15.72	15.73	15.72	15.73	0.30	0.17	0.29	0.19	0.74	0.95	0.99
	(0.06)	(0.06)	(0.06)	(0.06	(0.06)							
Married (=1 if married)	0.91	0.95	0.93	0.93	0.94	0.02**	0.47	0.57	0.14	0.17	0.16	0.52
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)							
Basic job characteristics												
Time till next promotion (in yrs)	6.05	6.05	5.93	6.36	5.97	1.00	0.75	0.44	0.81	0.75	0.44	0.91
	(0.44)	(0.48)	(0.48)	(0.43)	(0.43)							
HT's school's enrollment capacity	237	267	330	256	246	0.32	0.04**	0.64	0.79	0.15	0.77	0.06
	(26.65)	(26.55)	(35.78)	(31.67)	(31.67)							
School Location of HT (=1 if urban)	0.11	0.15	0.17	0.07	0.08	0.35	0.19	0.30	0.39	0.68	0.08	0.06
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)							
Baseline Performance												
Pre Test (Incentivized)	-0.11	-0.13	-0.18	-0.28	-0.33	0.87	0.51	0.14	0.05**	0.72	0.29	0.18
	(0.15)	(0.17)	(0.15)	(0.14)	(0.14)							
Pre Test (Overall)	-0.04	0.02	-0.05	-0.09	-0.14	0.70	0.84	0.64	0.33	0.58	0.45	0.40
	(0.13)	(0.15)	(0.13)	(0.12)	(0.14)							
Non-Cognitive Traits												
Overall BFI Index	0.09	0.05	0.06	0.08	0.03	0.21	0.34	0.69	0.07	0.78	0.46	0.39
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)							
Self-efficacy Index	-0.04	-0.03	-0.03	-0.04	-0.02	0.87	0.95	0.99	0.80	0.91	0.86	0.82
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)							
Intrinsic Motivation	0.51	0.48	0.52	0.50	0.51	0.35	0.73	0.90	0.97	0.22	0.53	0.75
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)							
Extrinsic Motivation	0.20	0.21	0.17	0.20	0.21	0.61	0.26	0.80	0.51	0.06	0.80	0.03**
	(0.03)	(0.03)	(0.03)	(0.03	(0.03)							
Pro-social Motivation	0.27	0.29	0.29	0.28	0.26	0.54	0.52	0.90	0.56	0.97	0.67	0.23
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)							
PSM Index	0.08	0.08	0.08	0.07	0.06	0.98	0.96	0.79	0.48	0.93	0.75	0.46
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)							
Joint F-Test						0.31	0.61	0.76	0.32	0.95	0.73	0.14
Observations	716	649	687	635	707							

Notes:The first five columns report the mean and standard errors of the four recognition treatments and the control group. The last eight columns show equality of means between the control group and the treatment group, and between each treatment, for each variable of interest. Estimates are significant at the **5%, and ***1% level

A. 3: Attrited Sample and Treatments

	(1)
	Attrited(=1 if sample attrited)
Peer	0.006
	(0.019)
Career	-0.004
	(0.013)
Peer PLUS	-0.009
	(0.014)
Career PLUS	-0.008
	(0.013)
Observations	3493
Controls	No
District FE	Yes

Notes:Errors clustered at the training session level which is the unit of randomization. Estimates are significant at the *10%, **5%, and ***1% level.

A. 4: Balance across Attrited and Main Sample

	(1) Attrited Sample	(2) Main Sample	(3) P-value difference
Basic teacher characteristics			
Age	46.02	45.87	0.89
	(1.22)	(0.69)	
Gender (=1 if male)	0.45	0.50	0.38
	(0.06)	(0.04)	
Salary	73545	73186	0.39
	(4472)	(2885)	
Years of Experience	21.19	20.11	0.95
	(1.43)	(0.90)	
Years of Education	15.77	15.72	0.42
	(0.10)	(0.05)	
Married (=1 if married)	0.91	0.93	0.39
	(0.04)	(0.01)	
Basic job characteristics			
Time till next promotion (in yrs)	5.26	6.10	0.26
	(0.88)	(0.38)	
HT's school's enrollment capacity	206	269	0.07
	(38.20)	(16.36)	
School Location of HT (=1 if urban)	0.18	0.12	0.21
	(0.06)	(0.03)	
Baseline Performance			
Pre Test Scores (normalised)	-0.06	-0.20	0.26
	(0.18)	(0.14)	
Non-Cognitive Traits			
Overall BFI Index	0.00	0.06	0.31
	(0.07)	(0.03)	
Self-Efficacy Index	0.10	-0.04	0.15
	(0.12)	(0.06)	
Intrinsic Motivation	0.47	0.50	0.49
	(0.06)	(0.03)	
Extrinsic Motivation	0.24	0.19	0.35
	(0.06)	(0.02)	
Pro-social Motivation	0.28	0.28	0.99
	(0.06)	(0.02)	
PSM Index	0.01	0.07	0.09
	(0.06)	(0.02)	
Joint F			0.11
Observations	100	3394	

Notes: Errors are clustered at the training session level which is the unit of randomization. The first two columns present the means for the attrited and the main sample, whereas the third column presents the p-value difference for each variable of interest. Estimates are significant at the *10%, **5%, and ***1% level.

