Parental Investments and Early Childhood Development: Short and Long Run Evidence from India

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Abstract

The overall impacts of early childhood programs depend on both the direct impacts on exposed cohorts, as well as the indirect impacts that arise due to intra-household reallocation of parental investments. To study these effects, I collected historical administrative data from the rollout of the Integrated Child Development Services program in India, the largest early childhood development program in the world. Children exposed to the program were significantly less likely to be malnourished, and more likely to be able to read and do math. Adults exposed to the program when young showed significant improvements along a range of health measures. They were also significantly more likely to be literate, employed, and earn a higher wage. However, I show that parents reallocated their investments towards children with greater program exposure, as evidenced by crowd-out of program impacts from exposed siblings. This crowd-out is particularly severe for girls with siblings who were exposed to greater program intensity. Taking into account the spillovers on siblings reduces the internal rate of return of the program by approximately 10%.

JEL: I15, O15, I18, I38, D15

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I Introduction

The question of how to build human capital with limited resources remains a key policy problem in developing countries. In India, for example, this problem is particularly salient given the higher rates of stunting and malnutrition in comparison to other developing nations.[1] The Indian government has responded in the form of direct provision of health and education services for children, a strategy also seen in other developing countries. However, little is known about the parental responses to such programs in developing countries. The effects that such programs have on exposed children and their siblings depend on the interaction between investments by the government and parents, which in turn depend on parental preferences and the technology for human capital formation. Parents could reallocate their investments within children over time, or across children. This in turn, could have important distributional impacts.

To understand the household economics of parental investment responses to investments by the government, one needs to introduce households to an exogenous source of variation. I use the rollout of the Integrated Child Development Services (ICDS) program in India, the largest early childhood development program in the world, for this purpose. The Indian government launched the ICDS program in 1975 to help address India's high rates of child malnutrition and has substantially expanded the program in the last decade.[2] The program provides pre-school education and primary healthcare services to children under 6 years of age. The decades-long expansion since 1975 and detailed administrative data from the ICDS program make it apt for a study of the direct and indirect impacts of early childhood interventions in developing countries.

I study these impacts by constructing a unique dataset merging historical administrative data on the ICDS program that I collected with a large number of household survey datasets. I employ a differences-in-differences strategy that exploits variation in the timing of program expansion across Indian districts. Children exposed to the program showed significant improvements on health and education. They were significantly less likely to be malnourished, or have very low weight-for-age, and were more likely to be able to read or do any math. I show that these effects are persistent - adults exposed to the

[1] For example, 38% of children under five years of age are stunted in India, a number larger than many countries with similar incomes (World Bank, 2015).

[2] The recent expansion came in large part following a Supreme Court order in December 2006 that called for a renewed expansion of the program.

program when young showed significant impacts along a range of health, education, and labor market outcomes. These health measures include objective measures of blood iron deficiency and blood glucose, as well as subjective measures of general health. Adults exposed to the program were also significantly more likely to be literate, have more years of schooling, be employed, and earn a higher wage. They were more likely to engage in healthy behaviors, reflected in lower alcohol consumption, smoking, and tobacco use. In general, women exposed to greater program intensity when young showed greater improvements in health and education than men.

Importantly, however, parents can respond to the investments made by the government in the form of intra-household as well as inter-temporal substitution of investments. I use a two period, two child model to illustrate the trade-offs between inequality averse parental preferences and the production technology for human capital that is a function of investments in children over time. Government programs that are complementary to parental investments raise the marginal utility of investing in the child with greater program exposure at earlier ages. Parents respond by increasing investments in children with greater program exposure. However, this crowds out investments in children who received less program exposure.

I show that parents reallocate their investments towards children with greater program exposure, as evidenced by crowd-out of program impacts from exposed siblings. This reallocation of investments leads to a worsening of health and education outcomes of children with siblings exposed to greater program intensity. This crowd-out is particularly severe for girls with siblings who were exposed to greater program intensity. To obtain a better understanding of the relative magnitude of the direct and indirect impacts, I conduct a cost-benefit analysis of the program. While taking into account only the direct impacts of the program yields an internal rate of return (IRR) of 8.1% - 8.3%, an anlysis that accounts for both the direct and indirect impacts yields an IRR of 7.3% - 7.5%, a 10% decrease.

I also show that parents respond in their investments within children, across time. Such intertemporal reallocation of parental investments towards earlier ages of child development can play an important role in explaining the impacts of the program. I present evidence for this using direct measures of investments in nutrition and education, as well as indirect measures such as a decrease in adult good consumption. Parents shift resources to earlier ages of child development by taking on more debt. This intertemporal reallocation is especially important given dynamic complementarities in health and education, whereby skills produced at one age raise the productivity of investment at subsequent ages. I present evidence for this using the interaction of program exposure with rainfall shocks, given the strong link between rainfall and human capital in India (Shah and Steinberg, 2017). In studying possible mechanisms of the program, I rule out an income channel by which parents increase employment in response to the program. In particular, mothers do not increase employment along extensive or intensive margins of employment. These zero impacts on employment are relatively precisely estimated.

This paper contributes to a growing literature on parental investments in children in developing countries. Two ideas are of importance here. First, there is a substantial literature that documents favoritism towards boys in developing countries. Behrman (1988), Barcellos et al. (2014), and Jayachandran and Pande (2017), for example, document differential allocation of resources by gender. I show that the differential gender impact of a large government program can play an important role in counteracting parents' biases in investments in children. Second, there is a growing empirical and theoretical literature that studies the interaction of investments by parents and government programs. Adhvaryu and Nyshadham (2014), for example, find that children with higher exposure to an iodine supplementation programme in Tanzania were breastfed for longer. Cunha et al. (2010), Cunha and Heckman (2007) and Almond and Currie (2011) develop theoretical models of skill development, stressing the key role played by parental investments.

This paper also builds on prior work on short-term impact evaluations of the ICDS program. Jain (2015), Chakravarty (2010), and Lokshin et. al (2005) show short-term impacts of the program on immunizations and stunting. I improve on these papers in several key ways. First, I do not use household survey data to determine ICDS coverage. Given large measurement error in determining when ICDS centers were opened in the household survey data, an analysis that exploits exposure to the program at particular ages is difficult[3]. To solve this problem, I collected historical administrative data on the program to determine program exposure at different ages. This allows me to present the

[3] In the India Human Development Survey, for example, respondents are asked the number of years that have elapsed since opening of the nearest ICDS center. A simple plot of the data reveals bunching at five year intervals.

first evidence of long-term impacts of the largest early childhood development program in the world.

I also contribute to several evaluations of early childhood development programs in developing countries and the U.S. Notably, the psychosocial stimulation experiment in Jamaica (Gertler et al, 2014) that was shown to have long-term effects on wages has received significant attention in the literature. Further evidence from Mexico (Parker and Vogl, 2018), Tanzania (Field et al, 2009), and Guatemala (Hoddinott et al, 2008) show that exposure to early childhood programs have long-term impacts[4]. In the U.S., three programs stand out - the Perry Preschool Program (Heckman et al, 2013), two early childhood randomized trials in North Carolina (Garcia et al, 2016), and the Head Start program (Carneiro and Ginja, 2014). These studies collectively show that early childhood interventions can have significant impacts on adult outcomes including education, employment, earnings, marriage, health, participation in healthy behaviors, and reduced participation in crime. The ICDS program I evaluate is orders of magnitude larger than other early childhood development programs in the world: while Head Start has served on average 0.55 million children per year and the Jamaica experiment had 129 participants, the ICDS served 40 million children in 2010 alone, and has been operating for more than 40 years.

The remainder of this paper is organized as follows. Section II describes the program in greater detail. Section III describes the datasets used and presents various summary statistics, trends, and heat maps. Section IV discusses the empirical strategy employed and Section V presents the results from these specifications for cohorts exposed to the program. Section VI presents a simple model to illustrate the trade-offs between parental preferences and the technology of skill formation. Section VII considers several possible mechanisms by which I observe impacts for exposed cohorts. Section VIII discusses the evidence on intra-household re-allocation of parental investments. Section IX describes a cost-benefit analysis of the program, and Section X concludes.

II The Program

The ICDS was launched in 1975 by the Indian government to provide pre-school education and primary healthcare services to children under 6 years of age. There are several health components under the scheme, including immunizations, supplementary nutri-

[4] Currie and Vogl (2013) provide an excellent summary of key interventions in developing countries.

tion, health checkups, referral services and provision of health information. ICDS centers also provide pre-natal services and supplementary nutrition to pregnant mothers. While launched in 1975 primarily with funding from UNICEF, the Indian government has been expanding the program over the last 40 years. Today, the program is large – by 2010, the program reached about 25% of all children in India under the age of 6 (39.7 million children), and during the 2018-19 fiscal year alone, the Indian government is expected to spend Rs. 230 billion (US $3.2 billion) on the program.

ICDS centers are also known as courtyard play centers, given the physical infrastructure of the centers. Centers typically consist of a room for indoor activities, and open space for outdoor activities. ICDS centers are typically run for 3.5 hours a day, after which the ICDS worker conducts two or three home visits for about an hour. Guidelines on typical daily tasks and the corresponding time allocation is given in Table 1.

[Table 1 about here.]

ICDS centers are typically open from morning to the early afternoon, although there is significant variation in the hours of operation across India. In addition to these daily tasks, ICDS workers also conduct health check-ups, immunizations and height and weight growth monitoring on a monthly basis.

ICDS centers were built based on population guidelines, which have changed over the years.[5] Prior to 2009, population guidelines stipulated that there should be one ICDS center for every 1,500 people. Specifically, in an area with population of 1,500 or less, one center should be built. For an area with population of 1,500 to 3,000, two centers should be built, and so on. In 2008, this rule was changed such that for 2009 and later, there should be one ICDS center for every 800 people. The change in rule was motivated in large part by the Supreme Court ruling of 2006 that called for an expansion of the program. After describing the datasets used in this study, including the administrative data on the program in Section III, I present several plots that describe the expansion of the program over time and across India.

