Feeding Discrimination? Caste Heterogeneity in Impacts of School Lunches in India*

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Abstract

India's free school lunch program has been widely acknowledged as a success in terms of raising primary school enrollment. However, heterogeneity within its effects has not been examined in the literature. In particular, I hypothesize that the nature of food as a site of systematic caste-based discrimination causes differential (lower) enrollment effects for marginalized castes. I use administrative data from the initial years of the universal program in the poor northern states of Uttar Pradesh and Bihar to show plausibly causal estimates of caste-based heterogeneity in effects. I find that are statistically significant 12-14 percentage point gaps in enrollment between Scheduled Caste and other students.

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1 Introduction

School feeding programs (SFPs) have been instituted across the world, in both developed and developing countries. Cupertino et al. (2022) document SFPs in at least 117 countries. SFPs may have numerous simultaneous and potentially overlapping objectives, including incentivizing enrollment and attendance, raising educational achievement, raising nutrition and health levels, redistributing public resources, and increasing equity by reducing net costs for lower-income students. (Jomaa, McDonnell, and Probart 2011) SFPs may incentivize student enrollment in particular by reducing the net costs of education for families, by reducing drop-outs due to malnutrition-induced health issues, or by leading to higher educational attainment and therefore a higher perceived investment value in a student's education.

In principle, as a subsidy program, SFPs ought benefit the most disadvantaged students, who may otherwise drop out of school to work, or who may otherwise suffer from the worst malnourishment which in turn impedes their educational attainment. While aggregate effects are certainly important, especially with SFPs being generally universal programs and being a part of overall developmental strategy, understanding heterogeneity within SFPs is central to assessing whether they are an equalizing force and are effective at improving outcomes for the worst-off.

In theory, heterogeneity of effect by socioeconomic grouping may run in either direction. If SFPs are working as intended, worse-off students are likely to benefit the most. They have lower baseline enrollment, lower nutrition, and lower educational attainment. Their potential educational attainment may be bound by a nutritional resource constraint, unlike better-off students, and therefore the SFP serves as a genuinely material incentive for their enrollment and attendance; it also moves outward their resource constraint and potentially directly enables higher educational attainment.

Conversely, however, SFPs in highly resource-constrained environments may benefit better-off groups more. Better-off socioecononomic groups may be able to capture more of the benefits of the SFP, by unequally distributing the SFP resources between school units (relevant for highly-segregated contexts) or between students within a school. The worst-off students may also have their education attainment bound by simultaneous constraints in addition to nutrition, such as infectious disease, sanitation access, or strong demand for household labor. The gains of the SFP may therefore relax the resource constraint of relatively better-off students, while being insufficient to expand the frontier for the worst-off students.

In the particular case of India's caste system, there is reason to suspect that SFPs may differentially benefit better-off groups. Food is traditionally a site of discrimination in India's caste system, and there has been widespread media reportage of such discrimination in practice.[1]

These differential effects may contribute to changes in student enrollment through a number of mechanisms. Parents who expect that their child will be ostracized at lunch time may be less likely to send their child to school. Students who feel discriminated against may be more likely to drop out intentionally. Students facing discrimination and/or reduced SFP access due to their caste may have relatively worse educational outcomes, through social and nutrition effect channels; with worse outcomes, parents may judge them to be relatively worse educational investments and prompt them to drop out of school.

A number of studies have assessed SFPs in India and found positive aggregate effects, dating back nearly four decades. (Saxena and Mittal 1985) More recent literature has found "dramatic" positive effects on student enrollment. (Chakraborty and Jayaraman 2019) However, the literature is notably sparse in providing empirical estimates of caste-based heterogeneity in India's SFPs that can resolve the theoretical

1. For example, Abraham (2019), Reddy (2018), and V (2015).

ambiguity outlined above. Only Jayaraman (2009) makes a direct estimate, but their scope of inquiry is limited to more-prosperous South India, enrollment effects for grade 1 only, and for a limited timeframe.

