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# When the Roof Reflects: Heat, Learning, and Adaptation in Early Childhood Settings

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# When the Roof Reflects: Heat, Learning, and Adaptation in Early Childhood Settings

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**Abstract**

Cool roof technologies, especially cool roof paint, offer a low-cost, easily scalable, and low-emission alternative to energy-intensive air-conditioning for reducing heat exposure in buildings - an increasingly urgent need in developing countries facing rising temperatures due to climate change. We evaluate the effectiveness of a cool roof intervention - white reflective paint applied to the roofs of government pre-schools (anganwadis) in Thiruvananthapuram district of the Indian state of Kerala—using a randomized controlled trial. The cool roof paint reduces indoor temperatures in treated pre-schools by approximately 1.3°C. Staff in treatment pre-schools report significantly lower thermal discomfort. We also find meaningful improvements in children's cognitive performance, amounting to roughly 6.4% of the baseline mean. The intervention has no detectable effect on children's attendance. Overall, our findings demonstrate that cool roofs can serve as a practical and scalable adaptation strategy to mitigate heat stress in low-resource educational settings.

Keywords: Adaptation to Heat, RCT, Pre-schools, Temperature, Thermal comfort, Cognitive performance, Learning outcome, India

JEL Codes: I21, I25, Q54, Q56

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# 1. Introduction

## 1.1 Background

Rising global temperatures pose a growing threat to human development, shaping not only physical health and livelihoods but also the foundations of human capital. Beyond mortality and productivity losses, an expanding literature demonstrates that heat exposure undermines cognitive performance, learning, and educational attainment—core components of long-run human capital formation. High temperatures during school hours or across academic years reduce concentration, attendance, and test scores, with cumulative exposure compounding losses, particularly among disadvantaged students (Goodman et al., 2020; Graff Zivin et al., 2020; Li & Patel, 2021; Park, 2022; Vasilakopoulou & Santamouris, 2025). These effects represent persistent, rather than transitory, channels through which climate change erodes human capital accumulation.

Institutional adaptation to rising heat remains uneven. Global reviews show that most documented heat responses are autonomous and incremental, concentrated in health or livelihood sectors, with few directed toward educational environments (Turek-Hankins et al., 2021). Within low- and middle-income countries, infrastructural constraints magnify this gap: schools and early childhood centers rarely have systematic heat management strategies despite their high thermal sensitivity. This institutional vacuum is particularly consequential in early childhood, when environmental stress can affect not only attention and behavior but also socio-emotional and cognitive development.

This paper evaluates a low-cost infrastructural adaptation in government-run preschools (also known as *Anganwadis*) in the state of Kerala, in south India. We test whether applying a high-albedo, white "cool-roof" paint can reduce indoor temperature and improve comfort and learning conditions. Using a randomized controlled trial, we assess impacts of the cool roof paint intervention on indoor temperature, thermal comfort among pre-school staff and children's cognitive performance and attendance.

These government run pre-schools or pre-schools form the core of India's Integrated Child Development Services (ICDS) program, offering pre-school education, nutrition, and health services to children. They typically operate in one - room buildings with limited insulation or cooling, making them highly sensitive to outdoor temperature fluctuations. A typical pre-school in Kerala has a roof area of 45–55 sq.meters., a teacher and helper as staff, and 15–20 children attending from 9:30 a.m. to 3:30 p.m., six days a week. Such physical layouts, combined with low ventilation and basic roof structures, leave these centers vulnerable to heat accumulation during peak hours.

Maximum temperatures in Kerala have risen on average by 1.6°C between 1980–2020 (Ajithkumar & Riya, 2022), and the Indian Meteorological Department issued its first heat-wave warning for the state in 2016. April 2024 saw 16 days above 40°C - the highest on record, the previous high being 8 days in 2016 (The New Indian Express, May 4, 2024). Long-term meteorological data from the India Meteorological Department show a discernible upward trend in extreme temperatures in Thiruvananthapuram, the site of our experiment (see Appendix B.1). Several of the highest recorded maximum temperatures in Thiruvananthapuram's history occurred during 2024–2025, underscoring the growing urgency of heat-mitigation strategies in urban Kerala.

The field experiment, conducted in Thiruvananthapuram district of Kerala was undertaken in partnership with the Energy Management Centre (EMC), Government of Kerala. *Kulirma*, an EMC initiative, promotes reflective white roof coatings as part of a state-level plan to convert 45 million sq.meters of roof area into cool roofs. Our randomized pilot study in five panchayats contributes to the evaluation of this initiative by linking building-level temperature reduction to human-capital outcomes in pre-school settings.

## 1.2 Heat, Productivity and Human Capital: Existing Evidence

A growing empirical literature documents that temperature affects economic output, health, and cognition. Using micro-data from Indian manufacturing firms, Somanathan et al. (2021) show that productivity and attendance decline on hotter days, while climate control mitigates losses. Gupta and Somanathan (2023) find higher absenteeism among formal-sector workers lacking cooling facilities, and Adhvaryu et al. (2020) demonstrate that energy-efficient LED lighting in garment factories near Bangalore increases productivity on hot days by lowering indoor heat. P. Zhang et al. (2018), analyzing half a million Chinese manufacturing plants, reveal an inverted-U temperature–productivity gradient and project annual output losses of 12% by mid-century without additional adaptation. Evidence from Delhi's informal sector (Das & Somanathan, 2024) further shows that high summer temperatures reduce sleep, increase illness, and significantly depress earnings.

A parallel body of work identifies heat as a determinant of educational outcomes. T. Garg et al. (2020) show that high temperatures reduce math and reading scores among Indian students, partly through income effects. At a physiological level, elevated ambient temperature increases brain temperature and disrupts neural functioning (Bowler & Tirri, 1974; Yablonskiy et al., 2000). Empirical work from the

United States finds that hotter school years reduce cumulative learning by nearly 1% per °F, with air-conditioning offsetting much of the loss (Goodman et al., 2020). Similar exam-day effects appear in New York and China's National College Entrance Examination (Graff Zivin et al., 2020; Park, 2022), while results from Brazil suggest adaptation moderates impacts (Li & Patel, 2021). Experimental and longitudinal studies confirm that even low-stakes cognitive tasks deteriorate under heat, with environmental adaptations such as air-conditioning and ventilation offsetting about half of observed deficits (Graff Zivin et al., 2018; X. Zhang et al., 2024).

