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Abstract

India is home to the most undernourished women and children and the world’s largest school feeding program, the Mid-Day Meal (MDM) scheme. Previous work has found school meal benefits on educational and nutritional outcomes in participants themselves, but no studies have examined whether effects carry over to their children. Using eleven nationally representative datasets spanning 1993-2016, difference-in-difference regressions and mediation analysis, we find that mothers who received free meals during primary school are less likely to have stunted children compared to mothers who did not receive free meals. Findings also indicate that this effect operates through direct participant benefits on education and height. MDM scale up between 1995 and 2005 accounted for 12-15% of the actual ten percentage point stunting reduction in Indian children between 2006 and 2016. These findings suggest that stunting reductions can be supported through school-based programs targeting underlying determinants such as women’s education and height.

Keywords	social protection; school feeding; stunting; height; education; mother; child; nutrition

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INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
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Dear Editor, July 22, 2018

We are submitting a Research Article titled "Intergenerational benefits of India's national school feeding program: effects on women's height and education, and stunting in their children" to be considered for publication. The material included in this article is original research, has not been previously published, and will not be submitted for publication elsewhere while under consideration at this journal.

Thirty percent of the 155 million children who are too short for their age (i.e. stunted, height-for-age Z-score <-2) live in India. Stunting has large implications for human capital and economic productivity, and the World Health Assembly set a goal of reducing stunting by forty percent by 2025. This goal will not be met given current rates of stunting reduction. The current policy thrust around reducing stunting focuses on interventions targeted at the "1000-day window" from conception to the child's second birthday. In the current paper, we suggest that intervening well outside of this window, during late childhood and adolescence, may help accelerate stunting reductions.

In addition to having the most stunted children of any country, India also has the largest government-led school feeding program, the Mid-Day Meal Scheme (MDM), which provides a daily free meal to around 100 million primary-school-aged children (6-10 years). The MDM is mandated by the Supreme Court in India as a social protection program addressing food insecurity. In the submitted paper, we explored the hypothesis that mothers who participated in the MDM have children who are less likely to be stunted than those of mothers who did not participate.

Applying difference-in-difference regressions and mediation analysis using eleven population datasets spanning 1993-2016, we find that between twelve and fifteen percent of the total stunting reduction from 2006 to 2016 can be accounted for by the MDM. Two-thirds of this impact operates through improved educational attainment attributable to the scheme. Impacts may be even greater if the scheme were to be extended to cover children in secondary school (11-15 years).

To our knowledge, this is the first study to show that a school feeding program can impact stunting. School feeding programs exist in almost all countries. This reinforces an increased attention to seeking opportunities to improve nutrition in the 'next 7,000 days' (Bundy et al. Lancet 2017; https://doi.org/10.1016/S0140-6736(17)32417-0), that is, to find means of addressing undernutrition should efforts in the high priority period prior to a child's second birthday not be fully successful.

These findings may help the global health community understand how countries can accelerate progress toward stunting reduction. We feel that multiple audiences—among them, health economists, nutrition investigators, and policymakers—will benefit from the insights presented in the submitted article.

If I can provide further information, please email me at samuel.scott@cgiar.org.

Yours sincerely,

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Intergenerational benefits of India's national school feeding program: effects on women's height and education, and stunting in their children

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Abstract

India is home to the most undernourished women and children and the world's largest school feeding program, the Mid-Day Meal (MDM) scheme. Previous work has found school meal benefits on educational and nutritional outcomes in participants themselves, but no studies have examined whether effects carry over to their children. Using eleven nationally representative datasets spanning 1993-2016, difference-in-difference regressions and mediation analysis, we find that mothers who received free meals during primary school are less likely to have stunted children compared to mothers who did not receive free meals. Findings also indicate that this effect operates through direct participant benefits on education and height. MDM scale up between 1995 and 2005 accounted for 12-15% of the actual ten percentage point stunting reduction in Indian children between 2006 and 2016. These findings suggest that stunting reductions can be supported through school-based programs targeting underlying determinants such as women's education and height.

Keywords: social protection; school feeding; stunting; height; education; mother; child; nutrition

Highlights

- Midday meals at school improves height and educational attainment
- Maternal height and education predict child stunting
- India's midday meal scheme reduces next generation stunting
- Programs targeting underlying determinants can help accelerate stunting reduction

Introduction

Globally, 155 million children are too short for their age and thirty percent of these children live in India (Development Initiatives, 2017). Linear growth failure is a marker of chronic undernutrition and multiple pathological changes which, together, have been termed the 'stunting syndrome' (Prendergast and Humphrey, 2014). Stunted children are at risk of not reaching their developmental potential, thus stunting has large implications for human capital and the economic productivity of entire societies (Black et al., 2017; de Onis and Branca, 2016; Development Initiatives, 2017). To motivate actions to fight stunting, the World Health Assembly set the ambitious target of reducing childhood stunting by forty percent from 2010 to 2025 (de Onis et al., 2013). If current trends continue, this target will not be met (Development Initiatives, 2017). Thus, it is imperative for the global health community to understand how countries can accelerate progress toward stunting reduction.

Though much focus has been placed on nutrition-specific interventions during the 1000-day period from conception to the child's second birthday, it is understood that investments across multiple life periods and which address multiple underlying determinants are important to achieve stunting reductions (Black et al., 2013; Bundy et al., 2017). Researchers examining determinants of stunting in India have found that women's height and educational attainment are among the strongest predictors of child outcomes (Alderman and Headey, 2017; Cavatorta et al., 2015; Corsi et al., 2016; Headey et al., 2016; Kim et al., 2017). However, interventions to improve maternal height and education must be implemented years before those girls and young women become mothers. Despite prior criticism of the role of school feeding programs in addressing nutrition challenges, their role in reducing the intergenerational transmission of poor nutrition has not been explored.

Evidence from several developing countries suggests that school feeding programs have mixed or small effects in terms of improving anthropometry of program beneficiaries themselves (Jomaa et al., 2011; Kristjansson et al., 2007; Lawson, 2012). Given that linear growth velocity peaks earlier in life (Prendergast and Humphrey, 2014), the effects of school feeding programs on anthropometric outcomes may not be fully appreciated if only program beneficiaries themselves are studied; looking at the next generation may reveal further insights.

In the Indian context, a candidate intervention which potentially improves both women's height and education—and which, therefore, may lead to reductions in stunting among children born to these women—is the national school feeding program, the Mid-Day Meal (MDM) scheme (Raghunathan et al., 2017). Launched in 1995 by the Government of India, the MDM scheme provides a free cooked meal to children in government and government-assisted primary schools (classes I-V; ages 6-10 years). In 2016-2017, 97.8 million children received a free cooked meal through the scheme every day, making India's MDM scheme the largest school feeding program in the world (Ministry of Human Resource Development, 2017).

Econometric evaluations of the MDM scheme have shown a positive impact on beneficiaries' school attendance (Afridi, 2011; Drèze and Kingdon, 1999), hunger and protein-energy malnutrition (Afridi, 2010), and resilience to health shocks such as drought (Singh et al., 2014)—all of which may have carryover benefits to children born to mothers who participated in the program. No studies to date have explored whether program benefits for the MDM or similar programs in other countries extend to the next generation. Enough time has passed for girls who benefited from the program in the late 1990s and early 2000s to become mothers so we are able to study intergenerational program effects with India's 2016 National Family Health Survey data. Filling this research gap is critical, as we know that 1) stunting carries over from one generation to the next and is therefore optimally studied on a multigenerational time horizon (Addo et al., 2013; Hambidge et al., 2012; Nabwera et al., 2017; Stein et al., 2004), 2) school feeding programs are implemented in almost every country in the world (Bundy et al., 2013) and 3) social safety nets such as India's MDM scheme have the potential for population-level stunting reduction as they are implemented at large scale and target multiple underlying determinants in vulnerable groups (Ruel et al., 2013).

This paper studies the intergenerational benefits of India's MDM scheme. We apply difference-in-difference models using eleven population level datasets spanning 1993-2016, including multiple rounds of National Sample Surveys of Consumer Expenditure, National Family Household Surveys, Indian Human Development Surveys, and the District Level Household Survey. We investigate whether states which implemented the scheme early have better outcomes (women's height and education, and child stunting) in 2016 compared to states which implemented the scheme late—after accounting for maternal, child, household, village, and state-level factors—and how these effects differ by wealth status. To link these effects more closely to school level interventions, we then perform a causal mediation analysis to look at whether mothers' exposure to the MDM scheme is associated with child stunting, and whether maternal height and education mediate this association. In secondary analyses, we support these findings by investigating 1) the continuity of trends in education and height by year of entrance into primary school, 2) associations between MDM participation in a panel survey and education and height seven years after attending primary school, 3) cross-sectional associations between maternal mediators and child stunting in a large national survey in 2016, 4) whether a continuation of the program beyond primary school may provide additional benefits and 5) what percentage of the total reduction in child stunting from 2006 to 2016 can be accounted for by the MDM.

We find that higher coverage of the MDM scheme among primary school-aged girls in 2004 predicts more years of education in women, greater height in women, and reduced stunting prevalence in children in 2016. These effects are robust to the inclusion of a broad set of controls at multiple levels, and are larger among poor households. Our causal mediation analysis supports the plausibility of a mediating role of women's education and height in the association between MDM coverage and next generation child stunting, with approximately two-thirds of the effects working through improvements in women's education. Secondary analyses provide further evidence in support of our proposed impact pathway, with even larger effects when using coverage among girls aged 11-15 years as a predictor, and suggest that the MDM scheme accounted for 12-15% of the total stunting reduction from 2006 to 2016.