> *Note:* Kaur (2021) was published after this paper was originally written in 2020, likely superseding it. It is notably superior to the present study, making use of granular survey data which is likely to be more reliable than the administrative data used here, and using a much larger sample of states. I include it here in the October 2024 update to this paper for completeness.

In this paper, I use administrative data at the school level from two of India's largest states to separately estimate the enrollment effects of SFPs on marginalized caste groups as against other students. I draw upon nearly 950,000 school-year observations. I control for potential socioeconomic confounders with proxies such as electricity access and district GDP. I set this study right around the widespread deployment of SFPs in my states of choice, and so I can exploit the varying exposure to the SFP of students at different grade levels to roughly estimate the per-year SFP effect size. I find a statistically significant difference between enrollment effects for marginalized-caste students and for other students of approximately 12-14 percentage points.

This paper contributes to the literature by providing the second extant estimate of caste-based heterogeneity in enrollment effects of SFPs, based on a large panel of administrative data. This is the first paper to estimate enrollment effects by caste in low-income North Indian states. To my knowledge, this is also the only paper to use a long-duration variation in exposure to estimate SFP effects, with a panel that extends for six years following the implementation of an SFP.

2 Literature Review

The global literature on SFPs is sizeable. Impact evaluations of SFPs, including multiple randomized controlled trials, generally find positive effects on student outcomes. A systematic review of SFPs in sub-Saharan Africa by Wall et al. (2022) finds a positive correlation with educational outcomes;Cohen et al. (2021) conduct a systematic review of SFPs in OECD countries, and find positive associations with diet quality, food security, and educational outcomes, and limited evidence to suggest that SFPs differentially benefit lower-income households; Wang et al. (2021) analyse studies of SFPs in lower and middle income countries (LMICs) and find significant positive effects on height, weight, and attendance.

India's SFP is conventionally called the "Mid-Day Meal" (MDM) program. Despite its size and importance, feeding over 100 million children as of 2019 (Ramachandran 2019), there are very few quantitative, causal assessments of its effects.

Jayaraman (2009) uses administrative data to investigate the effects of mid-day meals on class 1 enrollment in two states in southern India, one which had a pre-existing MDM program, and another which did not. It uses a differences-in-differences technique and finds an 8% increase in class 1 enrollment, and a 25% increase when accounting for "aggregate trends." Considering heterogeneity in effects, it finds that school meals "are not closing the overall gender gap," but they are narrowing the gender gap among marginalized castes. Additionally, it does separately estimate enrollment effects by caste, finding (consistent with this paper) that marginalized castes are *not* more responsive to MDMs than others.

Jayaraman and Simroth (2015) use a strategy similar to the present study to investigate the effects of MDMs on aggregate enrollment using administrative data. They use a panel from 2002-2004 and the quasi-control group of private schools, to find a 13 percentage point increase in public school enrollment due to MDMs.

Chakraborty and Jayaraman (2019) find "dramatic" positive effects of MDMs on learning achievement. The authors measure of learning achievement with math and reading scores from the well-known Annual Status of Education Report (ASER) survey by the nonprofit Pratham. The authors control for gender, household size, whether or not the child's mother attended school, state fixed effects, cohort fixed effects, year fixed effects, and a linear state-specific time trend. They find that relative to students with less than a year of exposure to MDMs, students who have been exposed to MDMs throughout primary school have 18% higher reading and 9% math test scores. The authors consider heterogeneity by gender and economic status, proxied by housing quality, and find "no evidence that disadvantaged children enjoy higher marginal benefits from program exposure."

Finally, Chakrabarti et al. (2021) use district-level health survey panels to estimate intergenerational benefits of the MDM program, finding that children born to mothers exposed to MDMs have better anthropometric outcomes (namely, height-for-age scores). Notably, they find stronger effects among worse-off socioeconomic groups.

I note that the literature on caste and SFPs does contain one important survey that motivates the analysis in this paper. Sabharwal et al. (2014) finds strong indications of widespread caste-discrimination in mid-day meals. The paper analyses a survey of 709 households from seven poor Indian states, and reports discrimination among an aggregate of 30% of marginalized-caste respondents, 20% of whom reported discrimination in food quantity, 14% of whom reported segregated seating, and 20% who reported a disinterest in education due to discrimination.