## 1.3 Pre-school Environments and Heat Exposure

A substantial literature shows that early cognitive and socio-emotional skills form the foundation for later learning, with gains and deficits accumulating over time. Heckman (2006) emphasizes that early skill formation follows a hierarchical and cumulative structure: early investments raise the productivity of later investments, while early disadvantages become increasingly costly to remediate. Extending this framework, Cunha and Heckman (2007) formalize skill formation as a multi-stage process characterized by self-productivity and dynamic complementarity, implying that improvements in early cognitive functioning can generate sustained benefits throughout subsequent schooling.

These theoretical insights are supported by long-term experimental evidence from Tennessee's Project STAR. Chetty et al. (2011) show that students exposed to higher-quality early classrooms experience improved adult outcomes - including higher earnings and college attendance - even when early test score effects fade. Persistent impacts on non-cognitive skills such as effort and engagement suggest a mechanism through which early gains continue to influence later performance.

Recent research highlights that pre-school and childcare settings constitute a distinct, understudied context of heat vulnerability. Malmquist et al. (2021) document how the 2018 Swedish heatwave strained pre-schools, with educators' discomfort amplifying children's vulnerability. Otto and Thieken (2024) document that childcare centers in Germany experience notable strain during heatwaves, with impacts on staff comfort, scheduling, and children's well-being, yet with few durable adaptation measures in place. These findings underscore that even in temperate climates, heat can affect the functioning of early-learning environments—an issue magnified in warmer settings such as southern India. Physiological studies confirm that pre-school-aged children have lower thermal-comfort thresholds than adults (Nam et al., 2015). Field evidence links warmer pre-school yards to reduced physical activity and attentiveness (Wallenberg et al., 2023) and experimental work finds that temperature and humidity extremes systematically impair toddlers' attention and behavior (Ciucci et al., 2013). Together, these findings show that early childhood environments experience multi-dimensional effects of heat—physiological, behavioral, and pedagogical—mediated by limited institutional capacity for thermal management.

## 1.4 Cool Roofs and Building-Level Adaptation

A complementary body of work evaluates the effectiveness of cool-roof technologies. High-albedo coatings reflect a larger share of solar radiation, lowering roof and ceiling temperatures and, consequently, indoor heat loads. Experimental studies confirm measurable thermal benefits: Androutsopoulos et al. (2017) find 1.3–1.9°C indoor reductions in Greek school buildings after roof coating, and V. Garg et al. (2016) report significant declines in under-deck and indoor temperatures in monitored Indian schools in Hyderabad and Nagpur. In Ahmedabad's urban slums, Vellingiri et al.

(2020) show that thermocol insulation and reflective white paint effectively reduce indoor heat. A comprehensive review by Black-Ingersoll et al. (2022) corroborates these physical benefits but emphasizes the paucity of rigorous impact evaluations linking cool-roof interventions to human outcomes.

Recent evaluations of educational adaptations underscore this point. Chatterjee and Pope (2023) examine a $135 million air-conditioning roll-out across Chicago Public Schools and find no significant improvement in end-of-year scores, suggesting that infrastructure investments alone may be insufficient absent complementary pedagogical measures. Conversely, emerging field trials of community-based cool-roof programs reveal measurable temperature reductions and improved comfort. McCormack (2024) show that hot school days increase absenteeism and disciplinary incidents, particularly in schools without cooling. Evidence from Africa extends this research to early childhood: Vidogbena (2025) report that heat exposure reduces attentiveness and executive function among pre-schoolers, and cumulative exposure impairs math and reading outcomes across West and Central Africa. Together, these studies identify temperature as a key determinant of educational outcomes and highlight the potential of low-cost environmental adaptations in schooling systems.

## 1.5 Contribution and Findings

Our study contributes to the growing literature on heat, learning, and adaptation by demonstrating the potential of a low-cost, building-level intervention to mitigate the effects of heat exposure in early childhood settings. We provide experimental evidence from a randomized cool-roof intervention in government-run pre-schools, showing that simple reflective paint coatings—one of the most affordable passive-cooling technologies—can substantially improve thermal and learning conditions. Thermal imaging confirms large reductions in roof and ceiling surface temperatures, illustrating how the coating curtails heat transfer into indoor spaces. As a result, indoor temperatures fall by an average of 1.2°C in treated centers relative to controls, accompanied by improved thermal comfort among pre-school staff and lower perceived heat intensity. Children in treated pre-schools exhibit a 6.6% improvement in puzzle-based cognitive performance, suggesting that even inexpensive physical adaptations can yield measurable gains in early learning outcomes. By linking cost-effective micro-level adaptation to human capital formation, the study offers evidence for scalable, climate-resilient policy design in heat-vulnerable regions.

## 2. Intervention

The intervention employs a simple cool-roof technology in the form of white, high-reflective paint applied to rooftop surfaces. Implementation, including the choice of paint and financing, was undertaken by the Energy Management Centre (EMC), Government of Kerala. EMC considered alternative cool-roof options—such as green canopies using creepers, rooftop gardens, and reflective tiles—but selected white reflective paint owing to its low cost, ease of application and maintenance, minimal structural modification requirements and limited risk to existing roofs. Budgetary constraints of EMC determined the study's geographic scope and the sample size, leading to its rollout across five panchayats (village councils) in Thiruvananthapuram district: Andoorkonam, Kattakada, Manikal, Perumkadavila, and Pullumpara.

Pre-schools with exposed concrete roofs were first identified through preliminary field visits by the research team following the data provided by EMC to assess structural suitability. Eligible centers were then randomly assigned to treatment and control groups within each *panchayat* (village council). In total, 73 pre-schools were randomized, yielding 38 in the treatment group and 35 in the control group. Five pre-schools were later excluded following decisions by the respective *panchayats* to add aluminum sheets on top of the existing roof structure. Consequently, the final baseline sample consisted of 36 treated and 32 control pre-schools.

