Performance Pay and Malnutrition: Evidence from an Experiment targeting Child Malnutrition in West Bengal*

Prakarsh Singh[†], Amherst College/University of Pennsylvania
Sandip Mitra, Indian Statistical Institute

September 12, 2014

Abstract

We carry out a randomized controlled experiment in West Bengal, India to test three separate performance pay treatments in the public health sector. Performance is judged on improvements in child malnutrition. First, we exogenously change wages of government employed child care workers through a basic level of absolute incentives. The second treatment introduces high absolute incentives. Finally, we also

*We acknowledge funding for this project by the Dean of the Faculty at Amherst College. We are grateful to Hongye Guo, Alvaro Morales, Darius Onul and Arup Ratan Poddar for excellent research assistance and Chris Kingston, Jun Ishii and Geof Woglom for their comments. We also thank the mothers, workers and children who took part in this experiment and the enumerators who painstakingly carried out the interviews. Thanks also go to the Social Welfare Department at Maheshtala for their co-operation. Finally, we would like to thank the seminar and conference participants at NEUDC (Harvard University), Midwest Economic Development Conference (University of Minnesota), PAC-Dev (UCLA), George Washington University, World Bank, Washington and Lee University, Boston University, Swarthmore College, Williams College, ISI Kolkata, Five College Seminar, University of the Basque Country and NOVA Business School.

[†]Corresponding author and PI: psingh@amherst.edu.

test for the impact of basic relative incentives on child health. All treatments include supplying mothers with recipe books. The main results suggest that high absolute incentives reduce severe malnutrition by about 6.3 percentage points over three months. There are no significant effects on health outcomes of basic absolute or basic relative incentives. Results are robust to controlling for prior trends, propensity score matching, and reversion-to-the-mean. This result is consistent with a reported increase in protein-rich diet at home in the high absolute treatment.

Word count: 8416

Keywords: performance pay; child malnutrition; absolute and relative incentives

JEL Classification: M52; I12; I38; J38

1 Introduction

Performance pay is often taken to mean piece rates where a payout is linked to only individual productivity or output. However, relative performance pay schemes (especially tournaments) are also widespread in organizations. In this study, we carry out a randomized experiment to compare absolute with relative performance pay in a public sector organization engaged in service delivery. The incentives are provided to child care workers to lower child malnutrition. We also test for the gradient of the absolute performance pay scheme in this experiment.

There are 1.31 million child day care centers in India under the Integrated Child Development Services (ICDS) government-sponsored program.[1] Each center is staffed by a child care worker who is responsible for supervising children between ages 3-6 years during day-time, providing them mid-day meals, teaching mothers about child nutrition, imparting non-formal pre-school ed-

[1] Between 2007-2012, the value of the funds allocated by the central government to the Integrated Child Development Scheme was $7.4 billion (Lok Sabha, 2012).

ucation and facilitating health check-ups by doctors.[2] They are typically on fixed wages. The centers are widespread across India and admission is free. Nevertheless, quality of service delivery has often come under scrutiny (see for example, Chaudhury et al. (2006) on health worker absenteeism and Das and Hammer (2005) on quality of doctors in India). A recent household survey in 100 Indian districts reveals that 96 percent of the villages are served by these centers, although only 50 percent provide food on the day of survey and 19 percent of the mothers report that the center worker provides nutrition counselling (HUNGaMA report, 2011). A study on Bihar's day care centers found that 71 percent of the funds received by centers for the mid-day meal component were not spent on the beneficiaries and the performance of the programme should be monitored using outcome data rather than inputs (IGC report, 2013). Malnutrition is known to be associated with children's susceptibility to disease (Behrman et al. 2004), decreased labor productivity and other economic costs (Alderman and Behrman, 2006). Solutions based purely on improving individual diets through economic growth are of limited effectiveness, as Behrman and Deolalikar (1987) showed that nutrient elasticities with respect to income may be close to zero.

One way of tackling the supply-side inefficiency can be through performance-based incentives. Performance pay has been shown to have a positive effect on productivity of workers in the public sector under certain conditions (Singh, 2013; Basinga et al. 2011) even though there could be crowding out of intrinsic motivation if incentives are too low (Gneezy and Rustichini, 2000). In Singh (2013), absolute performance pay to workers improves worker effort but child malnutrition only decreases when performance incentives are combined with information to the demand-side (recipe books given to mothers of children in day-care centers). In particular, the results from this experiment conducted in Chandigarh provided evidence for the complementar-

[2] Centers also act as food distribution centers for pregnant women, adolescent girls and children under the age of three years.

ity between supply-side incentives and demand-side information in affecting child health. However, it was not able to address how performance is affected by a change in slope of absolute performance pay. This may be useful to know for policy-makers to have a better idea of the cost-effectiveness of such schemes. Secondly, there was no comparison of absolute pay with respect to relative pay, which may be more effective for public sector workers. Both these questions are addressed in the present experiment conducted in a different region of India – West Bengal in Maheshtala Municipality on the outskirts of Kolkata. As of December 2011, the percentage of malnourished children under 5 in West Bengal, in terms of weight-for-age, was 38.7%, below the national figure of 42.5% (Rajya Sabha, 2011). Exogenous treatments were assigned through cluster randomization contemporaneously along with a pure control group. All centers were based entirely within one geographic block and there was no endogenous selection into the treatment.

There has been very little experimental research on performance incentives in health programs of low and middle-income developing countries according to an excellent literature review by Miller and Babiarz (2013). An exception in providing incentives on the demand-side is Banerjee, Kothari and Duflo (2010) who incentivize immunization coverage in rural Rajasthan for mothers and find large increases in uptake. In education, a working paper by Behrman et al. (2012) shows that providing performance incentives to students and teachers simultaneously may be complementary in improving test grades. Hasnain, Manning and Pierskalla (2012) review the experimental evidence on performance pay in the public sector and conclude that it is extremely scarce, especially in developing countries.[3] The only two studies they cite in this sub-field are Basinga et al. (2011) in Rwanda and Singh (2013) in

[3] Christianson et al. (2008) make the same point about developed countries stating that control groups are often not comparable. One of the first experimental papers on performance incentives for nursing homes in US found that incentives lead to better resident health outcomes and shorter stays (Norton 1992). Figlio and Kenny (2007) find that merit pay for teachers matters and more so for parents who are more involved.

Chandigarh, India where positive effects are found on health. Another study by Miller et al. (2012) shows that financial incentives for anaemia reduction are modestly successful in China. Recently, De Walque et al. (2013) and Gertler and Vermeersch (2012) provide evidence to show positive effects of performance pay on HIV-testing and on child health outcomes in Rwanda. It is rare to implement performance incentives for service delivery in the public sector and also have a control group. Moreover, comparing relative and absolute incentive schemes as well as changing the gradient of the incentive pay have never been studied in the public health domain. Finally, there may be multitasking or gaming of performance incentives as shown by Figlio and Winicky (2005) but we do not find any evidence for gaming.

We carry out a randomized controlled experiment in West Bengal, India to test three separate performance pay treatments in the public health service delivery sector. Performance is judged on improvements in child malnutrition. First, we exogenously change wages of government employed child caregivers through a basic level of absolute incentives. The second treatment introduces high absolute incentives. Finally, we also test for the impact of basic relative incentives on child health. All treatments include supplying mothers with recipe books. Overall, the results suggest that high absolute incentives reduce severe malnutrition by about 6.3 percentage points over three months. There are no significant effects on health of the basic absolute or basic relative incentives during this period and the point estimates are close to zero. In order to check for common trends prior to the randomization we also have a placebo check that shows no differential trends between the different groups.

Latest research also focuses on social distance and interaction of incentives. Kingdon and Rawal (2010) show that a student's achievement in a subject in which the teacher shares the child's gender, caste and religion, is on average nearly a quarter of a standard deviation higher than the same child's achievement in a subject taught by a teacher who does not share the child's gender, caste or religion. Our results reveal that incentive pay interacts with improving health of boys more than girls. Similarly, a child is more likely to show significant gains in weight if the high-powered incentivized worker and the child's mother follow the same religion as compared to them following different religions.[4] This may indicate an interaction of taste-based preferences with incentives in improving child health, which could have implications about how an unequal distribution may result in response to performance incentives even as public sector efficiency is enhanced.

We delineate the theoretical framework in Section 2, the setting in Section 3, and treatment, methodology and empirical specification in Sections 4, 5 and 6 respectively. Section 7 reports the summary statistics, Sections 8, 9 and 10 provide main results, robustness checks and mechanisms. Section 11 concludes.

2 Theoretical Framework

Theoretically, under risk neutrality, there is no difference between absolute and relative incentives for the policy maker to induce the same high effort for agents (Lazear and Rosen, 1981). With risk aversion and common shocks, however, relative incentives can dominate absolute incentives (Green and Stokey, 1983). Relative pay filters the common shock making agents face lower risk as compared to absolute pay. Under the relative incentive scheme, workers' pay depends on the ratio of individual productivity to average productivity among all co-workers in a field. Another practical advantage is that of budget predictability under the relative scheme. Recent experimental evidence by Gangadharan et al. (2013) suggests that an endogenous-prize tournament leads to a Pareto improvement in participants' payoffs and also increases collective output. Under the absolute incentive scheme – piece rates – individual pay only depends on individual productivity. Bandiera,

[4]The caste of workers and mothers was not collected in this study.

Barankay and Rasul (2004) find that moving from relative to absolute incentives increases the productivity of a farm worker by 50%. In the public sector, there has been no such empirical study comparing relative and absolute incentives. This may matter because of several reasons. First, shocks to output may be salient. Second, output may be less easily observable. Third, output may not directly respond to an increase in effort (may depend on demand-side also). Fourth, public sector workers may be more risk averse (Buurman et al., 2012). Fifth, workers may be differently motivated (Besley and Ghatak, 2005) and may exert more effort in response to non-financial awards as shown by Ashraf, Bandiera and Jack (2012). We motivate the treatments by proving that the costs associated with the absolute scheme are always greater than the relative scheme when a common shock is possible and public sector agents are risk-averse.

Assume one risk neutral principal (the government) and n risk averse agents (center workers), each responsible for producing output. In our scenario, the output could mean healthier (and less malnourished) children. Each agent exerts an effort and receives a wage from the principal. The agents' efforts are not visible to the principal, and therefore the principal can only contract based on the agents' output levels. For simplicity, we assume that the agents' effort levels are discrete, namely 0, 1, and 2. Agents produce two levels of outputs: 0 or 1. The probability of attaining the high output depends on the agents' effort level: the higher the agent's effort, the higher her chance for producing 1 as opposed to 0.