Data sources

The data used in this paper come from eleven large nationally representative surveys spanning two decades (Table 1). The first data source is the National Sample Survey of Consumer Expenditure (NSS-CES). The NSS-CES allow us to track a cohort of girls 6-10 years of age for the years 1999, 2004 and 2011. NSS-CES data from 2009 were also used in a secondary analysis for a single state (Tamil Nadu). Only girls were considered given our interest in examining next generation effects on child stunting (Özaltin et al., 2010), our hypothesis that these effects work through maternal height and education (Kim et al., 2017), and given that previous evidence shows larger program impacts on girls than on boys

(Afridi, 2011). The NSS-CES indicates whether children receive free meals at school, allowing us to measure coverage of the MDM across districts in India. Data on the three primary outcomes in this paper—maternal education, maternal height and child (girls and boys) stunting—were taken from four waves of India's National Family Health Surveys (NFHS) collected in 1993, 1999, 2006 and 2016. We support our main findings by showing our primary results across other data sources including the 2004 and 2011 rounds of Indian Human Development Surveys and the 2012 round of India's District Level Household Survey. All analyses were performed using STATA version 15.

Program description

The MDM scheme, initiated by the central government in 1995, was intended to cover all government schools under the National Programme of Nutritional Support for Primary Education, (Afridi, 2010). Due to institutional challenges, only a few states scaled up the program immediately. NSS-CES data from 1999 show that only 6% of girls aged 6-10 years received midday meals in school (Figure 1). Between 1999 and 2004, program coverage increased in many other states, largely due to an order from the Supreme Court of India directing state governments to provide cooked midday meals in primary schools (Drèze and Khera, 2017). In 2004, 32% of Indian girls aged 6-10 years were covered by the program. Finally, following a substantial increase in the budget allocation for the program in 2006, by 2011, 46% of the girls in primary school benefited from the program.

State variability in MDM rollout per NSS-CES data lends itself to categorization into three distinct mutually exclusive phases (Table 2), which we define as 'Phase 1', 'Phase 2' and 'Phase 3'. Phase 1 states (50 districts) implemented a state-level MDM program prior to the national MDM program and had at least 25% coverage among girls in primary school by 1999. Large states in this category include Tamil Nadu, Kerala and Odisha. While researchers have reported other early implementers such as Gujarat and Chhattisgarh, NSS data show only 10% coverage in these two states in 1999 while all other states had coverage close to zero (Figure 1). Similarly, Phase 2 states (including Chhattisgarh, Himachal Pradesh, Karnataka, Uttaranchal, Andhra Pradesh, Maharashtra, Madhya Pradesh, Gujarat, and West Bengal, among others) had at least 25% coverage (292 districts total including Phase 1 districts) by 2004 (Table 2). Phase 3 states had at least 25% coverage by 2011 (441 districts). Thus, given the pattern of roll-out, a wider age range of women of reproductive age in 2016 would be have been exposed to the program in Phase 1 states and districts, followed by Phase 2 and the lowest likelihood of exposure in Phase 3 (**Table 2**).

Identification strategy

Date of birth and district of residence were used to determine an individual's exposure to the program. In India, children attend primary school between the ages of 6 and 10 years. Therefore, children born in 1985 or before were 10 years or older in 1995, when the first schools implemented the centrally sponsored MDM, could not have benefited from exposure to the program. Using district of residence, we matched the district averages of NFHS4 (2016) outcome data with district-level NSS-CES data for the percentage of girls covered by the MDM in 1999 and 2004.

Association between historical MDM participation and current nutrition outcomes

For district *d* in year *t*, we ran ordinary least squares (OLS) regression models.

$$Y_{dt} = \alpha + MDM_{dt-n}\delta + Wealth_{dt}\eta + \epsilon_{dt} \quad (1)$$

where Y is district-level maternal educational attainment, maternal height, or child stunting prevalence. MDM is district-level coverage of the MDM in time *t* minus *n* years (see Table 2 for age ranges for each phase). Wealth is a variable that measures average district level socio-economic status (Filmer and Pritchett, 2001) and ϵ_{it} is the district-specific error term. Using equation 1, we tested for an association between MDM coverage during years when girls attended primary school and their attained outcomes in early adulthood. As a prior, we expected the associations from 1999 MDM coverage to be stronger than those from 2004 due to more women being exposed to the program in states that implemented the MDM first. As a robustness check, we also ran regressions with MDM coverage using NSS-CES data from 2011. We expected the effect size for stunting to be much smaller in these regressions because the cohort of girls aged 6-10 years exposed to MDM in 2011 would be 11-16 years old in 2016 and thus very few would be of reproductive age.

Table 3 shows the regression results from equation 1. MDM coverage in prior years was strongly positively associated with maternal education and negatively associated child stunting in 2016, but less significantly with maternal height in 2016. As expected, the effect sizes decreased in a stepwise fashion by year of coverage, with the largest coefficients in the 1999 coverage model and the smallest coefficients in the 2011 coverage model. Ten percentage point (pp) coverage increases in 1999 and 2004, respectively, predicted 0.35 year and 0.20 year increases in maternal educational attainment, 0.02 cm and 0.04 cm increases in maternal height and 1.3 pp and 0.4 pp decreases in child stunting prevalence in 2016. While 2011 coefficients were much smaller compared to 1999 and 2004, they were significant for education and stunting. This is likely because the 2011 coverage indicator may pick up some variation from the intervening years between 2004 and 2011, which may include some women who have reached the reproductive age by 2016.

Differences-in-differences analyses

A limitation of estimating program treatment effects using equation 1 is that policy variables in observational data are unlikely to be independent of latent individual and institutional characteristics (Barrett and Carter, 2010). In an ideal experiment, girls would be randomly assigned access to free lunches in primary school and we would compare the average outcomes of the beneficiaries versus non-beneficiaries in adulthood. This was the approach that Cesarini and colleagues (Cesarini et al., 2016) adopted when dealing with a similar research question. In the absence of randomized treatment allotment, we chose to use methods that mimic a randomized allocation setting provided validation of a key set of assumptions (Varian, 2016). A major concern in the current analysis is that states that introduce free meals in primary school at scale could be systematically different from other states, and these differences may be correlated with outcomes. For example, states with residents who had lower education or nutritional status on average may have been more likely to scale up the MDM, or states with better governance may have been better equipped to implement the MDM program. In either case, the correlation between outcomes and MDM implementation could be confounded with unobserved variables. An additional issue is self-selection of households into government primary schools. If poorer parents—who may not send girl children to school due to social liabilities (Alfano, 2017)—are more incentivized by the scheme, then OLS estimates without fixed effects would likely be downward biased. In contrast, if the richer states with greater capacity for implementation were the first to scale-up the program, then estimates from equation 1 might be biased upward due to these states having better enabling environments to begin with.

A common method of controlling for time-invariant unobserved heterogeneity is to use difference-in-differences (DID) models. The staggered rollout of MDM across states creates a natural experiment setting which we exploited to implement our DID strategy. With DID, we controlled for observed and unobserved time-invariant state-level characteristics that might be correlated with the decision to scale up MDM as well as with maternal- and child-level outcomes. In other words, outcomes are determined by the sum of a time-invariant state effect, a year effect that is common across states and the effect of the MDM (Galiani et al., 2005). In the absence of unobserved time-varying factors unique to treatment or control states, the DID is estimated for individuals as a two-way fixed-effect linear regression model as expressed in equation 2:

$$Y_{ist} = \beta_0 + \beta_1 P_{it} * T_{is} + \beta_2 P_{it} + \beta_3 T_{is} + \varepsilon_{ist} \quad (2)$$

where $Y_{??????}$ is the outcome variable of interest for individual ?? in state ?? at time ?? (corresponding to either 2006 or 2016 NFHS data,). $P_{????}$ is an indicator coded as 1 for individuals in Phase 1 and Phase 2 states, and 0 for those in Phase 3 states. $T_{????}$ is a dummy variable coded as 1 for observations from the post-treatment period (NFHS4, 2016) and coded 0 for observations from the pre-treatment period (NFHS3, 2006). Phase 3 states serve as controls having very little to no MDM coverage before 2004 per NSS-CES data (Table 2). β_3 estimates average change in the outcome in the control states between 2006 and 2016, β_2 estimates the difference between control and treatment states in 2006, and β_1 estimates the difference in the changes in outcomes between control and treatment states between 2006 and 2016, or the impact of the MDM.

Parallel trends in the pre-treatment period

The key identifying assumption for this interpretation is that the change in outcomes in control states is an unbiased estimate of the true counterfactual, where the outcomes would end up in the absence of the treatment. This assumption is not directly testable, as the true counterfactual (states where the MDM did not exist) is not actually observed. However, one can test whether time trends in the control and treatment states were the same prior to the intervention. If secular trends were parallel in the pre-MDM period, then it is likely that they would have been similarly parallel in the post-MDM period, had the treated states not scaled-up the MDM per the central government's mandate. To check for evidence of pre-intervention parallel trends, we graphically plotted pre-intervention trends in outcomes using data from NFHS1 (1993), NFHS2 (1999) and NFHS3 (2006).

Figure 2 shows that trends in the considered outcomes were indeed largely parallel for early- and late-implementing states during the period from 1993 to 2005. The validation of similar pre-intervention trends lends confidence to our DID strategy.

Generalized differences-in-differences

Given a ten-year gap between the pre- and post-treatment periods, time-varying unobserved factors are a potential concern for the DID model estimated in equation 2. It is likely that, between the two rounds of NFHS (2006 and 2016), policy changes occurred in some states but not in other states, and these changes could bias the parameter estimates from equation 2. For example, differing programmatic innovations or reforms such as scaling up health or nutrition-specific interventions or educational subsidies across states could also affect education and nutrition. If these other programs were better implemented in treatment states, we would likely over-estimate the impact of the MDM. Instead, if programs were stronger in control states, we would underestimate the impact. Moreover, underlying determinants of undernutrition such as household wealth and access to improved sanitation may have also changed over this period.