3 Institutional Setting

SFPs have existed in various forms in different parts of India, beginning before Indian Independence. The earliest MDM was initiated by the erstwhile Madras Municipal Corporation in southern India in 1925. Several states instituted state-wide SFPs at the primary level throughout the 1980s and 1990s, but coverage was far from universal. The Central government intervened in 1995, providing states with a fixed allotment of foodgrains per student to provide to students in turn, as an incentive for continued enrollment and attendance.(Ramachandran 2019) This Central program did not lead to universal MDM coverage, and most often was implemented as a (leaky) distribution of dry foodgrain to students. (Jayaraman and Simroth 2015)

By 2001, there remained significant heterogeneity in coverage and program type across India. Some states still had essentially no SFP, while others had been providing hot cooked meals for decades. In 2001, the Supreme Court of India passed a landmark order mandating that every government-run or government-assisted primary school in India provide hot cooked mid-day meals. Students from grades 1-5 were entitled to a minimum of 300 calories and 12 grams of protein daily, for at least 200 days each year. Food grains were to be provided by the state-owned Food Corporation of India.(Right to Food Campaign 2009). The court order was implemented by states in different years, staggered from 2002 to 2006.(Chakraborty and Jayaraman 2019) I utilize the Supreme Court order as an exogenous shock to SFP provision in the states of Uttar Pradesh (U.P.) and Bihar. The MDM program was implemented in September 2004 in U.P. and January 2005 in Bihar.

I am specifically interested in the effect of MDMs on Scheduled Caste students. Indian society is divided by caste, an endogamous, hereditary hierarchical arrangement of people. Caste discrimination is rampant even in modern India, and those considered to be at the bottom of the hierarchy are often underrepresented in institutions, socially marginalized, segregated, and otherwise denied resources and full participation in society. The Indian Constitution lists certain communities, historically the most marginalized in the caste system as “Scheduled Castes” (SCs).

A common practice associated with discrimination against SCs is the untouchability. SCs may be prevented from sharing communal resources, or, notably, inter-dining with non-SCs.(Sharanya Deepak 2018) Dominant castes practicing untouchability consider any physical contact SCs violate norms of ritual purity, therefore force them to sit separately, eat separately, refuse to consume food they have prepared, and so on.

The interaction of caste and food is particularly relevant to the MDM program, as it brings the politics of food into the classroom. There have been widespread reports of caste discrimination playing out over mid-day meal consumption, including segregation of SC students (Press Trust of India 2019) and dominant caste students bring separate eating utensils to school or refuse to share food with Scheduled Castes. (Abraham 2019)

SC communities continue to face widespread discrimination, and remain educationally, economically, and nutritionally worse-off others in India. (Raushan, Acharya, and Raushan 2022) This paper seeks to understand whether the MDM program addresses these persistent socioeconomic inequalities.

4 Data

The data used for this investigation is drawn primarily from the Indian Ministry of Human Resources and Development's Unified District Information System for Education (U-DISE). The U-DISE database contains School Report Cards (SRC) for nearly every school in India, covering around 1.5 million schools. The SRCs are self-reported forms of school information, including details of student enrollment and school facilities. Enrollment numbers are provided separately for the legal caste categories in India - SCs, Scheduled Tribe (ST), Other Backward Classes (OBCs), and General.(NUEPA, n.d.)

The first DISE database was published in 1995, but only data from 2005 onwards was readily available online. Data was available for each academic year, from 2005-06 to 2017-18. There are no missing observations anywhere. The data is self-reported by schools, and 5% of schools are randomly selected for external verification, to ensure data reliability.(NUEPA, n.d.)

U-DISE SRCs were available through an online platform of the National University of Educational Planning and Administration, schoolreportcards.in. Schools are identified by unique IDs.