[5] Unfortunately, these guidelines could not be used for identification, given large heterogeneity across India in the population figures used for funding requests, and the time taken for construction of the centers.

III Data

[Table 2 about here.]

To study the various impacts from the program, I put together a large number of datasets as described in Table 2. All datasets are merged at the district sub-division level - by district sub-division, I refer to the distinction between rural and urban areas of a district. This is the finest geographic level at which the datasets, including the administrative ICDS data, are identified. The NFHS, IHDS, NSS, and ASER datasets contain individual-level data. For adults, I exploit data on location of birth to ensure that individuals are assigned the appropriate level of program exposure according to their location and time of birth. Unfortunately, this data is not available for all children, in particular when using the NSS and ASER datasets. Given the low rates of migration across district sub-divisions by children, however, I include all children in the analysis.

The first dataset I use is an administrative dataset that contains historical data on all ICDS centers. This data was obtained from the Ministry of Women and Child Development, India. The rich dataset contains details on the location of the centers, the year of opening, and the types of services that each center provides. The dataset is large and has information on nearly a million centers across India.

The National Family Health Survey (NFHS) is also known as the Demographic Health Survey (DHS) for India. I utilize three rounds of the survey, in particular rounds 1 (1992-1993), 2 (1998-1999), and 4 (2015-2016). Identifiers below the state level were not released for round 3 of the data due to HIV testing, and hence this round of data was not used. The NFHS is the key source of data for education, health, and healthy behaviors of individuals.

The third dataset I use is the India Human Development Survey (IHDS), conducted by the University of Maryland. Although this is a panel dataset with two rounds of data, I only use one round of data so as to avoid inclusion of the same individual more than once in the analysis. I chose to use round 2 of the data so as to include a greater number of exposed cohorts of adults in the analysis. The IHDS dataset is nationally representative, with detailed data on approximately 200,000 individuals households across India. I obtain information on wages and debt from the IHDS, and also obtain additional health measures to supplement the NFHS data.

The National Sample Survey (NSS) is the largest nationally representative household survey in India. The employment schedule of the survey details daily employment and hours of work for all working household members in a given week. I use the NSS employment rounds 55 (1999-2000), 60 (2004), 61 (2004-2005), 62 (2005-2006), 64 (2007-2008), 66 (2009-2010), and 68 (2011-2012) to study parents' employment and child labor. The education expenditure schedule of the survey details expenses on education by parents. I use rounds 64 (2007-2008) and 71 (2014) of the survey to study education expenditure.

The Annual Status of Education Report (ASER) is the largest citizen-led survey in India and is facilitated by the Pratham NGO network. This dataset contains reading and math test score data of children in rural areas across India. The dataset is large, with approximately five million observations across the years 2006-2014, and includes both in and out of school children. Each child is asked four questions each in math and reading in their native language. The four math questions are whether the child can recognize numbers 1-9, recognize numbers 10-99, subtract, and divide. The scores are recorded as 1 if the child correctly answers the question, and 0 otherwise. The four reading questions are whether the child can recognize letters, recognize words, read a paragraph, and read a story. I calculate math and reading scores by summing the scores of the four math and reading questions, respectively.

In addition to the survey datasets described above, I use two additional datasets for the analysis. Given the importance of population in determining the number of centers one is exposed to, I use population data from the Census of India. The Census of India is conducted every 10 years, and population figures for non-census years are calculated at the district sub-division level by interpolation. I also obtain annual rainfall data from the University of Delaware. The dataset covers all of India between 1900 - 2014. The data is gridded by longitude and latitude lines, so to match these to districts, I use the closest point on the grid to the center of the district, and assign that level of rainfall to the district for each year.

III.A Summary Statistics

[Table 3 about here.]

Table 3 presents summary statistics for several key variables of interest. The NFHS data contains several key variables on education, health, and healthy behaviors. As an important indicator of early childhood health, I use the under-five mortality rate. The mean of 0.08 indicates that 8 out of every 100 children born in India die before age five. For adults, I use two related measures of health, namely weight and blood glucose levels. While a blood glucose level of 70 - 140 mg/dL is considered normal, individuals with blood glucose less than 70 mg/dL are considered hypoglycemic and individuals with blood glucose greater than 140 mg/dL are considered hyperglycemic or diabetic. I consider two common "healthy behaviors" measured in the NFHS - the absence of smoking and drinking alcohol. We see that 21% of individuals in the sample smoke or use tobacco, while 11% report drinking alcohol.

Although the smallest dataset as seen from the number of observations, the IHDS data contains rich data on wages, loans, and other indicators of health. Individuals earned on average, an hourly wage of 25 rupees (2012 prices), approximately USD 50 cents. Furthermore, 57% of individuals had taken out at least one loan in the past five years. 14% of individuals suffered from some type of short-term illness including fever, cough and diarrhea in the last 30 days.

The ASER dataset is large, with approximately five million observations on reading and math test scores. On average, 90% of children can read and do some basic math. The NSS data is an excellent source of employment data. We see that 2% of children aged 7-13 are engaged in some form of child labor. Looking next at parents of children aged 0-6, 97% of father are employed, while only 31% of mothers are employed. Mothers on average worked only 1.7 days per week - conditional on being employed, however, they worked an average of 5.5 days per week.

I next present several key summary statistics based on the ICDS administrative data, which has detailed information on 964,165 ICDS centers. The next two sections discuss the expansion of ICDS centers over time, as well as the expansion over time and space.

III.B Rollout of the ICDS Program

Figure 1 plots the expansion of the ICDS program in India over time. While the number of centers has been expanding steadily over time, it has kept up with population growth. Specifically, the number of centers per capita has also been climbing steadily over time. We see that there was approximately one center for every 1,500 people around 1995, 20 years after the start of the program. Given that the target population rule had been achieved, program intensity stayed close to this level until 2006, when the Supreme Court called for a renewed expansion of the program. The new population guidelines of one center for every 800 people were introduced in 2008, after which we see a significant expansion of the program.

Figure 2 presents a number of heat maps showing variation in program intensity over geographic space and time. The maps illustrate program intensity 10, 20, 30, and 40 years since 1975, the start of program implementation. The heat maps confirm that there is substantial variation in program intensity across India over time.

[Figure 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

IV Empirical Strategy

To exploit the variation in program intensity across geographic space and time, I use a differences-in-differences strategy. This strategy exploits differences across district sub-divisions in program intensity along with differences across cohorts induced by timing of program arrival in district sub-divisions. In particular, for individual i in district sub-division j of state s and birth year k, I run the following differences-in-differences specification:

$$Y_{ijk} = \alpha + \gamma_j + \lambda_{ks} + \beta P_{jk} + X_{ijk}\delta + \epsilon_{ijk} \tag{1}$$

where Y_{ijk} is the outcome variable of interest, γ_j are district sub-division fixed effects, λ_{ks} are cohort x state fixed effects, P_{jk} refers to the intensity of the program (number of centers per 1,000 children) in the district sub-division of birth at the time of birth, and X_{ijk} are controls including gender, birth order, gender x birth order interaction, a quadratic population polynomial, caste, religion, and mother's education. Although the policy variable based on the population guidelines is the number of centers per capita, I scale this policy variable to number of centers per 1,000 children to be consistent with the literature and for ease of interpretation. β is the coefficient of interest. Note that by including cohort x state fixed effects, I only compare across district sub-divisions individuals born in the same year and living in the same state. The cohort x state fixed effects effectively control for any state-year level characteristics that might have affected program placement.

To account for the fact that individuals are treated by the program over 8 years from age -1 (pre-natal care) to 6, P_{jk} is constructed as the average program intensity over these years. $\widetilde{P_{jk}}$ refers to the program intensity in any given year. In cases where the individual is aged a where $a < 6$, $k + a$ is used as the upper bound in the sum above, and the average is taken over the corresponding number of years.

$$P_{jk} = \begin{cases} \frac{\sum_{y=k-1}^{k+6} \widetilde{P_{jk}}}{8} \text{ if } a \geq 6 \\ \frac{\sum_{y=k-1}^{k+a} \widetilde{P_{jk}}}{a+1} \text{ if } a < 6 \end{cases}$$

A key assumption for the differences-in-differences strategy is that of parallel trends. This assumption states that absent the program, outcome variables of interest in treatment and control district sub-divisions should have identical trends. While one cannot directly test this counter-factual, I present results from the following placebo test by age of impact to show that this assumption likely holds (see Appendix B):

$$Y_{ijk} = \alpha + \gamma_j + \lambda_{ks} + \sum_{y=k-m}^{k+q} \beta_y \Delta P_{jy} + \mu_k P_{jk} + X_{ijk}\delta + \epsilon_{ijk} \tag{2}$$

where I include m leads and q lags of year-on-year *changes* in program intensity, while controlling for the level of program intensity in the individual's birth year k.

The idea behind this placebo test is the following: leads and lags of program intensity should not have an impact on the outcome variables of interest outside of the age range over which individuals should be affected by the program, i.e. outside of the age range -1 to 6. This helps to rule out three major types of concerns: (1) systematic placement of centers in district sub-divisions that were getting better (or worse) over time, (2) anticipation effects from knowing that program intensity would increase in the district sub-division in the near future, and (3) confounding programs that might have been introduced in the same district sub-divisions and at the same time as the ICDS.

To illustrate how this placebo test addresses concerns of type (1) outlined above, consider the scenario in which the program has zero impact, but centers are systematically placed in areas where child outcomes are improving over time. If centers are systematically placed, one would worry that the regressions would simply pick up the trend, and not the impact of the program. If systematic program placement was indeed driving the results, however, we should see significant coefficients for ages 7 to 10. Plots that only exhibit significant impacts in the age range -1 to 6 thus help alleviate this concern.