We also assume a common shock in production. This could be thought of as a shock that causes output to shrink for all workers and is outside their control. In our setting, this could represent the onset of a disease (for example, malaria especially during the rainy season). With probability θ, all the agents produce 0 regardless of their effort level. The agents' utility function is given as follows:

$$U_A = V(w) - \frac{1}{2}cx^2$$

.

Here, w is the wage this agent receives, c is the multiplier of the disutility caused by the agents' effort and x is the agents' effort level. Agents are assumed to be risk averse, thus V is an increasing and concave in w.

The principal's utility function is as follows:

$$U_p = M\sum_{i=1}^{n} p_i - \sum_{i=1}^{n} w_i$$

p_i is the output level for agent i, n is the number of the agents, M is the multiplier for the agents' outputs.[5] Moreover, it is always worthwhile for the principal to engage the agents in the highest level of effort ($x = 2$). Thus, the products are sufficiently valuable to the principal, i.e. M is sufficiently large.

2.1 Cost for an Absolute Performance Pay Scheme

Suppose the wage for the agent is a for output $= 0$, and b for output $= 1$. Clearly $b > a$. The expected utility for agents with each of the different effort levels is:

$$E(U_A(0)) = V(a)$$

$$E(U_A(1)) = \frac{1+\theta}{2}V(a) + \frac{1-\theta}{2}V(b) - \frac{1}{2}c$$

$$E(U_A(2)) = \theta V(a) + (1-\theta)V(b) - 2c$$

[5] M is assumed to be greater than one.

To implement the highest effort level, the principal needs to make sure that the agent's utility with highest level of effort ($x = 2$) is the greatest in comparison to the other two effort levels. This boils down to the following condition:[6]

$$V(b) - V(a) > \frac{3c}{1-\theta}$$

Thus, the difference between the utilities generated by the high wage and the low wage should be large enough. The principal could achieve this by lowering a. However, practically, there is a lower bound on a. If an agent produces 0, the principal needs to make sure that the agent can survive on her wage. This condition is particularly relevant in the public sector, where workers are difficult to fire and where unionization resists cutting down on wages of unproductive workers. We can suppose that $V(a) > U$. It follows that $V(b) > \frac{3c}{1-\theta} + U$. The total cost for the principal to implement a high effort for all agents under the absolute performance pay is as follows:

$$C_{absolute} = n \times (\theta V^{-1}(U) + (1-\theta)V^{-1}(\frac{3c}{1-\theta} + U)).$$

2.2 Cost for a Relative Performance Pay Scheme

When there are n agents, a complete relative performance pay scheme should have $n+1$ contingencies, which boils down to $2 \times (n-1) + 2 = 2n$ number of payments. For example, in a three agents case, a complete tournament scheme would need to specify payments for output combinations (1, 1, 1), (1, 1, 0), (1, 0, 0), (0, 0, 0), which contains six kinds of pay. Denoting the pay structure $(H_{0,}L_0; H_{1,}L_{1;}...; H_{n,}L_n)$, H corresponds to pay on high output, and L corresponds to low output pay. The subscript n on L_n and H_n corresponds to the number of agents who produce low output.

When all agents produce the same output – be it 1 or 0 – the relative rank

[6]See Appendix for details.

for each agent is the same. For example, if there is a common shock, output will be low for all agents and all of them will receive L_n. On the other hand, if everyone exerts high effort and there is no common shock, the output will be high and all agents will receive H_0. As the rank structure is exactly the same in both cases, all workers should receive the same wage under a relative scheme: $H_0 = L_n$.

We only need to compute the cost for the principal to make effort level portfolio (2, 2, 2,..., 2) a Nash Equilibrium. agent choose 0 or 1 over 2, provided everyone else chooses 2. From our previous assumptions,

$$H_0 = L_n = T$$

Assuming that $(n-1)$ agents have already chosen effort level of 2, the expected utilities of the n^{th} agent to choose 0, 1, 2 are respectively:

$$E(U_A(0)) = \theta V(T) + (1-\theta)V(L_1)$$

$$E(U_A(1)) = \frac{1+\theta}{2}V(T) + \frac{1-\theta}{2}V(L_1) - \frac{1}{2}c$$

$$E(U_A(2)) = V(T) - 2c$$

The inequality that arises out of solving the above problem along with the minimum utility assumption leads to $V(T) \geqslant U + 3c$. The minimized total cost for a principal using tournament is

$$C_{relative} = n \times V^{-1}(U + 3c).$$

2.3 Comparison between absolute and relative schemes

The difference between the two cost functions is as follows:

$$C_{absolute} - C_{relative} = n(\theta V^{-1}(U) + (1-\theta)V^{-1}(\frac{3c}{1-\theta} + U) - V^{-1}(U + 3c)).$$

Notice the difference is actually 0 when $\theta = 0$. To see how this difference varies with θ, we take the derivative with respect to θ. We can prove that when $V(w)$ is concave:[7]

$$C_{absolute} > C_{relative} \text{ for } \theta > 0.$$

The cost for an absolute scheme is higher than that for a relative scheme whenever common shock is possible. This result is in contrast to the stylized one in the current literature, which states that the absolute scheme should dominate the relative schemes when the probability of common shock is low enough or when it is not present (Green and Stokey, 1983). The "public sector assumption" that assumes that agents should obtain a minimum level of utility even when they perform poorly leads to the principal optimally choosing a more cost effective relative scheme for extracting high effort from its agents. How these schemes fare in terms of heterogeneous effects of social interaction between mother and worker, depends on whether the communication is able to help in filtering the common shock, in which case the relative treatment would lose some of its advantage over the absolute treatment. However, communication may also signal greater transfer of a common shock through contagion. In this scenario, relative treatment would increase its superiority in the face of a negative shock.

3 Setting

There are 1.31 million day care centers across India that offer child care and nutritional counseling services. These are run by the government under the

[7] See Appendix for proof.

umbrella of Integrated Child Development Services (ICDS) through the Social Welfare Department. Each center is usually staffed by one government worker and an assistant. Workers can affect health of the child through two primary channels: first, providing mid-day meals to children and second, advising mothers on a nutritious diet. We study child care workers employed by the West Bengal government in Maheshtala Municipality in 24 South Pariganas District. Maheshtala is located in the Kolkata Metropolitan Region. According to the 2011 Indian census, the population of Maheshtala was 449,423. The sex ratio of Maheshtala city was 945 females per 1000 males. Average literacy rate of Maheshtala was 82.63 percent of which male and female literacy was 86.08 and 78.98 percent. Children constituted 9.67 % of the total population of Maheshtala. We were able to carry out this study in Maheshtala as the Social Welfare Department was keen to implement an experiment to tackle malnutrition. Here, the worker in a day care center has a fixed monthly salary of Rs. 4350 in Kolkata, which increases to Rs. 4413 after 10 years of service. All workers in this Municipality have similar tasks and operate under the ICDS scheme. Education, knowledge and experience of worker along with quality of infrastructure in the centers are controlled for in regressions below.

4 Treatment

There were three treatments that were implemented in the research project. All three treatments entailed free distribution of recipe books to all mothers apart from performance pay to workers. This was done because the combined treatment of incentives and information in Singh (2013) had been shown to increase weight in children and only incentives to workers or only recipes to mothers were individually ineffective. The recipe book is described later in the section. To understand each of the performance pay treatments, consider the categories established by WHO (2007), as these are also employed by the government workers. A child is classified as malnourished if she is more than two standard deviations away from her WHO standard weight-for-age mean.[8] She is moderately malnourished if she is more than two standard deviations but less than three standard deviations from the weight-for-age mean. A child is severely malnourished if she is more than 3 standard deviations away from the weight-for-age mean.

The first treatment, titled Basic Absolute (BA treatment), was the replication of the combined treatment from Singh (2013), which had reduced malnutrition by 4.2 percent over three months. This entailed Rs. 100 per child if the child's malnutrition grade improved from severe to moderate or moderate to normal and a corresponding Rs. 100 deduction from the total for a drop in grade from normal to moderate or moderate to severe. In other words, if:

N for each worker = # children who jump at least one grade - # children who drop at least one grade

The total payment promised for each worker was Rs. 100 * N after three months.[9] From the earlier experiment, it was not clear how the slope of performance pay was related to effort. In the second treatment, called High Absolute (HA treatment), the payout promised to the workers after three months was Rs. 200 * N, where N was defined in the same way. However, if more children suffered declines as opposed to improvements, the workers were not asked to make payments. As the schemes were implemented in the presence of senior staff and under the signed approval of the local Director of Social Welfare Department, the promises could be seen as credible commitments to the workers. For example, if the number of children who jump from severe to moderate = 4 and the number of children who drop from normal to moderate = 2, the total payment would be Rs. (4-2) * 100 = Rs. 200 in the BA treatment and (4-2) * 200 = Rs. 400 in the HA treatment.

[8] The standard also differs for males and females.

[9] Approximately, 1 US$ = Rs. 60 in July, 2013.

The average payout in Chandigarh for the basic absolute incentive with recipe book had been Rs. 291 per worker but the monthly worker salary was Rs. 2000 per month in 2010 (Singh, 2013). Since the workers' salary was almost twice in Maheshtala as compared to Chandigarh, the high absolute treatment can also be considered a test of the previous experiment's treatment if the slope is considered to be a proportion of the salary. Thus, the first two treatments can also throw light on the relative effectiveness of a constant slope of Rs. 100 versus the same slope as a proportion of total income.

The third treatment, or the basic relative (BR treatment), was allocated a pot of money containing on average Rs. 291 per worker to keep it consistent with the ex-ante expected payout in the basic absolute treatment.

$$\text{T for each worker} = \text{sum of all positive N in that treatment group}$$
$$\text{Payout} = \text{55 workers} * 291 * (N/T) = 16000\ (N/T)$$

The total amount for 55 workers would be approximately Rs. 16000. However, the payout to each worker would depend upon her performance relative to others in the group. For example, if the worker's N = 10 and the sum of all positive N = 100 in her treatment group of 55 workers, the worker would get 10 percent of the total amount = Rs. 1600. If each worker performs equally, they each get approximately Rs. 300 in the basic relative treatment.[10] The relative treatment is also similar to Bandiera et al. (2004), where the workers' pay depended on the ratio of individual productivity to average productivity among all co-workers in a field. None of the schemes could reduce workers' income, and all were accompanied by information provided directly to mothers.