A. 5: Non-Consenting Sample and Treatments

	(1)
	Non-Consent(=1 if did not consent)
Peer	0.004
	(0.05)
Career	0.040
	(0.05)
Peer PLUS	0.008
	(0.05)
Career PLUS	0.030
	(0.05)
Observations	3394
Controls	No
District Dummies	Yes

Notes:Errors clustered at the training session level which is the unit of randomization. Estimates are significant at the *10%, **5%, and ***1% level.

A. 6: Treatment Effects on Motivation and Self Beliefs

	Intrinsic Motivation	External Locus	Self Efficacy
Peer	0.062	-0.064	0.031
	(0.043)	(0.062)	(0.047)
Career	-0.002	-0.022	0.001
	(0.044)	(0.064)	(0.058)
Net Impact of Framing:			
Peer PLUS	-0.026	-0.071	0.089*
	(0.048)	(0.066)	(0.052)
Net Impact of Framing:			
Career PLUS	0.092*	-0.114	0.134**
	(0.050)	(0.070)	(0.066)
Peer PLUS*	0.04	-0.13*	0.12**
Career PLUS*	0.09*	-0.14*	0.14**
Observations	3337	3306	3364
PDS LASSO controls	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes

Notes:Errors clustered at the training session level which is the unit of randomization. All regressions are an ANCOVA estimation with baseline values of the dependent variable and district FE. Controls include trainee-level teacher controls, master trainer controls, and enumerator controls that have been selected through the PDS lasso procedure. All dependent variables are normalized by the mean and standard deviation of the control group. Estimates are significant at the *10%, **5%, and ***1% level.

A. 7: Correlation between Actual and Predicted Overconfidence

	(1)	(2)	(3)
	Actual Overconfidence	Predicted Overconfidence	Post Test Scores
Actual Overconfidence	1.000		
Predicted Overconfidence	0.303	1.000	
Post Test Scores	-0.735	-0.366	1.000

Notes: Predicted overconfidence is estimated by predicting actual overconfidence using baseline variables (restricted to control group) using LASSO. Actual overconfidence is constructed as a continuous variable that is the difference between teacher beliefs of how well they scored on the test and actual post-test score at endline.

A. 8: Treatment Effects on Predicted Overconfidence

	(1)	(2)	(3)	(4)
Peer	0.758	0.539		
	(0.676)	(0.514)		
Career	0.623	0.430		
	(0.646)	(0.565)		
Net Impact of Framing: Peer PLUS	1.999***	1.579***		
	(0.674)	(0.554)		
Net Impact of Framing: Career PLUS	1.439**	0.910		
	(0.662)	(0.588)		
Peer and Career			-0.055	0.695
			(0.941)	(0.560)
Net Impact of Framing: Pooled PLUS			1.403*	1.694***
			(0.752)	(0.492)
Observations	3259	3259	3259	3259
PDS LASSO controls	No	Yes	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes

Notes: Errors clustered at the training session level which is the unit of randomization. The dependent variable is predicted overconfidence. All regressions include district FE. Controls have been selected using the PDS lasso procedure. Estimates are significant at the *10%, **5%, and ***1% level.

A. 9: Heterogeneous Treatment Effects - by Teacher Characteristics

	Post Test Scores				
	(1)	(2)	(3)	(4)	(5)
Heterogeneous effects by:	Gender	PSM	BFI	Experience	Ability
Above Median (Male) x Peer	-0.023	0.056	0.015	0.001	0.125
	(0.175)	(0.158)	(0.165)	(0.158)	(0.193)
Below Median (Female) x Peer	0.102	-0.019	0.020	0.058	-0.128
	(0.163)	(0.157)	(0.151)	(0.162)	(0.134)
Above Median (Male) x Career	0.147	0.215	0.177	0.137	0.301
	(0.181)	(0.154)	(0.159)	(0.165)	(0.191)
Below Median (Female) x Career	0.310**	0.263*	0.320**	0.354**	0.153
	(0.150)	(0.156)	(0.148)	(0.156)	(0.133)
Above Median (Male) x Peer PLUS	-0.345*	-0.130	-0.229	-0.166	-0.091
	(0.206)	(0.176)	(0.175)	(0.155)	(0.199)
Below Median (Female) x Peer PLUS	0.100	-0.162	-0.075	-0.092	-0.224
	(0.150)	(0.169)	(0.167)	(0.190)	(0.149)
Above Median (Male) x Career PLUS	-0.113	0.030	-0.022	-0.040	0.059
	(0.185)	(0.154)	(0.156)	(0.137)	(0.181)
Below Median (Female) x Career PLUS	0.050	-0.044	0.011	0.027	-0.110
	(0.149)	(0.149)	(0.149)	(0.169)	(0.124)
Observations	3394	3393	3382	3394	3394
Controls	No	No	No	No	No
District Fixed Effects	Yes	Yes	Yes	Yes	Yes