To illustrate how the test addresses concerns of type (2), consider the scenario in which the program actually has zero impact, but parents anticipate that program intensity is going to increase in their district sub-division in the near future. To be specific, take the case of parents considering having a child five years in the future (child is aged -5). Anticipating the increase in intensity, parents might choose to set aside fewer funds to invest in child health and education, given that these services will be provided by the ICDS in future. This represents an "income effect" that might have an effect on outcomes of interest after the child is born. If anticipation effects were indeed driving the results, we should observe significant coefficients for ages -5 to -2. Once again, plots that only exhibit significant impacts in the age range -1 to 6 help alleviate this concern.

With regard to concerns of type (3), consider the specific case of the Mid-day Meal Scheme, a program introduced in 2004 by the Indian government to provide free lunches to primary school children.[6] Given that the nutrition provision component of the program overlaps with the ICDS, a potential concern might be that one would pick up the impact of the Mid-day Meal Scheme, and not the ICDS. However, the scheme only affects primary school children, i.e. those aged 6 and above. As such, plots that only exhibit significant impacts in the age range -1 to 6 would not pick up the impact of the Mid-day Meal Scheme. I present additional robustness checks for the Mid-day Meal program in Appendix C.

V Program Impacts for Exposed Cohorts

V.A Short-run Impacts on Children

In this section, I present the short-run impacts of the program on children. I begin by presenting the health impacts of the program in Panel A of Table 4.

[6] Today, the program is covered by the National Food Security Act of 2013.

[Table 4 about here.]

Columns (1) and (2) present results on weight and height, respectively. These variables have been standardized using the mean and standard deviation of individuals in district sub-divisions without the program. Columns (3) and (4) present results on malnutrition and stunting, respectively. An individual is defined as malnourished (stunted) if her weight-for-age (height-for-age) z-score was more than two standard deviations below zero, in accordance with tables developed by the World Health Organization (2007). We see that children who were exposed to an additional ICDS center per 1,000 children in their district sub-division when aged -1 to 6 were 0.013 standard deviations heavier in their youth. Furthermore, they were 4.5 percentage points less likely to be malnourished, on a base of 30.6%. This represents a large, 15% decrease. However, there were no significant impacts on height and stunting.

Panel B of Table 4 presents results on test scores of children. Columns (1) and (2) present results on reading and math scores, respectively. These scores have been standardized using the mean and standard deviation of individuals in district sub-divisions without the program. Columns (3) and (4) present results on the ability of children to read and do any math, respectively. We see that while the program did not affect test scores overall, individuals who were exposed to an additional ICDS center per 1,000 children in their district sub-division when aged -1 to 6 were 0.3 percentage points more likely to be able to read and do math, on a base of 90.6%.

Panel C of Table 4 presents results for program impacts on child labor. Children who were exposed to an additional ICDS center per 1,000 children in their district sub-division when aged -1 to 6 were 0.2 percentage points less likely to engage in child labor. On a base of 1.9%, this represents a 9% decrease in child labor.

[Figure 4 about here.]

Figure 4 summarizes impacts of the program for children. All estimates have been standardized using the mean and standard deviation on individuals with no ICDS program exposure. I also display the 95% confidence interval bars corresponding to each point estimate. Overall, we see that the program had significant impacts on malnutrition and the ability of children do read and do math. While the estimates for malnutrition and child labor display relatively large standard error bars, the other estimates are relatively precisely estimated. In particular, the estimates for education are very tightly estimated, given the large sample size of more than five million children.

V.B Long-run Impacts on Adults

In this section, I present the long-term impacts of the program on adults who were exposed to the program when young. I begin by presenting the health impacts of the program in Table 5:

[Table 5 about here.]

Panel A presents outcomes from biometric data on blood hemoglobin and glucose levels. A low blood hemoglobin level, or anemia, is an important indicator of iron deficiency. Similarly, hypoglycemia, or a low blood glucose level, is an important indicator of under-nutrition. Panel B presents outcomes from self-reported data on illnesses and general health. Difficulties with activities of daily living (ADL) include difficulties with the ability to speak, hear, or walk normally, and thus reflect long-term health problems. Short term illnesses include fever, cough, or diarrhea in the last 30 days. A sub-group of female IHDS respondents were also asked to state their general level of health on a scale from 1 - 5. Individuals responding with a value of 1 were coded as being in very poor health. Panel C presents two measures of "healthy behaviors" as commonly defined in the literature. In particular, I focus on smoking and tobacco use, as well as consumption of alcohol.

Column (1) of panel A shows that individuals who were exposed to an additional ICDS center per 1,000 children in their district sub-division when aged -1 to 6 had 0.009% higher blood hemoglobin levels as adults. These results are particularly strong at the lower tail of the distribution - column (2) shows that such individuals were 0.2 percentage points less likely to be anemic. Column (3) shows that individuals who were exposed to an additional ICDS center per 1,000 children in their district sub-division when aged -1 to 6 had 0.3% higher blood glucose levels as adults. Furthermore, they were 0.007 percentage points less likely to be hypoglycemic.

While column (1) of panel B shows that individuals exposed to greater program intensity were not less likely to experience difficulties with ADL as adults, column (2) shows that these individuals were 0.3 percentage points less likely to suffer from short-term illness. Furthermore, while such individuals were not more likely to report a higher score of general health, they were 0.005 percentage points less likely to report being in very poor health. Taken together, the results on biometric and self-reported measures of adult health show that the ICDS program had significant long-term impacts on adult health.

Column (1) of panel C shows that individuals exposed to an additional ICDS center per 1,000 children in their district sub-division when aged -1 to 6 were 0.5 percentage points less likely to smoke or use tobacco as adults, on a base of 27.3%. Furthermore, column (2) shows that such individuals were 0.3 percentage points less likely to consume alcohol, on a smaller base of 13.8%. These results show that the ICDS program had significant impacts on long-term healthy behaviors of adults.

[Table 6 about here.]

Columns (1) - (2) and columns (3) - (4) of table 6 presents long-term program impacts on adult education and labor market outcomes, respectively. Column (1) highlights that individuals exposed to an additional ICDS center per 1,000 children in their district sub-division when aged -1 to 6 were 1.2 percentage points more likely to be literate. Furthermore, we see in column (2) that such individuals also had 0.06 more years of schooling, on a base of 5.2 years. Column (3) shows that individuals exposed to an additional ICDS center were 0.2 percentage points less likely to be unemployed as adults. They also earned 1.2% more in hourly wages. These results highlight the long-term education and labor market impacts of the program.

[Figure 5 about here.]

Figure 5 summarizes the health, education, and labor market impacts of the ICDS program for adults. All estimates have been standardized using the mean and standard deviation on individuals with no ICDS program exposure. I also display the 95% confidence interval bars corresponding to each point estimate. Overall, we see that the program had significant impacts on health, healthy behaviors, education, and labor market outcomes. While the impacts range from 0.006 - 0.016 standard deviation units for health and labor market outcomes, the impacts on education are slightly larger, in particular 0.024 standard deviation units for literacy.

V.C Gender Heterogeneity in Program Impacts

[Figure 6 about here.]

[Figure 7 about here.]

Given the large literature on parents' bias towards boys in developing countries, the heterogeneous impacts of the ICDS program by gender are particularly important. Figures 6 and 7 presents results for heterogeneity of program impacts by gender for short-run and long-run outcomes, respectively. In particular, the point estimates represent estimates of the coefficient on an interaction term between female and program intensity. Thus positive point estimates capture additional impacts of the program for females, while negative point estimates represent additional impacts of the program for males. All estimates have been standardized using the mean and standard deviation for individuals with no ICDS program exposure. I also display the 95% confidence interval bars corresponding to each point estimate.

We see that in general, girls and women exposed to greater program intensity when young had greater program impacts than boys and men, respectively, across health, education and labor market impacts. Notably for children, we see that the overall program impacts mask important heterogeneity for girls. While estimates for height, reading scores and math scores were not statistically significant for all children, the interaction terms exhibit significant differential impacts for girls. These estimates are also large in magnitude - for adults, in particular, these effect sizes range from 0.009 - 0.037 standard deviation units. Men, however, had greater program impacts along healthy behaviors of lower alcohol consumption, smoking, and tobacco use.

VI A Simple Two Period, Two Child Model of Parental Investments

Before presenting empirical results on intertemporal and intra-household reallocation of parental investments in response to the ICDS program, I build a simple two period, two child model of parental investments to illustrate the trade-offs between preferences and the production technology for human capital. I note, however, that this is one of several possible models that are consistent with the data.

VI.A Preferences and Production Technology

This section builds on the parental investments framework introduced by Almond and Currie (2011). Within-family investment decisions depend on the tension between parental preferences and the production technology for human capital. To capture parental preferences with inequality aversion among children, I use a Cobb-Douglas function for parental preferences and assume that parents only care about the human capital of their two children. $h_a \geq 0$ and $h_b \geq 0$ refer to human capital at the completion of childhood for child a

and b, respectively:

$$U_P = U(h_a, h_b) = h_a^{\beta} h_b^{1-\beta}$$

As suggested by Cunha and Heckman (2007), I use a constant elasticity of substitution (CES) function that allows one to characterize the production technology for early childhood development in a flexible manner:

$$h = A[\gamma I_1^{\phi} + (1-\gamma) I_2^{\phi}]^{\frac{1}{\phi}}$$

where $I_1 \geq 0$ and $I_2 \geq 0$ refer to investments by parents in childhood development periods 1 and 2, respectively. $\phi > 0$ implies that substitution of parental investments between period 1 and period 2 is relatively easy, while $\phi < 0$ implies that substitution is relatively difficult. I consider the period of potential exposure to the ICDS program as period 1 (ages -1 to 6), and a later period of childhood (ages 7 to 13) as period 2.