In the treatment group, roofs were coated with a white reflective paint possessing a Solar Reflective Index (SRI) of 100. Two coats were applied following surface cleaning. Painting began on 20 March 2024 and was completed across all pre-schools by 16 April 2024. The intervention could not be implemented in three centers (in addition to the five mentioned above)—two due to unavailability of water for application and one where aluminum roofing was installed after treatment assignment but before rollout of the intervention.

Baseline surveys were conducted during the first two weeks of March 2024, prior to the intervention. Endline surveys and thermal imaging were completed in the third week of May 2024.

The trial was registered in the AEA RCT Registry in January 2024 with ID: AEARCTR-0012888. The data collection and the intervention strictly followed the details provided in the registry.

## 3. Data

This section describes the data sources and the key variables used in the analysis: temperature, thermal comfort, cognitive effort, and attendance.

## 3.1 Temperature

Temperature data were collected using thermometers installed by us in all participating pre-schools during the last week of February 2024. The devices recorded daily temperature extremes, which were reset each morning. Teachers photographed or video-recorded the thermometer display at 10 a.m. each working day and transmitted the records to the research team. Data collection continued until the end of May 2024, after which the instruments were removed.

To assess the physical mechanism underlying the intervention, infrared thermal imaging was conducted between 8–18 May 2024 in four of the five panchayats.

Infrared thermography, a non-contact technique that detects emitted radiation to estimate surface temperature, was used to measure roof and ceiling temperatures in treated and untreated centers. These images provided spatially precise evidence on how the reflective coating reduced roof heat absorption and transmission indoors.

Heavy rainfall in Perumkadavila panchayat and subsequent mould growth on several roofs prevented completion of the thermal imaging exercise there.

## 3.2 Thermal Comfort

Thermal-comfort surveys were administered to both staff members—the teacher and the helper—at each pre-school before (baseline) and after (endline) the intervention. The baseline survey was conducted between 21 February and 6 March 2024, and the endline between 8–21 May 2024. Respondents rated their perceptions on three questions using Likert-type scales:

- **Heat Perception Index:** "How do you feel about the temperature of this classroom at the moment?" (1 = cold, 7 = hot). Higher values indicate a hotter perceived temperature.

- **Discomfort Index:** "How comfortable are you with the thermal environment in your classroom at the moment?" (1 = very comfortable, 7 = very uncomfortable). Higher values indicate greater discomfort.
- **Desired Temperature Change:** "What is your desired temperature state in the classroom?" (1 = cooler, 2 = no change, 3 = warmer).

## 3.3 Cognitive Performance

Children's cognitive performance was measured through an age-appropriate puzzle activity administered prior to the intervention (baseline) and post-intervention (endline). Each child was asked to arrange according to the shapes, nine blocks on a wooden board within a maximum of four minutes. Two outcomes will be considered: (i) the number of blocks correctly placed within two minutes (*score*- ranging from 0 - 9), and (ii) whether the child successfully finished the full activity within four minutes; (*activity completed* = 0, otherwise = 1).

## 3.4 Attendance

Attendance records maintained in the pre-school registers were collected for the months of January–May 2024. For each pre-school, the daily attendance rate was computed as the ratio of the number of children present to the total enrolled. These daily rates form the basis for the attendance analysis presented later.

Descriptive statistics for all variables used in the analysis—including temperature logger and thermal imaging measures, pre-school staff perceptions of heat and comfort, and child-level demographic and cognitive outcomes—are presented in Appendix

Table A.1.

# 4. Methodology and Results

## 4.1 Temperature

### 4.1.1 Effect on indoor temperature

Table 1 gives the mean of daily maximum indoor temperatures for the pre-schools in the control and treatment groups both before the painting of the roofs (pre-intervention) and after the painting was completed (post-intervention) . The days on which the rooftop painting were done have been excluded. Standard errors are clustered at the pre-school level. Accounting for the difference in means across the two groups prior to the intervention, we see a double difference estimate of $-1.18°$ C. We can see that the treatment preschools are significantly cooler than the control group pre-schools.

Since the randomization was stratified by panchayat, we also ran the below given regression,

$$temp_{ipd} = \alpha_p + \beta_1.T_{ip} + \beta_2.Post_d + \beta_3.T_{ip} * Post_d + \epsilon_{ipd} \tag{1}$$

where $i$ denotes a pre-school, $p$ a panchayat, $d$ a day, with standard errors clustered by pre-school. $T_{ip}$ takes a value 1 if pre-school $i$ in panchayat $p$ is in the treatment group and 0 otherwise, $Post_d$ takes a value 1 for all days in the post-intervention period and 0 otherwise.

The above regression was run with panchayat fixed effects and the estimate for the

DiD coefficient $\beta_3$, 1.32°C (standard error = 0.221), was significant at the 1% level.

| | Control Group | Treatment Group | Difference |
|---|---|---|---|
| Pre-Intervention | 33.34<br>(0.294)<br>[446] | 33.48<br>(0.240)<br>[538] | 0.13<br>(0.380) |
| Post Intervention | 33.46<br>(0.295)<br>[480] | 32.41<br>(0.149)<br>[587] | -1.05***<br>(0.330) |
| | Double Difference = -1.18***<br>(0.251) | | |

i. Total number of observations = 2051. ii. Standard errors are clustered at the pre-school level and are given in parentheses. iii. The number of observatons in each group is given in square brackets
iv. Asterisks *,**,*** represent significant difference at 10%, 5% and 1% significance respectively.

