India's School Feeding Programs: Investigating its Persistent Impact on School Participation

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Introduction

School feeding programs have been a cornerstone of educational policies worldwide, aiming to address both hunger and educational outcomes. According to the World Food Program, in 2013 alone, 368 million children—equivalent to one in five—received school meals, reflecting a global investment of US$75 billion. This substantial investment underscores the global importance of the dual objectives of alleviating hunger and enhancing educational outcomes.

In the Indian context, the school feeding program, locally known as the "midday meals" scheme, has evolved significantly over the years. Mandated by the Indian Supreme Court in 2001, the program aimed to provide free lunches to primary school children across the country. This initiative marked a pivotal moment in India's educational landscape, with the program expanding rapidly to become the largest school nutrition program globally, reaching over 120 million children by 2006.

The rationale behind the midday meals scheme encompasses not only addressing immediate nutritional needs but also fostering better educational outcomes. Proponents argue that school feeding programs positively influence learning outcomes through two primary channels: incentivizing school participation, thus enhancing enrollment and attendance rates, and improving children's nutritional intake, leading to better concentration and cognitive abilities.

Against this backdrop, this policy brief seeks to analyze the long-term impact of India's midday meal scheme on school participation trends. While the short and medium-term effects of this program have been well documented, there remains a significant gap in understanding the long-run persistence of its impacts. By leveraging data from the Annual Status of Education Report (ASER), we aim to assess the sustained causal effect of the program on primary school enrollment and attendance. Furthermore, this analysis delves into the nuances of program implementation and uptake, providing insights into its efficacy and identifying potential areas for improvement.

The significance of this analysis lies in its contribution to evidence-based policymaking. As India continues to grapple with educational challenges, understanding the persistent impact of school feeding programs is imperative for continual investments and designing effective interventions around the intervention. By elucidating the relationship between school meals and

educational outcomes, this policy brief aims to inform policymakers and practitioners, ultimately contributing to the enhancement of educational equity and child well-being in India.

Relevant Past Research

Previous research has consistently highlighted the positive impact of school feeding programs on school participation in India, establishing its significance beyond question. However, very little has been done to assess its sustained relevance over five years after its implementation. Analyzing trends over time can provide valuable insights into the program's ongoing relevance.

One notable study in this field is Chakraborty and Jayaraman's 2018 paper titled "School Feeding and Learning Achievement: Evidence from India's Midday Meal Program." By the time of their research, there was substantial literature on the effect of school feeding programs on school participation and nutritional outcomes. Most of these studies focused on young, typically primary-school-aged children, and generally found positive treatment effects on both participation (e.g., higher school enrollment or attendance) and nutritional status (e.g., lower anemia or higher BMI). Papers in the past that focused on the effect of school feeding programs on learning achievement did this on a small scale and had relatively short-term (up to two years), randomized field experiments. Secondly, past papers explored the effect of India's midday meal program on children's nutritional and schooling outcomes using quasi-experimental methods, which in Chakraborty and Jayaraman's view was not the best method of measurement. To the best of their knowledge, only two studies, one by Singh (2008) and another by Afridi et al. (2014), examined its effect specifically on learning outcomes, and both were limited by their use of variation at the local level.

Chakraborty and Jayaraman contributed to these two strands of literature in a couple of ways. First, they explored the effect of up to five years of program exposure, using a large dataset, which provided statistical power and allowed the study of an intervention implemented on a massive scale. Their results found an unambiguously positive effect of school feeding after the almost five-year exposure period, and in line with past literature found negligible effects in the short run, measured by both reading and math test scores. They discussed several possible explanations for the difference between their findings and previous literature key of which were the sample size and their sampling mainly from rural India.

Table 3
Effect of midday meal exposure on test scores.

	Reading Score				Math Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure (β) (in months)	0.0352***	0.0081***	0.0059***	0.0175***	0.0300***	0.0042**	0.0024	0.0122***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Exposure^2				−0.0002***				−0.0001***
				(0.000)				(0.000)
Female			−0.0265***				−0.0552***	
			(0.007)				(0.006)	
Household Size			−0.0025***				−0.0023***	
			(0.001)				(0.001)	
Mother Attended School			0.3995***				0.3603***	
			(0.016)				(0.016)	
State FE	NO	YES	YES	YES	NO	YES	YES	YES
Birth Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Time FE	NO	YES	YES	YES	NO	YES	YES	YES
State × Trend	NO	YES	YES	YES	NO	YES	YES	YES
Mean at 4 months	1.072	1.072	1.061	1.072	1.061	1.061	1.068	1.061
Observations	1,238,781	1,238,781	1,048,509	1,238,781	1,238,781	1,238,781	1,048,509	1,238,781
Adjusted R-squared	0.163	0.273	0.302	0.274	0.136	0.264	0.297	0.265

Notes. This table presents OLS estimates for equation (1). Exposure measures months of potential program exposure. The dependent variable is the reading test score (columns 1–4) and the math test score (columns 5–8); they take integer values ranging from 0 to 4. Each column represents a different regression. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses are clustered by state and year of birth.

In Randeep Kaur's paper "Estimating the Impact of School Feeding Programs: Evidence from the Mid-Day Meal Scheme of India" (2021), another relevant paper in the field, he states that various studies have shown that School Feeding Programs (SFPs) are effective in boosting school attendance, yet the extent of this effect varies considerably across studies due to methodological limitations such as small-scale surveys and reliance on intent-to-treat (ITT) estimations. Addressing these concerns, Kaur employs a large dataset and estimates the local average treatment effect to examine the impact of the Mid-Day Meal Scheme (MDMS) on primary school enrollment.

Using data from the Indian Human Development Survey (IHDS) 2005 and the National Family Health Survey (NFHS) 1998-99, Kaur investigates the impact of MDMS on primary school enrollment, accounting for variations in policy implementation across states. Kaur's findings reveal a significant increase in the probability of primary school enrollment due to the program, particularly among girls and disadvantaged population groups. The study contributes to the literature by providing generalized findings on the impact of SFPs, unlike previous small-scale studies, and by estimating the local average treatment effect, which considers variations in policy implementation. Furthermore, it adds to the specific literature on the Mid-Day Meal Scheme, offering insights into its effects on educational outcomes, particularly in terms of primary school enrollment.