Parents can borrow $B \geq 0$ so as to move resources from period 2 to period 1. I assume that income in each period is exogenously determined, and is given by $\bar{y}_1 > 0$ and $\bar{y}_2 > 0$ in periods 1 and 2, respectively. Then the household's budget constraint in each period is given by:

$$\text{Period 1: } I_{1a} + I_{1b} \leq \bar{y}_1 + B$$
$$\text{Period 2: } I_{2a} + I_{2b} \leq \bar{y}_2 - \frac{B}{\delta}$$

where $\delta = \frac{1}{1+r}$ and $r > 0$ is the interest rate between periods 1 and 2.

I consider the effect of exogenous positive shocks $\mu_g > 0$ to investments in the first period of childhood - these shocks capture exposure to the ICDS program. In many ways, investments by parents and the ICDS program are complements. For example, ICDS workers perform door-to-door visits and stress the importance of child nutrition to parents, urging them to feed their children adequately, while also doing so in ICDS centers. Furthermore, ICDS workers often deliver pre-school services to children in small groups tailored to their level of language development, motor skills, and cognitive development (Ministry of Women and Child Development, 2017). This allows ICDS centers to build upon pre-school investments made by parents in a complementary manner.

Hence I choose to model investments by parents and the ICDS program as complements - the ICDS shock μ_g enters multiplicatively with period 1 parental investments I_1 in period 1. I also allow first period investments I_1 to respond to μ_g. Thus, the technology of human capital formation for child a and b are as follows:

$$h_a = A[\gamma(I_{1a} * \mu_g)^{\phi} + (1-\gamma)I_{2a}^{\phi}]^{\frac{1}{\phi}}$$
$$h_b = B[\gamma I_{1b}^{\phi} + (1-\gamma)I_{2b}^{\phi}]^{\frac{1}{\phi}}$$

where A and B represent the factor productivities of child a and b, respectively. Without loss of generality, I assume that child a receives the exogenous ICDS exposure shock μ_g to period 1 investments, while child b does not experience the shock.

VI.B Theoretical Predictions

For $\phi > 0$, we have the following theoretical predictions (see Appendix for proofs):

1. Intertemporal Reallocation. Parents will increase period 1 investments and decrease period 2 investments as their child is exposed to an increase in ICDS program intensity: $\frac{\partial I_{1a}}{\partial \mu_g} > 0$ and $\frac{\partial I_{2a}}{\partial \mu_g} < 0$. This result is driven by the fact that period 1 investments and ICDS investments are complements, and substitution of parental investments between period 1 and period 2 is relatively easy. As a result, it would be optimal for parents to increase period 1 investments as their child receives is exposed to an increase in ICDS program intensity, by substituting period 2 investments.

2. Intra-household Reallocation. Parents will decrease period 1 and period 2 investments in the sibling of the child that is exposed to an increase in ICDS program intensity: $\frac{\partial I_{1b}}{\partial \mu_g} < 0$ and $\frac{\partial I_{2b}}{\partial \mu_g} < 0$. On the one hand, parents are inequality averse and derive utility from jointly maximizing their children's human capital. However, the complementarity between ICDS investments and period 1 investments raises the marginal utility of investing in the child that is exposed to an increase in ICDS program intensity, at the expense of their other child. This leads to parents investing less in periods 1 and 2 in the sibling of the child that is exposed to an increase in ICDS program intensity.

3. Borrowing. Parents will increase borrowing in response to an increase in ICDS program intensity: $\frac{\partial B}{\partial \mu_g} > 0$. Parents borrow to cover the difference between period 1 expenses (investments) and income. However, parents invest more in the child that is exposed to an increase in ICDS program intensity, and less in their other child. Thus the overall impact on period 1 expenditure is not immediately clear. The model shows, however, that since parents decrease investments in both children in period 2, this must imply that parents borrow more in response to greater ICDS exposure, so as to shift resources to period 1.

VII Mechanisms

While direct investments by the ICDS program are responsible for many of the health, education, and labor market impacts observed, there may be other important mechanisms by which individuals benefit from the program. In this section, I rule in and rule out several such mechanisms. I start first, by showing that the program had no significant impacts on parents' employment and wages. This rules out an income channel by which the centers allow parents to work more, thereby increasing household income. Furthermore, this provides justification for the assumption of exogenously determined income $\bar{y}$ in section VI. I then show that investments by parents play an important role in child development. I present evidence that suggests parents reallocate their investments in children so as to invest earlier in them. I then show that this intertemporal reallocation is important due to dynamic complementarities in early childhood development at early ages.

VII.A Program Impact on Parental Employment & Wages

[Table 7 about here.]

Table 7 presents program impacts on parental employment and wages. Panel A focuses on children aged 0-6, given that children older than 6 are no longer eligible to avail services from the ICDS program. Columns (1) - (3) and (4) - (6) present outcomes for mothers and fathers, respectively. For each parent, I consider the extensive margin of employment, intensive margin (days worked), and the daily wage. Overall, I find no significant impacts of the program on parental employment and wages. This result may not be too surprising, given that ICDS centers are typically only open for about three hours a day, as shown in Table 1. As a result, parents may not be able to respond to the presence of the program in a meaningul way along dimensions of employment and wages. However, one may argue that it may be difficult for parents to drop off very young babies at the center so as to work longer hours. I investigate this by studying the program impact on employment and wages of parents of children aged 3-6 in panel B. Again, I find no significant impacts of the program on parental employment and wages.

[Figure 8 about here.]

Figure 8 summarizes the results on parental employment and wages. Notably, these estimates are relatively precisely estimated, in particular for children aged 0-6, where the sample sizes are larger. This shows that one can rule out a mechanism by which the ICDS program enables parents to work and earn more, thereby leading to an income effect that affects child outcomes.

VII.B Intertemporal Reallocation of Parental Investments

There are several ways in which one can measure parental investments. These can broadly be categorized into direct and indirect measures of investments. Direct measures of parental investments can take the form of monetary investments, such as food, education, and tuition on children, or non-monetary time investments, such as time spent with teachers. Deaton and Subramanian (1991) stress that a household's budget constraint can be exploited to study expenditures on one category of goods based on expenditures on other categories of goods, an idea that dates back to Rothbarth (1943). In particular, the consumption of "adult goods" such as alcohol and tobacco should decrease as investments in children increase.

[Table 8 about here.]

Panel A of table 12 presents results on adult good consumption, the indirect measure of parental investments, and debt. Columns (1) and (2) consider consumption and borrowing by parents when their children are aged 0-6. Column (1) presents results on per capita consumption of adult goods. Although the coefficient is not statistically significant, its direction indicates that parents reduce consumption of adult goods when their child aged 0-6 is exposed to greater ICDS program intensity. This in turn is indicative of greater investments in the child. Column (2) presents results on borrowing by parents of young children aged 0-6 in the past five years. Parents in district sub-divisions with an additional ICDS center per 1,000 children are 1.8 percentage points more likely to have taken out a loan in the past five years, on a base of 52.1%.

Columns (3) and (4) study consumption and borrowing by parents when their children are aged 7-13. Column (3) shows that parents in district sub-divisions with an additional ICDS center per 1,000 children increase consumption of adult goods by 3.2%. This result, statistically significant at the 5% level, suggests that parents decrease their investments in children aged 7-13 when exposed to greater ICDS program intensity. Furthermore, column (4) shows that parents decrease borrowing of such children aged 7-13. The magnitude of the estimate is not very different from that obtained in column (2). It is thus possible that the decrease in loans taken out when children were older is a reflection of parents paying off the increase in debt taken out when their children were younger. These results are in line with theoretical predictions (1) and (3) outlined in Section VI.B.

Panel B of table 12 presents results using direct measures of parental investments. Column (1) presents results on consumption of a list of nutritious food and drink by the child when aged 0-6. Children in district sub-divisions with an additional ICDS center per 1,000 children increased their consumption of nutritious food and drink by 0.2 percentage points, on a base of 83.3%. Note, however, that since the survey question did not explicitly ask “did you feed your child nutritious food and drink”, but rather “did your child consume nutritious food and drink”, this result could also capture direct feeding by ICDS centers and should hence be treated with caution.

Columns (2) - (3) capture monetary investments, while column (4) captures non-monetary time investments when children are aged 7-13. Column (2) shows that children in district sub-divisions with an additional ICDS center per 1,000 children were 0.3 percentage points less likely to receive any tuition, on a base of 15.8%, i.e. a 2% decrease. This result is statistically significant at the 5% level. Column (3) shows that parents also spend less overall on educational expenses when children are exposed to greater ICDS program intensity, although this result is not statistically significant. Column (4) also shows that parents are less likely to spend time participating in parent-teacher assocation meetings when their children are exposed to greater ICDS program intensity.

[Figure 9 about here.]

[Figure 10 about here.]

Figure 9 summarizes the results on intertemporal reallocation of parental investments. The results on direct measures of investments, when combined with the indirect measure of adult good consumption and borrowing, show that parents respond to the ICDS program by intertemporally reallocating parental investments. Figure 10 shows that there is little, if any, heterogeneity by gender in intertemporal reallocation of parental investments.

VII.C Dynamic Complementarities

The intertemporal reallocation of parental investments described above would not be important to understand the mechanisms behind the impacts of the program if investments in children at all ages were equally important. However, Cunha and Heckman (2007) note the importance of "sensitive" or "critical" periods for skill formation, where certain ages are more or alone effective for production of skills, respectively. They also stress the role of "dynamic complementarities", where skills produced at one age raise the productivity of investment at subsequent ages. This implies that levels of skill investments at different ages bolster each other. A large literature and the ICDS program stress the first 1,000 days of life as crucial for the development of skills. Empirical evidence of dynamic complementarities, however, remains limited.