Workers in each treatment group participated in three separate workshops at the end of the baseline round (one for each treatment), where they were handed goal cards. The goal cards listed target weight for each child in

[10]These wards were numbered 1, 10, 14, 18, 22, 25, 29, 30.

their center after three months. Goal was the threshold for achieving moderate malnutrition status for the presently severely malnourished child (after accounting for the increase in age at endline) and achieving normal malnutrition status if the child is currently moderately malnourished. If the child was currently in the normal range, a maximum threshold was provided below which the child would become malnourished and penalty imposed. The workers were told about their respective treatments with the help of illustrative examples and all doubts were clarified.

The recipe book that was distributed in all treatments had ten economical and nutritious recipes for 3-6 year old children. These were government approved recipes and the recipes were chosen with the help of the Food and Nutrition Board, Kolkata. Each recipe could be made within a budget of Rs. 5 at home, contained local ingredients and listed the step-by-step method of preparation and nutritive values per 100 gms. The individual nutritive values were of calories, protein, iron and carotene. The book was translated and printed in Bengali, the local language. Some of the recipes were as follows: Puffed Rice Bengal Gram Mix, Rice Food Mix, Suji Porridge, Dalia Porridge, Chidwa Pulao and Chidwa Laddoo. These were rich in protein and calories to counter child malnutrition. Most used either lentils for increasing protein and rice, wheat or jaggery for increasing calorie count.

5 Methodology

We obtained preliminary data from the Social Welfare Department, Government of West Bengal on the number of registered students and average malnutrition in each center, manual randomization at the cluster level was conducted at the Department by a lottery. Each cluster consists of several centers. All centers with fewer than 20 registered students were dropped from the sample at this initial stage to improve power. In total, 34 clusters were selected for the study covering 209 centers.[11] The senior department officials (supervisors) asked to be involved in the selection procedure, so they were invited to participate in the lottery.

Four boxes were placed in the Department's head office, each corresponding to an undisclosed treatment or control group. The supervisors placed a folded slip (representing the cluster number and total centers in that cluster) inside each box sequentially. When the total number of centers accumulated for a treatment exceeded 50, the assistant was asked to shut the box. This was done to have at least 50 centers in each group for adequate sample size according to power calculations. This would also avoid the exceptional case where the wards with the highest or fewest number of centers get assigned to one treatment by chance. Cluster was chosen as the level to randomize to remove the possibility of contaminating spillover effects between workers within a cluster. Table 1 shows the total clusters and centers allocated to each group and Figure 1 plots the assignment on a map provided by the Department.

<Table 1 and Figure 1 about here>

The baseline was carried out during March-May, 2012 and the endline three months later between August-September, 2012. A window of three months was chosen for the experiment because it is the average time between two medical check-ups by the local Health Department. The duration was verified to be sufficient for a grade improvement to occur by doctors at the local office of the Health Department, Government of India and was comparable to the earlier experiment. At baseline and endline, a team of enumerators (supervised by an assistant and project manager) weighed all children present in the center on a digital weighing machine, interviewed their mothers and the center workers. The recipe books were distributed to all the

[11] Out of 35 clusters in the Municipality, only one cluster did not have any centers with 20 or more students registered at the time.

mothers (except in the control group) after their interviews were taken at the centers. Previous weights of children (on average two months prior to baseline) were also recorded at baseline from the weight record registers of the workers.

6 Empirical Specification

The main regression specification for finding the average effect of the treatments on weight of a child is as follows:

$$\begin{aligned} w_{ijt} &= \alpha(post)_t + \beta(BA)_j + \gamma(HA)_j + \rho(BR)_j + \eta(post * BA)_{jt} + \\ &\quad \theta(post * HA)_{jt} + \omega(post * BR)_{jt} + X_{ijt} + \varepsilon_{ijt} \end{aligned}$$

w_{ijt} is the weight of a child i in cluster j at time t. The variable *post* is a dummy that is 0 for baseline and 1 for endline. The variables BA, HA and BR are 1 if the child is in the treatment basic absolute, high absolute or basic relative respectively and 0 otherwise. The omitted category is the control group. X_{ijt} are individual and center specific controls specified in the following section. The error term is clustered at the cluster level. The variable *post* accounts for the natural increase in weight in three months, all seasonal effects on weight, regional shocks to food prices and any management changes or unobservables that would impact all groups in the same way. β, γ and ρ are the baseline differences between the individual treatments and the control. η, θ and ω give us the difference-in-differences estimates for the effect of each of the three treatments. This interpretation rests on the identification assumption that there are no time varying and group-specific effects that are correlated with the treatments (common trend assumption). As the clusters were randomly assigned into one of the four groups, we should not expect there to be common trends amongst the groups.

Although usually it is not required to check this assumption with randomization, we carry out a placebo check to corroborate that pre-trends are similar across all groups. For the placebo check, we define $post = 1$ for baseline and 0 for the weight recorded in registers prior to baseline (on average about two months before). Running the above regression with this new definition should allow us to test if there are changes in the difference-in-difference estimates from what we had obtained earlier. We should not observe any significant difference-in-difference estimates with the placebo regression for common pre-trends assumption to hold.

7 Summary statistics and attrition

The summary statistics at baseline in Table 2 reveal that mother's age is on average 27 years and is similar across the four groups.[12] 73% of the mothers in the control group can read and this is also similar across groups, which is comparable to the 2011 Indian Census finding of 78% literacy for women in Maheshtala. The normalized differences show that differences between groups are not significant as long as the normalized difference is less than 0.25 (Imbens and Rubin, 2007). The weights and ages of children (around 13.5 kilograms and 4.2 years) as well as the malnutrition status are similar across all groups. The malnutrition rate is 33% at baseline with close to 9% being severely malnourished and the rest being moderately malnourished. The monthly income of a household was approximately $70 for four members (two adults and two children), showing that families on average live below the poverty line in this sample. This is also statistically insignificant between the groups with HA group being the most similar to the control group along all variables. Ownership of mobile phones is high and water filters is low. The least similar group, overall, is the BA group where mobile phone ownership

[12] Mother's age was around 28 years for the experiment in Chandigarh (Singh, 2013).

and presence of water tap at home is significantly higher than the control. Anganwadi infrastructure as measured by presence of access to drinking water in the center or toilet in the center are also similar with close to 40% having a toilet and three quarters having drinking water. Thus, on average the variables appear to be well matched across groups with the HA group being the most similar to the control, followed by the BR group and then the HA group.

We might be worried about selective weighing of children in these groups despite checking by an independent supervisor and enumerator. Table 3 shows attrition rates. These are around 26% and similar across the four groups. Attrition rates tend to be higher in these centers as most students use the centers as a temporary pre-school before they gain admission to a government school. This is because the pre-school educational quality is poor with no official syllabus or exams. As many of the fathers are daily wage laborers who are prone to migrating where a higher wage is offered, their family also keeps moving with them. Attrition is not different by the main outcome variables depending upon treatment. This is illustrated by Appendix Table A2 where all coefficients of the variable interacting treatments with main outcome variables (weight, malnourished, grade, severe malnourished) are insignificant. Stand-alone coefficients on health outcomes and individual treatments are also insignificant (not shown).

8 Main results

The regression results from specification (1) are reported in Table 4 for a panel of children who were weighed twice during the study. The dependent variables in the first four columns are weight, dummy for malnourished status, weight-for-age grade (ordered 0 to 2 from normal to severely malnourished) according to the WHO, and dummy for severely malnourished status. The results reveal that the weight increase in the control group over three months was on average 283 grams and significant (similar to Chandigarh). The baseline levels of weight and other measures are similar in the four groups. There appears to be no significant impact of the basic absolute (HA) and basic relative (BR) treatments. Moreover, BR appears to do slightly but insignificantly better than BA. The high absolute treatment shows a significant effect of an increase of 191 grams over and top of the 283 grams. Although malnutrition decrease is not significant at the 10% level, there appears to be a 4.6 percentage points reduction just under the 10% significance level. Relative risk of death from infection by malnutrition is twice as high for severely malnourished as for moderately malnourished children and nine times higher than normal weight children (Caulfield et al., 2004). Ordered grades decrease (as 0 is normal) on average in the HA treatment. The weight increase is driven by the movement towards moderate status of severely malnourished children as can be shown by column (4). Severe malnutrition declines by almost 5 percentage points and is significant at the 5% level. The next four columns have the same dependent variables but also include control variables. The control variables used in columns (5)-(8) are household demographics (age of child, gender of child, total number of siblings), household assets (monthly income, food expenditure, number of rooms, proportion of goods owned in the kitchen, proportion of non-kitchen goods), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet). The preceding result on severe malnutrition is now more significant and the decline in severe malnutrition is now estimated to be 6.3 percentage points for HA treatment.[13] This is a big decrease given the time period and may be able to sustain itself after three months because of immunity and resistance acquired by moderately malnourished children. Long-term positive effects were observed in Singh (2013) after discontinuation of a similar incentive scheme. Next, we consider the placebo results wherein we look for differences in the rates of growth in children between the groups pre-treatment. This is shown in Table A1 in the Appendix. We observe that even on average two months prior to treatment, the weight increase was not different across the different treatment and control groups and they were on same trajectories. There may be measurement error here as the weights were recorded by the center workers in their registers but there is no reason to expect a systematic upward or downward bias in any of the treatment groups. Figure 2 shows the differential trend in the high absolute treatment immediately after the treatment (located at two months) in comparison to the control group. The pre-baseline and baseline values are very similar in the high absolute and control groups. It is interesting to note that basic relative treatment appears to do better than the basic absolute treatment in the graph but the difference is not statistically significant and neither is the difference at baseline between these groups and the control group significant.

<Table 4 and Figure 2 about here>

As high absolute treatment seems to be effective in improving weights of children, we can conclude that slope of the incentive treatment as a proportion of salary matters in this context. In Table A3, we reproduce the main regression using Moulton clustering correction (as opposed to the standard clustering) as suggested by Angrist and Pischke (2008) in situations where the main regressors (treatments) are fixed within a cluster and heteroskedasticity is not a huge problem. While all the coefficients stay the same, the standard

[13]The results are robust to including an intermediate set of controls. For details, see Table A4 in the Appendix.

errors increase across the board, as expected, leading to a few changes in the degree of significance of some coefficients. Thus, the coefficient Post*HA becomes insignificant in the weight regression, but it is still significant at 5% and 10% in the grade and severely malnourished regressions, respectively.

9 Robustness checks

The main result of the paper is that the high absolute incentive works to reduce severe malnutrition. We subject this result to three additional robustness checks: propensity score matching, controlling for reversion to the mean, and providing Lee (2009) bounds on our main result after accounting for attrition.