Table 1: Daily Maximum Temperature (in degree Celsius)

To identify clearly the mechanism whereby the roof paint works, thermal imaging of the roofs and the ceilings was conducted in all the study pre-schools in 4 out of 5 panchayats during the endline surveys. [1]

[1] As explained earlier this exercise could not be completed due to heavy rains in Perumkadavila panchayat

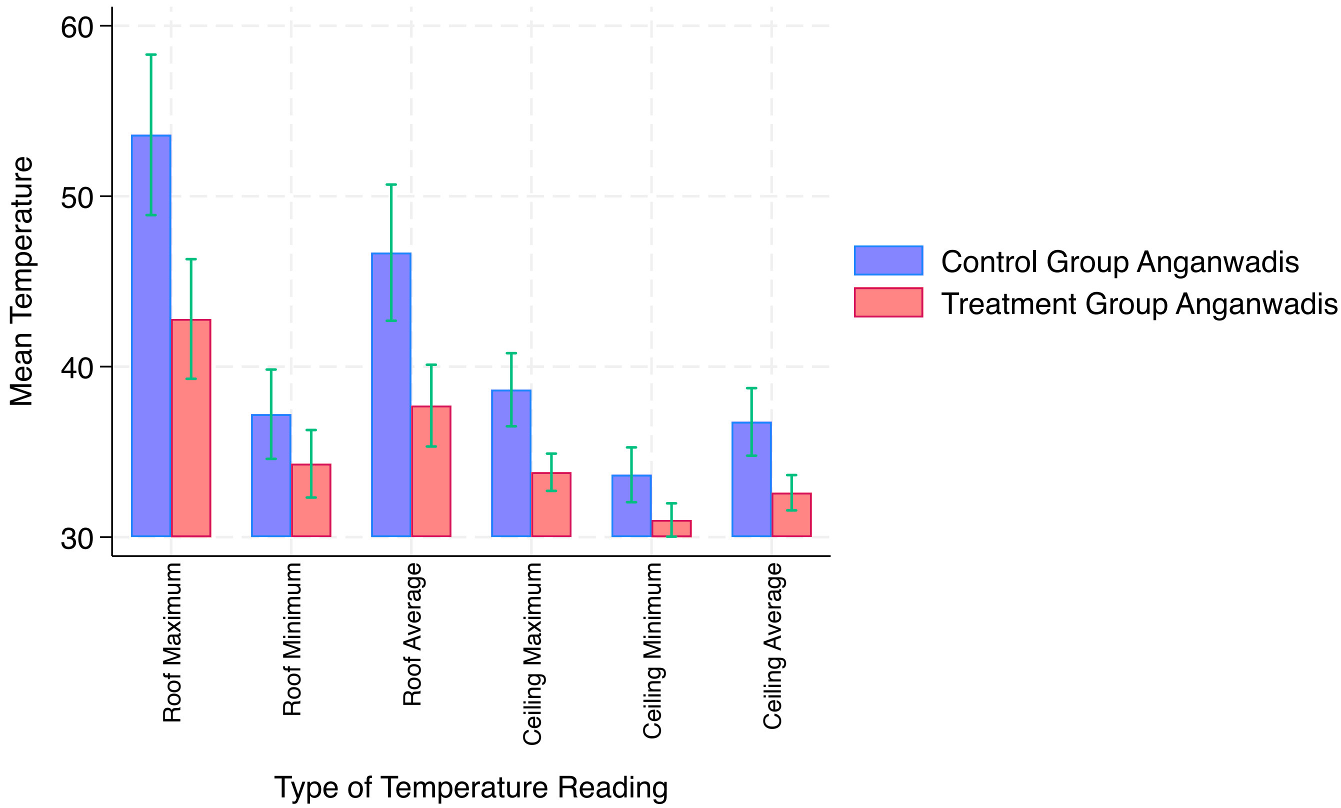


Figure 1: Results from the thermal imaging done at the endline

Pre-schools from 4 out of the 5 panchayats are included in this analysis. (30 from the treatment group and 26 from the control group)

Figure 1 summarizes the results from this exercise and confirms the mechanism whereby the paint that was used reduces indoor temperature. Both the roofs and the ceiling of pre-schools are significantly cooler in the treatment group. The mean of the maximum roof temperature is approximately 11 degrees lower in the treatment pre-schools as compared to the control group. The ceilings of the pre-schools in the treatment group are approximately 5 degrees cooler than those in the control group. It is clear from these results that the cool roof paint reflects sunlight from the roofs thereby reducing heat transfer to the ceilings and indoors. This results in significantly lower indoor temperature in the treatment group pre-schools.

## 4.2 Effects on Thermal Comfort

Thermal comfort surveys with pre-school staff were held both before the intervention and in the post-intervention period. These surveys were held during a rough window between 11 am - 1 pm in both the groups to ensure comparability. 113 out of the 135 respondents who took part in the survey at the baseline also took part in the endline survey. Cases of attrition here were mostly driven by teachers being away on election related duties and training programmes as part of the parliament elections in India held during April - June 2024. There were also a few instances of retirement/transfer of teachers.

The staff were asked three questions on thermal comfort. These were related to their perception of heat, discomfort and also their desired change in the temperature of the indoor environment. We refer to these variables as Heat Perception Index, Discomfort Index and Desired Temperature Change. The responses were on a Likert scale with a higher number denoting a hotter perception, more discomfort and also a desire to have a warmer temperature in the indoor environment.

Table 2 gives the results from the thermal comfort survey at the baseline. We see no significant difference between the control and treatment groups.

The thermal comfort survey was repeated in the post-intervention period. Table 3 summarizes the results from the endline thermal comfort survey.

These results confirm the impact of the intervention in improving thermal comfort. Respondents in the treatment group pre-schools report a lower value for the Heat Perception Index and Discomfort Index. There is no significant difference across the

| | (1) Control Group | (2) Treatment Group | (3) Difference |
|---|---|---|---|
| Heat Perception | 5.41 | 5.65 | 0.24 |
| Index | (0.185) | (0.160) | (0.244) |
| Discomfort | 4.92 | 5.25 | 0.33 |
| Index | (0.232) | (0.183) | (0.30) |
| Desired Temp | 1.14 | 1.10 | -0.04 |
| Change | (0.558) | (0.039) | (0.068) |
| N | 64 | 71 | 135 |

Standard errors are clustered at the preschool level and are given in parentheses. Asterisks *,**,*** represent significant difference at 10%, 5% and 1% significance respectively.

Table 2: Thermal Comfort at baseline

| | (1) Control Group | (2) Treatment Group | (3) Difference |
|---|---|---|---|
| Heat Perception | 5.12 | 4.25 | -0.87** |
| Index | (0.313) | (0.215) | (0.379) |
| Discomfort | 5.04 | 4.07 | -0.97*** |
| Index | (0.294) | (0.196) | (0.354) |
| Desired Temp | 1.18 | 1.29 | 0.11 |
| Change | (0.063) | (0.066) | (0.091) |
| N | 51 | 56 | 107 |

Standard errors are clustered at the preschool level and are given in parentheses. Asterisks *,**,*** represent significant difference at 10%, 5% and 1% significance respectively.