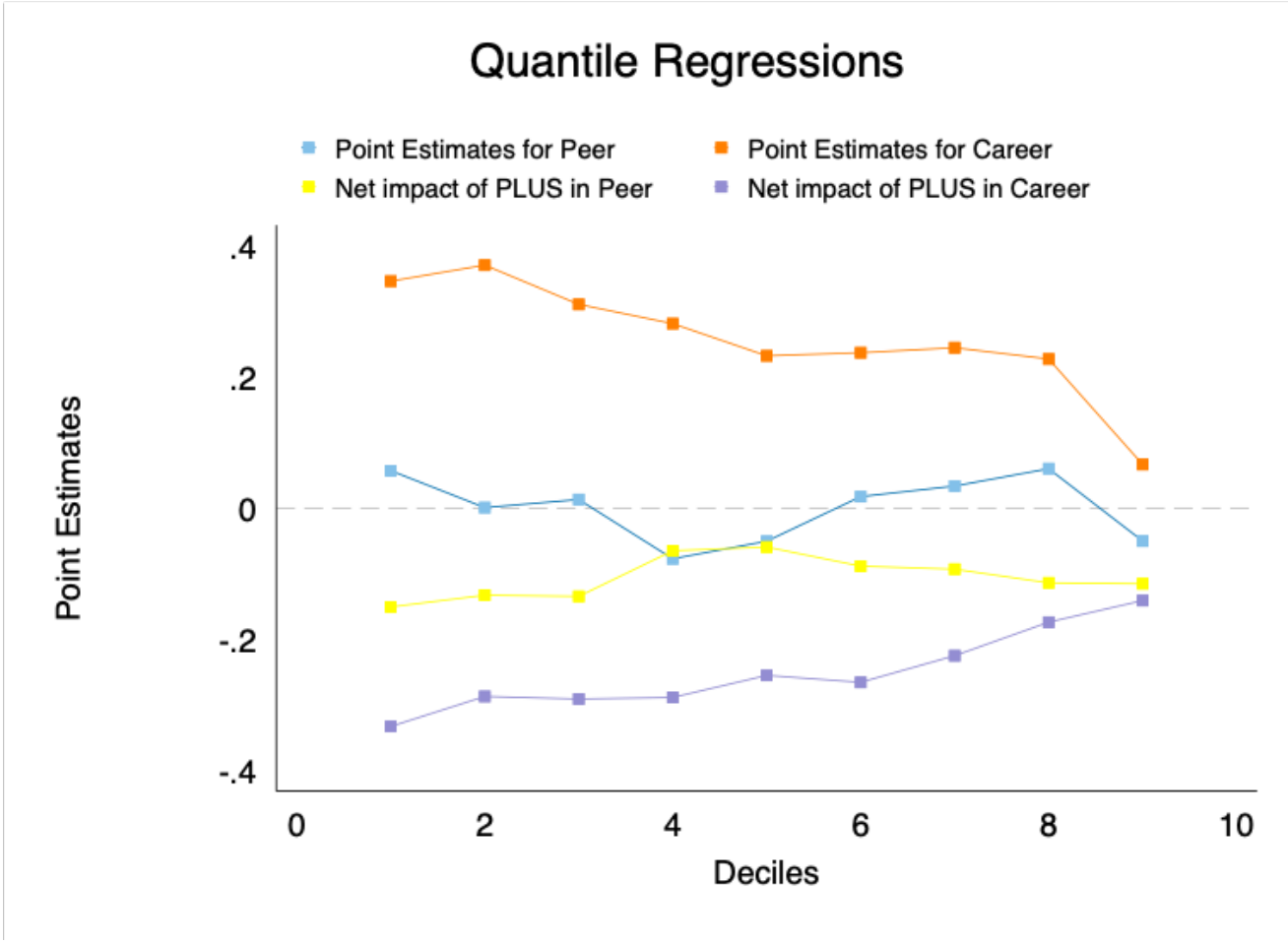
Notes: Errors clustered at the training session level which is the unit of randomization. All regressions include district FE. The Public Sector Motivation (PSM) and Big Five Personality Index (BFI) are first normalized and the above and below median categories are defined based on the normalised indices. Years of experience is based on the reported years of experience in our baseline survey. We use normalised pretest scores as a proxy for ability. Estimates are significant at the *10%, **5%, and ***1% level.