We addressed these concerns by modifying equation 2 into a continuous treatment DID model including household controls (Card, 1992).

$$Y_{ist} = \beta_0 + \beta_1 MDM_{ds(t-n)} * P_{it} * T_{is} + \beta_2 P_{it} + \beta_3 T_{is} + \beta_4 C_{ist} + \varepsilon_{ist} \quad (3)$$

Where *MDM* is the average coverage of the program in district *d* for state *s*, at time *t-n*. *n* is the difference between the average age at first birth for women in the NFHS4 sample (20.5 years) and the average age of girls attending primary school (8 years); thus, n = 12.5. We use data from 2004 as it the closest available to the required year (2016-12.5 = 2003.5). β_1 measures the impact of the program as an increasing function of the percentage of children exposed to the program in districts in Phase 1 and 2 states in the year 2004. Using this form, we can parse out the marginal effect of the program and interpret its effect per unit coverage in a district while simultaneously retaining the advantages of the DID model in equation 2. While the DID estimator in equation 2 would pick up the effect of all changes unique to treatment states, the continuous treatment DID in equation 3 would only reflect changes correlated to the MDM. C_{ist} represents individual and household-level socioeconomic and demographic covariates including women's age, access to improved drinking water, open-defecation, clean cooking fuel, type of house (permanent, semi-permanent, impermanent), household ownership, type of floor, roof, and walls materials, number of durable household assets (score of 1-10 for sum of ownership of mattress, pressure cooker, chair, bed, table, fan, radio, sewing machine, phone and watch), and socio-economic group dummies for scheduled caste or tribe. Including these covariates increases the precision of our estimates by reducing the residual variation to be explained. ??$_{??????}$ is the individual-specific error term. All standard errors were clustered at the village level to control for intra-village (cluster) correlations and to allow for variability in program implementation capacity that could drive poverty as well as the quality of education and nutrition related services (Kim et al., 2016). Clustering standard errors corrects for heteroskedasticity and allows for correlation of errors within villages but does not change the magnitude of point estimates.

Summary statistics for the NFHS samples are shown in Supplemental Table 2. Table 4 Panel A shows the results from the DID models estimated in equation 2. In the binary model, where we compared Phase 1 and Phase 2 states combined against Phase 3 states, the DID estimator was highly significant for maternal education, maternal height, and child HAZ but was only a trend ($p<0.1$) for child stunting.

The average treatment effects were approximately 0.18 years of education and 0.18 cm of height among mothers in 2016, and 0.05 SD in HAZ for their children after controlling for child age and sex.

The continuous treatment model which exploits district level variation in MDM coverage (Table 4 Panel B) shows highly significant effects for all outcomes. For example, a 10 pp increase in coverage in Phase 1 and Phase 2 states in 2004 predicts benefits of 0.19 years of additional education and 0.04 cm of additional height among mothers in 2016, and 0.33 pp lower stunting prevalence in their children. These findings were slightly attenuated though still robust to the addition of household-level controls and village-level clustering of standard errors (Table 4 Panel C). After adding controls, a 10 pp increase in coverage of MDM in Phase 1 and Phase 2 states in 2004 predicted benefits of 0.16 years of additional education and 0.03 cm of additional height among mothers in 2016, and 0.23 pp lower stunting prevalence in their children. Thus, it is likely that the effects are attributable to the MDM itself rather than observable changes in underlying sociodemographic determinants such as household wealth, sanitation and access to improved water.

Accounting for state-specific time varying confounders

Although the estimates from the continuous treatment model with household controls (equation 3) provide a more robust estimate than a dichotomous DID model (equation 2), they may be susceptible to the effects of unobserved time-varying state-specific factors. Moreover, the 25% cut-off used to select phase 1 and 2 states, though based on coverage data, is arbitrary. We addressed both these concern by estimating equation 4 (Acemoglu et al., 2004).

$$Y_{ist} = \gamma_0 + \gamma_1 MDM_{ds(t-n)} * T_{it} + \gamma_2 T_{it} + \gamma_3 S_{is} + \gamma_4 S_{is} * T_{it} + \gamma_5 C_{ist} + \varepsilon_{ist} \qquad (4)$$

Where S_{is} represents state of residence dummies (state fixed effects). γ_1 measures whether districts with higher rates of MDM coverage in 2004 experienced a greater improvement in outcomes between 2006 and 2016. The inclusion of state dummy variables controls for all unobserved time-invariant state-level heterogeneity such as geography or deeply ingrained dietary habits. $S_{is} * T_{it}$ or state-year fixed effects controls for unobserved state-specific time varying factors that could be correlated with the outcome such as changes in the state's political climate, varying degrees of implementation of welfare programs, agricultural policies and educational subsidies.

Table 5 shows the regression results for the impact of continuous district level coverage of the MDM program in 2004 on maternal and child outcomes, with adjustment for time-invariant and time-variant state-level factors. Accounting for state-level unobservable factors reduced the effect size of a 10% increase in coverage in 2004 on maternal education in 2016 from 0.16 years and in the continuous treatment with household and village controls (equation 3, Table 4) to 0.04 years in the model with state controls (equation 4, Table 5). This likely reflects the presence of differing state level initiatives that could have also benefitted maternal education between 2006 and 2016, factors that were unaccounted for in the model estimated through equation 3. The effect on maternal height, however, showed no attenuation with a stable and statistically significant effect size of 0.04 cm for both equations 3 and 4. Treatment effects on next generation child linear growth were substantially attenuated and lost significance.

Testing for differential impacts on the poor

The MDM was implemented in government schools rather than private schools as an incentive for children from poor households to attend primary school (and to improve nutrition), therefore the estimates in equation 4 are likely to be downward biased due to self-selection. This is because outcome data from children sampled from non-poor households, who would likely opt out of the government school system in favor of private schools, would affect average effect sizes and correlations and therefore weaken associations with the MDM coverage variable. To investigate the existence of such biases we compared treatment effects across SES groups. We estimated models for differential treatment effects for poor versus non-poor households by modifying equation 4 as follows.

$$Y_{ist} = \gamma_0 + \gamma_1 MDM_{ds(t-n)} * T_{it} * W_{it} + \gamma_2 MDM_{ds(t-n)} * T_{it} + \gamma_3 T_{it} * W_{it} + \gamma_4 T_{it} + \gamma_5 W_{it} + \gamma_6 S_{is} + \gamma_7 S_{is} * T_{it} + \gamma_8 C_{ist} + \varepsilon_{ist} \quad (5)$$

Where W_{it} is a dummy coded 0 for households in top three SES quintiles and 1 for households in the bottom two SES quintiles. γ_1 measures if poor households benefitted more from MDM coverage in 2004 compared to non-poor households. If $\gamma_1$is statistically significant and of a large order, then we have evidence that the MDM impact estimated in equation 4 did not fully account for self-selection of poor households into the program and that program impacts are differential across socio-economic strata.

Table 6 shows differential treatment effects for poor and non-poor households to account for self-selection into the program. In this model, we found an even larger impact of the MDM scheme on all outcomes considered. A 10 pp increase in MDM coverage in 2004 predicted 0.09 years of additional education and 0.07 cm of additional height in poor mothers in 2016, and 0.53 pp lower prevalence of stunting in their children. Taken together, these estimates show that the effects of the MDM on the poor were of a larger order than those on the non-poor.

Causal mediation of the MDM for the poor

We next investigated if the observed pattern of associations estimated in equation 1 was consistent with maternal height and education mediating a potential effect of the MDM program on next generation child outcomes for poor households. Mediation was tested using the 4-step regression approach by Baron and Kenny (Baron and Kenny, 1986; Zhao et al., 2010): 1) MDM coverage in 2004 is associated with child stunting in 2016, 2) MDM coverage in 2004 is associated with mother's education and height in 2016, 3) mother's education and height in 2016 are associated with child stunting in 2016, 4) associations between MDM coverage in 2004 and child stunting in 2016 are significantly attenuated by adjustment for maternal education and height.

Causal inference from the mediation estimates depends on the sequential ignorability assumption (SIA) (Imai et al., 2010b). The assumption is sequential because it plays out in two steps. First, it assumes that the treatment is statistically independent of potential outcomes and potential mediators. For observational studies where subjects may self-select into the treatment group, as is the case with MDM, a common strategy is to control for pre-treatment confounders so that the ignorability of treatment assignment is credible (Imai et al., 2010a). We follow this approach by controlling for district socio-demographic characteristics using NSS-CES data from 1999. Second, it assumes that the mediator is ignorable given the observed treatment and pre-treatment confounders. The ignorability of the mediator implies that among those mothers who share the same treatment status and the same pre-treatment characteristics, the mediator can be regarded as if it were randomized. This second assumption is strong given a high likelihood that child stunting and maternal height and education are all correlated with unobserved variables. Moreover, the second assumption cannot be directly tested from observational data. Instead it is standard practice to conduct sensitivity analyses to test the robustness to a potential violation of the SIA. If an inference is sensitive, a slight violation of the SIA may lead to substantively different conclusions. We conduct the standard prescribed sensitivity analysis for the mediation analysis using the *medsens* STATA routine (Imai et al., 2010b).

To account for self-selection, we ran regressions with equation 1 by calculating district averages of outcomes in the sub-sample of poorest households (lowest two wealth quintiles) in the NFHS4 sample. Further, to perform exact tests for these experiments, we use the Randomization Inference test (RITEST) developed by Fisher (Fisher, 1936)and later modified by Rosenbaum (Rosenbaum, 2002). This method is used to assess whether the association between MDM coverage in 2004 and child stunting in 2016 is observed purely by chance. Applied to non-experimental data (Heß, 2017), this test tells us if the estimate of the direct effect of the MDM program on child stunting is statistically larger than one obtained from a distribution of null effects. In other words, an RITEST with $p<0.05$ indicates that the estimate is unlikely to be produced by assigning random treatment groups over many repetitions.