I accessed data for two of India's largest and poorest states, where some of the worst media reports of caste discrimination in the MDM program has been reported – U.P. and Bihar. I used data from 2005-06 to 2010-11, covering 6 academic years in total. I cover this period for a couple of reasons. First, previous studies focus on the initial year of implementation. (Jayaraman 2009) (Jayaraman and Simroth 2015) Expanding the time of study to 2010-11 allows for an examination of accumulating effects, and for varying exposure across grade levels. Second, I terminate the sample window in 2010-11, because after this year, no variation in exposure within grade levels remains - all grade 1 students have 1 year, all grade 2 students have 2 years, and so on.

This resulted in a total of 941,246 observations of school-years, across the two states. Importantly, the data begin right around when both U.P. and Bihar institute their court-ordered universal MDM program.

The primary outcome variables of interest for this analysis are SC and non-SC student enrollment, was immediately available in the data as a pre-existing field.

The important independent variable here is years of exposure to the MDM program. In both U.P. and Bihar, MDMs were implemented around the same time (September 2004 in U.P. and January 2005 in Bihar). I generate an integer variable to count years of exposure that varies by year and grade level. In 2005, all students have their first year of exposure to the program, with epxosure set to 1. In each subsequent year, grade 1 students always have Exposure = 1. Grade 2 exposure was set to 1 in 2005, and 2 from 2006-2010. Similarly, Grade 3 exposure was set to 1 in 2005, 2 in 2006, and 3 from 2007-2010. A similar process is followed for Grade 4.

This strategy assumes that increasing exposure is is linked to its effects linearly. The study is limited by the possibility of non-linear relationships between exposure and enrollment, such as compounding super-linear effects on enrollment as the benefits of the program are widely disseminated.

Controls at the school level were drawn from the U-DISE dataset as well. Rural or urban status and electricity access were available as indicator variables. Rural schools serve far poorer populations, and may be expected to have different caste dynamics due to greater social familiarity. I also include the number of classrooms in a school as a proxy for its size. School size may be linked to quality and socioeconomic status of its students.(Moore 2018)

I restrict my analysis to schools that have reported a non-zero number of students in primary school. Importantly, I restrict the analysis to schools managed by the state government, thereby dropping all categories of private schools and Central government schools. State government schools are the ones responding to state-level MDM interventions, and therefore are the relevant unit of analysis for this study.

The U-DISE dataset has significant limitations. First, although schools may directly report whether they serve MDMs or not, the reporting field appears unused in both states for the first several years where data is available. Thus, I cannot detect between-school variation in program exposure. Implementation over time doubtless varies between districts and schools in a state. Due to data limitations, all estimates are limited to the coarseness of a year.

To provide an additional control of socioeconomic status that is likely more fine-grained than electricity access, I source district-level Gross Domestic Product (GDP) figures and match it to the U-DISE dataset. I acquire this data from from the Government of India Open Government Data platform.(NITI Aayog 2014) Constant-price GDP would have been preferred, but the 2010-11 constant-price data for Bihar was obviously incorrect, so nominal figures were used, introducing some error due to differences in price trends between the two states. Data is presented in crores of rupees.[2]

Descriptive statistics on the data used are presented in Table 1. Each school in the sample has an average of approximately 9 SC students and 24-29 non-SC students, with attrition of approximately 5 non-SC students and 2 SC students from grade 2-5. In grade 2, the mean exposure to MDMs is 1.84 years, in grade 3 it is 2.5 years, and in grade 4 it is 3 years. The decreasing trend in exposure by grade is as expected, since students in higher grades have fewer years left in primary school to receive MDMs, in the frame of our sample. Around 10% of schools have electricity, and the overwhelming majority at 96% are rural. 32% of our sample is from Bihar, with the rest from U.P. The average school has 3.5 classrooms, although there is huge variation, with the largest having 78.