A. 10: Randomization Balance - School-level Analysis

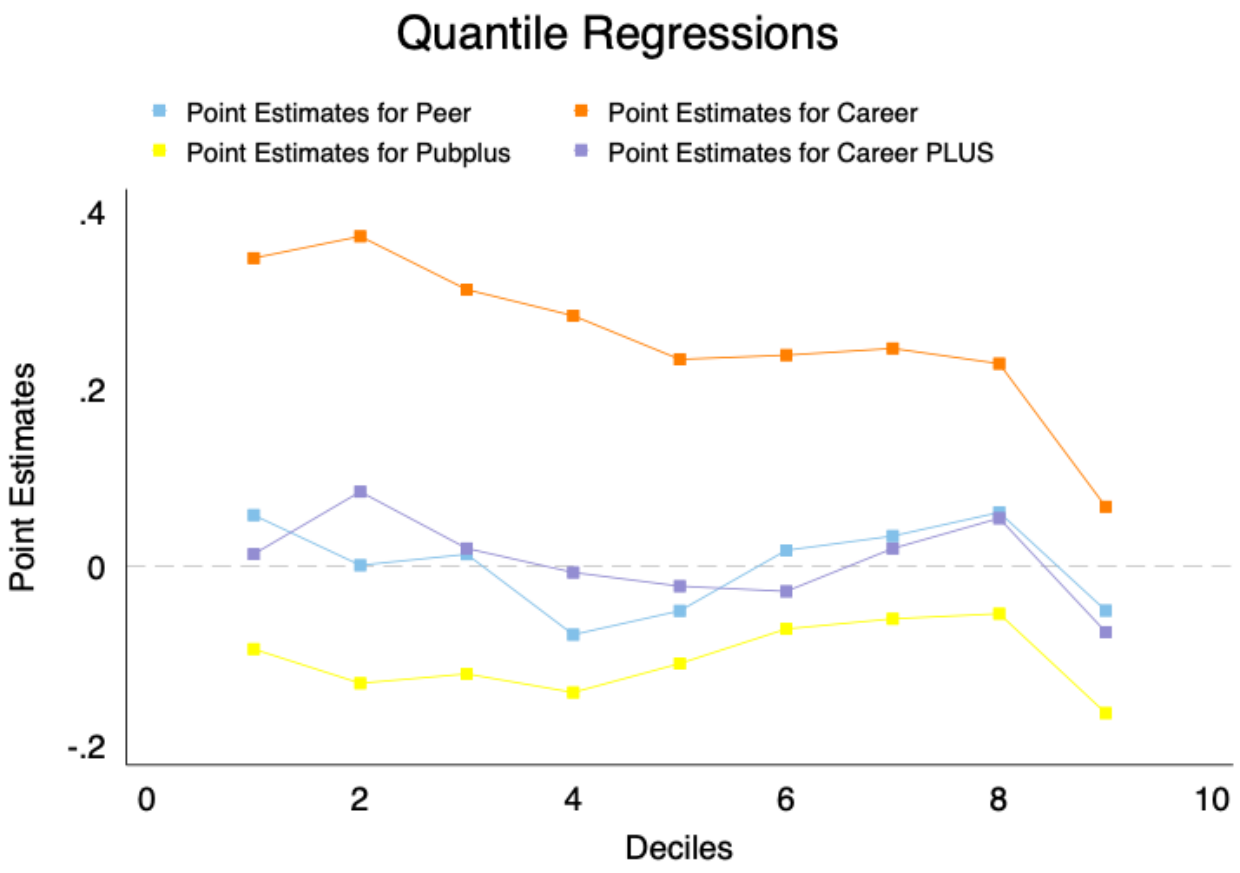
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Control	Peer	Career	Peer +	Career +	C-Peer	C-Career	C-Peer +	C-Career +
Age	45.01	46.85	46.90	45.40	46.33	0.08*	0.05**	0.73	0.22
	(0.94)	(0.92)	(0.84)	(1.00)	(0.96)				
Gender (=1 if male)	0.46	0.55	0.46	0.58	0.49	0.13	0.93	0.12	0.51
	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)				
Salary	70215	75454	78266	71820	71627	0.17	0.08*	0.68	0.72
	(3968)	(3548)	(4061)	(3509)	(4055)				
Years of Education	15.65	15.73	15.70	15.73	15.76	0.19	0.39	0.15	0.06*
	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)				
Married (=1 if married)	0.90	0.94	0.91	0.90	0.95	0.07*	0.73	0.79	0.03**
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)				
Basic job characteristics									
Time till next promotion (in yrs)	6.35	5.98	6.02	6.25	6.02	0.36	0.48	0.84	0.44
	(0.49)	(0.55)	(0.54)	(0.48)	(0.50)				
HT's school's enrollment capacity	250	261	355	246	235	0.76	0.07*	0.93	0.73
	(33.07)	(30.38)	(46.40)	(37.98)	(34.67)				
School Location of HT (=1 if urban)	0.11	0.15	0.20	0.06	0.06	0.52	0.19	0.20	0.22
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)				
Baseline Performance									
Pre Test	-0.09	-0.16	-0.15	-0.30	-0.31	0.62	0.65	0.15	0.11
	(0.15)	(0.17)	(0.16)	(0.15)	(0.16)				
Non-Cognitive Traits									
Overall BFI Index	0.09	0.04	0.07	0.08	0.05	0.29	0.70	0.84	0.36
	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)				
Self-efficacy Index	-0.10	0.02	-0.02	-0.09	0.03	0.17	0.29	0.97	0.09*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)				
Intrinsic Motivation	0.52	0.49	0.53	0.48	0.51	0.22	0.99	0.31	0.62
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)				
Extrinsic Motivation	0.20	0.22	0.16	0.23	0.22	0.53	0.17	0.45	0.47
	(0.03)	(0.03)	(0.03)	(0.03	(0.03)				
Pro-social Motivation	0.26	0.27	0.29	0.27	0.25	0.62	0.25	0.60	0.78
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)				
PSM Index	0.08	0.09	0.09	0.11	0.06	0.61	0.62	0.37	0.61
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)				
Teacher Absent (Proportion)	0.054	0.055	0.060	0.052	0.056	0.91	0.10*	0.35	0.69
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)				
Student Attendance (Proportion)	0.92	0.92	0.92	0.92	0.92	0.93	0.74	0.70	0.89
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)				
Student Council Meetings	1.70	1.66	1.54	1.50	1.67	0.84	0.33	0.28	0.90
	(0.28)	(0.24)	(0.25)	(0.23)	(0.28)				
Cleanliness rating (1 to 5)	4.09	4.07	4.18	3.98	4.06	0.88	0.23	0.26	0.79
	(0.08)	(0.10)	(0.10)	(0.11)	(0.10)				
Joint F-Test						0.363	0.229	0.044**	0.030**
Observations	496	459	476	404	485				