Table 3: Thermal Comfort at Endline

two groups for the desired temperature change variable. Respondents from both groups report a desire to have a cooler indoor environment.

Results from the impact of the intervention on indoor temperature confirm the mechanism behind the improvement in thermal comfort to the pre-school staff in the treatment group pre-schools. Lower indoor temperature and the resultant improved thermal comfort can mitigate negative productivity effects which would otherwise have resulted from higher temperature as observed in the literature. Also, by creating a more comfortable thermal environment for the staff we can avoid stress for the children as well. The analysis in Malmquist et al. (2021) shows how discomfort for the teachers amplifies stress faced by the children.

## 4.3 Effect on Cognitive Performance

We consider two main outcomes from the puzzle activity which was undertaken both prior to the intervention and following the painting; the score (number of puzzles correctly solved in two minutes, ranging from 0-9) and a binary outcome variable (activity completed) denoting completion of the activity taking a value 1 if the activity was completed by the child in four minutes and 0 otherwise.

Table 4 summarizes the results from the activity held in the pre-intervention period. The puzzle was fairly easy for the children to solve as is evident from the scores and also the completion rates. There are no significant differences across the two groups.

| | (1)<br>Control Group | (2)<br>Treatment Group | (3)<br>Difference |
|---|---|---|---|
| Age of the participant | 3.164<br>(0.058) | 3.205<br>(0.038) | 0.041<br>(0.069) |
| Activity Completed | 0.927<br>(0.017) | 0.882<br>(0.021) | -0.045<br>(0.027) |
| Score | 7.801<br>(0.181) | 7.620<br>(0.149) | 0.188<br>(0.261) |
| N | 261 | 297 | 558 |

Standard errors are clustered at the pre-school level and are given in parentheses. Asterisks *,**,*** represent significant difference at 10%, 5% and 1% significance respectively.

Table 4: pre-school activity summary at baseline

We had significant attrition at the time of the revisit to the pre-schools following the painting of the roofs. Schools in Kerala have summer holidays in the months of April and May. The pre-schools though functioning during these months, do witness a fall in the attendance rates owing to children visiting and staying at homes of their relatives/grand parents along with their older siblings, and also because many children may want to just stay back at their own homes when the elder siblings are around. Additionally the first week of May 2024 also witnessed closure of the pre-schools for almost a week due to heatwave conditions in the state.

Table 5 gives the summary from the baseline puzzle activity only for those children who attended both rounds of the puzzle activity. 170 students from the original group of participants in the pre-intervention period missed the activity during the revisit in the post-intervention period. There are no significant differences across the two groups in table 5) as well indicating that attrition between baseline and endline did not materially alter the composition of the treatment or control groups. Nonetheless, to verify that attrition was not correlated with baseline performance or treatment status, we conduct a formal attrition analysis presented in Appendix Table C.1. That analysis shows a small but statistically significant interaction between treatment and baseline performance, discussed there in the context of potential homogeneous/ heterogeneous treatment effects and equity implications. Overall, the evidence suggests that sample loss is limited and unlikely to seriously bias the main results.

We go ahead and use a simple Difference in Difference (DiD) framework to evaluate the impact of the treatment.

$$y_{it} = \delta_i + \delta_t + \delta_3.(treatment_i.post_t) + \epsilon_{it} \tag{2}$$

where $y_{it}$ is the relevant outcome variable of child $i$ in period $t$ (baseline/endline).

| | (1) Control Group | (2) Treatment Group | (3) Difference |
|---|---|---|---|
| Age of the participant | 3.219 | 3.144 | -0.075 |
| | (0.072) | (0.036) | (0.081) |
| Activity Completed | 0.971 | 0.972 | 0.001 |
| | (0.014) | (0.010) | (0.017) |
| Score | 7.908 | 7.460 | -0.453 |
| | (0.181) | (0.207) | (0.275) |
| N | 173 | 215 | 388 |

Standard errors are clustered at the pre-school level and are given in parentheses. Asterisks *,**,*** represent significant difference at 10%, 5% and 1% significance respectively.

Table 5: pre-school activity summary at baseline without the attrition group

We consider the number of puzzles correctly solved (score) and also whether the child completed the activity or not (a binary variable named 'activity completed'). $treatment_i$ is a dummy variable which takes a value 1 if child $i$ belongs to a treatment group pre-school and 0 otherwise. $post_t$ takes a value 1 for the activity at the endline and 0 otherwise. $\delta_3$ is the coefficient of interest for us (DiD parameter). Standard errors are clustered at the pre-school level. We include individual fixed effects (hence $\delta_i$). Additionally, to control for the weather and other relevant conditions on the days of the survey, we include day fixed effects too ($\delta_t$).

Table 6 gives the results from the DiD analysis.

The DiD analysis uses the sample of students who attended the puzzle activity at both the baseline and the endline. We have moderately significant effect on both the time taken and activity completion . For activity completion we see an impact which is roughly 6.6% of the treatment group mean and roughly 6.2% of the control group mean at baseline.

It is worth noting that the puzzle task used in our setting was intentionally simple and

| | Activity completed | Score |
|---|---|---|
| treated.post | 0.056** | 0.443* |
| | (0.028) | (0.264) |
| Individual fixed effects | Yes | Yes |
| Day fixed effects | Yes | Yes |
| Baseline mean (Control) | 0.93 | 7.801 |
| Baseline mean (Treatment) | 0.88 | 7.620 |
| N | 772 | 772 |

Notes: i. The dependent variable in (1) is the time taken for completing the puzzle in seconds. In (2) the dependent variable is a binary indicator equal to 1 if the puzzle activity was completed and 0 otherwise. In (3) the dependent variable is the score on the puzzle. ii. Cluster-robust standard errors are reported in the parentheses with clustering at the pre-school level. iii. Asterisks *, **, *** represent significance at 10%, 5% and 1% respectively.

Table 6: Difference in Difference estimation of Impact on pre-school Puzzle Activity

could be completed by most children with relative ease. The presence of a statistically significant treatment effect despite the low difficulty level of the task suggests that the intervention's cognitive benefits are likely conservative; under more demanding conditions, the impact on performance could be even stronger.