5 Empirical Strategy

I exploit variation in the number of years of exposure to MDMs, using this as the independent variable in a linear regression to estimate log enrollment for SC and non-SC students. I control for potential socioeconomic confounders including electricity access, rural/urban location, nominal district GDP, and school size (proxied

2. 1 crore = 10,000,000

Table 1. Summary statistics for regression independent and dependent variables, and controls

	Mean (1)	StdDev (2)	Min (3)	Max (4)
SC Enrolment (2nd Grade)	9.76307	11.90175	0	444
Non-SC Enrolment (2nd Grade)	29.67643	27.06429	0	1776
SC Enrolment (3rd Grade)	8.985779	11.22661	0	924
Non-SC Enrolment (3rd Grade)	27.37254	24.90789	0	1776
SC Enrolment (4th Grade)	8.041581	10.31632	0	886
Non-SC Enrolment (4th Grade)	24.32167	23.18848	0	1776
Grade 2 Exposure	1.848347	0.3586846	1	2
Grade 3 Exposure	2.538906	0.742828	1	3
Grade 4 Exposure	3.054967	1.130239	1	4
Has Electricity	0.0959331	0.2944997	0	1
Rural	0.9616914	0.1919404	0	1
School in Bihar State	0.3196699	0.4663489	0	1
Nominal District GDP (Rs. Cr.)	5085.124	4523.009	0	42724.62
Total No. of Classrooms	3.449533	1.91288	0	78
N		941,246		

by number of classrooms).

The empirical strategy followed relies on the fact that the introduction of mid-day meals was an exogenous policy change, stemming from a Supreme Court ruling. The causal effect of the program may therefore be approximated with a simple exposure-based regression while controlling for time trends and within-state fixed effects.

I follow Chakraborty and Jayaraman (2019) in estimating equations 1 and 2 to detect an Intention to Treat (ITT) effect of presumed exposure to the MDM program.

$$\ln\left[\text{Non-SC Enrollment}_{isgt}\right] = \alpha_0 + \alpha_1 X_{igt}^{\text{MDM exposure}} + \phi_{\text{non-SC}} X_{isgt}^{\text{controls}} + \delta_g + \delta_s + \gamma t + \epsilon_i \tag{1}$$

$$\ln\left[\text{SC Enrollment}_{isgt}\right] = \beta_0 + \beta_1 X_{igt}^{\text{MDM exposure}} + \phi_{\text{SC}} X_{isgt}^{\text{controls}} + \delta_g + \delta_s + \gamma t + \epsilon_i \tag{2}$$

where the subscript i indicates school index, g indicates grade level, s indicates the state index, and t indicates the year index. α_0 and β_0 are constant intercepts. The dependent variables are log-transformed enrollment of the non-SC and SC population respectively. The vector $\phi_{isgt}^{\text{controls}}$ includes controls for district GDP, whether the school has electricity, and whether the school is rural or urban. δ_g, δ_s account for grade and state fixed effects respectively. γt controls for a linear time trend. ϵ_{isgt} is the error term of the regression.

$X_{gt}^{\text{MDM exposure}}$ is the relevant independent variable, which measures the number of years of exposure to mid-day meals for a particular year and grade level.

MDM exposure for Grade 1 has no variation, and for Grade 5 it is collinear with the dummy for year, so I run this regression on the restricted sample of Grades 2-4.

The coefficients of interest are α_1 and β_1, which represent the percentage change in enrollment due to a 1-year increase in MDM exposure for non-SC and SC students, respectively.

Electricity access, rural or urban, and district GDP are included as control variables for the socioeconomic status of a school, which likely has causal links with enrollment.

The empirical strategy I use produces separate estimates for each grade level, following Jayaraman and Simroth (2015). This approach allows me to abstract from enrollment effects that are due to attrition between grade levels, documented in the summary statistics in Table 1. There may still be potentially confounding linear time trends in enrollment, however, such as population growth, shifts to or from public schooling, and diffusing information about MDMs, however, which I absorbed in the γt control in my specification.