Mediation analysis was done at the district level to allow us to use pretreatment controls to address the first assumption of the SIA. However, we can test the robustness of *step 3* in the mediation model using NFHS4 individual level data. For child *i* born to mother *m* belonging to village *v*, we ran regression models, estimated by OLS.

$$Stunting_{imv} = \alpha + \psi 1 Height_{mv} + \psi 2 Education_{mv} + \Omega C_{imv} + \eta M_{mv} + \gamma SES_{mv} + V_v + \epsilon_{imv} \quad (6)$$

where *Stunting* (a dummy variable for height-for-age Z score below -2, HAZ < -2) is the child-level outcome of interest. *Height* and *Education* are height (cm) and education (years) of the child's mother. *C* represents child-level covariates: child age (months), sex and parity. *M* is mother's age (years) and *SES* is an ordinal variable of household-level wealth quintiles. V_v is cluster-level (village) fixed effects and ϵ_{imhv} is the child-specific error term. To account for potential biases arising from unobserved village level factors that may affect stunting such as infrastructure, access to public programs and sanitation, we estimated the model with village fixed effects(Kim et al., 2016).

Supplementary Table 2 shows descriptive characteristics of the 548 districts included in the mediation analysis. Figure 3 visually depicts the mediation findings and Supplementary Table 3 provides the causal mediation and randomization inference test parameters as well as standard errors for each step of the analysis. All paths in the mediation model were significant, and the mediating effect of maternal education and height on the association between previous MDM coverage and stunting in their children was supported. The direct effect of 2004 coverage on 2016 child stunting was fully accounted for with the addition of maternal mediating factors to the model. The average causal mediation effect was larger for maternal education than for height, suggesting that the benefits maternal MDM exposure on child linear growth are working mostly through direct benefits on education; this finding agrees with our earlier findings of relatively stronger impacts on education rather than height. The randomization interference test provided further support that these findings were not observed by chance, with $p<0.01$ for each individual mediation path. The robustness of the estimates to the inclusion of pre-intervention controls and the sensitivity analyses lends confidence to the fulfilment of the SIA. Table 7 shows the results of associations between maternal and child factors from NFHS4 unit level data to rigorously test *step 3* in the mediation model. One additional cm of maternal height and one additional year of education were respectively associated with 1.2% and 0.7% lower stunting prevalence in their children. Effects sizes remained stable for a sub-sample of households in the lowest two wealth quintiles. Thus, effect sizes of the association between maternal height and education were slightly attenuated when using individual level with village-fixed effects, vis-à-vis district level data.

Secondary analyses

External validity of first generation treatment effects using IHDS panel data

To further test the validity of our DID estimates, we used panel data from the two rounds of Indian Human Development Surveys. We compared years of completed education and attained height of girls in IHDS2 (2011-2012) between groups of girls who were either MDM participants or nonparticipants in 2004-2005 based on IHDS1 (2004-2005), assuming that average program exposure was five years, the amount of time children typically spend in primary school. We estimated two equations for girl child *i* in state *s*,

$$Height_{is} = \alpha + \psi 3MDM_{is} + \Omega X_{is} + \gamma Z_{is} + \delta_s + \epsilon_{is} \quad (7)$$

$$Completed\ education_{is} = \alpha + \psi 4MDM_{is} + \Omega X_{is} + \gamma Z_{is} + \delta_s + \epsilon_{is} \quad (8)$$

where completed education (years) and attained height (cm) are the individual-level outcomes of interest in 2011. MDM is a dummy variable for program participation in 2004, X_{is} is child age, Z_{is} are covariates for individual *i*, including government school, household size, residence, monthly expenditure, assets, occupation of household and highest education attained by adult males and females in the household. δ_s is state-level fixed effects and ϵ_{is} is the individual-level error term.

The IHDS data are non-experimental survey data, and the children who received MDM treatment were not randomly selected. To estimate the casual effect of MDM, we used individual and household controls with state fixed effects, controlling for observable factors and unobserved state-level time invariant factors. Given that unobserved factors in the fixed effects model could be correlated both with the treatment and outcome, Nearest Neighbor Matching (NNM) using the *teffects* routine in STATA 15 was used to correct for potential endogeneity (Caliendo and Kopeinig, 2008; Stuart, 2010). NNM uses the distance between covariate patterns to define closest observation for comparison. In NNM, we use bias adjustment to remove the large-sample bias caused by matching on more than one continuous covariate. The estimated parameter from the matched models is the average treatment effect on the treated: the difference between expected outcomes after participation or nonparticipation, i.e. the expected effect on the outcome mimicking random program assignment. Matching methods can help to reduce large biases, but biases may remain because matching only controls for observed variables.

Therefore, there could be left-over unobserved factors that are correlated with a child's MDM participation and her height or educational status.

Table 8 shows findings from the IHDS panel analysis of the impact of MDM exposure on girls' education and height measured seven years later. Compared to girls who did not participate in the program in 2004, girls who did participate had 0.6 more years of education in 2011, with similar findings in both the state fixed-effects model and the NNM model. Likewise, a benefit on height was observed, with the NNM giving the lower estimate (0.66 cm), suggesting endogeneity in the unmatched model. These ATET (average treatment effect on the treated) have the same direction but are of a larger magnitude that than those we obtained in Table 6 (a 32% coverage predicted an effect of 0.3 years on attained maternal education and 0.2 cm on height).

External validity of first generation treatment effects from DLHS and NSS data

Tamil Nadu was one of the first states to implement the MDM (Drèze and Khera, 2017). Though not yet at scale, the state had a pre-existing school feeding program prior to 1995. Starting in 1995, the launch of the centrally sponsored MDM program provided a free supply of food grains and a large subsidy for transportation of grains (Planning Commission, 2010). This central support likely enabled Tamil Nadu to quickly scale up the MDM, in contrast to other states without implementation infrastructure. To gauge the effect of the central government's support in Tamil Nadu, we pooled data from DLHS4 (2012) and NFHS4 (2016) on adult height with data from NSS-CES66 (2009) and NSS-CES68 (2011) on maternal education. These surveys provide data on current age which we used to calculate year of birth. We expected the program to have effects on attained education and height in 2016 among women born in or after 1990 (who entered primary school in or after 1995), but not among women born earlier who would have entered primary school before the MDM program ran at scale with central support. In other words, outcomes ordered by year of entering primary school are expected to change significantly after 1995 if the MDM had an impact.

Supplementary Figure 1 shows the trends in education and height by primary school entrance year. A gap in the trend was evident for mothers who entered primary school in 1996 or later compared to those who entered primary school earlier, providing support for our hypothesis of a direct beneficiary effect on educational attainment. The pattern for height was less clear, with data during pre-program years being highly variable, which may reflect greater vulnerability of height prior to the MDM. There did appear to be a stabilization in the height trend around and after central program support.

Estimating total treatment effects on stunting in the children of the treated

To estimate the total impact of maternal MDM participation in 2004 on child stunting in 2016, we used three methods. First, we used the estimates of $\gamma 1$ and $\gamma 2$ from equation 5 and multiplied them with

MDM coverage in 2004. Second, we estimated the program impact on beneficiaries in the future by multiplying the coefficients from the mediation analysis in steps 2 (association between MDM coverage in 2004 and mother's education in 2016) and step 3 (association between mother's education and height in 2016 on child stunting in 2016). Third, from equations 6, 7 and 8 we use ψ1, ψ2, ψ3 and ψ4 to estimate the total program impact on beneficiaries in the future:

$$Expected\ Impact = \psi1 \bullet \psi3 + \psi2 \bullet \psi4 \quad (9)$$

Table 9 shows the estimates of the total program impact on next generation child stunting from the three methods. According to NFHS data, stunting in children under five years of age decreased by 10 percentage points from 2006 to 2016. All estimation methods found that the MDM accounted for at least 12% of this total decrease, a substantial effect.

The timing of school feeding and linear growth in children

The MDM scheme was initially targeted to children in primary school but later introduced in some secondary schools as well (Drèze and Khera, 2017). Given the adolescent growth spurt, we sought to determine whether coverage through secondary school (ages 11-15y) resulted in additional benefits on the outcomes of interest. To identify ages at which growth among Indian children is rapid, we graphed population level linear growth and growth velocity for males and females aged 0 to 24 years using DLHS4 data. DLHS4 data were used given that NFHS4 only provides data on children 0-5 years and women and men aged 15-49y. Since adolescents are still growing, they could potentially benefit from school meals being extended beyond primary school. We formally tested this hypothesis using equations 3 and 5, however, we used MDM coverage data from girls aged 11-15y instead of 6-10y from 2004 as the continuous treatment variable.

Figure 5 shows height and growth velocity for males and females aged 0-24 in the Indian population. Growth in females plateaus around 17 years, whereas growth in males plateaus slightly later around 19 years. The shaded grey portion in Figure 5 represents the ages that are currently covered by the MDM scheme, which represent primary school and a small proportion of secondary schools. Given that growth continues until around 18 years in both sexes, there is currently a 6-year gap in program coverage. In Table 10 (panel A) all coefficients are larger in magnitude than those in Table 4 (panel C), as is the case with Table 10 (panel B) compared to Table 6. This suggests that longer MDM exposure does indeed result in larger effects on women's education and height, and child stunting.

Discussion, policy implications, conclusions

Using recent data on young children and their care givers we have shown that improvements in both maternal and child nutrition as well as increases of women's completed school are associated with investments made in school meals in previous decades. As the analysis covers approximately 300,000 households over the nation, the results reflect a program implemented at scale, with all its flaws, and not a pilot program designed to provide proof of concept. This, of course, comes at a cost; we were not able to follow a randomized cohort of girls from their school years into their childbearing ages. To reinforce the plausibility of this result (Victora et al., 2004), we also verify that the change in stature over time is consistent with estimates of the change in schooling times an estimate of the impact of maternal schooling on child height plus the change in the height of women times an estimate of the relationship of maternal height and that of their child.