## 4.4 Impact on Attendance

The cool roof intervention has the potential to improve attendance in pre-schools via the effect on indoor temperature and improved thermal comfort. Children attending pre-schools are exposed to the conditions in the pre-schools for around 6 hours every day (roughly 9.30 am to 3.30 pm). We consider the daily attendance percentage defined as the ratio of the number of children attending an pre-school on a given day to the total number of children enrolled in the pre-schools. We employ a Difference in Difference framework to evaluate the impact of the cool roof paint on attendance in pre-schools as given below.

$$y_{jt} = \gamma_j + \gamma_2.post_t + \gamma_3.(treatment_j.post_t) + \epsilon_{jt} \quad (3)$$

where $y_{jt}$ is the daily attendance percentage in pre-school $j$ on day $t$, $treatment_j$ is a dummy variable which takes a value 1 if pre-school $j$ belongs to the treatment group and 0 otherwise, $post_t$ takes a value 1 during the post-intervention days and 0 during the pre-intervention period. $\gamma_3$ is the coefficient of interest for us (DiD parameter). We include pre-school fixed effects too ($\gamma_j$).

| | attendance |
|---|---|
| post | -0.081*** |
| | (0.020) |
| treatment.post | -0.005 |
| | (0.026) |
| Baseline Mean (Control) | 0.723 |
| | (0.003) |
| Pre-school fixed effects | Yes |
| N | 5063 |

Notes: i.The dependent variable is daily attendance percentage. ii.Standard errors are clustered at the pre-school level and are given in parentheses. iii.Asterisks *,**,*** represent significance at 10%, 5% and 1% respectively.

Table 7: Difference in Difference estimation of Impact on Attendance in pre-schools

Table 7 summarizes the results from the DiD analysis which shows no impact of the intervention on attendance in pre-schools. The months of April and May usually witness a fall in attendance in pre-schools as these months coincide with the summer break in schools as well. Additionally Kerala witnessed an extraordinarily hot summer in 2024 with the pre-schools closed for a week throughout the state in early May owning to heatwave like conditions. These factors would also have had an impact on what we observe in the attendance data. We can also see this in Table 7, the coefficient on the post-intervention period variable is negative and significant.

# 5. Discussion and Policy Implications

## 5.1 The cost advantage with the cool roof paint

The cool roof intervention cost approximately Rs.19,500 per pre-school, inclusive of paint, materials, and labour. Labour costs in Kerala are relatively high compared to much of India; nevertheless, the reflective paint remains cost-effective relative to alternative cool roof technologies due to its ease of application, low maintenance needs, and minimal risk to existing roof structures. The reflective properties of the coating can be maintained through periodic cleaning. Assuming one cleaning per quarter, and using the current daily wage for unskilled labour in Kerala (Rs.710) and 2 such person days in a year, the annual maintenance cost is approximately Rs.1,500. While manufacturers claim a lifespan of seven years for the coating, a more conservative estimate-given Kerala's heavy rainfall-is five years. Under these assumptions, in a typical pre-school with 15 children, the cost of the intervention amounts to approximately Rs.1 per child per day.

For comparison, the cost of cooling a similar room using air-conditioning is substantially higher. A 1.5-tonne (5.275 kW) unit priced at roughly Rs.30,000, with an energy efficiency ratio of 3.3, a real-world load factor of 70%, an electricity tariff of Rs.6.5 per kWh, and 26 operational days per month yields a per-child, per-day cost of approximately Rs.5. Although air-conditioning offers a larger temperature reduction, it is substantially more expensive on a per-user basis.

To situate these costs within the broader expenditure landscape of pre-schools, the Union government allocates Rs. 8 per child per day for supplementary nutrition (higher in cases of malnourishment), while in Kerala this typically ranges from Rs.10 to Rs.15, with some local governments providing up to Rs.20. Additional expenditures include wages for the pre-school worker and helper (currently Rs.12,000 and Rs.8,000 per month, respectively) and ongoing investments in infrastructure. Relative to these recurring costs—and to cooling via air conditioners—the per-child cost of the cool roof intervention is extremely low.

Given its low cost, ease of implementation, and demonstrated improvements in thermal comfort and cognitive effort, the cool roof intervention represents an attractive, scalable option for policymakers seeking to enhance learning environments and support climate adaptation objectives in pre-schools.

## 5.2 Policy Implications

Rising temperatures constitute an increasingly significant concern across India, particularly for populations whose living and working conditions limit their ability to avoid heat exposure. Heat stress affects productivity, learning, and both physical and mental health, with disproportionate impacts on groups lacking adequate adaptive mechanisms. Although climate change adaptation is often perceived as resource-intensive, several low-cost and effective strategies exist that can strengthen resilience to heat stress.

The cool roof intervention examined in this study demonstrates substantial reductions in indoor temperatures through enhanced solar reflectivity, thereby decreasing the heat load on roofs and ceilings. These reductions improve indoor thermal conditions and have the potential to mitigate heat-related health risks, especially for young children, aligning with broader public health and climate adaptation objectives.

Reports from pre-school staff in treatment group indicate improved thermal comfort and lower perceived heat stress. Prior literature documents significant productivity losses associated with elevated temperatures. For instance, Somanathan et al., 2021 show that, among weaving workers, a lagged hot day ($> 35°C$) reduces output by 1.4% through absenteeism and by 2.7% through diminished on-the-job productivity. Although staff attendance is not measured in our study, the observed improvements in comfort suggest that similar productivity benefits may arise in comparable institutional settings. Moreover, improved staff comfort may have indirect benefits for children, consistent with evidence from (Malmquist et al., 2021), who find that staff discomfort in pre-schools can magnify adverse effects on child outcomes.

The study also provides direct evidence that thermal conditions meaningfully shape cognitive performance among young children. Although evidence on very young learners is limited, substantial research on older students shows that high temperatures impair academic performance. The cognitive gains observed here therefore position cool roofs as a complementary educational intervention that improves learning conditions by reducing thermal stress.

Moreover, because learning is cumulative and early cognitive improvements enhance the productivity of later educational investments, these benefits may extend beyond the immediate gains observed. Even modest improvements in early learning environments have been shown to yield downstream effects on later academic and developmental outcomes (Chetty et al. (2011), Cunha and Heckman (2007), and Heckman (2006)). In hot climates where excessive indoor heat hampers concentration and engagement, the cool roof intervention offers a low-cost means of strengthening early childhood development and supporting longer-term learning trajectories.