My hypothesis is that $\alpha_1 > \beta_1$. That is, exposure to mid-day meals causes greater relative increases in enrollment for non-SC populations than for SC populations. Evidence in support of this hypothesis would be a large increase in enrollment of non-SC students in the years following the implementation of the mid-day meal program in a particular state, and a small increase or even a decrease in enrollment of SC students, the in the same years, across all grade levels. Evidence against this hypothesis would be uniform changes in enrollment across years and grade levels, with little caste-based heterogeneity.

6 Results

The results of the regression are summarized in Table 2.

Table 2. Estimates of Effect on Log Enrollment by Independent Variables and Controls

	(1) Grade 2 SC	(2) Grade 2 Non-SC	(3) Grade 3 SC	(4) Grade 3 Non-SC	(5) Grade 4 SC	(6) Grade 4 Non-SC
Years of Exposure to MDM	0.171***	0.278***	0.097***	0.202***	0.088***	0.213***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nominal District GDP	0.000	-0.000***	0.000***	-0.000***	0.000***	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Rural School	0.186***	-0.046***	0.208***	-0.001	0.228***	0.035***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Year	-0.138***	-0.209***	-0.144***	-0.223***	-0.156***	-0.262***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Has Electricity	-0.041***	-0.098***	-0.040***	-0.107***	-0.024***	-0.087***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bihar State Fixed Effect	-0.187***	0.619***	-0.272***	0.563***	-0.323***	0.526***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. of Classrooms	0.122***	0.129***	0.133***	0.152***	0.144***	0.181***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.269***	2.510***	1.251***	2.357***	1.113***	2.042***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N			941246			

Dependent variables are log of enrollment in each grade. Significance stars are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For each of grades 2, 3 and 4, the dependence of non-SC enrollment on exposure to mid-day meals is substantially higher than that of SC enrollment. In grade 2, exposure to an additional year of mid-day meals causes a 32% rise in non-SC enrollment,

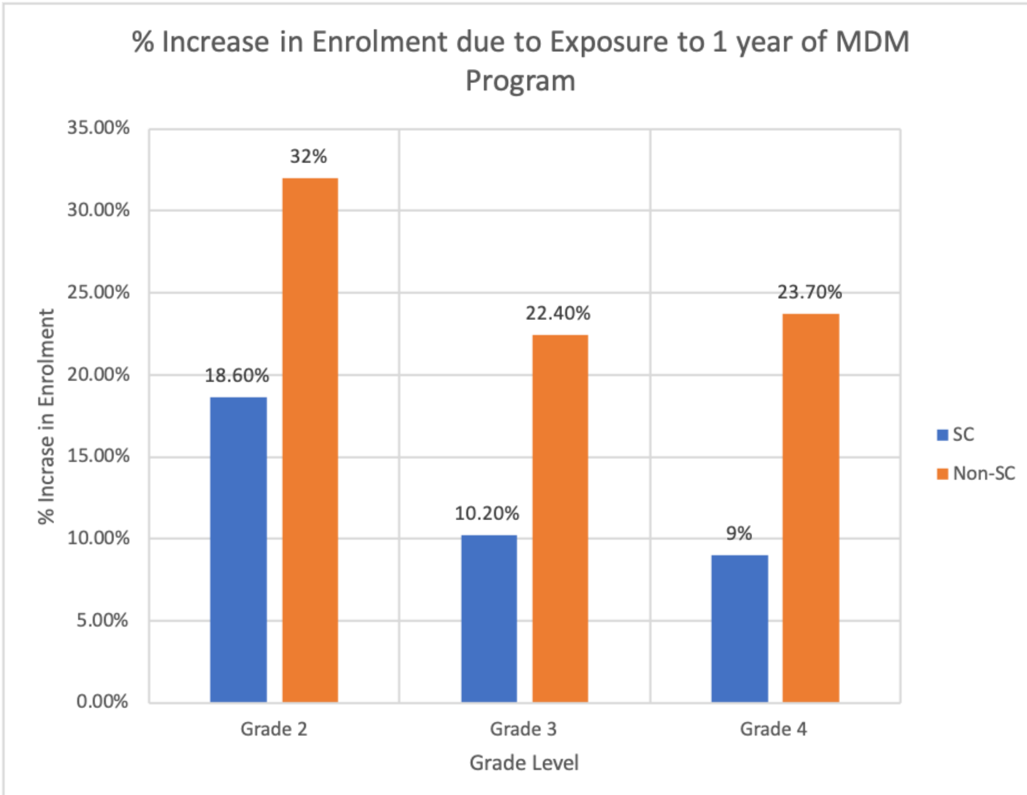

Figure 1. Bar graph comparing percentage increase in enrollment for SC and non-SC students across grade levels