School meal programs are often motivated by their potential to increase schooling, particularly that of girls. While enrolment parity is within reach in primary schooling – globally between 2000 and 2015, the number of primary school age children not in school declined globally from 100 million to 61 million (UNICEF, 2018) – there is a larger goal of primary and post primary school completion. Very little in the literature on school meal programs can quantify program contribution to total years of schooling completed. Moreover, while the role of school meals in nutrition is particularly context dependent given the dual risks of stunting and of obesity, evidence that the scale up of school meals is associated with increased heights of women—in a population in which stunting has been historically linked with maternal undernutrition— provides a new perspective on the contribution of such programs. This reinforces an increased attention to seeking opportunities to improve nutrition in the 'next 7,000 days' (Bundy et al. 2017), that is, to find means of addressing undernutrition should efforts in the high priority period prior to a child's second birthday not be fully successful. The results here show that school meals may contribute to the nutrition of school-aged girls and, further, by doing so, reduce the risk of undernutrition in the next generation. In its current form, MDM has the potential to improve nutrition by addressing the underlying determinants of undernutrition. Improving the quality of meals provided and adding appropriate context-specific components to this flagship program might allow further untapped potential to be effectively unleashed.

The MDM is mandated by the Supreme Court in India as a social protection program addressing food insecurity. This may be a justification by itself for school based transfers in many settings (Alderman et al., 2018). However, as low and middle-income countries seek to include sustainable funding of school meals and as donors hand over such financing, evidence such as presented here depict these programs as contributing to both equity and to improved outcomes in the next generation, thus, contribute to the policy framework for demand side schooling programs.

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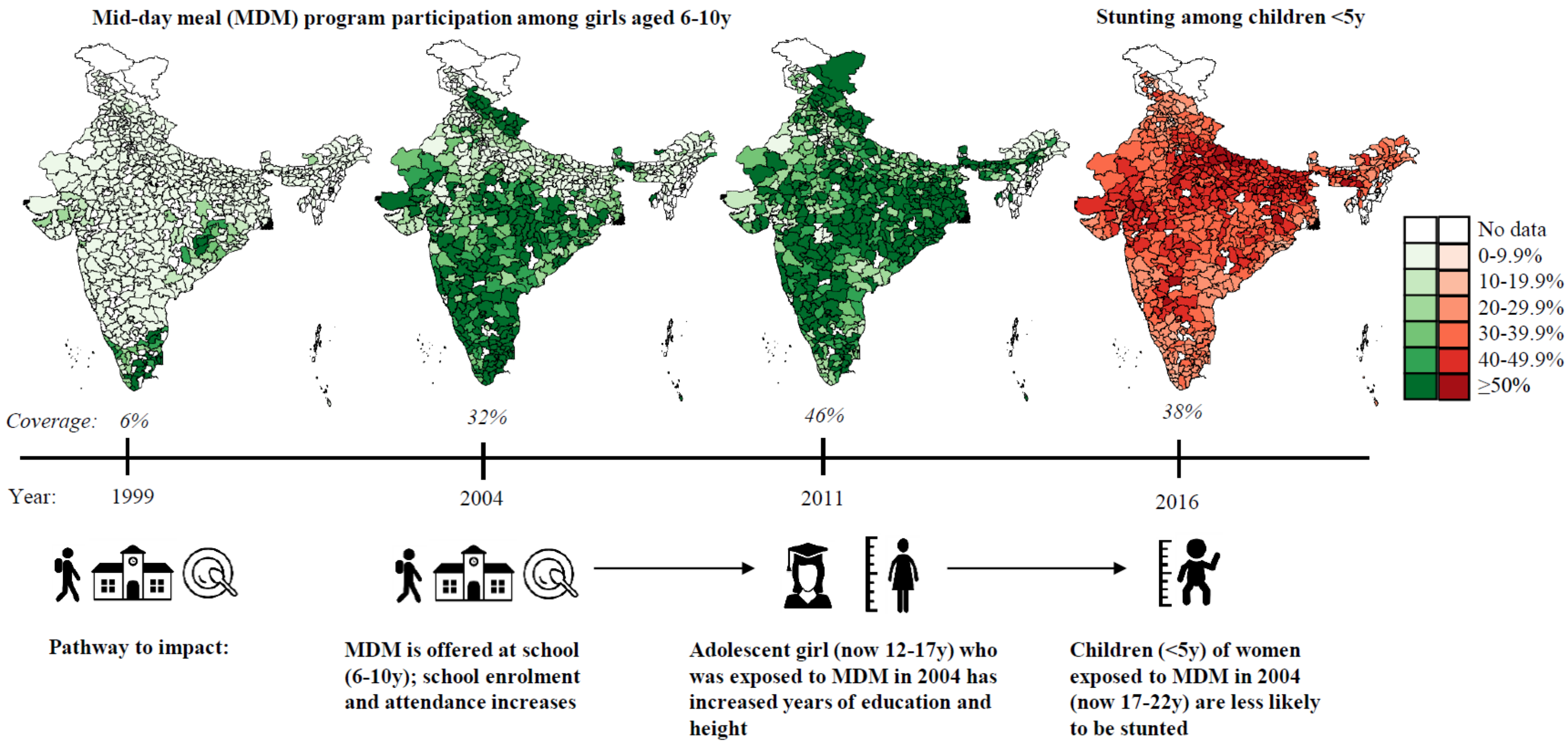


Figure 1. Overview of study design and proposed pathway to impact

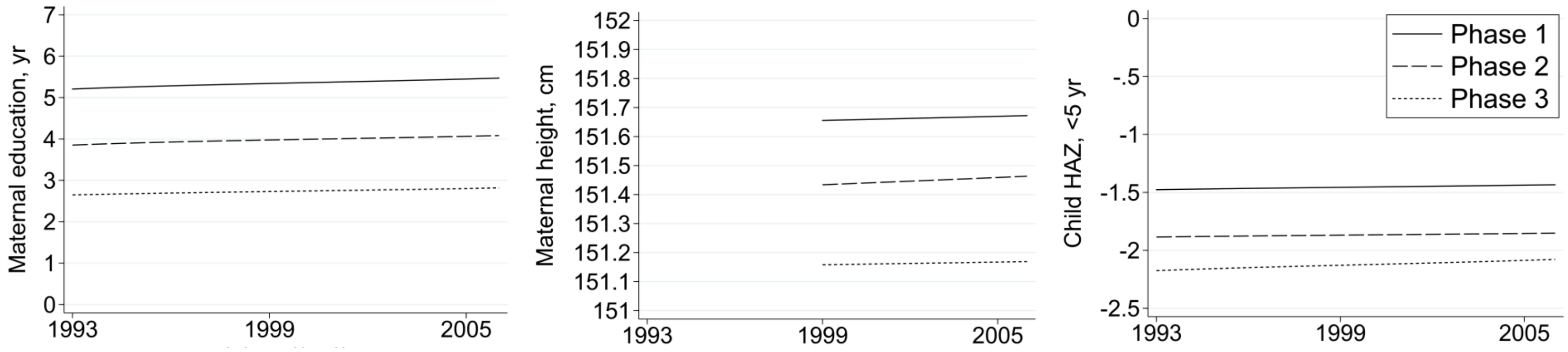


Figure 2. Parallel Trends in education and height among women and stunting in their children, by phase of program implementation. Lines represent Local Polynomial Smoothing. Trends are shown for phase 1 (solid), phase 2 (dashed), and phase 3 (dotted) states. Women's height data were not collected in 1993. Height for-age z-scores (HAZ) refer to children born to surveyed women in respective years. Phases refer to timing of program rollout (see Table 2). Source: National Family Health Survey waves 1 (1993), 2 (1999) and 3 (2005).

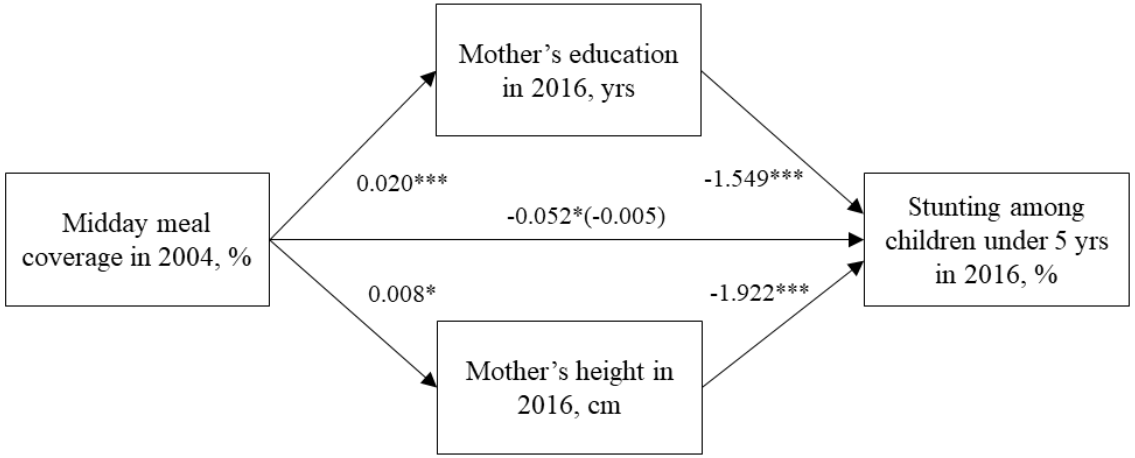


Figure 3. Maternal height and education mediate the association between midday meal participation and next generation child stunting for poor households. The mediation analysis was performed on the sub-sample of women with low wealth to increase the likelihood of program targeting. To validate the sequential ignorability assumption's first step, all models included pre-treatment (year=1999) district level covariates including monthly per-capita consumer expenditure, land owned, number of persons in households, household access to liquified petroleum gas and electricity, and percentage of illiterates, females, Hindus, Muslims, tribes, disadvantaged castes, self-employed and laborers in agriculture, and self-employed in non-agricultural. We also included current wealth status to attenuate for SES in 2016.