From a policy perspective, the findings support integrating cool roof technologies into public infrastructure programs, including those targeting early childhood education centers. Incorporating reflective roof coatings into construction and renovation efforts—especially in heat-prone regions—could provide substantial benefits for vulnerable populations who face significant physical, mental, and economic burdens from heat exposure. Evidence from Das and Somanathan, 2024 further highlights the considerable and often unrecorded heat-related costs borne by informal-sector workers.

The intervention may also reduce reliance on energy-intensive cooling solutions, contributing to sustainability and energy conservation objectives. Although the design of the pre-schools in this study does not allow for an assessment of energy savings—given the minimal presence of electrical appliances—future evaluations in more energy-intensive buildings could further quantify these benefits as the program scales across the state.

Overall, cool roof interventions represent a low-cost, passive adaptation strategy that can complement broader efforts to improve public infrastructure and strengthen resilience to heat stress. The successful implementation of the pilot by the Energy Management Centre (EMC), supported by local elected representatives and pre-school staff, underscores the importance of community engagement. Because the effectiveness of climate adaptation measures often depends on individual behavior, policy approaches in this domain must remain multi-dimensional and participatory. As the intervention is expanded statewide, greater involvement of local self-governments is likely to enhance its effectiveness. Low-cost yet impactful measures such as cool roof coatings constitute are promising tools for protecting heat-vulnerable populations and strengthening resilience in a warming climate.

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# Appendix A Summary Statistics

Appendix Table A.1 presents descriptive statistics for all key variables used in the analysis. The first panel reports physical measures of the thermal environment at the anganwadi level, drawn from temperature logger readings and infrared thermal imaging. The second panel summarizes pre-school staff perceptions of heat and comfort, recorded on a Likert scale. The final panel lists child-level demographic characteristics and cognitive performance outcomes from the puzzle-based assessment.

| **Variable** | **Obs.** | **Mean** | **SD** | **Min** | **Max** |
|---|---|---|---|---|---|
| *Thermal Environment (Pre-school level measures)* | | | | | |
| Indoor maximum temperature (°C) | 2907 | 33.06 | 1.67 | 26.9 | 37.9 |
| Maximum roof temperature (thermal imaging, °C) | 46 | 47.96 | 10.85 | 29.1 | 72.6 |
| Maximum ceiling temperature (thermal imaging, °C) | 56 | 36.05 | 4.8 | 29.6 | 50.7 |
| Average roof temperature (thermal imaging, °C) | 46 | 42.01 | 8.66 | 26.5 | 60.3 |
| Average ceiling temperature (thermal imaging, °C) | 56 | 34.53 | 4.40 | 28.6 | 47.3 |
| *Perceived Thermal Comfort (Pre-school staff responses)* | | | | | |
| Heat Perception Index | 257 | 5.16 | 1.46 | 2 | 7 |
| Discomfort Index | 257 | 4.83 | 1.55 | 2 | 7 |
| Desired Temperature Change (°C) | 257 | 1.17 | 0.38 | 1 | 2 |
| *Child-level characteristics and outcomes* | | | | | |
| Age of child (years) | 558 | 3.19 | 0.65 | 2 | 5 |
| Gender of child (Female = 1, Male = 0) | 558 | 0.48 | 0.50 | 0 | 1 |
| Puzzle completion (1 = completed within 4 min) | 944 | 0.93 | 0.25 | 0 | 1 |
| Puzzle score (pieces correctly placed at 2 min) | 944 | 8.01 | 2.20 | 0 | 9 |

*Notes:* This table reports descriptive statistics for all variables used in the analysis. Thermal environment variables are measured at the pre-school level using temperature loggers and infrared thermal imaging. The Heat Perception Index, Discomfort Index, and Desired Temperature Change are based on Likert-scale responses from pre-school staff regarding thermal comfort conditions within the pre-school. Child-level variables refer to children's performance in the cognitive puzzle task and their demographic characteristics. All temperatures are measured in degrees Celsius.

Table A.1: Summary Statistics of Key Variables

# Appendix B Historical Temperature Data for Thiruvananthapuram (1951 - Present)

To contextualize the study setting, Table B.1 presents historical records of the highest daily maximum temperatures in Thiruvananthapuram from 1951 onwards, compiled from India Meteorological Department data. The figures reveal a clear intensification of extreme heat events in recent years, with multiple monthly records occurring during the past decade—particularly between 2019 and 2025. Several of the all-time highs were observed in 2024 alone, coinciding with the period of our fieldwork. These data underscore the steady rise in peak temperatures and reinforce the relevance of evaluating passive cooling interventions such as reflective “cool” roofs in early-childhood centres exposed to growing thermal stress.