In summary, Kaur's study underscores the importance of assessing the impact of school feeding programs on education outcomes. The findings indicate a notable increase in both gross and net primary school enrollment, with a particularly large effect on net enrollment in Grade 1, suggesting a substantial extensive margin response. Moreover, the program's effect is found to be larger for socially disadvantaged groups and girls, indicating a reduction in the gender gap in school participation.

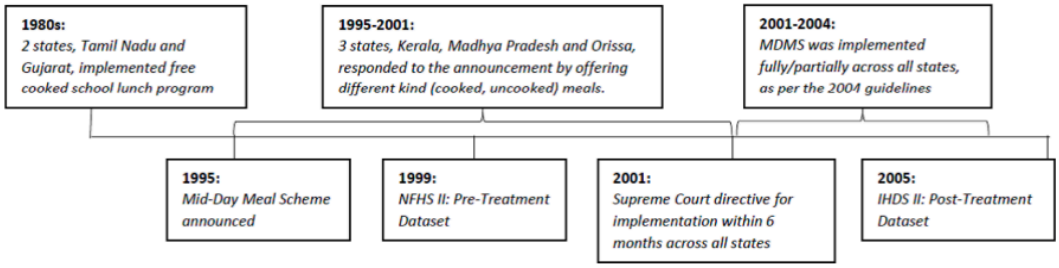


Fig. 1. Timeline for Mid Day Meal Policy and its Response.
Note: Tamil Nadu originally introduced free school meal scheme at a small scale in 1925 in rural areas, but it was expanded to cover the entire state in 1982.

Table 3
Exogeneity of policy.

	Rural	Female	SC	ST	OBC
Treat*Post	0.070***	−0.023	0.028*	0.064***	0.040**
	(0.016)	(0.020)	(0.015)	(0.008)	(0.016)
Observations	43,049	43,049	43,049	43,049	43,049
	Hindu	Muslim	Mother's Educ	Father's Educ	Siblings
Treat*Post	−0.003	−0.013	−0.088	0.011	0.035
	(0.012)	(0.011)	(0.069)	(0.057)	(0.049)
Observations	43,049	43,049	43,049	43,049	43,049
	Household Size	SGDP	Schools Per 1000		
Treat*Post	−0.551	−2.909***	0.686***		
	(0.095)	(0.068)	(0.011)		
Observations	43,049	43,049	43,049		

Notes: The sample includes 19 states and 1 UT consisting of 191 districts. Each cell denotes the coefficient from a regression of observable Y on Treat*Post variable, D05 variable, and district fixed effects. Bootstrapped standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4
Impact on gross and net enrollment.

	Primary School		Grade 1	
	Gross Enrollment	Net Enrollment	Gross Enrollment	Net Enrollment
First Stage				
Treat*Post	0.157***	0.161***	0.103***	0.136***
	(0.005)	(0.005)	(0.010)	(0.016)
2SLS				
Fraction Treated	0.158***	0.188***	0.031	0.515*
	(0.056)	(0.049)	(0.0.058)	(0.272)
Demographic Controls	Y	Y	Y	Y
District Fixed Effects	Y	Y	Y	Y
F-Stat for First Stage	1088.75	1177.7	117.44	68
Fraction Treated Mean	0.19	0.19	0.15	0.16
Pre-Reform Enrollment Mean	0.90	0.88	0.78	0.81
Observations	43,049	33,367	17,107	6426

Notes: The sample includes 19 states and 1 UT consisting of 191 districts. Demographic controls include primary institutions per 1000 children aged 6 - 10 years, type of residence (rural or urban), household size, number of children under 5 in the household, number of siblings, gender of the child, caste and religion of the household head, mother's education, and father's education. Bootstrapped standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Research Design and Relevance

Past research papers have proven a few things

- In the short term (between two weeks and 2 years) the impact of school feeding programs on school participation and the nutritional status of children is negligible.
- A small sample size also shows negligible effects of school feeding programs on school participation and nutritional status.
- In the longer term (between 2 years and 5 years) there is an unambiguously positive effect of school feeding programs on school participation and the nutritional status
- The effect of school feeding programs on school participation and nutritional status is larger in rural areas than in urban centers.
- We also saw a net gross marginal effect of school feeding programs on primary school (grade 1) enrollment, socially disadvantaged girl groups, and in closing the gender gap.

Previous research has consistently highlighted the positive impact of school feeding programs on school participation in India, establishing its significance beyond question. However, very little has been done to assess its sustained relevance decades after its implementation. Our study thus looks to contribute to this body of work in the following ways:

- We will examine schools in various districts of India that implemented school feeding programs in 2002.
- Schools across these districts in India currently show near-universal adoption of school feeding programs but experienced intermittent participation over the study period. Specifically, we will track the impacts on school participation rates in years when the program was temporarily discontinued and then reinstated.
- Utilizing data from the ASER dataset curated by Tanika Chakraborty and Rajshri (Raji) Jayaraman, we will analyze changes in school participation rates over five years to capture the effects of these interruptions.
- The focus of our study is to assess the participation effects of the school feeding program by comparing periods when the program was available to those when it was not, within the same schools. By examining these changes over time, we aim to capture the nuanced longitudinal impact trends of the program on school participation rates.
- We may explore how school characteristics such as size, teacher-to-student ratios, and infrastructure—including the distance from students' homes to school—might influence the effectiveness of the school feeding program and affect participation rates.

- Additionally, we will investigate the factors that may have contributed to the temporary suspension of the school feeding program in certain schools, such as funding changes, logistical challenges, or shifts in school leadership and policy priorities

Overall, our study will utilize a longitudinal approach to assess the sustained impact of school feeding programs on school participation rates in rural India.

Estimation Strategy

Data Source Overview:

Our investigation primarily leverages the Annual Status of Education Report (ASER) dataset, meticulously compiled by Tanika Chakraborty and Rajshri (Raji) Jayaraman. Renowned for its comprehensive coverage, the ASER dataset is instrumental in our analysis, offering granular insights into school enrollment and attendance patterns. Our focal point within this rich dataset will be the attendance and participation metrics for students in the foundational grades 1 to 3. The dataset's depth allows us to closely examine the nuances of class participation rates, a critical indicator of educational engagement at these essential learning stages.