Notes:The first five columns report the mean and standard errors of the four recognition treatments and the control group. The last four columns show equality of means between the control group and the treatment group for each variable of interest. The cleanliness rating is from 1-5, with 5 being the highest score. Estimates are significant at the **5%, and ***1% level

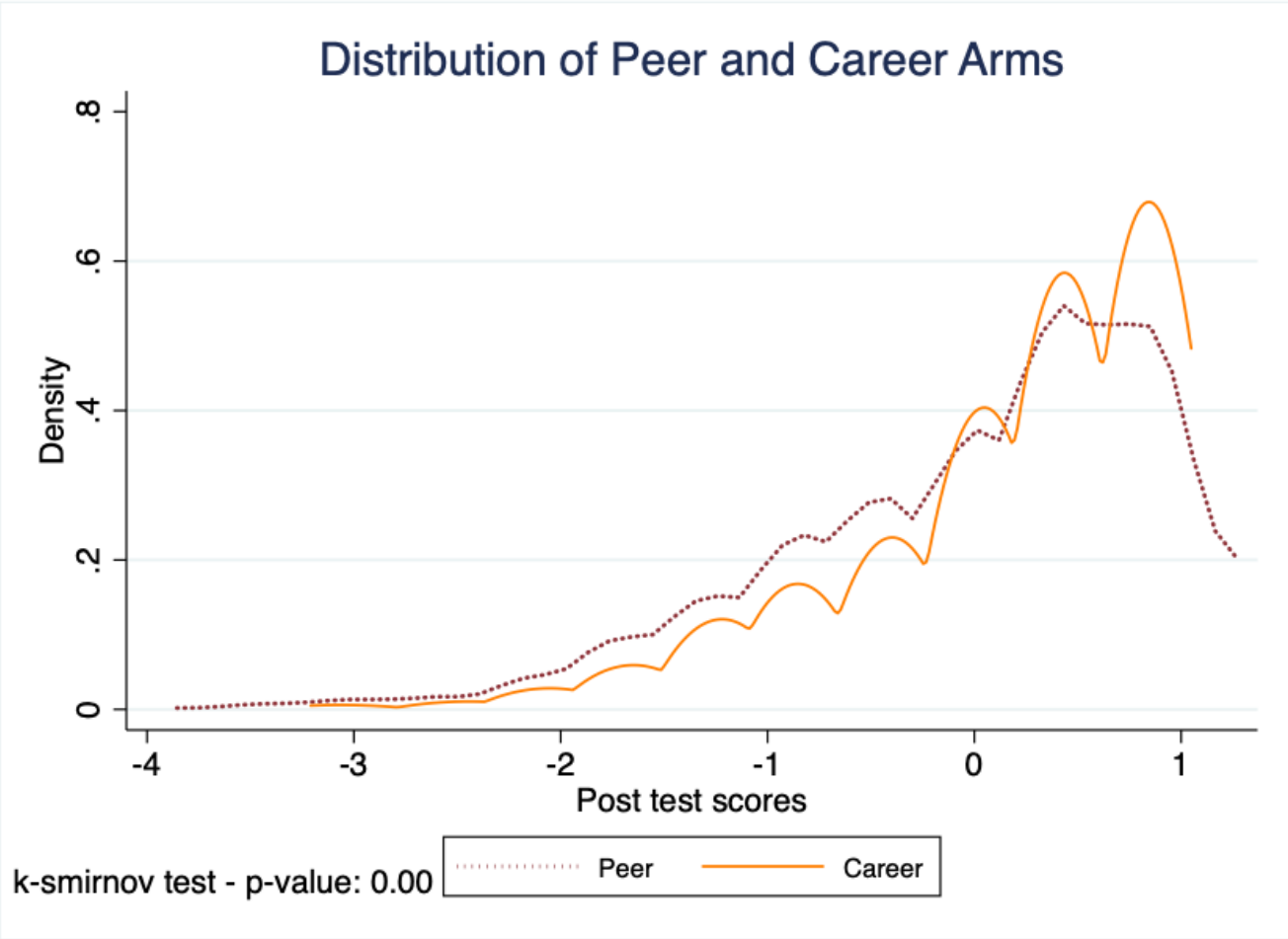
Appendix B: Figures



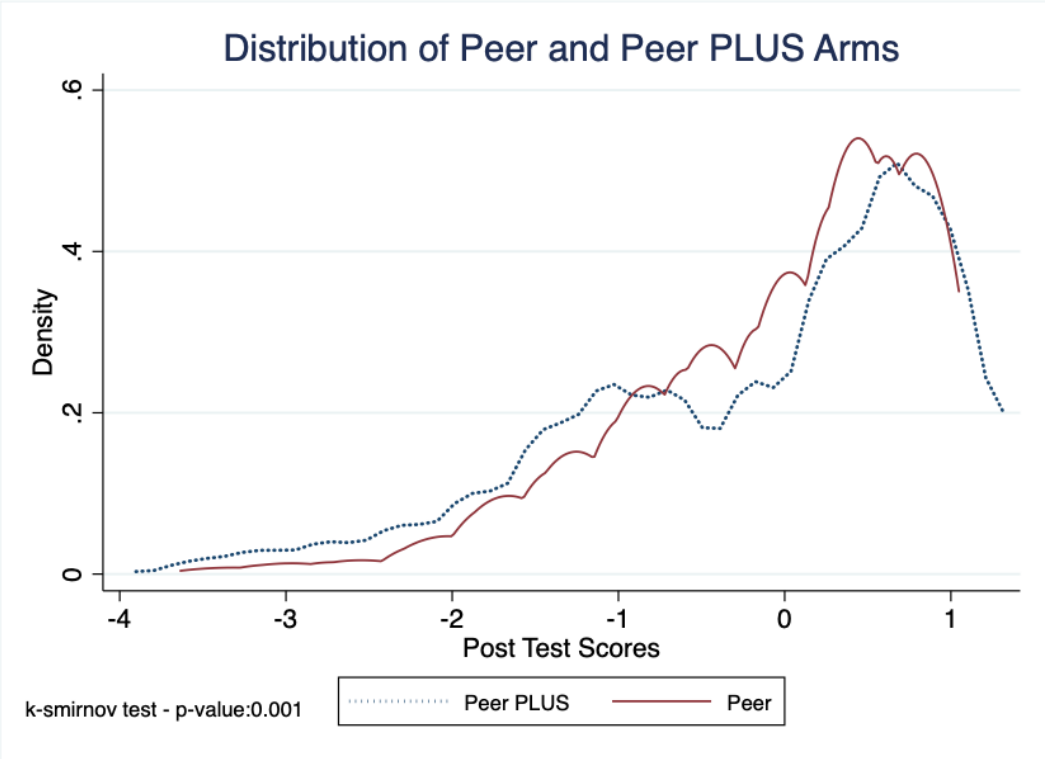
B. 1: Quantile Regression Estimates



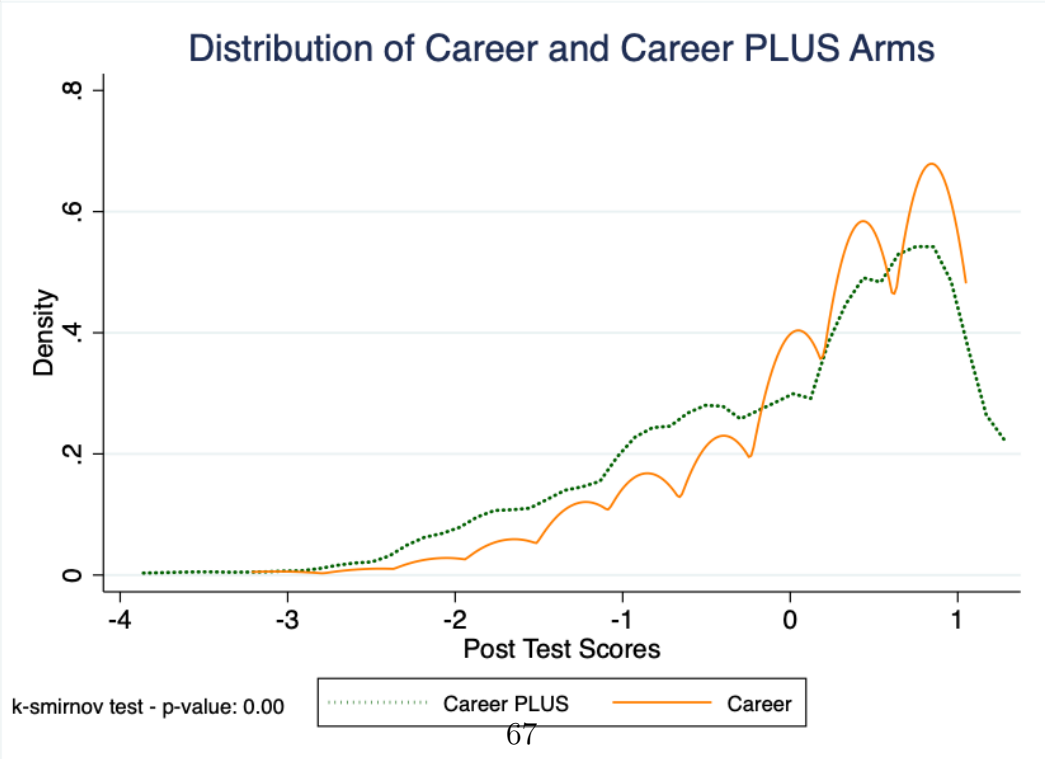
B. 2: Quantile Regression Estimates



B. 3: K smirnov-test: Peer and Career Distribution

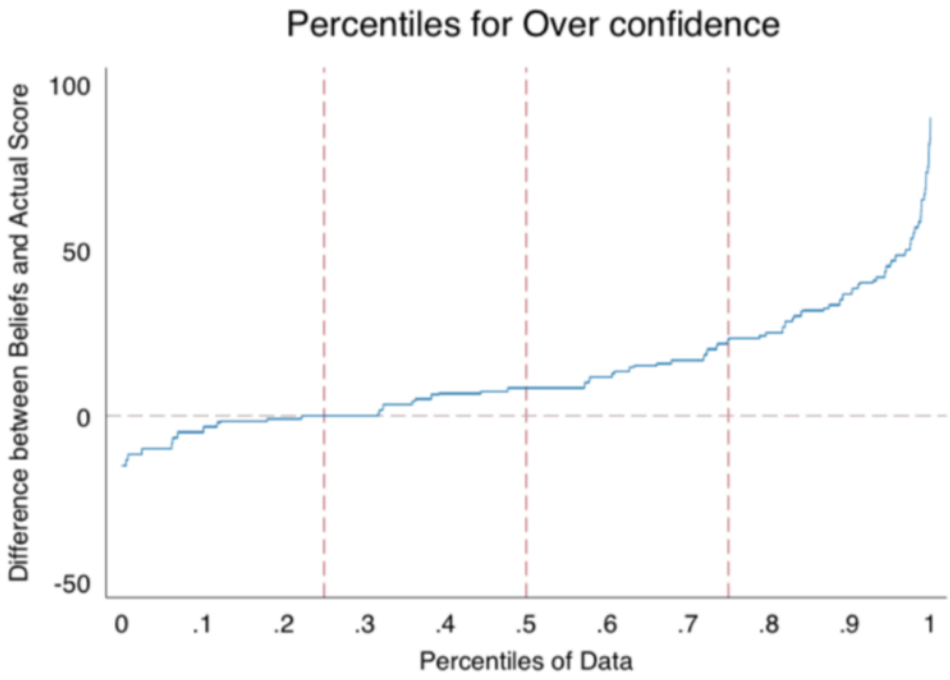


(a) Peer and Peer PLUS

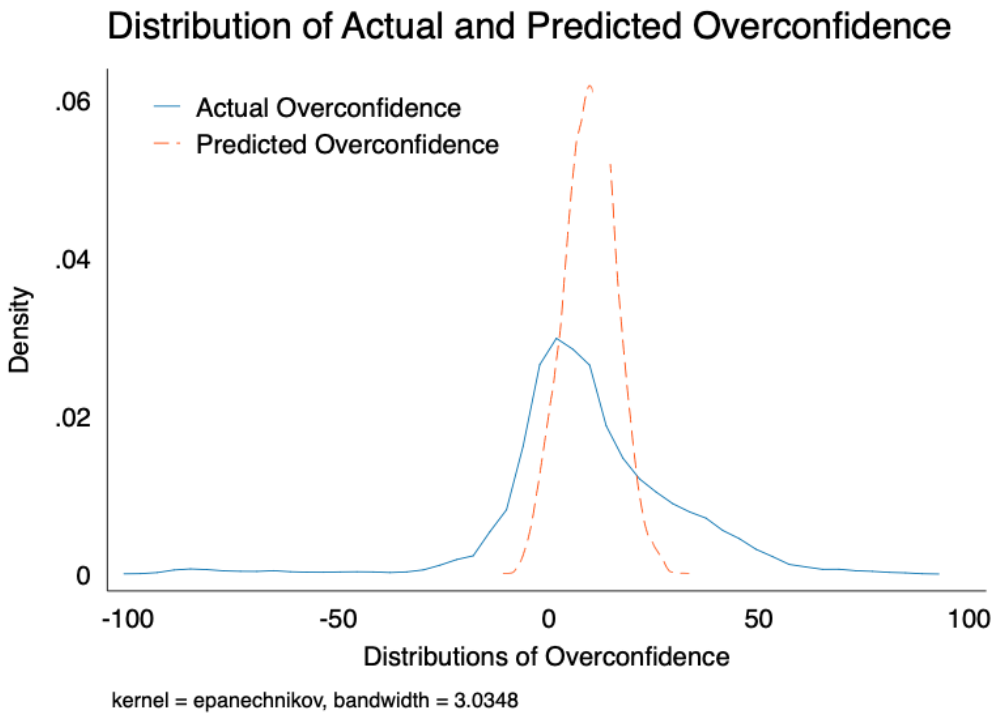


(b) Career and Career PLUS

B. 4: K smirnov-test: Peer/Career and PLUS Counterparts



B. 5: Qplot for Overconfidence



B. 6: Distribution of Actual and Predicted Overconfidence