| Rank | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | All Time |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 36.2 (27-01-2024) | 38.2 (21-02-2019) | 37.7 (16-03-1988) | 38.0 (04-04-2007) | 37.8 (09-05-2024) | 35.8 (10-06-2003) | 34.0 (15-07-2020) | 35.7 (23-08-2023) | 35.4 (24-09-1999) | 35.2 (10-10-2012) | 34.8 (17-11-2016) | 36.2 (30-12-2023) | 38.2 (21-02-2019) |
| 2 | 36.0 (14-01-2024) | 37.4 (27-02-2024) | 37.5 (12-03-2010) | 37.7 (14-04-2019) | 37.3 (08-05-2024) | 35.5 (04-06-1997) | 33.8 (07-07-2021) | 35.0 (16-08-2022) | 35.1 (12-09-2025) | 35.0 (10-10-2008) | 34.7 (18-11-2024) | 35.5 (28-12-2006) | 38.0 (04-04-2007) |
| 3 | 35.9 (17-01-2025) | 37.2 (22-02-2019) | 37.4 (22-03-2024) | 37.6 (08-04-2019) | 36.7 (01-05-2024) | 34.9 (08-06-2003) | 33.7 (12-07-2010) | 34.8 (25-08-2023) | 34.9 (12-09-2001) | 34.7 (09-10-2012) | 34.4 (27-11-2019) | 35.4 (22-12-2024) | 37.8 (09-05-2024) |
| 4 | 35.8 (16-01-2025) | 37.1 (05-02-2010) | 37.2 (22-03-2010) | 37.1 (18-04-2019) | 36.6 (03-05-2024) | 34.7 (09-06-2003) | 33.6 (05-07-2025) | 34.6 (18-08-2015) | 34.8 (28-09-2024) | 34.5 (06-10-2013) | 34.2 (28-11-2023) | 35.2 (31-12-2024) | 37.7 (14-04-2019) |
| 5 | 35.7 (31-01-1998) | 36.5 (19-02-2016) | 37.0 (22-03-1996) | 36.9 (29-04-2024) | 36.4 (07-05-2024) | 34.6 (05-06-2023) | 33.4 (15-07-2023) | 34.4 (04-08-2024) | 34.6 (13-09-2018) | 34.4 (06-10-2025) | 34.2 (28-11-2023) | 35.2 (31-12-2024) | 37.6 (08-04-2019) |
| 6 | 35.6 (02-01-2016) | 36.4 (08-02-2025) | 36.8 (23-03-1988) | 36.8 (13-04-2019) | 36.3 (05-05-2019) | 34.4 (07-06-2003) | 33.3 (30-07-2023) | 34.3 (24-08-2023) | 34.5 (04-09-2015) | 34.3 (10-10-2025) | 34.1 (08-11-2020) | 35.0 (07-12-2024) | 37.5 (12-03-2010) |
| 7 | 35.4 (05-01-2024) | 36.3 (11-02-2005) | 36.7 (29-03-2019) | 36.7 (05-04-1998) | 36.2 (23-05-2019) | 34.3 (03-06-2023) | 33.2 (10-07-2025) | 34.2 (29-08-2023) | 34.4 (26-09-2022) | 34.1 (11-10-2012) | 34.0 (13-11-2023) | 34.9 (15-12-2023) | 37.4 (22-03-2024) |
| 8 | 35.3 (08-01-2024) | 36.2 (07-02-2002) | 36.6 (30-03-2019) | 36.6 (01-04-2023) | 36.1 (02-05-2024) | 34.2 (05-06-2025) | 33.1 (29-07-2025) | 34.1 (06-08-2023) | 34.3 (28-09-2023) | 34.0 (09-10-2025) | 33.9 (18-11-2019) | 34.8 (24-12-2023) | 37.3 (08-05-2022) |
| 9 | 35.2 (10-01-2025) | 36.0 (28-02-2025) | 36.5 (14-03-2016) | 36.5 (05-04-2019) | 36.0 (06-05-2024) | 34.1 (02-06-2010) | 33.0 (04-07-2010) | 34.0 (10-08-2023) | 34.2 (28-09-2022) | 33.9 (04-10-2025) | 33.8 (17-11-2024) | 34.7 (28-12-2023) | 37.2 (22-02-2019) |
| 10 | 35.1 (29-01-2024) | 35.9 (24-02-2024) | 36.4 (28-03-2023) | 36.4 (24-04-2024) | 35.9 (04-05-2024) | 34.0 (01-06-2024) | 32.9 (06-07-2021) | 33.9 (28-08-2023) | 34.1 (18-09-2025) | 33.8 (03-10-2025) | 33.7 (19-11-2023) | 34.6 (20-12-2023) | 37.1 (18-04-2019) |

*Source:* India Meteorological Department (IMD), Thiruvananthapuram. Each cell shows the highest daily maximum temperature (°C) for that month and rank; dates in parentheses. The clustering of record highs in the 2019–2025 period indicates a steady intensification of heat extremes in the study region.

Table B.1: Highest Maximum Temperature (°C) — Thiruvananthapuram (1951 onwards)

# Appendix C Attrition

The puzzle activity to evaluate cognitive effort of pre-school children witnessed significant attrition at the endline. 170 out of the 558 children who participated in the baseline puzzle activity missed the endline. 88 of those who missed were from the control group and 82 were from the treatment group.

To examine whether attrition between baseline and endline could bias the estimation of treatment effects, we estimate a linear probability model where the dependent variable equals one if the respondent missed the puzzle activity at endline. Explanatory variables include treatment status, baseline puzzle performance, and their interactions, with age and gender as controls. Results presented in Table C.1 show that treatment assignment by itself is not significantly associated with attrition, implying that participation in the intervention did not generally affect the likelihood of remaining in the sample. Baseline cognitive performance—whether measured by completing the puzzle within four minutes or by the interim score at two minutes—also does not independently predict attrition.

However, the interaction between treatment and baseline score (*treatment_score*) is positive and statistically significant at the 1% level, indicating that among treated respondents, those who performed better at baseline were somewhat more likely to be lost to follow-up. Under the assumption of a homogeneous treatment effect across the ability distribution, such selective attrition would bias the estimated treatment effect downward, since higher-ability treated individuals are underrepresented in the endline sample. Yet, if treatment effects are heterogeneous and disproportionately larger for lower-ability children, the observed attrition pattern while still not threatening internal validity may even underscore the program's equity relevance. The intervention's effectiveness among the less-advantaged learners would, in that case, remain both statistically and substantively meaningful. Overall, the magnitude of the estimated coefficients suggests that selective attrition is limited and unlikely to materially affect the interpretation of the main results.

| | **Attrition** |
|---|---|
| Treatment | -0.231 |
| | (0.139) |
| Completed puzzle | 0.082 |
| | (0.173) |
| Score at two minutes | -0.021 |
| | (0.021) |
| Treatment $\times$ Completed puzzle | -0.334* |
| | (0.196) |
| Treatment $\times$ Score | 0.061*** |
| | (0.022) |
| Age (years) | 0.019 |
| | (0.036) |
| Gender (1 = Female) | 0.037 |
| | (0.038) |
| Constant | 0.306** |
| | (0.149) |
| Observations | 558 |

*Notes:* i.The dependent variable *attrition* takes a value 1 if the child missed the puzzle activity at endline and 0 otherwise. ii.Standard errors are clustered at the anganwadi level and are given in parentheses. iii.Asterisks *,**,*** represent significance at 10%, 5% and 1% respectively.

Table C.1: Model for Analysing Attrition