Targeted Sampling Strategy

Our sampling framework adopts a targeted approach, concentrating on schools within Chhattisgarh, Rajasthan, and Sikkim. These states are of particular interest due to the early adoption of the school feeding program in 2002, making them pivotal in our study of the program's long-term impacts. This deliberate focus aims to capture the program's effects in diverse educational settings, ranging from resource-constrained schools in Chhattisgarh and Rajasthan to the unique socio-economic context of Sikkim. By honing in on these states, we ensure that our analysis is grounded in regions where the feeding program's implications can be observed most distinctly.

Initial Observation Year and Baseline Establishment:

To anchor our longitudinal analysis, we choose 2007 as the initial observation year, marking the commencement of our period of study. This year serves as a crucial point for establishing a reference for school participation rates before the onset of intermittent disruptions to the school feeding program. This approach allows us to track the evolution of school participation over time and provides a robust foundation for analyzing both the immediate impacts and the longer-term trends resulting from changes in the program's availability. The choice of 2007,

supported by prior research documenting the benefits of the school feeding program on educational engagement, enables us to assess the initial conditions and subsequent fluctuations in participation rates. By starting our analysis in this year, we aim to uncover the dynamics of program suspension and reinstatement, offering a detailed understanding of the program's effectiveness across varying operational contexts and over the extended study period.

Analysis Framework for Evaluating the Impact of School Feeding Programs

Independent Variable: Participation in the School Feeding Program

A cornerstone of our study, the participation status in the school feeding program, is denoted by the variable midday_meal_in_school. This is a dichotomous variable where a value of 1 signifies active participation in the program, indicating the school's involvement in providing midday meals to its students. Conversely, a value of 2 denotes non-participation, highlighting schools that are not part of this initiative.

Dependent Variables: Enrollment and Attendance in Early Grades

We evaluate the school feeding program's efficacy through its influence on two pivotal educational outcomes:

- Enrollment for Classes 1-3: Reflected by childenrollment_class_1, childenrollment_class_2, and childenrollment_class_3, these variables capture the enrollment status in the respective grades, highlighting the program's potential to enhance educational access and encourage school participation among young learners.
- Attendance for Classes 1-3: Monitored through childattendence_class_1, childattendence_class_2, and childattendence_class_3, regular attendance serves as a key indicator of the program's success in sustaining student engagement and reducing dropout rates.

Control Variables: Socioeconomic and Infrastructure Indicators

Acknowledging the multifaceted influences on educational attainment, our analysis incorporates a set of control variables aimed at isolating the unique contribution of the school feeding program. These include:

- Infrastructure (room_total): Represents the total number of rooms, serving as a proxy for the school’s capacity and ability to support a conducive learning environment.

- School Resources (library_books_in_school, computer_in_school): Reflect the availability of library books and computers, indicators of a school's resource richness and its capability to offer comprehensive educational opportunities.
- School Location (state_name, district_name): These geographic identifiers are crucial for examining regional disparities and contextualizing the impact within diverse socioeconomic settings.

Variables of Interest

School and Location Identifiers: state_name, district_name, village_id

School Feeding Program Specifics: midday_meal_in_school (Indicator of program availability)

School Infrastructure and Resources: room_total, library_books__in_school, computer_in_school

School Participation Rates: childenrollment_class_1 to childenrollment_class_3, childattendence_class_1 to childattendence_class_3

Factors Potentially Affecting Program Suspension: grant_school_maintenance_2010, grant_school_development_2010,(Funding availability which might explain program suspensions due to financial constraints), official_visit_block (Frequency of official visits, potentially correlating with monitoring and program continuity)

Educational Support Indicators: sup_learning_material_class_2 (Availability of supportive learning materials)

Summary & Descriptive Statistics

To thoroughly evaluate the impact of school feeding programs, our analysis utilizes data from the Annual Status of Education Report (ASER) spanning five years—2007, 2009, 2010, 2011, and 2012. We categorize findings by state, district, and village to provide an in-depth view of the program's reach and the variability in participation across different administrative levels.

The data from 2007 to 2012 demonstrates high levels of participation across many districts, consistently exceeding 90%. While these figures suggest a strong uptake of the program, it is crucial to differentiate between program coverage and the actual effectiveness of the program. High coverage rates, as seen in districts like Bastar in Chhattisgarh and Ajmer in Rajasthan, indicate widespread acceptance and implementation of the feeding programs. However, to truly gauge the success of these initiatives, we must also consider their impact on key educational outcomes such as attendance rates, student health, and academic performance.

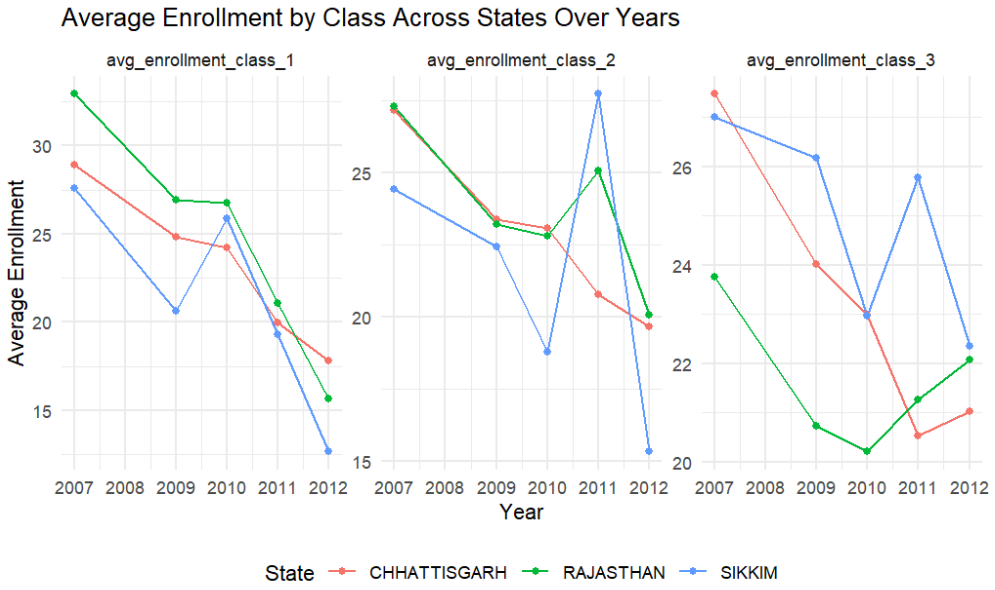
Moreover, the analysis reveals significant fluctuations in participation within certain years and locations, including at the village level. These variations often coincide with temporary suspensions of the program, potentially due to factors such as funding disruptions, logistical hurdles, or administrative changes. Our findings could underscore the necessity of targeted policy interventions aimed at ensuring the stability and continuity of school feeding programs, thereby enhancing their overall effectiveness and sustained impact on educational outcomes.