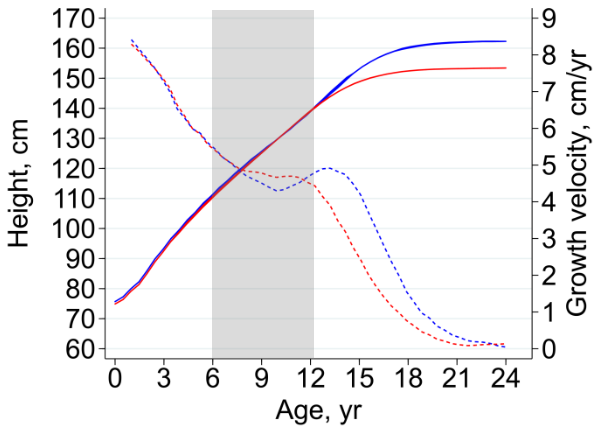


Figure 4. Population level growth curves for males and females ages 0-24. Local polynomial smoothing curves are shown for height (solid lines) and growth velocity (dashed lines), and for males (blue lines) and females (red lines). Shaded region indicates ages currently covered by MDM. Data source: District Level Household Survey 4 (2012-2013).

Table 1. Summary of datasets used to conduct the analyses

Data source	Survey rounds used	Survey Type	Variables used
Primary analysis			
National Sample Surveys of Consumer Expenditure (NSS-CES)	1999-2000 (NSS-CES55) 2004-2005 (NSS-CES61) 2011-2012 (NSS-CES68)	Repeated cross-section at individual level, representative at state and country level. Two-stage sample design selected with probability proportional to size followed by random sampling, separately for urban and rural areas.	Mid-day meal program participation among girls aged 6-10 years and female education.
National Family Health Survey (NFHS)	1993-1994 (NFHS1) 1999-2000 (NFHS2) 2005-2006 (NFHS3) 2015-2016 (NFHS4)	Cross-section at individual level, representative at state level and district level. Two-stage sample design selected with probability proportional to size followed by random sampling, separately for urban and rural areas.	Stunting, Height-for-age z-score, child age, birth order and sex, mother's age, height, education, and socio-economic status[2].
Secondary analysis			
Indian Human Development Survey (IHDS)	2004-2005 (IHDS1) 2011-2012 (IHDS2)	Panel at individual level, representative at country level. Revisited sample of 1994 Human Development Profile of India (HDPI) Survey. A three-stage sample was randomly drawn in each of new states or territories not covered in HDPI. Attrition between 2004-05 and 2011-12 rounds replaced by refresher sample randomly drawn with probability proportional to population size.	Mid-day meal program participation among girls aged 6-10 years, completed education, height, and school-related, demographic and socioeconomic variables[1]
National Sample Surveys of Consumer Expenditure (NSS-CES)	2009-2010 (NSS-CES66)	Cross-section at individual level, representative at state and country level. Two-stage sample design selected with probability proportional to size followed by random sampling, separately for urban and rural areas.	Maternal education and year of birth.
District Level Household Survey (DLHS)	2012-2013 (DLHS4)	Cross-section at individual level, representative at state level and district level. Two-stage sample design selected with probability proportional to size followed by random sampling, separately for urban and rural areas.	Maternal height, year of birth, height of children and adolescents.

[1] School-related covariates include: distance to school (km), government school (1/0). Demographic variables include: age (years), household size (persons). Socioeconomic variables include: urban residence (1/0), monthly consumption expenditure per-capita (INR), household assets (number), farming household (1/0), agricultural labor household (1/0), non-agricultural labor household (1/0), highest education attained by adult males and females in household (years), state of residence (1/0)

[2] Index of socio-economic status (SES) was constructed by conducting factor analysis using: household access to improved drinking water, improved latrine, clean cooking fuel, electricity and possession of durable household assets including a mattress, pressure cooker, chair, bed, table, fan, tv, sewing machine, phone; and housing materials for floor, roof and wall, if the household owned land or owned a house

Table 2. Indian states by timing of Midday Meal program rollout[1,2]

	Phase 1 At least 25% coverage by 1999	**Phase 2** At least 25% coverage by 2004	**Phase 3** At least 25% coverage by 2011
State names	Tamil Nadu, Odisha, Kerala, Pondicherry, Lakshadweep	Tripura, Chhattisgarh, Andaman and Nicobar Islands, Himachal Pradesh, Dadra and Nagar Haveli, Karnataka, Uttaranchal, Sikkim, Andhra Pradesh, Maharashtra, Madhya Pradesh, Gujarat, Daman and Diu, West Bengal	Jharkhand, Mizoram, Assam, Bihar, Rajasthan, Meghalaya, Punjab, Uttar Pradesh, Delhi, Jammu and Kashmir, Haryana, Goa, Manipur, Chandigarh, Nagaland, Arunachal Pradesh
MDM coverage in girls aged 6-10yr, %			
1999	36.1	2.8	0.0
2004	52.1	45.2	10.4
2011	48.5	51.6	40.2
Number of districts with >25% coverage	50	292	441
Age range of adult women in 2016 who could have been exposed to MDM in primary school, yr	18-30	18-25	18
Mean age at first birth of women in 2016, yr	21.1	20.2	20.7

[1]The criterion for categorization into each phase was having at least 25% of girls aged 6-10 years covered by the program by the end of the phase.
[2]Within each phase, states are listed in order of coverage, from highest to lowest.
Data sources: NSS-CES55 (1999), NSS-CES61 (2004), NSS-CES68 (2011)

Table 3. Association between district level coverage of India's Mid-Day Meal Program in previous years and district average maternal education, maternal height and child stunting prevalence in 2016

Outcome, β (SE)	**Predictor**
Education among women 15-49 years of age in 2016, yrs	MDM coverage among girls 6-10 years of age, %
0.035 (0.005) ***	1999, n=475
0.020 (0.003) ***	2004, n=548
0.009 (0.003) **	2011, n=574
Height among women 15-49 years of age in 2016, cm	MDM coverage among girls 6-10 years of age, %
0.002 (0.004)	1999, n=475
0.004 (0.002) *	2004, n=548
-0.003 (0.002)	2011, n=574
Stunting among children 0-5 years of age in 2016, %	MDM coverage among girls 6-10 years of age, %
-0.133 (0.020) ***	1999, n=475
-0.037 (0.011) ***	2004, n=548
-0.024 (0.011) *	2011, n=574

Each beta estimate refers to a separate regression of the association between historical MDM coverage and maternal and child outcomes in 2016, controlling for wealth.
MDM coverage refers to percentage of girls 6-10 years old who received the MDM in a district. Districts are administrative units nested within states. Number of districts in 1999, 2004, and 2011 was 475, 548, 574.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: National Family Health Survey Wave 4 (2016) for outcomes and National Sample Survey - Consumer Expenditure Survey (NSS-CES) rounds 55 (1999), 61 (2004) and 68 (2011) for MDM coverage.

Table 4. Difference-in-differences regressions for women in states that implemented the Midday Meal program early (phases 1 and 2) versus late (phase 3)[1,2]

	Outcomes in 2016			
	Women's education, yrs	Women's height, cm	Child HAZ, SDs	Child Stunting, %
Panel A: Difference in differences (DID) model (equation 2)				
2016 x Phase 1 and 2, *binary*	0.175***	0.181**	0.049**	-0.849+
	(0.05)	(0.06)	(0.02)	(0.51)
Year 2016, *binary* (ref 2006)	1.094***	-0.200***	0.226***	-5.277***
	(0.03)	(0.04)	(0.01)	(0.35)
Phase 1 and 2 states, *binary* (ref phase 3)	1.283***	0.413***	0.115***	-3.489***
	(0.04)	(0.05)	(0.02)	(0.47)
R-squared	0.025	0.002	0.041	0.016
Child age (*months*) and sex (*binary*)	No	No	Yes	Yes
N	311181	279553	275071	275071
Panel B: DID with a continuous treatment (equation 3)				
2016 x Phase 1 and 2 x MDM 2004 coverage, %	0.019***	0.004***	0.001***	-0.033***
	(0.00)	(0.00)	(0.00)	(0.01)
Year 2016, *binary* (ref 2006)	0.633***	-0.318***	0.183***	-3.958***
	(0.03)	(0.04)	(0.01)	(0.30)
Phase 1 and 2 states, *binary* (ref phase 3)	0.937***	0.603***	0.158***	-4.413***
	(0.03)	(0.04)	(0.01)	(0.33)
R-squared	0.036	0.005	0.042	0.018
Child age (*months*) and sex (*binary*)	No	No	Yes	Yes
N	273810	245680	241682	241682
Panel C: DID with a continuous treatment and full set of controls (equation 3)				
2016 x Phase 1 and 2 x MDM 2004 coverage, %	0.016***	0.003*	0.001*	-0.023**
	(0.00)	(0.00)	(0.00)	(0.01)
Year 2016, *binary* (ref 2006)	0.035	-0.520***	0.146***	-2.618***
	(0.05)	(0.06)	(0.02)	(0.40)
Phase 1 and 2 states, *binary* (ref phase 3)	0.444***	0.396***	0.100***	-2.746***
	(0.05)	(0.06)	(0.02)	(0.43)
R-squared	0.397	0.058	0.081	0.057
Child age (*months*) and sex (*binary*)	No	No	Yes	Yes
Controls[3]	Yes	Yes	Yes	Yes
Village-level clustering of std. errors	Yes	Yes	Yes	Yes
N	241358	236758	213820	213820