compared to an 18.6% rise in SC enrollment. Similarly, in grade 3 there is a 22.4% increase in enrollment for non-SC students compared to 10.2% for SC students, and in grade 4 there is a 23.7% effect for non-SC students compared to an 9.2% effect for SC students.[3] All results are statistically significant at the 0.1% significance level. The results described are depicted in Figure 1.

The gap in mid-day meal effect remains wide across grades. In grade 2, there is a 14 percentage point difference in program effect, while in grade 3 it is 12 percentage points and 14 percentage points in grade 4.

In most cases, the controls for district GDP, rural/urban location, linear time trend, electricity access, and number of classrooms, are statistically significant. Schools

3. The regression table shows coefficient estimates for a log-transformed regression. To convert these coefficients to odds ratios, the coefficient β was transformed to $(e^{\beta} - 1) \times 100\%$

with electricity have lower enrollment, likely because most of rural India was not electrified during the study period, and especially not the more populous, lower-income parts. Rural schools have higher SC enrollment than urban schools, perhaps due to the fact that SCs are demographically concentrated in rural areas.(Hnatkovska and Lahiri 2012) The linear time trend coefficient is negative across all grades and SC/non-SC enrollment, pointing to a long-term trend of students moving from public to private schools.(ET Bureau 2012) The Bihar state fixed effect is consistently negative for SC enrollment and positive for non-SC enrollment. This implies that all else equal, the mid-day meal program in Bihar is associated with a 17% decrease in SC enrollment relative to U.P., and a 86% increase in non-SC enrollment, for grade 2, with similarly large relative disparities in grades 3 and 4. This may reflect differential caste dynamics in the two states, or worse casteism in program implementation in Bihar than U.P.

7 Conclusion

I find that in two of India's largest states, Uttar Pradesh and Bihar, the effect of the mid-day meal program has increased primary school enrollment for Scheduled Caste students, but significantly less than it has for non-SC students. Regressing SC and non-SC enrollment on exposure to the mid-day meal program, and controlling for socioeconomic confounders and time trends, disaggregated by grade and accounting for state fixed effects, I find that the program effect is up to 14 percentage points smaller for SC students across grades of primary school. Based upon the survey by Sabharwal et al. (2014), media reportage, and the theoretical channels I have outlined previously, I speculate that the root cause of this heterogeneity is caste-based discrimination.

Further study on the relationships of interest in this paper could proceed through alternative study designs. Randomized controlled trials to resolve identification challenges for are no longer possible, due to the universal nature of MDMs. Political proposals to expand the MDM program to Grade 12 have been floated, although there has been no serious effort in that direction. Unless the MDM program is expanded, future analysis of MDMs will therefore have to be largely limited to retrospective analysis of survey and administrative data.

School breakfasts are not universal in India yet, although they have been implemented in some states.(Menon 2023) The rollout of school breakfasts in other states could be done in a randomized phased fashion, to allow for clear identification of treatment effects.

Chakrabarti et al. (2021) show another interesting direction for future research by looking at intergenerational effects of MDM exposure. Future research could therefore investigate long-term downstream outcomes of MDM exposure beyond educational and nutritional outcomes, such as on rates of entrepreneurship, mental illness, or ethnic violence, while continuing to factor in heterogeneity.

Further research on caste-based heterogeneity in educational interventions is necessary, particularly when evaluating proposed policies such as to merge or privatize schools, or reconfigure curricula under the new National Education Policy (Govt. of India, n.d.).

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