1. Detailed Average Participation Rate in the Midday Meal Program

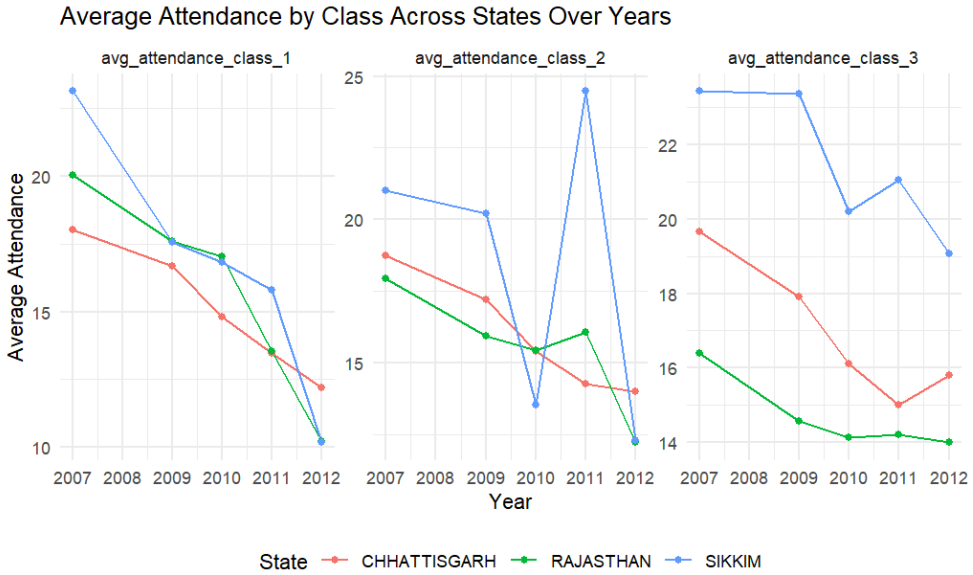
This table presents the average participation rate in the midday meal program, segmented by state, district, and year. A value of 1 indicates 100% participation in the program, while a value of 0 indicates no participation.

state_name	district_name	2007	2009	2010	2011	2012
CHHATTISGARH	Bastar	1.0000000	1.0000000	0.8421053	0.9500000	0.9032258
CHHATTISGARH	Bilaspur	1.0000000	1.0000000	0.9523810	1.0000000	1.0000000
CHHATTISGARH	Dhamtari *	1.0000000	1.0000000	0.8695652	1.0000000	0.9666667
CHHATTISGARH	Durg	1.0000000	1.0000000	0.8750000	0.9000000	0.9666667
CHHATTISGARH	Janjgir Champa*	0.9655172	1.0000000	0.9500000	0.8823529	0.9333333
CHHATTISGARH	Jashpur *	0.9642857	1.0000000	0.9411765	0.8888889	1.0000000
CHHATTISGARH	Kanker *	0.8461538	0.8695652	0.9047619	0.9473684	0.9666667
CHHATTISGARH	Kawardha *	1.0000000	0.8571429	1.0000000	0.9444444	0.9666667
CHHATTISGARH	Korba *	0.9655172	0.9090909	0.9545455	0.7368421	0.5384615
CHHATTISGARH	Koriya *	0.9642857	1.0000000	0.9565217	1.0000000	0.9333333
CHHATTISGARH	Mahasamund *	1.0000000	0.8750000	1.0000000	0.8750000	1.0000000
CHHATTISGARH	Raigarh	0.9310345	1.0000000	1.0000000	1.0000000	0.6333333
CHHATTISGARH	Raipur	1.0000000	1.0000000	0.9500000	1.0000000	1.0000000
CHHATTISGARH	Rajnandgaon	0.9642857	1.0000000	1.0000000	1.0000000	1.0000000
CHHATTISGARH	Surguja	1.0000000	0.9565217	1.0000000	0.9230769	0.9310345
RAJASTHAN	Ajmer	1.0000000	0.8518519	0.9259259	0.9642857	0.9333333
RAJASTHAN	Alwar	1.0000000	0.9629630	1.0000000	0.9230769	0.9666667
RAJASTHAN	Banswara	0.9615385	0.8846154	1.0000000	1.0000000	0.9655172
RAJASTHAN	Baran *	1.0000000	0.9444444	1.0000000	0.9583333	0.9166667
RAJASTHAN	Barmer	1.0000000	1.0000000	0.8333333	0.9500000	0.9333333
RAJASTHAN	Bharatpur	1.0000000	1.0000000	1.0000000		0.8571429
RAJASTHAN	Bhilwara	1.0000000	1.0000000	0.9411765	1.0000000	1.0000000
RAJASTHAN	Bikaner	1.0000000	0.9130435	1.0000000	0.9500000	1.0000000
RAJASTHAN	Bundi	1.0000000	0.8846154	1.0000000	1.0000000	0.9285714
RAJASTHAN	Chittaurgarh	1.0000000	0.9259259	0.9615385	0.9090909	0.9655172
RAJASTHAN	Churu	0.9642857	1.0000000	0.9230769	1.0000000	0.9200000
RAJASTHAN	Dausa *	1.0000000	0.9545455	1.0000000	1.0000000	0.8571429
RAJASTHAN	Dhaulpur	1.0000000	1.0000000	0.8947368	1.0000000	0.9230769
RAJASTHAN	Dungarpur	1.0000000	0.9629630	1.0000000	1.0000000	0.9259259
RAJASTHAN	Ganganagar	1.0000000	0.9583333	0.8235294	1.0000000	0.9655172
RAJASTHAN	Hanumangarh *	1.0000000	0.9000000	0.9166667	0.9500000	1.0000000
RAJASTHAN	Jaipur	1.0000000	0.9629630	0.8750000	1.0000000	0.9655172
RAJASTHAN	Jaisalmer	1.0000000	1.0000000	1.0000000	1.0000000	0.9200000
RAJASTHAN	Jalor	1.0000000	0.9583333	0.9500000	0.7500000	0.5862069
RAJASTHAN	Jhalawar	1.0000000	1.0000000	0.8500000	1.0000000	0.9333333
RAJASTHAN	Jhunjhunun	1.0000000	0.9473684	0.9565217	1.0000000	0.9666667
RAJASTHAN	Jodhpur	0.9615385	1.0000000	1.0000000	0.7500000	1.0000000
RAJASTHAN	Karauli *	0.9642857	0.8148148	0.9600000	1.0000000	1.0000000
RAJASTHAN	Kota	1.0000000	0.9545455	0.9047619	1.0000000	0.9615385
RAJASTHAN	Nagaur	0.9523810	0.9600000	0.9444444	1.0000000	0.9310345
RAJASTHAN	Pali	0.9642857	1.0000000	1.0000000	0.9600000	1.0000000
RAJASTHAN	Rajsamand *	1.0000000	1.0000000	1.0000000	0.9473684	0.9655172
RAJASTHAN	Sawai Madhopur	1.0000000	0.9642857	1.0000000	0.9500000	0.9310345
RAJASTHAN	Sikar	1.0000000	0.8888889	0.9565217	1.0000000	1.0000000
RAJASTHAN	Sirohi	1.0000000	0.9166667	0.6923077	1.0000000	1.0000000
RAJASTHAN	Tonk	1.0000000	1.0000000	1.0000000	0.9000000	1.0000000
RAJASTHAN	Udaipur	0.9583333	0.9166667	0.9200000	1.0000000	0.9000000
SIKKIM	East	1.0000000	0.9230769	0.9230769	1.0000000	0.9090909
SIKKIM	North		1.0000000	1.0000000	1.0000000	1.0000000
SIKKIM	South		0.8000000	1.0000000	1.0000000	0.6666667
SIKKIM	West		0.9230769	1.0000000	1.0000000	0.5000000