9.1 Propensity Score Matching

First, we carry out propensity score matching to account for differences in observables across the high absolute treatment and control groups that may be driving our result. It also helps us restrict our analysis to a counterfactual sample in the control group that looks very similar at baseline to the high absolute treatment sample. Propensity score is defined as the probability that a unit in the full sample receives the treatment, given a set of observed variables at baseline. We model the probability of being in the combined treatment as a function of all pre-treatment variables using the control group and high absolute treatment observations. These variables are the usual control variables used in the main results table. Next, we test for the robustness of our difference-in-differences estimates using three types of commonly employed propensity score matching techniques: nearest neighbor, radius, and kernel. Panels A, B and C in Table 5 illustrate how the average change in weight in the combined treatment group varies relative to the control group under these methodologies. Moreover, the first row in each panel shows the average change in weight for the unmatched sample in the two groups and the second row displays the treatment effect on treated with the matched sample. The results for the unmatched and matched samples reveal similar estimates. The results indicate that the additional change in weight in the high absolute treatment is between 170 and 180 grams and this is significantly different from the change in the control group.

9.2 Reversion to the mean

It is possible that on average we get a significant effect on improving weight for the high absolute treatment but this may simply be a reversion-to-the-mean effect if the lighter children in that group showed faster catch-up (even though average weights were similar across groups at baseline). The placebo check above makes this possibility less likely but we propose another robustness check running a regression in wide form as follows:

$$w_{ij1} = \alpha w_{ij0} + \beta(BA)_j + \gamma(HA)_j + \rho(BR)_j + X_{ijt} + \varepsilon_{ijt}$$

By controlling for baseline weights of children as an independent variable, we allow the regression to determine the natural catch-up rate as opposed to imposing $\alpha = 1$, as in the difference-in-differences specification. The results in Table 6 show that the significance of the main result survives this conservative check, making the main result more credible.

9.3 Lee bounds

We present bounds for samples with non-random selection as proposed by Lee (2009) in Table 7. The lower and upper bound correspond to extreme assumptions about the missing information that are consistent with the observed data (Tauchmann, 2012). These suggest a causal impact on the weight of the high absolute treatment should range between 157 grams and 204 grams in the worst and best case scenarios.

10 Mechanisms

One of the channels through which the weight may have increased may have been food at home. We test if mothers report changes in diet at home as this would lend more credence to the change in outcomes. In Table 8, we explore the demand-side channel of mother-reported diet given to child. The dietary variables considered here are lentils or pulses, fish, meat, green vegetables and sweets or desserts. Note that baseline levels of consumption are similar across all groups. Lentils or pulses intake (at least twice a week) shows a significant increase in consumption and so does meat. Lentil intake is consistent with mothers being asked to prepare recipes by the HA treatment workers. Recall that several recipes (six out of ten) contained lentils as their main ingredient. This is rich in protein and would help lower protein deficiency. There is no change in other types of dietary intakes for the HA group mothers. The mothers in the BA and BR group show no change in their reported food provision, which is again consistent with their results on weight change in Table 4.

Next, we explore heterogeneous effects of the treatments by age and gender of child. In Table 9, we run a triple difference regression to check for significant differences in average treatment effects for boys and girls. Surprisingly, we find that boys show a much greater increase in the high absolute treatment relative to girls (345 grams higher and this is significant at the 10% level). There may be an underlying gender bias that becomes more salient with the introduction of high absolute incentives. It may also be that boys have greater appetite or ask for more food in the centers and thus are able to get more food from the incentivized worker. Workers may expect that boys will show more weight gain in response to food in the center or that mothers will be less likely to cut down on food for boys leading to complementarity. However, this expectation may be incorrect, as we do not observe differential food intakes reported at home for boys and girls suggesting that gender bias is getting triggered at the center and not at home.

We also disaggregate our results on weight-for-age z-scores of children by age and gender in Table 10. The mean z-score in the sampled population at baseline is -1.43. This means that the average child is 1.43 standard deviations away from the WHO (2007) standard for the child's age. We find that the high absolute treatment appears to drive greater changes in weights for children between the ages of 4 and 5 years. We also observe a significant increase for boys and a negligible and insignificant effect for girls and this is consistent with the estimates shown in Table 9.

Finally, we check for selective targeting of children who are close to the target threshold that may occur at the expense of those who are further away. The variable 'closetotarget' is defined to be 1 if the child is malnourished at baseline and her deficit weight (difference between the target weight and the actual weight) is less than the mean deficit weight and 0 otherwise. Target weight is defined as the threshold at which the child will improve her grade (i.e. would go from severely malnourished to moderately malnourished or from moderately malnourished to not malnourished). If there was selective targeting of those children in the incentive treatments who are close to the target threshold, the disincentive for a drop in grade may not have been as effective as anticipated. However, in Table 11, we observe that children close to the threshold do not appear to be selectively targeted in any of the treatments. Children who are closer to the target weight do not increase their weight at a statistically different pace than the ones who are further away from their target, which provides evidence against gaming of positive incentives. This seems to reiterate the importance of having disincentives for worse outcomes along with incentives for better outcomes.[14]

Do incentivized workers who have a greater proportion of malnourished children in their class show greater gains in weight for their children? This

[14] One may also be concerned about kids being given water by workers before the measurement of weights at endline. However, 'center has access to drinking water' is one of the controls used in the main regression, and this access is associated with an insignificant and negative increase in weight on average.

can be tested via a triple differences "dose response" regression as shown in Table 12. Indeed, we do observe a dose response for workers in the high absolute treatment implying greater rewards for centers who have a higher proportion of malnourished children at baseline. This may be because workers exert more effort when they know that they can get an even higher bonus if targets for malnourished children are achieved. However, it may also be driven mechanically because children who are more malnourished may show more gains at lower margin for the same inputs.

11 Policy implications and Conclusion

This paper is one of the first pieces of evidence in public health focusing on the elasticity of outcomes with respect to gradient of performance pay and also comparing absolute with relative treatments. We carry out a randomized controlled experiment to test three performance pay schemes in the government run childcare sector in India. First, we exogenously change wages of government employed child care workers to a component with basic absolute incentives to lower child malnutrition. The second treatment introduces high absolute incentives. Finally, we also test for the impact of basic relative incentives on child health. All treatments also include supplying mothers with recipe books. Overall, the results suggest that high absolute incentive works to reduce severe malnutrition by about 6.3 percentage points with controls and 4.9 percentage points without controls over three months. This is a strong result and is in line with an earlier experiment carried out in Chandigarh in Singh (2013) that found a benefit-cost ratio of around 20 due to the expected increase in class participation rates and future wages. This is on top of the reductions in child mortality that may arise due to a decrease in severe malnutrition. As the government expands access to centers across the country, results from this paper suggest that worker pay should not remain fixed even though the gains may be distributed unequally. Compensation needs to have a component of performance pay that increases as the fixed income goes up. The component should be based on weight-for-age grade that is easily observable and well understood. Additionally, the worker should not have perverse incentives to reduce weights of children who are not malnourished. Apart from incentivizing workers, it is also imperative to create awareness on the demand-side. One way of spreading this information is through simple and concise recipe books that are customized by regional tastes, availability of ingredients and social norms.

Possible channels that may be generating this high incentive effect on weight include using recipe books to remind mothers to increase protein intake at home and also food distribution by worker in the center. The literacy rate for women is particularly high in comparison to only 45% in Chandigarh even though ownership of mobiles was high and filters low in the earlier experiment (Singh, 2013). In the Chandigarh study, there was a similar reduction in overall malnutrition over three months (driven by more malnourished children), and malnutrition did not go back to its original level after a year when the incentive treatment was no longer in place. Large increases in weight are observed in boys as opposed to girls, for 4 to 5 year old children, and especially for those classes that had a higher proportion of malnourished children. This suggests that designing performance incentive schemes may create inequities in wages of workers depending on the demographic, gender and health profile of the class at baseline. In the future, we would also like to test the high relative treatment which we were unable to test here due to a small sample size. There could also be research on changing the slope of performance incentives along an observable dimension like gender to target both inefficiency and gender inequality.

The funds released for ICDS by the central government totalled \$193.6 million in 2011-2012 for West Bengal. If the state-allocated funds are included, this figure goes up to \$221.5 million. A large proportion of these funds goes towards fixed wages of child care workers. Yet, little is known about the most effective way of organizing labor contracts in this important area of public sector service. Through field experiments with the government, we can have a better handle at understanding what nudges work to motivate child care workers and reduce malnutrition rates, which have remained stagnant in India despite economic growth. Even without external validity, this has potentially life-saving implications on a large scale. Nevertheless, different settings within India can pose very different challenges, but one advantage of working within the same public organization can be easier replicability. We hope that further experimentation in this area can inform policy-makers on how to make public health service delivery more efficient.

References

[1] Alderman, Harold and Jere R. Behrman. (2006) Reducing the Incidence of Low Birth Weight in Low-Income Countries Has Substantial Economic Benefits, *World Bank Research Observer*, World Bank Group, vol. 21(1), pages 25-48.

[2] Angrist, J. D. & J. S. Pischke (2008). Mostly harmless econometrics: An empiricist's companion. Princeton University Press.

[3] Ashraf, N., O. Bandiera, and K. Jack (2012) No Margin, no Mission? A Field Experiment on Incentives for Pro-Social Tasks, CEPR Discussion Paper No. 8834.

[4] Bandiera, O., I. Barankay, and I. Rasul (2004) Relative and Absolute Incentives: Evidence on Worker Productivity, CEPR Discussion Paper No. 4431.

[5] Banerjee, A., D. Kothari, and E. Duflo (2010) Improving Immunisation Coverage in Rural India: Clustered Randomised Controlled Evaluation of Immunisation Campaigns with and without Incentives, *BMJ*, 340, c2220.

[6] Basinga, P., P. Gertler, A. Binagwaho, A. Soucat, J. Sturdy, and C. Vermeersch (2011) Effect on maternal and child health services in Rwanda of payment to primary health-care providers for performance: an impact evaluation, *Lancet*, 377(9775), 1421 – 1428.

[7] Behrman, Jere R., Susan W. Parker, Petra E. Todd, Kenneth I. Wolpin (2012) Aligning Learning Incentives of Students and Teachers: Results from a Social Experiment in Mexican High Schools, PIER Working Paper Archive 13-004, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania.

[8] Behrman, Jere R. and Anil B. Deolalikar (1987) Will Developing Country Nutrition Improve with Income? A Case Study for Rural South India, *Journal of Political Economy*, University of Chicago Press, vol. 95(3), pages 492-507, June.