Several recent papers have exploited a "shock-shock" methodology to investigate dynamic complementarities in early childhood skill formation. Malamud et al. (2016) do not find any dynamic complementarities in human capital formation when studying access to abortion and access to better schools in Romania. However, Adhvaryu et al. (2016) show that children whose families were randomized to receive conditional cash transfers through the Mexican government's Progresa policy experiment experienced a smaller decline in education and employment outcomes than control group children who experienced adverse rainfall in the year of birth. Gunnsteinsson et al. (2016) also show that infants that received randomized access to vitamin A supplementation at birth were protected from adverse health effects due to tornado exposure in utero and in infancy in Bangladesh.

In this section, I employ a similar methodology and ask: do rainfall shocks at birth raise the productivity of ICDS program exposure? Rainfall shocks are particularly important in countries that are primarily agricultural, since rainfed agricultural productivity decreases in drought years (Shah and Steinberg, 2017). As a result of the negative income effect, families have fewer resources to spend on human capital production, in the form of educational and nutritional inputs.

To study the interaction between rainfall shocks and the ICDS program, I construct rainfall shocks in a similar manner to Shah and Steinberg (2017). I first define district-year-level positive rainfall shock variables equal to one if rainfall in the district in the given year exceeded the 80th percentile of historical rainfall for the district. Negative rainfall shock variables were constructed in a similar manner if rainfall fell below the 20th percentile of historical rainfall for the district. I then define an individual to be hit with a positive (negative) rainfall shock if her district received a positive (negative) rainfall shock in either (i) her year of birth, (ii) the year preceding her birth, or (iii) the year after her birth. The inclusion of years before and after birth reduces noise in the estimates that might arise due to mis-reporting of age in the household survey data.

For individual i in district sub-division j of district d of state s and birth year k, I then run the following specification:

$$Y_{ijdsk} = \alpha + \gamma_j + \lambda_{ks} + \beta_1 P_{jk} + \beta_2 Shock_{dk} + \beta_3 P_{jk} * Shock_{dk} + X_{ijk}\delta + \epsilon_{ijdsk} \tag{3}$$

where Y_{ijk} is the outcome variable of interest, γ_j represent district sub-division fixed effects, λ_{ks} represent cohort x state fixed effects, P_{jk} refers to the intensity of the program (number of centers per 1,000 children) in the district sub-division of birth at the time of birth, $Shock_{dk}$ refers to the rainfall shock (positive or negative), and X_{ijk} are controls including gender, birth order, gender x birth order interaction, a quadratic population polynomial, caste, religion, and mother's education. The interaction term β_3 then captures dynamic complementarities that might arise due to the interaction of rainfall shocks with ICDS program exposure.

[Table 9 about here.]

[Table 10 about here.]

[Figure 11 about here.]

Figure 11 presents results separately for dynamic complementarities with negative rainfall shocks and positive rainfall shocks. The point estimates capture the interaction term β_3 in specification (3). All estimates have been standardized using the mean and standard deviation of individuals with no ICDS program exposure. I also display the 90% confidence interval bars corresponding to each point estimate. I present all child outcome variables considered, comprising child health, education, and labor.

We see immediately that there are no dynamic complementarities that arise due to positive rainfall shocks. The zero point estimates on education, in particular, are very tightly estimated due to the large sample size. However, there are significant dynamic complementarities due to negative rainfall shocks that affect child height as well as reading and math test scores. While we do not see any statistically significant interactions with the extreme cases of malnourishment, stunting, and ability to read and do math, three of the four measures of health and education exhibit significant complementarities. I do not observe any complementarities with child labor.

These results suggest that dynamic complementarities are important in the context of the ICDS program. In particular, children exposed to negative rainfall shocks in-utero, during their year of birth, or at age 1 are significantly less likely to be able to take advantage of subsequent investments made by the ICDS program. Taken together with the results on intertemporal reallocation of parental investments towards earlier periods of development, dynamic complementarities highlight a key mechanism by which individuals are impacted by the ICDS program.

VIII Indirect Impacts: Intra-Household Reallocation of Investments

A key theoretical prediction outlined in Section VI.B states that parents would invest less in siblings of the child exposed to greater ICDS program intensity, during early and late stages of childhood. In this section, I empirically test this prediction. In particular, I consider the impact of having siblings exposed to greater program intensity when such siblings were aged -1 to 6 and eligible to receive services from the ICDS program. To capture these indirect effects, I study measures of parental investments as well as health, education, and labor outcomes.

To study the impact of having siblings with greater program exposure, it is important to control for one's own program exposure. While it is possible to directly control for the program intensity one was exposed to, I opt to use district sub-division x cohort x age fixed effects specification that is far more restrictive. Notably, the inclusion of these fixed effects absorbs one's own program intensity, rendering it unnecessary to include in the regression. Due to the high correlation between one's program intensity and that of her siblings, it is best to avoid inclusion of both variables in the regression when possible. I thus run the following specification for individual i aged a in district sub-division j and birth year k:

$$Y_{ijk} = \alpha + \lambda_{jka} + \beta \tilde{P}_{ijk} + X_{ijk}\delta + \epsilon_{ijk} \tag{4}$$

where Y_{ijk} is the outcome variable of interest, λ_{jka} represent district sub-division x cohort x age fixed effects, $\tilde{P}_{ijk}$ refers to the average program intensity of siblings (number of centers per 1,000 children) in the district sub-division of birth at their time of birth, and X_{ijk} are controls including gender, birth order, gender x birth order interaction, a quadratic population polynomial, caste, religion, and mother's education. β then captures the impact of having siblings exposed to greater ICDS program intensity, while controling for one's own program exposure. The analysis exlcudes individuals who are the single child of the household.

[Table 11 about here.]

[Table 12 about here.]

[Figure 12 about here.]

Figure 12 captures the impacts of having siblings exposed to greater ICDS program exposure, on a range of health, education, labor, and investment measures. The point estimates capture the term β in specification (4). All estimates have been standardized using the mean and standard deviation of individuals with no ICDS program exposure. I also display the 95% confidence interval bars corresponding to each point estimate.

We immediately see that there are significant negative impacts of having siblings exposed to greater ICDS program exposure. The point estimates should be interpreted as follows: if, hypothetically, it were possible to have all of one's siblings exposed to an additional ICDS center per 1,000 children in the district sub-division at her time of birth, the individual experiences a β standard deviation decrease in outcome variables considered. Individuals experience an approximate 0.025 standard deviation decrease in health outcomes and a 0.015 standard deviation decrease in education outcomes. This is driven by a 0.015 - 0.045 standard deviation decrease in investments in children by parents.

[Figure 13 about here.]

Given the large literature on parents' bias towards boys in developing countries, the heterogeneous impacts of this intra-household reallocation of resources by gender are particularly important. Figure 13 presents results by gender of the individual in question, as well as the gender of her siblings. We see immediately that the negative impacts on education arise for all four combinations of gender of the individual and gender of siblings.

However, the negative health impacts from siblings exposed to greater program intensity arise only for girls. Interestingly, the gender of the sibling does not seem to matter for girls - girls with male and female siblings experience negative health impacts of similar magnitudes. Thus while we have seen in Section V.C that the positive direct impacts of the program were larger for women, it is also important to note that the negative indirect impacts of the program, particularly in health, are also larger for women.

IX Cost-Benefit Analysis

In this section, I present a cost-benefit analysis of the ICDS program, taking into account the direct impacts of the program, as well as the indirect impacts on siblings due to intra-household reallocation of resources. The benefit from the program stems from the increase in wages that accrue to individuals exposed to greater program intensity. Notably, this is an under-estimate of the program impact, as I have not included the impacts of the program that stem from improved health outcomes.

The direct benefits from the program are calculated as follows:

$$B = \frac{1}{N}\sum_{i=1}^{N}\left(\beta_k * P_{jk} * NPV_{ijk}\right) \tag{5}$$

where β_k refers to the percentage increase in wages accruing to cohort k that arises from an additional center per 1000 children in their district sub-division when aged -1 to 6, P_{jk} refers to the average program intensity that cohort k in district sub-division j was exposed to, and NPV_{ijk} refers to the net present value of individual i's lifetime income stream. An average is then taken across all individuals. The estimates of β_k are obtained from the following regression similar to equation (1):

$$Y_{ijk} = \alpha + \gamma_j + \lambda_{ks} + \sum_k \beta_k P_{jk} + X_{ijk}\delta + \epsilon_{ijk} \tag{6}$$

where γ_j represents district sub-division fixed effects and λ_{ks} represents cohort x state fixed effects. Estimates of β_k are obtained by interacting program intensity P_{jk} with the full set of cohort dummies. In computing the benefits of the program, I only include estimates of β_k that are statistically significant at the 10% level - all other estimates are set to zero.

The indirect costs from the program are calculated as follows:

$$C_I = \frac{1}{N}\sum_{i=1}^{N}\sum_{l=1}^{L}\left(\tilde{\theta}_k * P_{jk} * \widetilde{NPV}_{iljk}\right) \tag{7}$$

where $\tilde{\theta}_k$ refers to the percentage decrease in wages accruing to sibling l of an individual i in cohort k, where individual i was exposed to an additional center per 1000 children in their district sub-division when aged -1 to 6. P_{jk} refers to the average program intensity that cohort k in district sub-division j was exposed to, and $\widetilde{NPV}_{ijk}$ refers to the net present value of sibling l's lifetime income stream. A sum is taken over all siblings for each individual, after which an average is taken across all individuals. Estimates of $\tilde{\theta}_k = \frac{\theta_k}{L}$ are obtained from the following regression similar to equation (4):

$$Y_{ijk} = \alpha + \lambda_{jka} + \sum_k \theta_k \tilde{P}_{ijk} + X_{ijk}\delta + \epsilon_{ijk} \tag{8}$$

where λ_{jka} represents district sub-division x cohort x age fixed effects. Estimates of θ_k are obtained by interacting average sibling program intensity $\tilde{P}_{jk}$ with the full set of cohort dummies. In computing the indirect costs of the program, I only include estimates of θ_k that are statistically significant at the 10% level - all other estimates are set to zero.