The line graph below illustrates the average enrollment by class across Chhattisgarh, Rajasthan, and Sikkim from 2007 to 2012. Across all three states, enrollment figures for Classes 1 and 2 exhibit volatility, with significant dips and peaks throughout the period. Class 3 in Sikkim, for instance, shows a sharp decline in enrollment in 2010, followed by a dramatic increase in 2011 and another drop in 2012. This erratic pattern indicates inconsistencies in school retention or reporting across the years, which could be attributed to various factors such as changes in policy, reporting accuracy, or external socio-economic factors. Chhattisgarh's enrollment rates, while declining over the years, suggest a more gradual change that may align more closely with demographic trends or policy impacts.



The line graph below depicts the average attendance by class for three states in India over five years. Notably, attendance in all classes started on a high note in 2007 but demonstrates a declining trend in Chhattisgarh and Rajasthan, with occasional fluctuations. For instance, Class 2 attendance in Sikkim shows a steep rise in 2010 followed by a sharp decline in 2011. In contrast, Rajasthan's attendance, particularly in Class 1, remained relatively stable until a notable drop in 2010. The data suggests potential underlying issues affecting attendance rates that may warrant further investigation to identify causes and develop targeted interventions.



Empirical Strategy: Longitudinal Fixed-Effects Analysis of School Feeding Program Impacts

To comprehensively understand the school feeding program's impact across different temporal and geographical contexts, this study utilizes a longitudinal fixed-effects analysis. This robust methodological framework consolidates all available data from 2007 to 2012, applying a single model that effectively accounts for both time-invariant characteristics and observable variabilities across villages and years.

Estimation of Program Impact:

The core of our empirical strategy involves estimating the influence of the school feeding program on educational outcomes such as student attendance and enrollment. Instead of segregating the data annually, we apply a fixed-effects model that considers all years simultaneously but distinguishes the effects per year, state, district, and village. This approach allows for a detailed comparison of outcomes within the same schools when the program was active versus when it was not, effectively isolating the impact of the program from other confounding factors.

Statistical Framework:

In this section, we detail the statistical methods used to assess the impact of the school feeding program on educational outcomes like enrollment and attendance. Our approach utilizes a robust fixed-effects model, which incorporates multiple control variables to ensure a comprehensive evaluation. By including both school-level resources and structural attributes as covariates, we aim to isolate the pure effect of the feeding program. This methodology is implemented using the *felm* function from the *lfe* package in R, which is adept at handling complex models with multiple fixed effects.

$$\text{Educational Outcome}_{its} = \beta_0 + \beta_1(\text{Program Participation}_{its}) + \beta_2(\text{room\_total}_{its}) + \beta_3(\text{library\_books\_in\_school}_{its}) + \beta_4(\text{computer\_in\_school}_{its}) + \mu_s + \mu_t + \epsilon_{its}$$

Where:

- **Educational Outcome**$_{its}$ represents the dependent variables, which include student attendance and enrollment rates.
- **Program Participation**$_{its}$ is a binary indicator that denotes whether the school participated in the feeding program during a particular year.
- **room_total**$_{its}$: Total number of rooms available in the school, indicating the school's infrastructural capacity.
- **library_books_in_school**$_{its}$: Availability of library books, which reflects the educational resources available to students.
- **computer_in_school**$_{its}$: Indicates the availability of computers at the school, another proxy for resource richness.
- μ_s and μ_t are the fixed effects for villages (treated as proxies for schools) and years, respectively. These fixed effects capture all time-invariant characteristics specific to each school and common temporal effects across all schools.
- ϵ_{its} is the error term, accounting for random, unexplained variability.

$$Outcome_{it} = \beta_0 + \beta_1 Program_{it} + \beta_2 RoomTotal_{it} + \beta_3 LibraryBooks_{it} + \beta_4 Computers_{it} + \epsilon_{it}$$

Where:

- $Outcome_{it}$: Signifies the dependent variable of interest (enrollment or attendance rate) for school i in year t.
- $Program_{it}$: is a binary variable indicating whether the school feeding program is active (1) or not (0) in school i in year t.
- $RoomTotal_{it}$: represents the total number of rooms available in school i in year, serving as a proxy for school size and capacity.
- $LibraryBooks_{it}$: denotes the presence (1) or absence (0) of library books in school i in year t, reflecting resource availability for students.
- $Computers_{it}$: indicates the presence (1) or absence (0) of computers in school i in year t, capturing the technological resources available for student use.
- β_0, β_1, β_2, β_3, β_4: are the coefficients to be estimated, reflecting the base level of the outcome variable, the impact of the feeding program, and the contributions of the other variables, respectively.