Appendix C: Training Details

Training Topics

sr.no	Topic
1	Power of Coaching
2	Student Leadership
3	Pupil Voice
4	Protecting Children
5	Staff and Distributed Leadership
6	Co-curricular Activities
7	Staff Leave Rules

Appendix D: Training Test Sample

Date:	School emiscode:	Teacher Name:
☐☐/☐☐/☐☐	☐☐☐☐☐☐☐	_____
		Teacher CNIC:
		_____

Marks: 15 **Time: 15 minutes**

Section A:

Encircle the right option for the given statements / questions.

Q1.	In SHEEP Model "S" stands for ---------- a) Size b) Score c) Stay Safe d) Scale
Q2.	The most appropriate way of pupil voice in School is: a) Student Council b) Sports Team c) Monitors d) Focus Group
Q3.	When a civil servant completes his continuous service of more than 10 years he may be granted extraordinary leave at a time for the maximum period of: a) Two years b) Three years c) Four years d) Five years
Q4.	In Pupil Voice SLT stand for: a) Super Leading Team b) Student Leading Team c) Senior Leadership Team d) Student Learning Team
Q5.	Delayed development of the child is: a) Physical abuse b) Emotional abuse c) Sexual abuse d) Neglect
Q6.	The 4MAT system or (4 Mode Application Techniques) was developed by Mc Carthy in 1996 for a) Teaching b) Learning c) Teaching-Learning d) Mentoring
Q7.	Disability Leave may be granted, outside the leave account up to a maximum -------- days. a) 720 days b) 120 days c) 180 days d) 365 days
Q8.	The most commonly used Coaching Model is: a) SWOT Model b) GROW Model c) SMARTER Model d) 4MAT Model

Q9.	The Term ECM stands for: a) Every Child Movement b) Early Childhood Management c) Early Childhood Motivation d) Every Child Matters
Q10	Professional development consists of reflective activity designed to improve an individual's……. a) Attributes b) Knowledge c) Understanding and skills d) All above mentioned
Q11.	--------- provides the means to develop school capacity and reduce the workload of head teacher freeing him/her to do those key things that only heads can do. a) Democratic Leadership b) Transformational Leadership c) Distributed leadership d) Team work
Q12.	Where did the idea of Coaching come from…….? a) Sports Psychology b)Learning Psychology c) Health Psychology d)All of them

Section B:

Encircle the right option for the given statements / questions.

Q1.	Which acronym of SHEEP we are considering in subsequent statement "Children and young people live in decent homes and sustainable communities"… A)Be safe b)Be healthy C Achieve Economic well-being d) Make a positive contribution
Q2.	Which is not included in three "Big Basic Skills of Coaching"…….. a) Listening b) Leading c) Reviewing d) Questioning
Q3.	Those learners who learn by observing, analysing, classifying and theorising are called…….. a) "WHY" learners b) "WHAT" learners c) "HOW" learners d) "What If" learners