[9] Behrman, Jere R., S.W. Parker, P.E. Todd (2004) Long-Term Impacts of the Oportunidades Conditional Cash Transfer Program on Rural Youth in Mexico. Ibero America Institute for Economic Research, Discussion Paper No. 122.

[10] Besley, T. and M. Ghatak (2005) Competition and incentives with motivated agents. *American Economic Review,* 95, 616-636.

[11] Buurman, M., J. Delfgaauw, and R. Dur, S. Van den Bossche (2012) Public sector employees: Risk averse and altruistic?, *Journal of Economic Behavior & Organization*, 83(3), 279-291.

[12] Chaudhury, N., J. Hammer, M. Kremer, K. Muralidharan, and F. Rogers (2006) Missing in Action: Teacher and Health Worker Absence in Developing Countries. *The Journal of Economic Perspectives*, 20(1), 91-116.

[13] Christianson, J., S. Leatherman, and K. Sutherland (2008) Lessons From Evaluations of Purchaser Pay-for-Performance Programs—A Review of the Evidence, *Medical Care Research and Review*, 65(6), 5S-35S.

[14] Census of India (2011) Office of the Registrar General & Census Commissioner, India (ORGI).

[15] Das, J. and J. Hammer (2005) Which doctor? Combining vignettes and item response to measure clinical competence, *Journal of Development Economics*, Elsevier, vol. 78(2), pages 348-383, December.

[16] De Walque, D., P. Gertler, S. Bautista-Arredondo, A. Kwan, C. Vermeersch, J. de Dieu Bizimana, A. Binagwaho, J. Condo (2013) Using

Provider Performance Rewards to Increase HIV testing and Counselling services in Rwanda, World Bank Policy Research Working Paper No. 6364.

[17] Figlio, David N. and Lawrence W. Kenny (2007) Individual teacher incentives and student performance, *Journal of Public Economics*, 91(5-6), pages 901-914, June.

[18] Figlio, D. N., and J. Winicki (2005) Food for Thought: The Effects of School Accountability Plans on School Nutrition, *Journal of Public Economics*, 89, 381-94.

[19] Gangadharan, L., G. Musto, J. Rulliere (2013) Win for Being the Best or for Getting the Best: Theoretical and Experimental Evidence on Tournaments with Endogenous Prizes, 2013 Conference on Tournaments, Contests and Relative Performance Evaluation.

[20] Gertler, P. and C. Vermeersch (2012) Using Performance Incentives to Improve Health Outcomes (June 1, 2012). World Bank Policy Research Working Paper No. 6100.

[21] Gneezy, U. and A. Rustichini (2000) Pay Enough or Don't Pay at All, *The Quarterly Journal of Economics*, 115 (3), 791-810.

[22] Green, J., and N. Stokey (1983) A Comparison of Tournaments and Contracts, *Journal of Political Economy*, 91(3), 349- 364.

[23] Hasnain, Z., N. Manning, J. Pierskalla (2012) Performance-related Pay in the Public Sector : A Review of Theory and Evidence, World Bank Policy Research Working Paper No. WPS6043.

[24] HUNGaMA Survey Report (2011) The Hunger and Malnutrition (HUNGaMA) Survey Report 2011, The Naandi Foundation.

[25] IGC Report (2013) Assessment of Bihar's ICDS Supplementary Nutrition Programme, IDinsight, available at: <http://www.theigc.org/events/assessment-bihar%E2%80%99s-icds-supplementary-nutrition-programme>

[26] Kingdon, G. and S. Rawal (2010) Akin to My Teacher: Does Caste, Religious and Gender Distance Between Student and Teacher Matter? Some Evidence from India. Department of Quantitative Social Science Working Paper 10-18, Institute of Education, University of London.

[27] Lazear, E. (2000) The Power of Incentives, *American Economic Review*, 90(2), 410-414.

[28] Lazear, E. and S. Rosen (1981) Rank-Order Tournaments as Optimum Labor Contracts, *Journal of Political Economy*, 89(5), 841-864.

[29] Lee, D. (2009) Training, Wages, and Sample Selection: Estimating Sharp Bounds on Treatment Effects, *Review of Economic Studies*, 76(3): 1071-1102.

[30] Lok Sabha (2012) Unstarred Question No. 1343, 21.03.2012. *available on IndiaStat.com*

[31] Miller, G. and K. Babiarz (2013) Pay-For-Performance Incentives in Low- and Middle-Income Country Health Programs, NBER Working Paper No. 18932.

[32] Miller, G., R. Luo, L. Zhang, S. Sylvia, Y. Shi, P. Foo, Q. Zhao, R. Martorell, A. Medina, S. Rozelle (2012) Effectiveness of provider incentives for anaemia reduction in rural China: a cluster randomised trial, *BMJ*, 345, e4809.

[33] Moulton B.R. (1986) Random Group Effects and the Precision of Regression Estimates, *Journal of Econometrics* 32, 385-397.

[34] Norton, E.C. (1992) Incentive regulation of nursing homes, *Journal of Health Economics,* 11, 105-128.

[35] Rajya Sabha (2011) Unstarred Question No. 2808, 19.12.2011. *available on IndiaStat.com*

[36] Singh, P. (2013) Performance Pay and Information: Reducing Child Undernutrition in India. Available at SSRN: http://ssrn.com/abstract=2270751 or http://dx.doi.org/10.2139/ssrn.2270751

[37] Tauchmann, H. (2012) Lee bounds: Stata module for estimating Lee (2009) treatment effect bounds, Boston College Department of Economics Working Paper.

[38] WHO (2007) The WHO Child Growth Reference Standards. Available at: <http://www.who.int/childgrowth/en>.

12 Tables and Figures

Table 1: Total clusters and centers in each group

	Total clusters	Total centers
Basic Absolute Treatment	8	50
High Absolute Treatment	8	53
Basic Relative Treatment	8	55
Control group	10	51

Table 2: Summary statistics at baseline

Variables	BA	HA	BR	C	Normalized Differences BA-C	HA-C	BR-C
Mother's age	28.09	27.64	27.38	27.47	0.08	0.02	-0.01
	[5.11]	[5.43]	[5.23]	[5.67]			
Mother can read	0.73	0.67	0.75	0.73	0.00	-0.09	0.03
	[0.44]	[0.47]	[0.43]	[0.44]			
Monthly income	4556.27	4059.73	4400.02	3867.94	0.19	0.05	0.19
	[2608.34]	[2567.92]	[2823.25]	[2513.68]			
Number of rooms	1.43	1.39	1.43	1.40	0.02	-0.01	0.02
	[1.08]	[0.88]	[0.90]	[0.87]			
Mobile phone	0.84	0.66	0.83	0.66	0.30	0.00	0.28
	[0.37]	[0.47]	[0.37]	[0.47]			
Water tap at home	0.35	0.14	0.18	0.14	0.35	0.00	0.08
	[0.48]	[0.35]	[0.39]	[0.35]			
Weight of child	13.65	13.45	13.62	13.49	0.05	-0.01	0.04
	[2.05]	[2.09]	[2.28]	[2.10]			
Age of child	4.23	4.21	4.23	4.18	0.04	0.03	0.04
	[0.83]	[0.84]	[0.81]	[0.85]			
Fraction female	0.51	0.52	0.50	0.50	0.01	0.03	0.00
	[0.50]	[0.50]	[0.50]	[0.50]			
Total Siblings	1.29	1.15	1.21	1.43	-0.07	-0.15	-0.12
	[1.35]	[1.29]	[1.26]	[1.30]			
Toilet in AWC	0.39	0.30	0.49	0.39	0.00	-0.13	0.14
	[0.48]	[0.46]	[0.50]	[0.49]			
Drinking water in AWC	0.68	0.67	0.80	0.74	-0.09	-0.11	0.10
	[0.47]	[0.47]	[0.40]	[0.44]			

Notes: Standard deviations in parenthesis. Normalized differences are calculated using the formula as in Imbens and Wooldridge (2009) for a scale-free measure of the difference in distributions. A rule of thumb is that when normalized difference exceeds 0.25 in absolute value, linear regression methods tend to be sensitive to the specification (Imbens and Rubin (2007)).

Table 3: Attrition rates in children across groups

	BA	HA	BR	C
Baseline children	1333	1555	1369	1264
Endline children	971	1127	1031	933
Attrition (%)	0.27	0.28	0.25	0.26

Table 4: Main Results with and without Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Weight	Malnourished	Grade	Severe Malnourished	Weight	Malnourished	Grade	Severe Malnourished
Post	0.283***	-0.00291	0.00517	0.00807	0.271**	0.0234	0.0317	0.00830
	(0.0611)	(0.0206)	(0.0249)	(0.00835)	(0.114)	(0.0363)	(0.0416)	(0.0121)
Basic Absolute (BA)	0.165	-0.0123	-0.0413	-0.0289	0.0954	-0.0117	-0.0401	-0.0284
	(0.234)	(0.0355)	(0.0521)	(0.0186)	(0.155)	(0.0304)	(0.0453)	(0.0178)
High Absolute (HA)	-0.0411	0.0195	0.0290	0.00946	0.176	-0.0174	-0.0177	-0.000215
	(0.168)	(0.0247)	(0.0409)	(0.0191)	(0.126)	(0.0227)	(0.0373)	(0.0182)
Basic Relative (BR)	0.126	-0.0231	-0.0404	-0.0172	0.0193	0.00793	-0.0160	-0.0239
	(0.173)	(0.0318)	(0.0491)	(0.0202)	(0.145)	(0.0372)	(0.0512)	(0.0187)
Post*BA	-0.154	-0.00809	-0.00205	0.00604	0.0398	0.00229	0.00103	-0.00126
	(0.153)	(0.0258)	(0.0346)	(0.0149)	(0.176)	(0.0430)	(0.0551)	(0.0194)
Post*HA	0.191**	-0.0465	-0.0953**	-0.0488**	0.253*	-0.0557	-0.119**	-0.0630***
	(0.0899)	(0.0301)	(0.0444)	(0.0189)	(0.130)	(0.0405)	(0.0502)	(0.0175)
Post*BR	0.107	0.00682	-0.00385	-0.0107	0.225	-0.0439	-0.0530	-0.00906
	(0.0842)	(0.0239)	(0.0300)	(0.0136)	(0.141)	(0.0437)	(0.0518)	(0.0156)
Constant	13.49***	0.331***	0.416***	0.0848***	8.688***	0.0624	-0.0232	-0.0856
	(0.127)	(0.0172)	(0.0301)	(0.0142)	(0.341)	(0.0695)	(0.110)	(0.0694)
p-value Post*BA = Post*HA	0.0335	0.1617	0.0414	0.0134	0.1567	0.0611	0.011	0.0043
p-value Post*BA = Post*BR	0.0956	0.4513	0.9515	0.3124	0.2751	0.1918	0.273	0.6883
Control Variables					x	x	x	x
Observations	9376	9376	9376	9376	5342	5342	5342	5342