- ϵ_{it}: is the error term, capturing unobserved factors that may influence the outcome.

Empirical Evidence

Simple Linear Regression

```
Call:
lm(formula = attendance_formativeclasses ~ midday_meal_in_school +
    room_total, data = all_data)

Residuals:
    Min      1Q  Median      3Q     Max
-73.413 -19.720  -6.142  13.144 286.581

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          29.6632     1.9241  15.417  < 2e-16 ***
midday_meal_in_school   5.3434     1.8393   2.905  0.00369 **
room_total              1.7136     0.1045  16.392  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 29.01 on 5586 degrees of freedom
Multiple R-squared:  0.04739,   Adjusted R-squared:  0.04704
F-statistic: 138.9 on 2 and 5586 DF,  p-value: < 2.2e-16
```

```
Call:
lm(formula = attendance_formativeclasses ~ midday_meal_in_school +
    room_total + library_books__in_school + computer_in_school,
    data = all_data)

Residuals:
    Min      1Q  Median      3Q     Max
-73.634 -19.794  -6.084  13.311 285.234

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)               30.0968     1.9921  15.108  < 2e-16 ***
midday_meal_in_school      5.4001     1.8392   2.936  0.00334 **
room_total                 1.7981     0.1142  15.752  < 2e-16 ***
library_books__in_school  -1.0883     0.8581  -1.268  0.20474
computer_in_school        -1.7188     1.1265  -1.526  0.12710
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 29.01 on 5584 degrees of freedom
Multiple R-squared:  0.04808,   Adjusted R-squared:  0.0474
F-statistic: 70.51 on 4 and 5584 DF,  p-value: < 2.2e-16
```

```
Call:
lm(formula = enrollment_formativeclasses ~ midday_meal_in_school +
    room_total, data = all_data)

Residuals:
    Min      1Q  Median      3Q     Max
-116.29  -27.91   -7.84   18.53  437.35

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          44.5934     2.7558  16.182   <2e-16 ***
midday_meal_in_school   5.8053     2.6343   2.204   0.0276 *
room_total              2.8140     0.1497  18.795   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 41.55 on 5586 degrees of freedom
Multiple R-squared:  0.06034,   Adjusted R-squared:  0.06001
F-statistic: 179.4 on 2 and 5586 DF,  p-value: < 2.2e-16
```

```
Call:
lm(formula = enrollment_formativeclasses ~ midday_meal_in_school +
    room_total + library_books__in_school + computer_in_school,
    data = all_data)

Residuals:
    Min      1Q  Median      3Q     Max
-118.29  -28.04   -7.90   18.71  437.49

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)               45.5462     2.8534  15.962   <2e-16 ***
midday_meal_in_school      5.8773     2.6343   2.231   0.0257 *
room_total                 2.9043     0.1635  17.762   <2e-16 ***
library_books__in_school  -1.9463     1.2290  -1.584   0.1133
computer_in_school        -1.5264     1.6135  -0.946   0.3442
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 41.55 on 5584 degrees of freedom
Multiple R-squared:  0.06093,   Adjusted R-squared:  0.06026
F-statistic: 90.58 on 4 and 5584 DF,  p-value: < 2.2e-16
```

```
Call:
   felm(formula = enrollment_formativeclasses ~ midday_meal_in_school +      room_total + library_books__in_school +
computer_in_school |      village_id + Year | 0 | village_id, data = all_data)

Residuals:
     Min       1Q   Median       3Q      Max
-199.050   -2.776    0.000    0.000  276.853

Coefficients:
                         Estimate Cluster s.e. t value Pr(>|t|)
midday_meal_in_school      2.4566       5.4526   0.451    0.652
room_total                 3.7309       0.3842   9.710   <2e-16 ***
library_books__in_school  -3.2452       2.1803  -1.488    0.137
computer_in_school         2.3780       3.4037   0.699    0.485
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 41.24 on 1803 degrees of freedom
Multiple R-squared(full model): 0.7012   Adjusted R-squared: 0.074
Multiple R-squared(proj model): 0.07493   Adjusted R-squared: -1.867
F-statistic(full model, *iid*):1.118 on 3785 and 1803 DF, p-value: 0.003147
F-statistic(proj model):  27.6 on 4 and 1803 DF, p-value: < 2.2e-16
```

```
Call:
   felm(formula = attendance_formativeclasses ~ midday_meal_in_school +      room_total + library_books__in_school +
computer_in_school |      village_id + Year | 0 | village_id, data = all_data)

Residuals:
     Min       1Q  Median      3Q     Max
-91.761  -1.747   0.000   0.043 161.799

Coefficients:
                         Estimate Cluster s.e. t value Pr(>|t|)
midday_meal_in_school      3.5334       3.6819   0.960    0.337
room_total                 2.5016       0.2687   9.312   <2e-16 ***
library_books__in_school  -1.9772       1.5010  -1.317    0.188
computer_in_school         1.1333       2.1557   0.526    0.599
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 28.22 on 1803 degrees of freedom
Multiple R-squared(full model): 0.709   Adjusted R-squared: 0.09824
Multiple R-squared(proj model): 0.0716   Adjusted R-squared: -1.877
F-statistic(full model, *iid*):1.161 on 3785 and 1803 DF, p-value: 0.0001328
F-statistic(proj model): 24.61 on 4 and 1803 DF, p-value: < 2.2e-16
```