[1]Mid-day meal (MDM) 2004 coverage refers to percentage of girls 6-10 years old who received the MDM in 2004-05 in a district. Districts are administrative units nested within states.
[2]Phases refer to timing of program rollout (see Table 2)
[3]Controls include women's age, access to improved drinking water, open-defecation, clean cooking fuel, type of house (permanent, semi-permanent, impermanent), household ownership, type of floor, roof, and walls materials, number of durable household assets possessed (score of 1-10 for assets mattress, pressure cooker, chair, bed, table, fan, radio, sewing machine, phone and watch), and socio-economic group as scheduled caste or tribe.
Standard errors in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Sources: National Family Health Survey 3 (2006) and 4 (2016)

Table 5. Impact of coverage of India's Midday Meal program on women's education, women's height and child height in 2016 - accounting for the effects of unobserved state-level confounders

Equation 4	Outcomes in 2016							
	Women's education, yrs		Women's height, cm		Child HAZ, SDs		Child stunting, %	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2016 x [1]MDM 2004 coverage, %	0.020***	0.004***	0.015***	0.004**	0.002***	-0.000	-0.066***	-0.013
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
R-squared	0.392	0.419	0.060	0.109	0.081	0.090	0.057	0.065
Child age (*months*) and sex (*binary*)	No	No	No	No	Yes	Yes	Yes	Yes
Controls[2]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village-level clustering of std. errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State dummies	No	Yes	No	Yes	No	Yes	No	Yes
State x Year dummies	No	Yes	No	Yes	No	Yes	No	Yes
N	241358	241358	236758	236758	213820	213820	213820	213820

[1]Mid-day meal (MDM) 2004 coverage refers to percentage of girls 6-10 years old who received the MDM in 2004-05 in a district. Districts are administrative units nested within states.
[2]Controls include women's age, access to improved drinking water, open-defecation, clean cooking fuel, type of house (permanent, semi-permanent, impermanent), household ownership, type of floor, roof, and walls materials, number of durable household assets possessed (score of 1-10 for assets mattress, pressure cooker, chair, bed, table, fan, radio, sewing machine, phone and watch), and socio-economic group as scheduled caste or tribe.
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source National Family Health Survey Wave 3 (2006) and Wave 4 (2016)

Table 6. Impact of coverage of India's Midday Meal program on women's education, women's height and child height in 2016 - poor versus non-poor

Equation 5	Outcomes in 2016							
	Women's education, yrs		Women's height, cm		Child HAZ, SDs		Child stunting, %	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2016 x [1]MDM 2004 coverage x [2]Poor, %	0.004***	0.009***	0.015***	0.007***	0.002***	0.003***	-0.063***	-0.053***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
2016 x MDM 2004 coverage, %	0.017***	-0.001	0.007***	0.000	0.001***	-0.001**	-0.033***	0.016
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
2016 x poor	0.557***	0.379***	-0.411***	0.081	0.015	0.039	-1.409*	-2.124**
	(0.08)	(0.08)	(0.10)	(0.10)	(0.03)	(0.03)	(0.68)	(0.70)
2016	-0.620***	0.567*	-0.703***	0.630+	0.069***	0.075	0.137	1.697
	(0.07)	(0.25)	(0.08)	(0.37)	(0.02)	(0.10)	(0.55)	(2.22)
Poor	-2.088***	-1.975***	-0.777***	-0.808***	-0.249***	-0.235***	7.472***	6.912***
	(0.07)	(0.07)	(0.09)	(0.09)	(0.02)	(0.02)	(0.63)	(0.64)
R-squared	0.402	0.428	0.062	0.111	0.082	0.091	0.058	0.066
Child age (*months*) and sex (*binary*)	No	No	No	No	Yes	Yes	Yes	Yes
Controls[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village-level clustering of std. errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State dummies	No	Yes	No	Yes	No	Yes	No	Yes
State x Year dummies	No	Yes	No	Yes	No	Yes	No	Yes
N	241358	241358	236758	236758	213820	213820	213820	213820

[1]Mid-day meal (MDM) 2004 coverage refers to percentage of girls 6-10 years old who received the MDM in 2004-05 in a district. Districts are administrative units nested within states.
[2]Poor is defined as a household living in lowest two quintiles of the SES index.
[3]Controls include women's age, access to improved drinking water, open-defecation, clean cooking fuel, type of house (permanent, semi-permanent, impermanent), household ownership, type of floor, roof, and walls materials, number of durable household assets possessed (score of 1-10 for assets mattress, pressure cooker, chair, bed, table, fan, radio, sewing machine, phone and watch), and socio-economic group as scheduled caste or tribe.
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source National Family Health Survey Wave 3 (2006) and Wave 4 (2016)

Table 7. Robustness checks for impact pathways: Associations between stunting among children aged 0-5 years and maternal height and education in India 2016

	Child stunting, binary		HAZ, SD		Child stunting for poor households, binary	
Equation 6	*β*	*SE*	*β*	*SE*	*β*	*SE*
Mother's height, cm	-0.012***	(0.000)	0.043***	(0.001)	-0.013***	(0.000)
Mother's education, yr	-0.007***	(0.000)	0.022***	(0.001)	-0.007***	(0.001)
Mutually adjusted covariates						
Mother's age	Yes		Yes		Yes	
Child sex	Yes		Yes		Yes	
Child age	Yes		Yes		Yes	
Parity	Yes		Yes		Yes	
Household wealth	Yes		Yes		Yes	
Cluster (village) fixed effects	Included		Included		Included	
R-squared	0.049		0.077		0.049	
N	232036		232036		95557	

Source: NFHS4 data 2016.
*p<0.05, **p<0.01, ***p<0.001
Note: standard errors are corrected for clustering at the district level

Table 8. External validity for impact pathways: Impact of receiving midday meal during primary school on completed education and height among girls surveyed in 2005 and 2012

	Girls aged 12-17 years in 2012	
	Completed education, yrs	Height, cm
	β2 (SE)	β3 (SE)
Mid-day meal exposure, (0/1)		
Model 1: Covariate-adjusted state fixed effects	0.571 (0.05) ***	1.29 (0.25) ***
R-squared	0.48	0.19
Model 2: Nearest neighbour matching- ATET	0.607 (0.06) ***	0.665*
N	7096	7096

Mid-day meal exposure was detected in 2004-2005 when girls were aged 6-10 years and were attending primary school, assuming girls spend five years in primary school on average.
The nearest neighbor matching model included an exact match on age
Model 1 is fully adjusted for government school (1/0). Demographic variables include: age (years), household size (persons). Socioeconomic variables include: urban residence (1/0), monthly consumption expenditure per-capita (INR), household assets (number), farming household (1/0), agricultural labor household (1/0), non-agricultural labor household (1/0), highest education attained by adult males and females in household (years) and state of residence (1/0). Coefficients are reported in Appendix table A1.
Model 2 is matched on all covariates used in Model 1 but also bias adjusts for age, household size, expenditure, assets, and education. Exact matching on child age was used in model 2.
Only data from children that had valid anthropometric measurements were used in the final analysis for 2012.
*p<0.05, **p<0.01, ***p<0.001
Source: India Human Development Survey (IHDS) rounds 1 (2005) and 2 (2012)

Table 9. Total effect of midday meal exposure on next generation child stunting

	Estimating equation	Percentage point (pp) change in stunting	% explained out of total change in stunting between 2006 and 2016
Total observed change in stunting from all factors between 2006 (NFHS3) and 2016 (NFHS4)	48pp (2006) to 38pp (2016)	10.0	100.0
Method 1 Estimated observed change in stunting due to MDM from $\gamma 1$ and $\gamma 2$ from equation 5	(32% • 0.053) - (32% • 0.016)	1.2	12.0
Method 2 Estimated observed change in stunting due to MDM from mediation analysis	(32% • 0.020y/% • -1.549 pp/y) + (32% • 0.008cm/% • -1.922pp/cm)	1.5	15.0
Method 3 Estimated expected change in stunting due to MDM from $\psi 1$, $\psi 2$, $\psi 3$ and $\psi 4$	(0.607y • -0.006 pp/y) + (0.665cm • -0.013 pp/cm)	1.2	12.0

MDM, Midday Meal; NFHS, National Family Health Survey

Table 10. Effect of midday meal exposure at ages 11-15 years on attained height, education and child stunting

	Women's education, yrs	**Women's height, cm**	**Child HAZ, SDs**	**Child Stunting, %**
Panel A: Equation 3				
2016 x Phase 1 and 2 x MDM 2004 coverage[1], %	0.021***	0.007***	0.003***	-0.032*
	(0.00)	(0.00)	(0.00)	(0.01)
Year dummy	Yes	Yes	Yes	Yes
Phase 1 and 2	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Village clustering of standard errors	Yes	Yes	Yes	Yes
R-squared	0.396	0.058	0.082	0.057
N	241670	237070	214115	214115
Panel B: Equation 5				
2016 x MDM 2004 coverage x Poor[2], %	0.015***	0.010***	0.003***	-0.063**
	(0.00)	(0.00)	(0.00)	(0.02)
2016 x MDM 2004	-0.009***	0.000	-0.001	0.036^{+}
	(0.00)	(0.00)	(0.00)	(0.02)
Controls[3]	Yes	Yes	Yes	Yes
Village clustering of standard errors	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes
State x Year dummy	Yes	Yes	Yes	Yes
R-squared	0.110	0.090	0.065	0.428
N	237070	214115	214115	241670