Notes: The control variables used in this regression are household demographics (age of child, gender of child, total number of siblings), household assets (monthly income, food expenditure, number of rooms, proportion of goods owned in the kitchen, proportion of non-kitchen goods), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet).
*** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effect of propensity matching on change in weight for the high absolute treatment

Panel A: Nearest neighbors matching (k=5)

	Treated	Controls	Difference	Standard Error	T-statistic
Unmatched	0.567	0.387	0.180	0.060	2.99
ATT	0.570	0.401	0.170	0.063	2.69

Panel B: Kernel matching

	Treated	Controls	Difference	Standard Error	T-statistic
Unmatched	0.567	0.387	0.180	0.060	2.99
ATT	0.567	0.389	0.178	0.060	2.95

Panel C: Radius matching

	Treated	Controls	Difference	Standard Error	T-statistic
Unmatched	0.567	0.387	0.180	0.060	2.99
ATT	0.567	0.388	0.180	0.060	2.98

Table 6: Checking reversion to the mean

	Weight at endline	Weight at endline
	(1)	(2)
Weight at baseline	0.800***	0.799***
	(0.0455)	(0.0454)
Basic Absolute (BA)	0.133	0.134
	(0.113)	(0.112)
High Absoute (HA)	0.375***	0.377***
	(0.0894)	(0.0893)
Basic Relative (BR)	0.193	0.195*
	(0.115)	(0.115)
Age of child		Yes
Age of child squared		Yes
Control variables	Yes	Yes
p-value (HA - BA = 0)	0.014	0.013
p-value (BR - BA = 0)	0.594	0.593
Constant	1.710***	2.136***
	(0.477)	(0.719)
Observations	4649	4649
R-squared	0.669	0.669

Notes: The control variables used in this regression are household demographics (age of child, gender of child, total number of siblings), household assets (monthly income, food expenditure, number of rooms, proportion of goods owned in the kitchen, proportion of non-kitchen goods), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet).
*** p<0.01, ** p<0.05, * p<0.1.

Table 7: Lee (2009) treatment effect bounds on change in weight

Number of observations	=	3657
Number of selected observations	=	2054
Number of cells	=	16
Overall trimming proportion	=	0.1413
Effect 95% conf. interval		: [-0.0077, 0.3823]

Change in weight	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
High absolute treatment						
lower	0.157	0.093	1.70	0.090	-0.024	0.339
upper	0.204	0.100	2.03	0.042	0.007	0.400

Notes: The number of cells is based on tightening the Lee bounds using the gender of child, mother's literacy, father's literacy and religion (Hindu/Muslim) indicator variables. Adding more control variables was not possible with implementation of the bounds in STATA.

Table 8: Diet Results with Control Variables

	(1)	(2)	(3)	(4)	(5)
	Pulses	Fish	Meat	Green	Sweet
Post	-0.0523	0.0271	-0.0308	-0.0466	-0.123**
	(0.0435)	(0.0470)	(0.0499)	(0.0362)	(0.0516)
Basic Absolute (BA)	0.0617	0.122	0.0330	0.0900	-0.0252
	(0.0742)	(0.0882)	(0.0767)	(0.0700)	(0.0608)
High Absolute (HA)	-0.117	0.0373	-0.0446	-0.0309	-0.0874
	(0.0931)	(0.0872)	(0.0815)	(0.0906)	(0.0648)
Basic Relative (BR)	0.0752	0.133	0.0183	0.0291	0.00818
	(0.0735)	(0.105)	(0.0701)	(0.0730)	(0.0793)
Post*BA	0.0797	-0.00203	0.101	0.0189	0.0607
	(0.0964)	(0.100)	(0.0989)	(0.0914)	(0.100)
Post*HA	0.217**	0.0169	0.127*	0.000472	-0.00706
	(0.0803)	(0.106)	(0.0716)	(0.0876)	(0.0706)
Post*BR	0.109	-0.102	0.0221	0.0342	-0.0183
	(0.0689)	(0.0790)	(0.0695)	(0.0583)	(0.111)
Constant	0.235	0.177	-0.156	0.345**	0.130
	(0.179)	(0.166)	(0.164)	(0.152)	(0.0972)
Control Variables	x	x	x	x	x
p-value Post*BA = Post*HA	0.2246	0.886	0.8039	0.8782	0.5036
p-value Post*BA = Post*BR	0.7784	0.3688	0.433	0.8791	0.5519
Observations	5421	5430	5446	5441	5328

Notes: The control variables used in this regression are household demographics (age of child, gender of child, total number of siblings), household assets (monthly income, food expenditure, number of rooms, proportion of goods owned in the kitchen, proportion of non-kitchen goods), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet).
*** p<0.01, ** p<0.05, * p<0.1.

Table 9: Gender Difference in average treatment effects

	(1)	(2)	(3)	(4)
	Weight	Malnourished	Grade	Severe Malnourished
Post*BA	0.142	-0.0226	-0.0339	-0.0113
	(0.216)	(0.0428)	(0.0712)	(0.0391)
Post*HA	0.432***	-0.0989**	-0.191***	-0.0924**
	(0.145)	(0.0397)	(0.0620)	(0.0350)
Post*BR	0.219	-0.0548	-0.0682	-0.0133
	(0.164)	(0.0371)	(0.0548)	(0.0307)
Gender*BA*Post	-0.197	0.0475	0.0678	0.0203
	(0.163)	(0.0469)	(0.0887)	(0.0548)
Gender*HA*Post	-0.345*	0.0830*	0.140*	0.0567
	(0.193)	(0.0483)	(0.0780)	(0.0435)
Gender*BR*Post	0.0188	0.0202	0.0283	0.00811
	(0.176)	(0.0426)	(0.0726)	(0.0424)
Constant	8.784***	0.0442	-0.0635	-0.108
	(0.349)	(0.0699)	(0.109)	(0.0708)
Control Variables	x	x	x	x
Observations	5342	5342	5342	5342

Notes: Gender = 1 if girl and 0 if boy. The control variables used in this regression are household demographics (age of child, gender of child, total number of siblings), household assets (monthly income, food expenditure, number of rooms, proportion of goods owned in the kitchen, proportion of non-kitchen goods), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet).
*** p<0.01, ** p<0.05, * p<0.1.

Table 10: Results on z-score disaggregated by age and gender

	(1)	(2)	(3)	(4)	(5)	(6)
	All sample	Age 3-4	Age 4-5	Age 5-6	Boys	Girls
Post	0.175***	0.237***	0.119*	0.104**	0.143***	0.206***
	(0.0352)	(0.0427)	(0.0600)	(0.0484)	(0.0478)	(0.0420)
Basic Absolute (BA)	0.0481	0.0958	-0.0484	0.155	0.0294	0.0662
	(0.0959)	(0.123)	(0.0880)	(0.161)	(0.115)	(0.0873)
High Absolute (HA)	-0.0308	-0.00457	-0.0184	-0.0724	-0.0637	0.00165
	(0.0679)	(0.0802)	(0.0691)	(0.113)	(0.105)	(0.0562)
Basic Relative (BR)	0.0375	0.00130	0.0224	0.143	0.0222	0.0519
	(0.0744)	(0.0752)	(0.0879)	(0.135)	(0.0905)	(0.0748)
Post*BA	-0.00448	-0.0986	0.103	-0.0389	0.0284	-0.0368
	(0.0611)	(0.0767)	(0.0845)	(0.0962)	(0.0745)	(0.0635)
Post*HA	0.107*	0.0681	0.162**	0.0948	0.203***	0.0191
	(0.0535)	(0.0713)	(0.0682)	(0.0962)	(0.0675)	(0.0627)
Post*BR	0.0493	0.0494	0.0355	0.102	0.0531	0.0462
	(0.0476)	(0.0644)	(0.0714)	(0.0938)	(0.0669)	(0.0504)
Constant	-1.433***	-1.309***	-1.477***	-1.647***	-1.395***	-1.470***
	(0.0498)	(0.0483)	(0.0579)	(0.0658)	(0.0690)	(0.0428)
Observations	9377	4164	3383	1720	4581	4796
R-squared	0.014	0.016	0.014	0.016	0.013	0.015

*** p<0.01, ** p<0.05, * p<0.1.

Table 11: Selective targeting test

	(1)	(2)	(3)	(4)
	Weight	Malnourished	Grade	Severe Malnourished
Post*BA	-0.0206	0.0526	0.0892	0.0366
	(0.158)	(0.0619)	(0.0799)	(0.0463)
Post*HA	0.469**	-0.109*	-0.301***	-0.193***
	(0.181)	(0.0623)	(0.0778)	(0.0410)
Post*BR	0.0483	-0.00445	-0.0204	-0.0159
	(0.194)	(0.0760)	(0.102)	(0.0359)
Close To Target*BA*Post	0.0700	-0.0862	-0.116	-0.0293
	(0.216)	(0.0967)	(0.110)	(0.0533)
Close To Target*HA*Post	0.239	0.0207	0.0582	0.0375
	(0.212)	(0.0915)	(0.0914)	(0.0447)
Close To Target*BR*Post	0.0265	-0.0522	-0.0670	-0.0148
	(0.299)	(0.126)	(0.162)	(0.0670)
Constant	5.987***	1.162***	1.104***	-0.0584
	(0.415)	(0.0835)	(0.210)	(0.191)
Control Variables	x	x	x	x
Observations	1739	1739	1739	1739

Notes: The control variables used in columns (5)-(8) are household demographics (age of child, gender of child, total number of siblings), household assets (monthly income, food expenditure, number of rooms, proportion of goods owned in the kitchen, proportion of non-kitchen goods), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet). Other variables in this regression include treatments on their own, close to target on its own, post on its own and pair-wise interactions of close to target with post. The variable closetotarget is defined to be 1 if the child is malnourished at the baseline and its deficit weight (difference between the target weight and the actual weight) is less than the mean deficit weight and 0 if the child is malnourished at the baseline, but his or her deficit weight is more than or equal to the mean deficit weight. Target weight is defined as the threshold at which the child's grade will decrease by 1 (i.e. would go from severely malnourished to only moderately malnourished or from moderately malnourished to not malnourished).