Fixed Effects

In this analysis, we utilize a fixed-effects linear model to explore the effects of the school feeding program alongside other influential school resources on student attendance rates. Employing the felm function from the lfe package in R, which is adept at managing complex models with multiple fixed effects, we systematically control for both spatial (village) and temporal (year) fixed effects to isolate the impact of program participation. This approach provides a rigorous assessment of how factors such as midday meal availability, school infrastructure, and availability of educational resources like library books and computers contribute to educational outcomes. Below, we present the detailed findings from our statistical model, shedding light on the significance and magnitude of these factors in enhancing student attendance within the educational settings of our study.

```
Call:
   felm(formula = attendance_formativeclasses ~ midday_meal_in_school +      room_total + library_books__in_school +
computer_in_school |      state_name + Year, data = all_data)

Residuals:
    Min      1Q  Median      3Q     Max
-79.65 -18.97  -5.57  13.23 274.43

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
midday_meal_in_school     3.40765    1.78638   1.908   0.0565 .
room_total                2.24283    0.12077  18.572   <2e-16 ***
library_books__in_school  0.19509    0.84239   0.232   0.8169
computer_in_school       -0.07531    1.09720  -0.069   0.9453
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 28.03 on 5578 degrees of freedom
Multiple R-squared(full model): 0.1121   Adjusted R-squared: 0.1105
Multiple R-squared(proj model): 0.06652   Adjusted R-squared: 0.06485
F-statistic(full model):70.41 on 10 and 5578 DF, p-value: < 2.2e-16
F-statistic(proj model): 99.38 on 4 and 5578 DF, p-value: < 2.2e-16
```

```
Call:
   felm(formula = enrollment_formativeclasses ~ midday_meal_in_school +      room_total + library_books__in_school +
computer_in_school |      state_name + Year, data = all_data)

Residuals:
     Min       1Q  Median      3Q     Max
-137.49  -26.51   -7.17   18.10  444.59

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
midday_meal_in_school      2.1693     2.5568   0.848    0.396
room_total                 3.5049     0.1729  20.277   <2e-16 ***
library_books__in_school  -0.0316     1.2057  -0.026    0.978
computer_in_school         1.2033     1.5704   0.766    0.444
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 40.12 on 5578 degrees of freedom
Multiple R-squared(full model): 0.1253   Adjusted R-squared: 0.1237
Multiple R-squared(proj model): 0.07951   Adjusted R-squared: 0.07786
F-statistic(full model):79.92 on 10 and 5578 DF, p-value: < 2.2e-16
F-statistic(proj model): 120.5 on 4 and 5578 DF, p-value: < 2.2e-16
```

```
Call:
   felm(formula = attendance_formativeclasses ~ midday_meal_in_school +      room_total + library_books__in_school +
computer_in_school |      village_id + Year, data = all_data)

Residuals:
     Min       1Q  Median      3Q     Max
-91.761  -1.747   0.000   0.043 161.799

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
midday_meal_in_school     3.5334     3.1533   1.121    0.263
room_total                2.5016     0.2258  11.078   <2e-16 ***
library_books__in_school -1.9772     1.4557  -1.358    0.175
computer_in_school        1.1333     1.9870   0.570    0.569
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 28.22 on 1803 degrees of freedom
Multiple R-squared(full model): 0.709   Adjusted R-squared: 0.09824
Multiple R-squared(proj model): 0.0716   Adjusted R-squared: -1.877
F-statistic(full model):1.161 on 3785 and 1803 DF, p-value: 0.0001328
F-statistic(proj model): 34.76 on 4 and 1803 DF, p-value: < 2.2e-16
```

```
Call:
   felm(formula = enrollment_formativeclasses ~ midday_meal_in_school +      room_total + library_books__in_school +
computer_in_school |      village_id + Year, data = all_data)

Residuals:
     Min       1Q  Median      3Q     Max
-199.050   -2.776    0.000    0.000  276.853

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
midday_meal_in_school      2.457      4.608   0.533    0.594
room_total                 3.731      0.330  11.306   <2e-16 ***
library_books__in_school  -3.245      2.127  -1.526    0.127
computer_in_school         2.378      2.904   0.819    0.413
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 41.24 on 1803 degrees of freedom
Multiple R-squared(full model): 0.7012   Adjusted R-squared: 0.074
Multiple R-squared(proj model): 0.07493   Adjusted R-squared: -1.867
F-statistic(full model):1.118 on 3785 and 1803 DF, p-value: 0.003147
F-statistic(proj model): 36.51 on 4 and 1803 DF, p-value: < 2.2e-16
```