It is important to stress, however, a caveat to the indirect cost analysis: matching of siblings among adults is difficult. While the IHDS data has some information on adult siblings, this may not include siblings who have left the household. The omission of one's siblings has two key impacts on the analysis: first, it may change the estimated value of $\tilde{\theta}_k$, the impact of higher program intensity on siblings. Second, a value of L lower than the true value would lead to an under-estimate of the indirect costs of the program, as per equation (7).

The direct cost of the program depends on the annual cost of the program to the government, as well as each individual's exposure to the program. The annual cost of the program is estimated by noting that in 2012, the Indian government spent Rs. 159 billion on the program on a population of 159 million kids aged 0-6. As such, the annual cost of the program per kid is an estimated Rs. 1,000 (2012 prices). Note that in order to be consistent with computation of the benefits, the costs are calculated using an intent-to-treat (ITT) methodology, rather than the treatment-on-treated (TOT). Each individual's exposure to the program in number of years is calculated using their birth year and the arrival of the program in their district sub-division. The total cost is then estimated as the product of the annual program cost and exposure to the program, and an average is taken across all individuals.

$$C_D = \frac{1}{N}\sum_{i=1}^{N}\left(AnnualCost * Exposure_i\right) \tag{9}$$

Two key assumptions are made in the cost-benefit analysis.[7] First, an assumption has to be made on the age until which individuals work. As such, I present the analysis for three scenarios corresponding to retirement at ages 50, 55, and 60. Second, an assumption has to be made on the discount rate used. I present calculations assuming a discount rate of 5%, but also calculate the internal rate of return (IRR), i.e. the discount rate that gives the program a net present value of zero. Table 13 presents results from the cost-benefit analysis.

[Table 13 about here.]

We see that the direct benefits of the program per person range from Rs. 7,746 to Rs. 8,321 (2012 rupees). In comparison, the cost is calculated to be Rs. 4,554 per person, 41% smaller than the lower bound of the benefits. This indicates that the direct benefits of the program far outweigh the costs. The internal rate of return (IRR) of the program, defined as the discount rate such that the net present value of the program is zero, ranges from 8.1% to 8.3% under the most and least conservative scenarios, respectively. However, it is also important to note the indirect costs of the program that arise due to intra-household reallocation of resources. These costs range from an estimated Rs. 610 to Rs. 656 (2012 rupees) per person. As a result, the IRR that takes into account the direct and indirect impacts of the program decreases slightly to 7.3% to 7.5%.

It is noteworthy that the returns calculated are in the range of other IRR estimates for education interventions in developing countries. For example, the range of IRR obtained is very comparable to (though slightly lower than) that obtained by Duflo (2001) of 8.8% to 12% for a large primary school construction program in Indonesia.

[7] I do not assume any wage growth over the lifetime, as the estimated coefficients on age and age^2 are not significantly different from zero in the wage regressions.

X Conclusion

This paper shows that the overall impacts of early childhood programs depend on both the direct impacts on exposed cohorts, as well as the indirect impacts that arise due to reallocation of parental investments. Cohorts exposed to the ICDS program had significant impacts along various dimensions of health, education, and economic well-being, in both the short and long run. Importantly, however, parents reallocate their investments towards children with greater program exposure, as evidenced by crowd-out of program impacts from exposed siblings. Parents also reallocate their investments in children towards earlier ages by taking on more debt.

While this paper takes an important step in presenting a particular type of indirect impacts, namely that of intra-household reallocation, little is known about other indirect impacts of such programs. Specifically, inter-generational impacts of program exposure might lead to persistence across generations. Furthermore, general equilibrium impacts within the village might mean that wages of unexposed cohorts are lower relative to wages of exposed cohorts within villages. I leave these questions to future research.

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A Theoretical Appendix

Parents solve the following maximization problem:

$$\max_{I_{1a},I_{1b},I_{2a},I_{2b}} U_P$$
$$\text{subject to budget constraint: } I_{1a}+I_{1b}+\delta(I_{2a}+I_{2b}) \le \bar{y}$$

where $\bar{y}=\bar{y}_1+\delta\bar{y}_2$.

Let $\phi>0$. Then since $U_P = A^{\frac{\beta}{\phi}}\left[\gamma(\mu_g I_{1a})^{\phi}+(1-\gamma)I_{2a}^{\phi}\right]^{\frac{\beta}{\phi}} B^{\frac{1-\beta}{\phi}}\left[\gamma I_{1b}^{\phi}+(1-\gamma)I_{2b}^{\phi}\right]^{\frac{1-\beta}{\phi}}$, this problem is equivalent to maximizing the following problem:

$$\max_{I_{1a},I_{1b},I_{2a},I_{2b}} \ln\Big(\frac{U_P^{\phi}}{A^{\beta}B^{1-\beta}}\Big)$$
$$\text{subject to budget constraint: } I_{1a}+I_{1b}+\delta(I_{2a}+I_{2b}) \le \bar{y}$$

Setting up the Lagrangean for the problem, we have:

$$\begin{aligned}\mathcal{L} &= \ln\Big(\frac{U_P^{\phi}}{A^{\beta}B^{1-\beta}}\Big)+\lambda(\bar{y}-I_{1a}-I_{1b}-\delta I_{2a}-\delta I_{2b})\\ &= \beta\ln\left[\gamma(\mu_g I_{1a})^{\phi}+(1-\gamma)I_{2a}^{\phi}\right]+(1-\beta)\ln\left[\gamma I_{1b}^{\phi}+(1-\gamma)I_{2b}^{\phi}\right]+\lambda(\bar{y}-I_{1a}-I_{1b}-\delta I_{2a}-\delta I_{2b})\end{aligned}$$

Taking first-order conditions, we obtain the following:

$$\frac{\partial\mathcal{L}}{\partial I_{1a}}=0:\ \frac{\beta\gamma(\mu_g I_{1a})^{\phi-1}\phi\mu_g}{\gamma(\mu_g I_{1a})^{\phi}+(1-\gamma)I_{2a}^{\phi}}=\lambda$$
$$\frac{\partial\mathcal{L}}{\partial I_{2a}}=0:\ \frac{\beta(1-\gamma)\phi I_{2a}^{\phi-1}}{\gamma(\mu_g I_{1a})^{\phi}+(1-\gamma)I_{2a}^{\phi}}=\delta\lambda$$
$$\frac{\partial\mathcal{L}}{\partial I_{1b}}=0:\ \frac{(1-\beta)\gamma\phi I_{1b}^{\phi-1}}{\gamma I_{1b}^{\phi}+(1-\gamma)I_{2b}^{\phi}}=\lambda$$
$$\frac{\partial\mathcal{L}}{\partial I_{2b}}=0:\ \frac{(1-\beta)(1-\gamma)\phi I_{2b}^{\phi-1}}{\gamma I_{1b}^{\phi}+(1-\gamma)I_{2b}^{\phi}}=\delta\lambda$$

Using FOC(I_{1a}) and FOC(I_{2a}), we obtain:

$$\begin{aligned}
\gamma(\mu_g I_{1a})^{\phi-1}\mu_g &= (1-\gamma)I_{2a}^{\phi-1}\delta \\
\Big(\frac{\mu_g I_{1a}}{I_{2a}}\Big)^{\phi-1} &= \frac{(1-\gamma)\delta}{\gamma\mu_g} \\
\frac{\mu_g I_{1a}}{I_{2a}} &= \Big(\frac{(1-\gamma)\delta}{\gamma\mu_g}\Big)^{\frac{1}{\phi-1}} \\
I_{2a} &= \mu_g\Big(\frac{(1-\gamma)\delta}{\gamma\mu_g}\Big)^{\frac{1}{1-\phi}} * I_{1a}
\end{aligned}$$

Using FOC(I_{1b}) and FOC(I_{2b}), we obtain:

$$\begin{aligned}
\gamma I_{1b}^{\phi-1} &= (1-\gamma)I_{2b}^{\phi-1}\delta \\
I_{2b} &= \Big(\frac{\delta(1-\gamma)}{\gamma}\Big)^{\frac{1}{1-\phi}} * I_{1b}
\end{aligned}$$

Using FOC(I_{1a}) and FOC(I_{1b}), we obtain:

$$\begin{aligned}
\frac{\beta\gamma(\mu_g I_{1a})^{\phi-1}\phi\mu_g}{\gamma(\mu_g I_{1a})^{\phi}+(1-\gamma)I_{2a}^{\phi}} &= \frac{(1-\beta)\gamma\phi I_{1b}^{\phi-1}}{\gamma I_{1b}^{\phi}+(1-\gamma)I_{2b}^{\phi}} \\
\frac{\beta\gamma(\mu_g I_{1a})^{\phi-1}\phi\mu_g}{\gamma(\mu_g I_{1a})^{\phi}+(1-\gamma)\Big(\mu_g\Big(\frac{(1-\gamma)\delta}{\gamma\mu_g}\Big)^{\frac{1}{1-\phi}}I_{1a}\Big)^{\phi}} &= \frac{(1-\beta)\gamma\phi I_{1b}^{\phi-1}}{\gamma I_{1b}^{\phi}+(1-\gamma)\Big(\Big(\frac{\delta(1-\gamma)}{\gamma}\Big)^{\frac{1}{1-\phi}}I_{1b}\Big)^{\phi}} \\
\frac{\beta(I_{1a})^{\phi-1}}{\gamma(I_{1a})^{\phi}+(1-\gamma)\Big(\Big(\frac{(1-\gamma)\delta}{\gamma\mu_g}\Big)^{\frac{1}{1-\phi}}I_{1a}\Big)^{\phi}} &= \frac{(1-\beta)I_{1b}^{\phi-1}}{\gamma I_{1b}^{\phi}+(1-\gamma)\Big(\Big(\frac{\delta(1-\gamma)}{\gamma}\Big)^{\frac{1}{1-\phi}}I_{1b}\Big)^{\phi}} \\
\frac{\beta I_{1a}^{-1}}{\gamma+(1-\gamma)\Big(\frac{(1-\gamma)\delta}{\gamma\mu_g}\Big)^{\frac{\phi}{1-\phi}}} &= \frac{(1-\beta)I_{1b}^{-1}}{\gamma+(1-\gamma)\Big(\frac{\delta(1-\gamma)}{\gamma}\Big)^{\frac{\phi}{1-\phi}}} \\
I_{1a} &= \frac{\beta\Big[\gamma+(1-\gamma)\Big(\frac{\delta(1-\gamma)}{\gamma}\Big)^{\frac{\phi}{1-\phi}}\Big]}{(1-\beta)\Big[\gamma+(1-\gamma)\Big(\frac{(1-\gamma)\delta}{\gamma\mu_g}\Big)^{\frac{\phi}{1-\phi}}\Big]} * I_{1b}
\end{aligned}$$