Table 12: Dose response check in terms of proportion of malnourished children

	(1)	(2)	(3)	(4)	(5)
	Weight	z-score	Grade	Malnourished	Severe Malnourished
Post	-0.0867	-0.00781	0.196**	0.161**	0.0349
	(0.180)	(0.0963)	(0.0877)	(0.0670)	(0.0279)
Post*HA	-0.283	-0.172	0.0791	0.0234	0.0557
	(0.382)	(0.199)	(0.118)	(0.0893)	(0.0349)
Dose*HA*Post	1.669*	0.909*	-0.613**	-0.253	-0.361***
	(0.956)	(0.485)	(0.269)	(0.207)	(0.0970)
Control Variables	x	x	x	x	x
Constant	9.541***	-0.191	-0.353***	-0.163***	-0.190**
	-0.355	-0.159	-0.111	-0.059	-0.0743
Observations	5342	5342	5342	5342	5342
R-squared	0.308	0.163	0.133	0.116	0.076

Notes: Dose represents the number of malnourished children divided by the total number of children weighed at the baseline in the Anganwadi (i.e. the proportion of malnourished children at the baseline in the center). The control variables used in this regression are BA, BR, Post*BA, Post*BR, household demographics (age of child, gender of child, total number of siblings), household assets (monthly income, food expenditure, number of rooms, proportion of goods owned in the kitchen, proportion of non-kitchen goods), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet).
*** p<0.01, ** p<0.05, * p<0.1.

MAHESHTALA BLOCK: TREATMENT AND CONTROL CLUSTERS

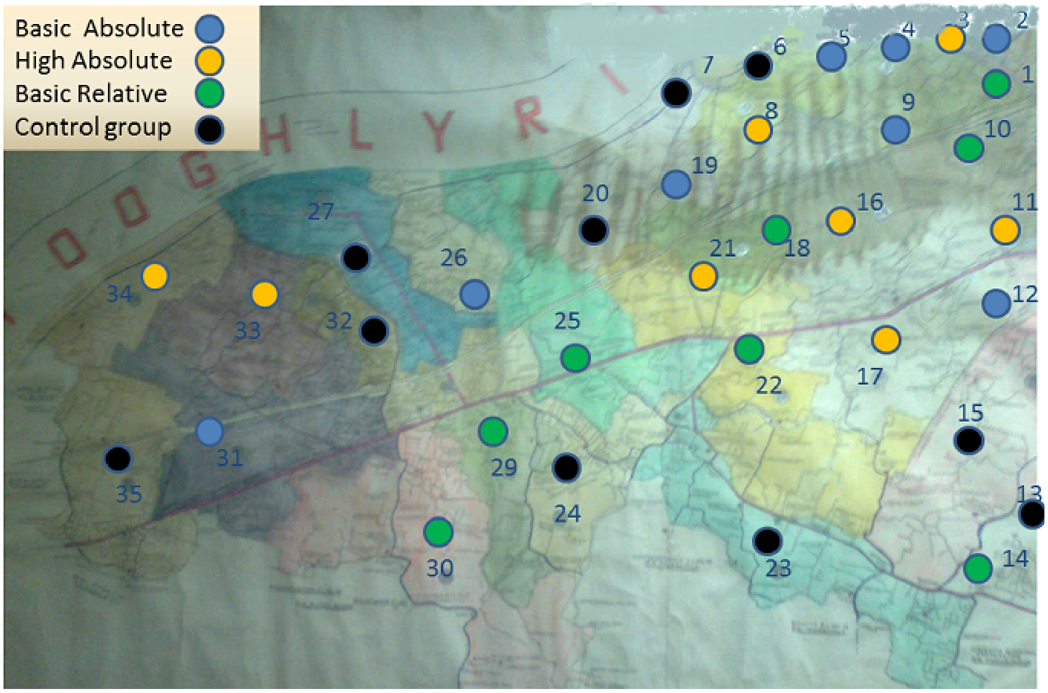

Figure 1: Map of Maheshtala Block and Clusters in the experiment

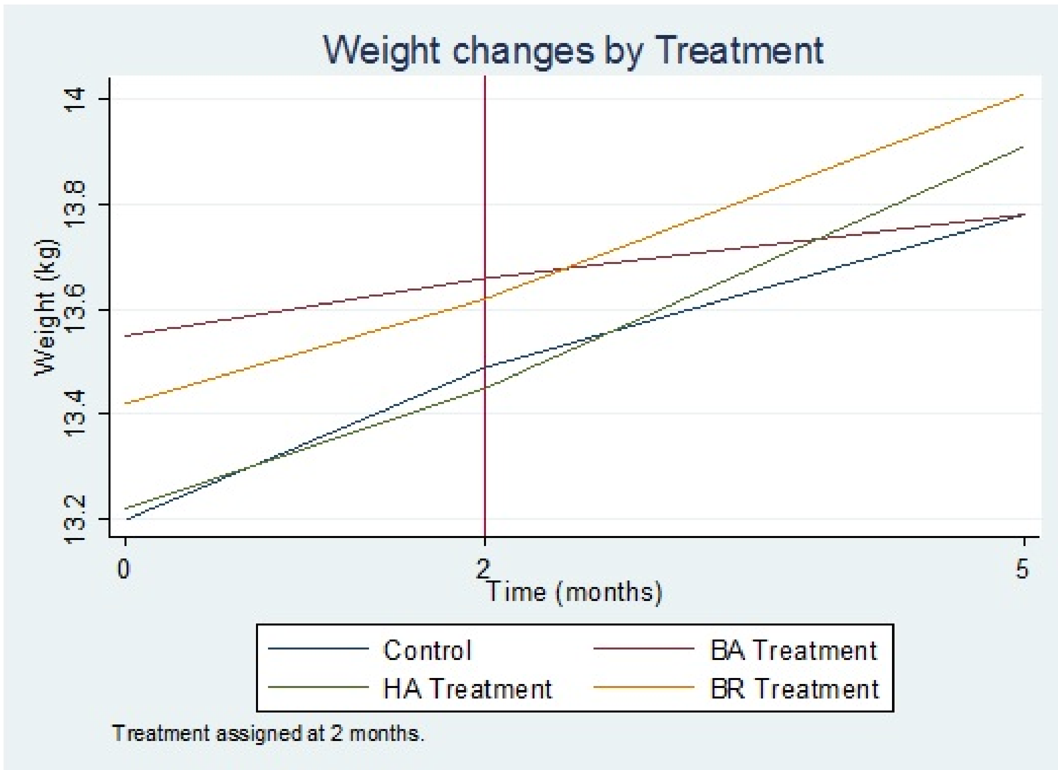

Figure 2: Weight changes by Treatment

13 Appendix

13.1 Tables

Table A1: Placebo test with and without Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Weight	Malnourished	Grade	Severe	Weight	Malnourished	Grade	Severe
Post	0.289**	0.0365	0.0703**	0.0338***	0.157**	0.0590**	0.0957***	0.0367***
	(0.111)	(0.0250)	(0.0302)	(0.00845)	(0.0621)	(0.0256)	(0.0312)	(0.0110)
Basic Absolute (BA)	0.353	-0.00926	-0.0223	-0.0131	0.0694	0.0339	0.0262	-0.00778
	(0.267)	(0.0432)	(0.0607)	(0.0191)	(0.181)	(0.0457)	(0.0596)	(0.0157)
High Absolute (HA)	0.0177	0.0225	0.0570	0.0346*	0.0253	0.0433	0.0662	0.0229
	(0.191)	(0.0402)	(0.0565)	(0.0185)	(0.153)	(0.0347)	(0.0516)	(0.0199)
Basic Relative (BR)	0.210	-0.0131	-0.0198	-0.00664	-0.161	0.0526	0.0612	0.00855
	(0.206)	(0.0354)	(0.0518)	(0.0199)	(0.161)	(0.0410)	(0.0532)	(0.0179)
Post*BA	-0.188	-0.00309	-0.0189	-0.0159	-0.0512	-0.0318	-0.0476	-0.0158
	(0.167)	(0.0298)	(0.0364)	(0.0100)	(0.0897)	(0.0294)	(0.0362)	(0.0137)
Post*HA	-0.0588	-0.00296	-0.0281	-0.0251	0.0466	-0.0396	-0.0580	-0.0184
	(0.164)	(0.0317)	(0.0440)	(0.0188)	(0.113)	(0.0300)	(0.0454)	(0.0233)
Post*BR	-0.0843	-0.00997	-0.0206	-0.0106	0.134	-0.0367	-0.0633	-0.0266
	(0.184)	(0.0356)	(0.0449)	(0.0138)	(0.111)	(0.0364)	(0.0437)	(0.0164)
Constant	13.20***	0.295***	0.346***	0.0510***	8.615***	-0.0329	-0.137	-0.104*
	(0.110)	(0.0280)	(0.0419)	(0.0151)	(0.417)	(0.109)	(0.124)	(0.0605)
N	9789	9789	9789	9789	5397	5397	5397	5397

Notes: The control variables used in this regression are household demographics (age of child, gender of child, total number of siblings), household assets (monthly income, food expenditure, number of rooms, proportion of goods owned in the kitchen, proportion of non-kitchen goods), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet).

Table A2: Attrition Table

	(1)	(2)	(3)	(4)
	Attrition	Attrition	Attrition	Attrition
Weight*BA	0.0190			
	(0.0155)			
Weight*HA	-0.00657			
	(0.0152)			
Weight*BR	-0.00680			
	(0.0169)			
Malnourished*BA		-0.0367		
		(0.0656)		
Malnourished*HA		0.0314		
		(0.0532)		
Malnourished*BR		0.0114		
		(0.0695)		
Grade*BA			-0.0301	
			(0.0555)	
Grade*HA			0.0114	
			(0.0460)	
Grade*BR			-0.00393	
			(0.0603)	
SevereMalnourished*BA				-0.0204
				(0.104)
SevereMalnourished*HA				-0.0297
				(0.101)
SevereMalnourished*BR				-0.0403
				(0.127)
Control Variables	x	x	x	x
Observations	3013	3013	3013	3013

Notes: The control variables used in this regression are household demographics (age of child, gender of child, total number of siblings), household assets (monthly income, food expenditure, number of rooms, proportion of goods owned in the kitchen, proportion of non-kitchen goods), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet). The attrition variable takes value 1 if the child's weight is unavailable in the second round, and 0 otherwise.
*** p<0.01, ** p<0.05, * p<0.1.