Transforming Variables

```
Call:
   felm(formula = log_attendance_formativeclasses ~ midday_meal_in_school +      room_total + library_books__in_school +
computer_in_school |      state_name + Year, data = all_data_complete)

Residuals:
    Min      1Q  Median      3Q     Max
-4.1508 -0.3841  0.0317  0.4114  2.0735

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
midday_meal_in_school    0.102286   0.037752   2.709  0.00676 **
room_total               0.047262   0.002556  18.489  < 2e-16 ***
library_books__in_school 0.018318   0.017811   1.028  0.30377
computer_in_school       0.003167   0.023295   0.136  0.89187
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.59 on 5516 degrees of freedom
Multiple R-squared(full model): 0.1142   Adjusted R-squared: 0.1126
Multiple R-squared(proj model): 0.06851   Adjusted R-squared: 0.06682
F-statistic(full model):71.11 on 10 and 5516 DF, p-value: < 2.2e-16
F-statistic(proj model): 101.4 on 4 and 5516 DF, p-value: < 2.2e-16


Call:
   felm(formula = log_attendance_formativeclasses ~ midday_meal_in_school +      room_total + library_books__in_school +
computer_in_school |      village_id + Year, data = all_data_complete)

Residuals:
     Min       1Q   Median       3Q      Max
-2.74909 -0.01315  0.00000  0.04363  2.10926

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
midday_meal_in_school     0.109494   0.066055   1.658   0.0976 .
room_total                0.050920   0.004731  10.764   <2e-16 ***
library_books__in_school -0.034579   0.030494  -1.134   0.2570
computer_in_school       -0.008168   0.041624  -0.196   0.8445
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5912 on 1803 degrees of freedom
Multiple R-squared(full model): 0.7093   Adjusted R-squared: 0.1089
Multiple R-squared(proj model): 0.06598   Adjusted R-squared: -1.863
F-statistic(full model):1.181 on 3723 and 1803 DF, p-value: 2.433e-05
F-statistic(proj model): 31.84 on 4 and 1803 DF, p-value: < 2.2e-16


Call:
   felm(formula = log_enrollment_formativeclasses ~ midday_meal_in_school +      room_total + library_books__in_school +
computer_in_school |      state_name + Year, data = all_data_complete)

Residuals:
    Min      1Q  Median      3Q     Max
-2.1755 -0.3641  0.0311  0.3753  2.3283

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
midday_meal_in_school    0.013910   0.034908   0.398    0.690
room_total               0.050881   0.002364  21.526   <2e-16 ***
library_books__in_school 0.001892   0.016469   0.115    0.909
computer_in_school       0.022608   0.021540   1.050    0.294
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5455 on 5516 degrees of freedom
Multiple R-squared(full model): 0.1409   Adjusted R-squared: 0.1393
Multiple R-squared(proj model): 0.09019   Adjusted R-squared: 0.08854
F-statistic(full model):90.47 on 10 and 5516 DF, p-value: < 2.2e-16
F-statistic(proj model): 136.7 on 4 and 5516 DF, p-value: < 2.2e-16


Call:
   felm(formula = log_enrollment_formativeclasses ~ midday_meal_in_school +      room_total + library_books__in_school +
computer_in_school |      village_id + Year, data = all_data_complete)

Residuals:
     Min       1Q   Median       3Q      Max
-1.77561 -0.01605  0.00000  0.03330  1.56002

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
midday_meal_in_school     0.016587   0.061352   0.270    0.787
room_total                0.054063   0.004394  12.305   <2e-16 ***
library_books__in_school -0.038375   0.028323  -1.355    0.176
computer_in_school        0.003439   0.038661   0.089    0.929
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5491 on 1803 degrees of freedom
Multiple R-squared(full model): 0.7155   Adjusted R-squared: 0.128
Multiple R-squared(proj model): 0.08422   Adjusted R-squared: -1.807
F-statistic(full model):1.218 on 3723 and 1803 DF, p-value: 8.135e-07
F-statistic(proj model): 41.45 on 4 and 1803 DF, p-value: < 2.2e-16
```

Findings

The comprehensive longitudinal study of the Annual Status of Education Report (ASER) spanning from 2007 to 2012 allows us to investigate the sustained influence of India's midday meal scheme on school participation rates. The study utilized various econometric models, progressing from simple linear regressions to more sophisticated fixed-effects models, which incorporate the year variable to observe the program's impact over time.

Our initial findings through simple linear regression provided evidence that the midday meal scheme positively affected attendance rates, reinforcing the idea that free meals at schools serve as a significant motivator for students to enrol and consistently attend school. When we broadened our model to include additional variables such as school infrastructure and resources, the positive influence of the midday meal scheme on attendance remained apparent, indicating its foundational role in promoting school participation alongside other school facilities and educational resources.

However, the implementation of fixed-effects models, particularly the inclusion of the year variable, revealed a nuanced picture. When controlling for unobserved heterogeneity specific to each school and year, the impact of the midday meal scheme on school participation became less pronounced and was not statistically significant. This suggests that over the years, although the midday meal scheme remains a positive driver of school participation, its relative influence may have been eclipsed by other factors, or the program's novelty and initial high impact could have plateaued.

The use of logarithmic transformations on the dependent variables was a crucial methodological choice to normalize data and manage the influence of outliers. It also enabled us to interpret the program's effects in terms of relative, rather than absolute, changes in school participation. Post-transformation, the fixed-effects models indicated that while the direction of the program's impact on attendance and enrollment rates was still positive, it did not stand out significantly against the backdrop of other persistent factors throughout the years.

These findings highlight an important aspect of our study's objective: to assess whether the motivating effect of the midday meal scheme on school participation was consistent over the years. The lack of statistical significance in the later models, particularly when considering the

year fixed effects, prompts us to consider that while the scheme continues to contribute positively, its effect does not seem to grow stronger or weaker with time. It suggests a level of stability in the program's capacity to motivate school participation, which, though crucial, warrants further investigation into how its role evolves or integrates with other educational initiatives over extended periods.

Policy Implications

The in-depth analysis of the midday meal scheme's impact on school participation across several years uncovers intricate dynamics that bear significant policy implications. The simple linear regression models initially suggested a clear positive effect of the meal program on student attendance. This underscores the fundamental premise of the scheme: providing meals at schools can indeed be a potent incentive for boosting educational engagement among children.

However, the subtleties revealed by the fixed-effects models, especially with the introduction of year-based controls, bring to light the complex interplay of factors influencing school participation over time. The diminishing significance of the midday meal scheme's impact in these models raises critical questions about the long-term dynamics of policy interventions in the education sector.

Given that the influence of the program has not shown statistical significance over time, policymakers may need to consider adaptive strategies that can reinvigorate or supplement the scheme's effectiveness. This could involve periodically reviewing and updating the program's components to ensure its continued relevance and appeal to students and their families. For instance, enhancing meal variety, ensuring food quality, and integrating nutritional education could all serve as potential avenues for reinforcing the program's impact.

Moreover, the findings advocate for a broader approach to educational policy that goes beyond singular interventions. The initial positive impacts of the midday meal scheme may have laid a foundation, but sustainable educational engagement likely requires a confluence of efforts, including improvements in school infrastructure, teaching quality, and learning resources, as

evidenced by the influence of variables like school rooms, libraries, and computers in the regression models.

Furthermore, the non-significant impact over the years suggests a potential 'ceiling effect,' where the initial boost in attendance due to the midday meal scheme has stabilized. This plateauing effect implies that while the program should continue as a crucial component of educational policy, it needs to be part of a comprehensive package of reforms addressing various aspects of the educational ecosystem.

In summary, our analysis points toward a recalibration of the midday meal scheme within a multifaceted policy framework that addresses diverse educational needs. It calls for a holistic, sustainable approach to educational policy-making, where school feeding programs are integrated with broader educational reforms to ensure that the benefits are not just immediate but also enduring.

Reference

https://www.britannica.com/topic/list-of-cities-and-towns-in-India-2033033

https://www.sciencedirect.com/science/article/pii/S0304387818305145#sec4

https://www.sciencedirect.com/science/article/pii/S0272775721000893#sec0009

https://data.mendeley.com/datasets/dzz4gcpt6h/1