Let:

$$
\begin{aligned}
I_{1a} &= c_1 * I_{1b}, \text{ where } c_1 = \frac{\beta\left[\gamma + (1-\gamma)\left(\frac{\delta(1-\gamma)}{\gamma}\right)^{\frac{\phi}{1-\phi}}\right]}{(1-\beta)\left[\gamma + (1-\gamma)\left(\frac{(1-\gamma)\delta}{\gamma\mu_g}\right)^{\frac{\phi}{1-\phi}}\right]} \\
I_{2a} &= c_3 * I_{1a}, \text{ where } c_3 = \mu_g\left(\frac{(1-\gamma)\delta}{\gamma\mu_g}\right)^{\frac{1}{1-\phi}} \\
I_{2b} &= c_2 * I_{1b}, \text{ where } c_2 = \left(\frac{\delta(1-\gamma)}{\gamma}\right)^{\frac{1}{1-\phi}}
\end{aligned}
$$

Note that $\frac{\partial c_1}{\partial \mu_g} > 0$ since $\frac{\phi}{1-\phi} > 0$, and $\frac{\partial c_2}{\partial \mu_g} = 0$. Furthermore,

$$
\begin{aligned}
\frac{\partial c_3}{\partial \mu_g} &= \frac{\partial}{\partial \mu_g}\left(\mu_g \mu_g^{\frac{1}{\phi-1}}\left(\frac{(1-\gamma)\delta}{\gamma}\right)^{\frac{1}{1-\phi}}\right) \\
&= \left(\frac{(1-\gamma)\delta}{\gamma}\right)^{\frac{1}{1-\phi}} * \left(\frac{\phi}{\phi-1}\right) * \mu_g^{\frac{1}{\phi-1}}
\end{aligned}
$$

Note that $\left(\frac{(1-\gamma)\delta}{\gamma}\right)^{\frac{1}{1-\phi}} > 0$ and $\mu_g^{\frac{1}{\phi-1}} > 0$. Thus $\text{sign}\left[\frac{\partial c_3}{\partial \mu_g}\right] = \text{sign}\left[\frac{\phi}{\phi-1}\right]$. Since $0 < \phi < 1$, $\frac{\phi}{\phi-1} < 0$ and $\frac{\partial c_3}{\partial \mu_g} < 0$.

To solve for I_{1b}, we use the budget constraint:

$$
\begin{aligned}
I_{1a} + I_{1b} + \delta(I_{2a} + I_{2b}) &= \bar{y} \\
I_{1b}(c_1 + 1 + \delta(c_1 c_3 + c_2)) &= \bar{y} \\
I_{1b} &= \frac{\bar{y}}{c_1 + 1 + \delta(c_1 c_3 + c_2)}
\end{aligned}
$$

$$
\begin{aligned}
I_{1a} &= \frac{\bar{y} * c_1}{c_1 + 1 + \delta(c_1 c_3 + c_2)} \\
&= \frac{\bar{y}}{\frac{1+\delta c_2}{c_1} + 1 + \delta c_3}
\end{aligned}
$$

Since $\frac{\partial c_1}{\partial \mu_g} > 0$, $\frac{\partial c_2}{\partial \mu_g} = 0$, and $\frac{\partial c_3}{\partial \mu_g} < 0$, $\frac{\partial I_{1a}}{\partial \mu_g} > 0$.

Let $x = c_1 + 1 + \delta(c_1 c_3 + c_2)$. Then:

$$\begin{aligned} x &= 1 + \delta c_2 + (1 + \delta c_3) c_1 \\ &= 1 + \delta\Big(\frac{\delta(1-\gamma)}{\gamma}\Big)^{\frac{1}{1-\phi}} + \left(1 + \delta\mu_g\Big(\frac{(1-\gamma)\delta}{\gamma\mu_g}\Big)^{\frac{1}{1-\phi}}\right) \frac{\beta\left[\gamma + (1-\gamma)\left(\frac{\delta(1-\gamma)}{\gamma}\right)^{\frac{\phi}{1-\phi}}\right]}{(1-\beta)\left[\gamma + (1-\gamma)\left(\frac{(1-\gamma)\delta}{\gamma\mu_g}\right)^{\frac{\phi}{1-\phi}}\right]} \end{aligned}$$

$$\begin{aligned} \frac{\partial x}{\partial \mu_g} = &\left(1 + \delta\mu_g\Big(\frac{(1-\gamma)\delta}{\gamma\mu_g}\Big)^{\frac{1}{1-\phi}}\right) \frac{\beta\left[-\left(\gamma + (1-\gamma)\left(\frac{\delta(1-\gamma)}{\gamma}\right)^{\frac{\phi}{1-\phi}}\right)(1-\gamma)\left(\frac{(1-\gamma)\delta}{\gamma}\right)^{\frac{\phi}{1-\phi}}\left(\frac{\phi}{\phi-1}\right)\mu_g^{\frac{1}{\phi-1}}\right]}{(1-\beta)\left[\gamma + (1-\gamma)\left(\frac{(1-\gamma)\delta}{\gamma\mu_g}\right)^{\frac{\phi}{1-\phi}}\right]^2} \\ &+ \delta\Big(\frac{\phi}{\phi-1}\Big)\mu_g^{\frac{1}{\phi-1}}\left(\frac{(1-\gamma)\delta}{\gamma}\right)^{\frac{1}{1-\phi}} \frac{\beta\left[\gamma + (1-\gamma)\left(\frac{\delta(1-\gamma)}{\gamma}\right)^{\frac{\phi}{1-\phi}}\right]}{(1-\beta)\left[\gamma + (1-\gamma)\left(\frac{(1-\gamma)\delta}{\gamma\mu_g}\right)^{\frac{\phi}{1-\phi}}\right]} \end{aligned}$$

Then $\frac{\partial x}{\partial \mu_g} > 0$ if and only if:

$$\begin{aligned} \frac{\left(1 + \delta\mu_g^{\frac{\phi}{\phi-1}}\left(\frac{(1-\gamma)\delta}{\gamma}\right)^{\frac{1}{1-\phi}}\right)(1-\gamma)\left(\frac{(1-\gamma)\delta}{\gamma}\right)^{\frac{\phi}{1-\phi}}}{\gamma + (1-\gamma)\left(\frac{(1-\gamma)\delta}{\gamma\mu_g}\right)^{\frac{\phi}{1-\phi}}} &> \delta\Big(\frac{(1-\gamma)\delta}{\gamma}\Big)^{\frac{1}{1-\phi}} \\ 1 + \delta\mu_g^{\frac{\phi}{\phi-1}}\Big(\frac{(1-\gamma)\delta}{\gamma}\Big)^{\frac{1}{1-\phi}} &> \delta^2 + \frac{\delta^2(1-\gamma)}{\gamma}\Big(\frac{(1-\gamma)\delta}{\gamma\mu_g}\Big)^{\frac{\phi}{1-\phi}} \\ 1 + \mu_g^{\frac{\phi}{\phi-1}}\left(\frac{1-\gamma}{\gamma}\right)^{\frac{1}{1-\phi}}\delta^{\frac{2-\phi}{1-\phi}} &> \delta^2 + \left(\frac{1-\gamma}{\gamma}\right)\left(\frac{1-\gamma}{\gamma\mu_g}\right)^{\frac{\phi}{1-\phi}}\delta^{\frac{2-\phi}{1-\phi}} \\ 1 + \mu_g^{\frac{\phi}{\phi-1}}\left(\frac{1-\gamma}{\gamma}\right)^{\frac{1}{1-\phi}}\delta^{\frac{2-\phi}{1-\phi}} &> \delta^2 + \mu_g^{\frac{\phi}{\phi-1}}\left(\frac{1-\gamma}{\gamma}\right)^{\frac{1}{1-\phi}}\delta^{\frac{2-\phi}{1-\phi}} \end{aligned}$$

Since $0 < \delta < 1$, $\delta^2 < 1$ for all δ. Thus the above expression is always true, and hence $\frac{\partial x}{\partial \mu_g} > 0$. Since $I_{1b} = \frac{\bar{y}}{x}$, $\frac{\partial I_{1b}}{\partial \mu_g} < 0$. Furthermore, since $I_{2b} = c_2 * I_{1b}$ and c_2 is independent of μ_g, we also have that $\frac{\partial I_{2b}}{\partial \mu_g} < 0$.