Table A3: Main Results with Control Variables and Moulton Correction

	(1)	(2)	(3)	(4)
	Weight	Malnourished	Grade	Severe Malnourished
Post	0.271**	0.0234	0.0317	0.00830
	(0.111)	(0.0270)	(0.0360)	(0.0153)
Basic Absolute (BA)	0.0954	-0.0117	-0.0401	-0.0284
	(0.197)	(0.0335)	(0.0500)	(0.0205)
High Absolute (HA)	0.176	-0.0174	-0.0177	-0.000215
	(0.193)	(0.0329)	(0.0491)	(0.0201)
Basic Relative (BR)	0.0193	0.00793	-0.0160	-0.0239
	(0.200)	(0.0341)	(0.0509)	(0.0208)
Post*BA	0.0398	0.00229	0.00103	-0.00126
	(0.206)	(0.0407)	(0.0576)	(0.0240)
Post*HA	0.253	-0.0557	-0.119**	-0.0630***
	(0.210)	(0.0408)	(0.0581)	(0.0242)
Post*BR	0.225	-0.0439	-0.0530	-0.00906
	(0.218)	(0.0428)	(0.0607)	(0.0253)
Constant	8.688***	0.0624	-0.0232	-0.0856
	(0.598)	(0.102)	(0.152)	(0.0622)
Control Variables	x	x	x	x
Observations	5342	5342	5342	5342

Notes: The control variables used in this regression are household demographics (age of child, gender of child, total number of siblings), household assets (monthly income, food expenditure, number of rooms, proportion of goods owned in the kitchen, proportion of non-kitchen goods), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet). Moulton correction for the standard errors is used in this table.
*** p<0.01, ** p<0.05, * p<0.1.

Table A4: Robustness Check for Main Results after excluding All Household Assets from Controls

	(1)	(2)	(3)	(4)
	Weight	Malnourished	Grade	Severe Malnourished
Post	0.281***	0.0131	0.0114	-0.00168
	(0.0792)	(0.0227)	(0.0265)	(0.00948)
Basic Absolute (BA)	0.281*	-0.0498	-0.0915**	-0.0417***
	(0.164)	(0.0317)	(0.0441)	(0.0152)
High Absolute (HA)	0.198	-0.0299	-0.0376	-0.00769
	(0.122)	(0.0219)	(0.0345)	(0.0162)
Basic Relative (BR)	0.155	-0.0323	-0.0608	-0.0286*
	(0.123)	(0.0275)	(0.0379)	(0.0150)
Post*BA	-0.00355	0.00528	0.0169	0.0116
	(0.146)	(0.0312)	(0.0413)	(0.0153)
Post*HA	0.263***	-0.0569**	-0.109***	-0.0518***
	(0.0844)	(0.0252)	(0.0342)	(0.0156)
Post*BR	0.162	-0.0277	-0.0268	0.000865
	(0.114)	(0.0291)	(0.0385)	(0.0140)
Constant	8.840***	0.0519	-0.0410	-0.0929*
	(0.293)	(0.0668)	(0.0944)	(0.0537)
Control Variables	x	x	x	x
p-value Post*BA = Post*HA	0.0567	0.0266	0.0039	0.0019
p-value Post*BA = Post*BR	0.2945	0.284	0.3301	0.5422
Observations	6564	6564	6564	6564

Notes: The control variables used in this regression are household demographics (age of child, gender of child, total number of siblings), parent-specific controls (mother's age, mother's religion, whether the mother is a housewife or not, literacy of mother and father, whether the mother scored a high or low quiz score), worker-specific controls (whether the worker is experienced or not, whether the worker is highly educated or not, whether the worker scored a high or low quiz score), and center-specific controls (dummy variables for the center's facilities: electricity, fan, helper, chart, blackboard, drinking water, and toilet).
*** p<0.01, ** p<0.05, * p<0.1.

Table A5: Results on z-score disaggregated by age and gender

	(1)	(2)	(3)	(4)	(5)	(6)
	All sample	Age 3-4	Age 4-5	Age 5-6	Boys	Girls
Post	0.175***	0.237***	0.119*	0.104**	0.143***	0.206***
	(0.0352)	(0.0427)	(0.0600)	(0.0484)	(0.0478)	(0.0420)
Basic Absolute (BA)	0.0481	0.0958	-0.0484	0.155	0.0294	0.0662
	(0.0959)	(0.123)	(0.0880)	(0.161)	(0.115)	(0.0873)
High Absolute (HA)	-0.0308	-0.00457	-0.0184	-0.0724	-0.0637	0.00165
	(0.0679)	(0.0802)	(0.0691)	(0.113)	(0.105)	(0.0562)
Basic Relative (BR)	0.0375	0.00130	0.0224	0.143	0.0222	0.0519
	(0.0744)	(0.0752)	(0.0879)	(0.135)	(0.0905)	(0.0748)
Post*BA	-0.00448	-0.0986	0.103	-0.0389	0.0284	-0.0368
	(0.0611)	(0.0767)	(0.0845)	(0.0962)	(0.0745)	(0.0635)
Post*HA	0.107*	0.0681	0.162**	0.0948	0.203***	0.0191
	(0.0535)	(0.0713)	(0.0682)	(0.0962)	(0.0675)	(0.0627)
Post*BR	0.0493	0.0494	0.0355	0.102	0.0531	0.0462
	(0.0476)	(0.0644)	(0.0714)	(0.0938)	(0.0669)	(0.0504)
Constant	-1.433***	-1.309***	-1.477***	-1.647***	-1.395***	-1.470***
	(0.0498)	(0.0483)	(0.0579)	(0.0658)	(0.0690)	(0.0428)
Observations	9377	4164	3383	1720	4581	4796
R-squared	0.014	0.016	0.014	0.016	0.013	0.015

Notes: *** p<0.01, ** p<0.05, * p<0.1.

13.2 Theory

In the absolute performance pay case:

$$\begin{aligned} E(U_A(2)) - E(U_A(0)) &= \theta V(a) + (1-\theta)V(b) - 2c - V(a) \\ &= (1-\theta)(V(b) - V(a)) - 2c > 0 \end{aligned}$$

i.e.

$$V(b) - V(a) > \frac{2c}{1-\theta}$$

$$\begin{aligned} E(U_A(2)) - E(U_A(1)) &= \theta V(a) + (1-\theta)V(b) - 2c - \frac{1+\theta}{2}V(a) - \frac{1-\theta}{2}V(b) + \frac{1}{2}c \\ &= \frac{1-\theta}{2}(V(b) - V(a)) - \frac{3}{2}c > 0 \end{aligned}$$

i.e.

$$V(b) - V(a) > \frac{3c}{1-\theta}$$

Notice that this condition dominates the first one.

In the relative performance pay case:

To make 2 a best response, it is necessary that:

$$\begin{aligned} E(U_A(2)) - E(U_A(0)) &= V(T) - 2c - \theta V(T) - (1-\theta)V(L_1) \\ &= (1-\theta)(V(T) - V(L_1)) - 2c > 0 \end{aligned}$$

which implies that

$$V(T) - V(L_1) > \frac{2c}{1-\theta}$$

$$\begin{aligned} E(U_A(2)) - E(U_A(1)) &= V(T) - 2c - \frac{1+\theta}{2}V(T) - \frac{1-\theta}{2}V(L_1) + \frac{1}{2}c \\ &= \frac{1-\theta}{2}(V(T) - V(L_1)) - \frac{3}{2}c > 0 \end{aligned}$$

which implies that V

$$(T) - V(L_1) > \frac{3c}{1-\theta}(*)$$

Notice this condition dominates the first one.

Similarly, we assume that in the worst case scenario, the agent should also attain the same minimum utility level U. This means that:

$$\theta V(T) + (1-\theta)V(L_1) \geqslant U \qquad (**)$$

The cost is minimized when $(**)$ holds, i.e., when $V(L_1) = \frac{U-\theta V(T)}{1-\theta}$. Plug it in $(*)$, it follows that:

$$V(T) - \frac{U - \theta V(T)}{1-\theta} \geqslant \frac{3c}{1-\theta},$$

which implies that

$$(1-\theta)V(T) - U + \theta V(T) \geqslant 3c.$$

$$\begin{aligned}
C_{absolute} - C_{relative} &= n \times (\theta V^{-1}(U) + (1-\theta)V^{-1}(\frac{3c}{1-\theta} + U)) - n \times V^{-1}(U+3c) \\
&= n(\theta V^{-1}(U) + (1-\theta)V^{-1}(\frac{3c}{1-\theta} + U) - V^{-1}(U+3c))
\end{aligned}$$

Notice the difference is actually 0 when $\theta = 0$. To see how this difference varies with θ, we take its derivative about θ. For convenience, suppose $V^{-1}(x) = h(x)$. Since $V(x)$ is concave and increasing, its inverse function $h(x)$ is convex and increasing.

$$\begin{aligned}
(C_{absolute} - C_{relative})' &= n(h(U) - h(\frac{3c}{1-\theta} + U) + (1-\theta)h'(\frac{3c}{1-\theta} + U) \times \frac{3c}{(1-\theta)^2}) \\
&= n(h(U) - h(\frac{3c}{1-\theta} + U) + h'(\frac{3c}{1-\theta} + U) \times \frac{3c}{(1-\theta)})
\end{aligned}$$

Since $h(x)$ is a continuous function on its domain, by Mean Value Theorem, it follows that

$$h(\frac{3c}{1-\theta} + U) - h(U) = (\frac{3c}{1-\theta} + U - U)h'(U^*) = \frac{3c}{1-\theta}h'(U^*)$$

where

$$U^* \in (U, \frac{3c}{1-\theta} + U)$$

Plug it back in, it follows that:

$$\begin{aligned}(C_{absolute} - C_{relative})' &= h'(\frac{3c}{1-\theta} + U) \times \frac{3c}{(1-\theta)} - \frac{3c}{1-\theta}h'(U^*) \\ &= \frac{3c}{1-\theta}(h'(\frac{3c}{1-\theta} + U) - h'(U^*))\end{aligned}$$

Notice that

$$\frac{3c}{1-\theta} + U > U^*$$

Since $h(x)$ is convex, it follows that

$$h'(\frac{3c}{1-\theta} + U) > h'(U^*)$$

and therefore

$$(C_{absolute} - C_{relative})' > 0$$

Now that $C_{absolute} - C_{relative} = 0$ for $\theta = 0$, then $C_{absolute} > C_{relative}$ for $\theta > 0$. To put it another way, the cost for an absolute scheme is higher than that for a relative scheme whenever common shock is present. This result is similar but not the same as that in the literature, which states that the absolute scheme should dominate the relative schemes when the common shock level is low, or at least when common shock is not present. This result is caused by the "public sector assumption", which assumes that agents should obtain a minimum level of utility even when they perform poorly.