[1]Mid-day meal (MDM) 2004 coverage refers to percentage of girls 11-15 years old who received the MDM in 2004-05 in a district. Districts are administrative units nested within states.
[2]Poor is defined as a household living in lowest two quintiles of the SES index.
[3]Controls include women's age, access to improved drinking water, open-defecation, clean cooking fuel, type of house (permanent, semi-permanent, impermanent), household ownership, type of floor, roof, and walls materials, number of durable household assets possessed (score of 1-10 for assets mattress, pressure cooker, chair, bed, table, fan, radio, sewing machine, phone and watch), and socio-economic group as scheduled caste or tribe and child age and sex.
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source National Family Health Survey Wave 3 (2006) and Wave 4 (2016)

Supplementary Table 1. Summary statistics of the NHFS3 and NFHS4 samples

	NFHS3 (2005) N=41793		NFHS4 (2016) n = 222458	
	Mean / proportion	*95% CI*	*Mean / proportion*	*95% CI*
Mother				
Mother’s age, yr	26.30	[26.23,26.37]	26.82	[26.79,26.85]
Mother's height, cm	151.65	[151.57,151.72]	151.69	[151.65,151.73]
Mother's education, yr	4.11	[4.05,4.16]	6.45	[6.42,6.48]
Child				
Stunting, (binary) (HAZ<-2)	0.48	[0.47,0.48]	0.38	[0.38,0.38]
Height-for-age z score	-1.82	[-1.84,-1.80]	-1.41	[-1.43,-1.40]
Male child, binary	0.52	[0.52,0.53]	0.52	[0.52,0.52]
Child age, months	29.82	[29.61,30.04]	29.88	[29.77,29.98]
Child birth order				
First born	0.30	[0.29,0.30]	0.38	[0.38,0.39]
Second born	0.28	[0.27,0.28]	0.32	[0.32,0.33]
Third born	0.17	[0.16,0.17]	0.15	[0.15,0.16]
≥ Fourth born	0.26	[0.25,0.27]	0.14	[0.14,0.14]
Household wealth score				
Quintile 1 (Poorest)	0.41	[0.41,0.42]	0.23	[0.23,0.23]
Quintile 2	0.28	[0.28,0.29]	0.22	[0.21,0.22]
Quintile 3	0.15	[0.15,0.15]	0.20	[0.20,0.20]
Quintile 4	0.09	[0.09,0.09]	0.19	[0.18,0.19]
Quintile 5 (Non-poor)	0.06	[0.06,0.07]	0.17	[0.16,0.17]
Household characteristics				
Improved drinking water, binary	0.86	[0.86,0.87]	0.90	[0.90,0.90]
No toilet facility, binary	0.64	[0.63,0.64]	0.46	[0.46,0.47]
Clean fuel for cooking, binary	0.17	[0.17,0.18]	0.34	[0.34,0.35]
Owns house, binary	0.90	[0.90,0.91]	0.80	[0.80,0.81]
Kachha house, binary	0.17	[0.16,0.17]	0.07	[0.07,0.07]
Semi-pucca house, binary	0.46	[0.46,0.47]	0.43	[0.43,0.43]
Pucca, binary	0.37	[0.36,0.38]	0.50	[0.49,0.50]
Floor				
Mud/clay/earth/sand/dung/planks/bamboo	0.57	[0.57,0.58]	0.44	[0.43,0.44]
Brick/stone/strips	0.05	[0.05,0.06]	0.06	[0.05,0.06]
Polished wood/tiles/cement/carpet/granite	0.37	[0.37,0.38]	0.51	[0.51,0.51]
Roof				
None/leaf/mud/grass/mat/bamboo/unburnt Bricks/timber/loosely packed stone	0.26	[0.25,0.26]	0.16	[0.16,0.16]
Polythene/metal/wood/asbestos sheets/roofing shingles	0.28	[0.27,0.28]	0.24	[0.24,0.24]
Concrete/tiles/slate/burnt brick	0.47	[0.46,0.47]	0.60	[0.60,0.60]
Wall				
None/palm/mud/grass/bamboo/stone/plywood/cardboard/unburrnt brick/raw wood	0.40	[0.39,0.40]	0.26	[0.26,0.26]
Shingles/asbestos sheets	0.60	[0.60,0.61]	0.74	[0.74,0.74]
Durable assets, 1-10	4.49	[4.45,4.52]	6.07	[6.06,6.08]
Social group				
Scheduled castes, binary	0.21	[0.20,0.21]	0.22	[0.22,0.22]
Scheduled tribe, binary	0.09	[0.09,0.10]	0.10	[0.10,0.10]

Supplementary Table 2. Summary statistics of samples used in mediation analyses in 548 districts

	Full sample n = 548	
	Mean / proportion	*95% CI*
Stunting, % (HAZ<-2)	36.3	35.5,37.2
Mid-day meal coverage among girls in 2004, %	31.9	29.6,34.1
Mother's height, cm	151.9	151.8,152.1
Mother's education, yr	6.7	6.5,6.9
Household wealth, 1-5	3.03	2.97,3.09

Source: NSSO CES data 2004 and NFHS4 data 2016.

Supplementary Table 3. Analysis for maternal education and height as mediators of the impact on MDM on stunting in their children

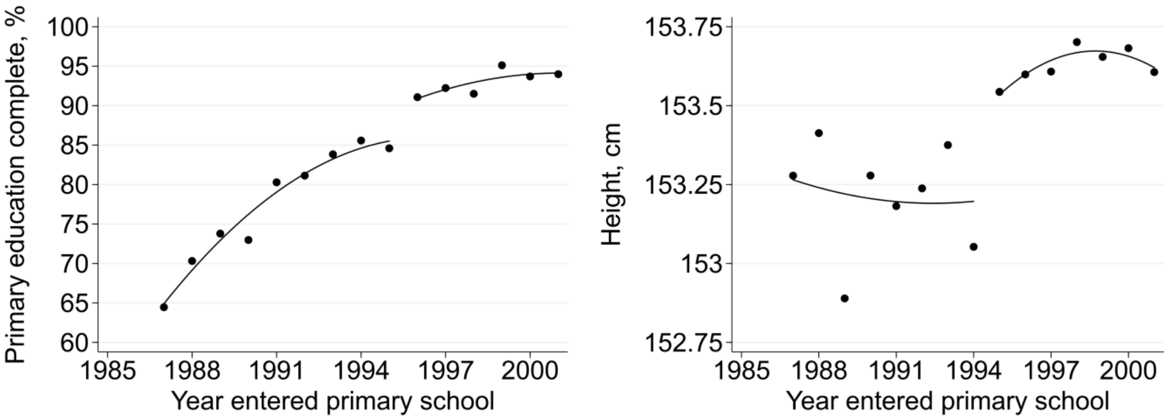
	Outcome= stunting prevalence, %			
	Path A1 - Direct effect of MDM on maternal height, cm	Path A2 - Direct effect of MDM on maternal education, yr	Path C - Direct effect on MDM on stunting, %	Paths B1, B2 and C'- Attenuated effect of MDM on stunting, %
Sub-sample of poor women (below median wealth quintile)				
MDM 2004 coverage, %	0.008*	0.020***	-0.052*	-0.005
	(0.00)	(0.00)	(0.02)	(0.02)
Maternal height, cm				-1.922***
				(0.25)
Maternal education, yr				-1.549***
				(0.28)
2016 wealth control	Yes	Yes	Yes	Yes
Pre-treatment controls	Yes	Yes	Yes	Yes
R-squared	0.411	0.670	0.372	0.476
N	474	474	474	474
Mediation tests				
ACME through maternal education				-0.031
ACME through maternal height				-0.015
Rho at which ACME through education is zero				-0.287
Rho at which ACME through height is zero				-0.341
P-value of Randomized Inference test for MDM	0.001	0.000	0.001	0.738

Medation tests were performed using the 'medeff' command and sensitivity analyses using 'medsens'. Average causal mediation effect=ACME. For Randomized Inference Tests the distribution of the test statistic was obtained under the null hypothesis that the program has no effect on stunting and use N=1000 re-randomizations. RI tests were conducted using the 'ritest' command in Stata developed by Hess (2017). Source: NSSO CES data 1999 and 2004 and NFHS4 data 2016.

Supplementary Table 4. Summary statistics of Indian Human Development Survey Samples

	MDM exposure in 2004 N = 3366		No MDM exposure in 2004 N = 3735	
	Mean	*95% CI*	*Mean*	*95% CI*
Outcomes in 2012				
Completed education, yr	7.63	7.56,7.71	6.72***	6.63,6.81
Height, yr	148.1	147.7,148.4	146.3**	145.9,146.6
Explanatory factors in 2012				
Government school, (0/1)	0.6	0.58,0.62	0.47**	0.45,0.49
Urban residence, (0/1)	0.2	0.18,0.21	0.4***	0.39,0.42
Farming household, (0/1)	1.08	1.03,1.13	0.76***	0.71,0.80
Agricultural labor household, (0/1)	0.56	0.53,0.60	0.36***	0.33,0.38
Labor in non-agriculture, (0/1)	0.64	0.60,0.67	0.51**	0.48,0.53
Age of child, yr	14.54	14.49,14.59	13.85***	13.79,13.91
Household size, persons	6.28	6.19,6.36	6.4*	6.31,6.49
Household expenditure per-person, INR	1564	1510,1618	1973***	1911,2034
Total household assets, number	13.44	13.25,13.62	15.84***	15.63,16.06
Highest education among females in household, yr	3.51	3.37,3.65	5.05***	4.88,5.22

*p<0.05, **p<0.01, ***p<0.001 for difference between MDM and non-MDM



Supplementary Figure 1. Trends in maternal education and height for women born before and after India's Mid-Day Meal Program was implemented in Tamil Nadu. Tamil Nadu is the first state where the MDM was implemented. Source: For primary education data were pooled using two rounds (66 and 68) of the National Sample Survey - Consumer Expenditure Survey (NSS-CES). For maternal height data were pooled from District Level Household Survey 4 (2013) and National Family Health Survey 4 (2016). Data sets were pooled to increase the sample sizes of the variables.