To solve for I_{2a}, we note that $I_{2a} = c_3 I_{1a} = c_3 c_1 I_{1b}$. Hence

$$I_{2a} = \frac{c_3 c_1 \bar{y}}{c_1 + 1 + \delta(c_1 c_3 + c_2)}$$

Note that $c_3 c_1$ can be expressed as follows:

$$\begin{aligned} c_3 c_1 &= \mu_g \left(\frac{(1-\gamma)\delta}{\gamma \mu_g} \right)^{\frac{1}{1-\phi}} \frac{\beta \left[\gamma + (1-\gamma) \left(\frac{\delta(1-\gamma)}{\gamma} \right)^{\frac{\phi}{1-\phi}} \right]}{(1-\beta) \left[\gamma + (1-\gamma) \left(\frac{(1-\gamma)\delta}{\gamma \mu_g} \right)^{\frac{\phi}{1-\phi}} \right]} \\ &= \frac{\theta \mu_g^{\frac{\phi}{\phi-1}}}{\gamma + (1-\gamma) \left(\frac{(1-\gamma)\delta}{\gamma \mu_g} \right)^{\frac{\phi}{1-\phi}}} \end{aligned}$$

where $\theta = \frac{\beta}{1-\beta} \left(\frac{(1-\gamma)\delta}{\gamma} \right)^{\frac{1}{1-\phi}} \left[\gamma + (1-\gamma) \left(\frac{(1-\gamma)\delta}{\gamma} \right)^{\frac{\phi}{1-\phi}} \right]$.

Note that $c_1 + 1 + \delta(c_1 c_3 + c_2)$ can be expressed as follows:

$$\begin{aligned} & c_1 + 1 + \delta(c_1 c_3 + c_2) \\ &= \frac{\beta \left[\gamma + (1-\gamma) \left(\frac{\delta(1-\gamma)}{\gamma} \right)^{\frac{\phi}{1-\phi}} \right]}{(1-\beta) \left[\gamma + (1-\gamma) \left(\frac{(1-\gamma)\delta}{\gamma \mu_g} \right)^{\frac{\phi}{1-\phi}} \right]} + 1 + \frac{\delta \theta \mu_g^{\frac{\phi}{\phi-1}}}{\gamma + (1-\gamma) \left(\frac{(1-\gamma)\delta}{\gamma \mu_g} \right)^{\frac{\phi}{1-\phi}}} + \delta \left(\frac{\delta(1-\gamma)}{\gamma} \right)^{\frac{1}{1-\phi}} \\ &= \frac{\frac{\beta}{1-\beta} \left[\gamma + (1-\gamma) \left(\frac{\delta(1-\gamma)}{\gamma} \right)^{\frac{\phi}{1-\phi}} \right] + \left[\gamma + (1-\gamma) \left(\frac{(1-\gamma)\delta}{\gamma \mu_g} \right)^{\frac{\phi}{1-\phi}} \right] \left(1 + \delta \left(\frac{\delta(1-\gamma)}{\gamma} \right)^{\frac{1}{1-\phi}} \right) + \delta \theta \mu_g^{\frac{\phi}{\phi-1}}}{\gamma + (1-\gamma) \left(\frac{(1-\gamma)\delta}{\gamma \mu_g} \right)^{\frac{\phi}{1-\phi}}} \end{aligned}$$

Therefore I_{2a} can be expressed as follows:

$$\begin{aligned} & I_{2a} \\ &= \frac{\theta \bar{y} \mu_g^{\frac{\phi}{\phi-1}}}{\frac{\beta}{1-\beta} \left[\gamma + (1-\gamma) \left(\frac{\delta(1-\gamma)}{\gamma} \right)^{\frac{\phi}{1-\phi}} \right] + \left[\gamma + (1-\gamma) \left(\frac{(1-\gamma)\delta}{\gamma \mu_g} \right)^{\frac{\phi}{1-\phi}} \right] \left(1 + \delta \left(\frac{\delta(1-\gamma)}{\gamma} \right)^{\frac{1}{1-\phi}} \right) + \delta \theta \mu_g^{\frac{\phi}{\phi-1}}} \end{aligned}$$

Let $\pi = \frac{\beta}{1-\beta}\left[\gamma + (1-\gamma)\left(\frac{\delta(1-\gamma)}{\gamma}\right)^{\frac{\phi}{1-\phi}}\right]$ and $\epsilon = 1 + \delta\left(\frac{\delta(1-\gamma)}{\gamma}\right)^{\frac{1}{1-\phi}}$. Then we have:

$$\begin{aligned}
I_{2a} &= \frac{\theta \bar{y} \mu_g^{\frac{\phi}{\phi-1}}}{\pi + \left[\gamma + (1-\gamma)\left(\frac{(1-\gamma)\delta}{\gamma \mu_g}\right)^{\frac{\phi}{1-\phi}}\right]\epsilon + \delta\theta\mu_g^{\frac{\phi}{\phi-1}}} \\
&= \frac{\theta \bar{y} \mu_g^{\frac{\phi}{\phi-1}}}{\pi + \gamma\epsilon + (1-\gamma)\epsilon\left(\frac{(1-\gamma)\delta}{\gamma}\right)^{\frac{\phi}{1-\phi}}\mu_g^{\frac{\phi}{\phi-1}} + \delta\theta\mu_g^{\frac{\phi}{\phi-1}}} \\
&= \frac{\theta \bar{y} \mu_g^{\frac{\phi}{\phi-1}}}{\pi + \gamma\epsilon + \left((1-\gamma)\epsilon\left(\frac{(1-\gamma)\delta}{\gamma}\right)^{\frac{\phi}{1-\phi}} + \delta\theta\right)\mu_g^{\frac{\phi}{\phi-1}}}
\end{aligned}$$

Let $\pi_1 = \pi + \gamma\epsilon$ and $\pi_2 = (1-\gamma)\epsilon\left(\frac{(1-\gamma)\delta}{\gamma}\right)^{\frac{\phi}{1-\phi}} + \delta\theta$. Then we have:

$$\begin{aligned}
I_{2a} &= \frac{\theta \bar{y} \mu_g^{\frac{\phi}{\phi-1}}}{\pi_1 + \pi_2 \mu_g^{\frac{\phi}{\phi-1}}} \\
&= \frac{\theta \bar{y}}{\frac{\pi_1}{\mu_g^{\frac{\phi}{\phi-1}}} + \pi_2}
\end{aligned}$$

Since $0 < \phi < 1$, $\frac{\phi}{\phi-1} < 0$ and $\mu_g^{\frac{\phi}{\phi-1}}$ is decreasing in μ_g. Thus $\frac{\partial I_{2a}}{\partial \mu_g} < 0$.

Lastly, to solve for B, I use the period 2 budget constraint:

$$\begin{aligned}
I_{2a} + I_{2b} &= \bar{y}_2 - \frac{B}{\delta} \\
B &= \delta\bar{y}_2 - \delta(I_{2a} + I_{2b})
\end{aligned}$$

Then we have that:

$$\frac{\partial B}{\partial \mu_g} = -\delta\left(\frac{\partial I_{2a}}{\partial \mu_g} + \frac{\partial I_{2b}}{\partial \mu_g}\right)$$

Since $\frac{\partial I_{2a}}{\partial \mu_g} < 0$ and $\frac{\partial I_{2b}}{\partial \mu_g} < 0$, we have that $\frac{\partial B}{\partial \mu_g} > 0$.

Thus, we have shown that for $\phi > 0$, we have $\frac{\partial I_{1b}}{\partial \mu_g} < 0$, $\frac{\partial I_{2b}}{\partial \mu_g} < 0$, $\frac{\partial I_{1a}}{\partial \mu_g} > 0$, $\frac{\partial I_{2a}}{\partial \mu_g} < 0$, and $\frac{\partial B}{\partial \mu_g} > 0$.

B Robustness Checks: Placebo Tests

In this section, I present results from the specification outlined in equation (2). Overall, we see that program impacts arise in the age range over which individuals are eligible to avail services from the program (ages -1 to 6), and not before or after.

[Figure B.1 about here.]

[Figure B.2 about here.]

[Figure B.3 about here.]

[Figure B.4 about here.]

[Figure B.5 about here.]

[Figure B.6 about here.]

[Figure B.7 about here.]

[Figure B.8 about here.]

[Figure B.9 about here.]

[Figure B.10 about here.]

[Figure B.11 about here.]

[Figure B.12 about here.]

[Figure B.13 about here.]

C Robustness Checks: Mid-Day Meal Program

In this section, I repeat my analysis, explicitly controlling for a large government program aimed at improving health and nutrition of children of primary school going age. As Chakraborty and Jayaraman (2016) note, India implemented a free school lunch program known as the mid-day meal program, in large part following a 2001 Indian Supreme Court Directive. The implementation of the program did not take place immediately or all at once, but over the next five years states across India implemented the program until, by 2006, every Indian state had instituted a free school lunch in primary schools. One possible concern might be that the rollout of the mid-day meal program was correlated with the rollout of the ICDS program. If this were the case, the impacts that I attribute to the ICDS program may in fact be contaminated by impacts from the mid-day meal program.

I present several pieces of evidence to argue that this is not a concern. First, the ICDS program and the mid-day meal program do not share the same infrastructure or budget allocations. Meals for children under six years of age are prepared in ICDS centers, while meals for primary-school going children are prepared in schools. Furthermore, the budget allocations, including the division of funding between the central and state governments, are different for the two programs. Second, the placebo tests I present by age show that we do not observe impacts from the ICDS program arising from primary school going ages. On the contrary, the impacts arise over the age range for which children are eligible to avail services from the ICDS program, i.e. ages -1 to 6. Third, and in this section, I explicitly control for the rollout of the mid-day meal program and rerun my analysis. I show that my results are robust to the inclusion of the mid-day meal controls. I construct mid-day meal exposure as per Chakraborty and Jayaraman (2016). I note, however, that data on mid-day meal program rollout is only available for 24 out of 36 states and union territories in India. Despite the reduction in sample sizes and power, I show that my results are robust to the inclusion of the control.

[Figure C.1 about here.]

[Figure C.2 about here.]

[Figure C.3 about here.]

[Figure C.4 about here.]

Figures C.1 and C.2 present short and long-term program impacts controlling for the mid-day meal program, while figures C.3 and C.4 present the results on intertemporal and intra-household reallocation of parental investments with the mid-day meal control. Overall, we see that the results are robust to explicitly controlling for the mid-day meal program.

Figure 1: Rollout of the ICDS Program over Time

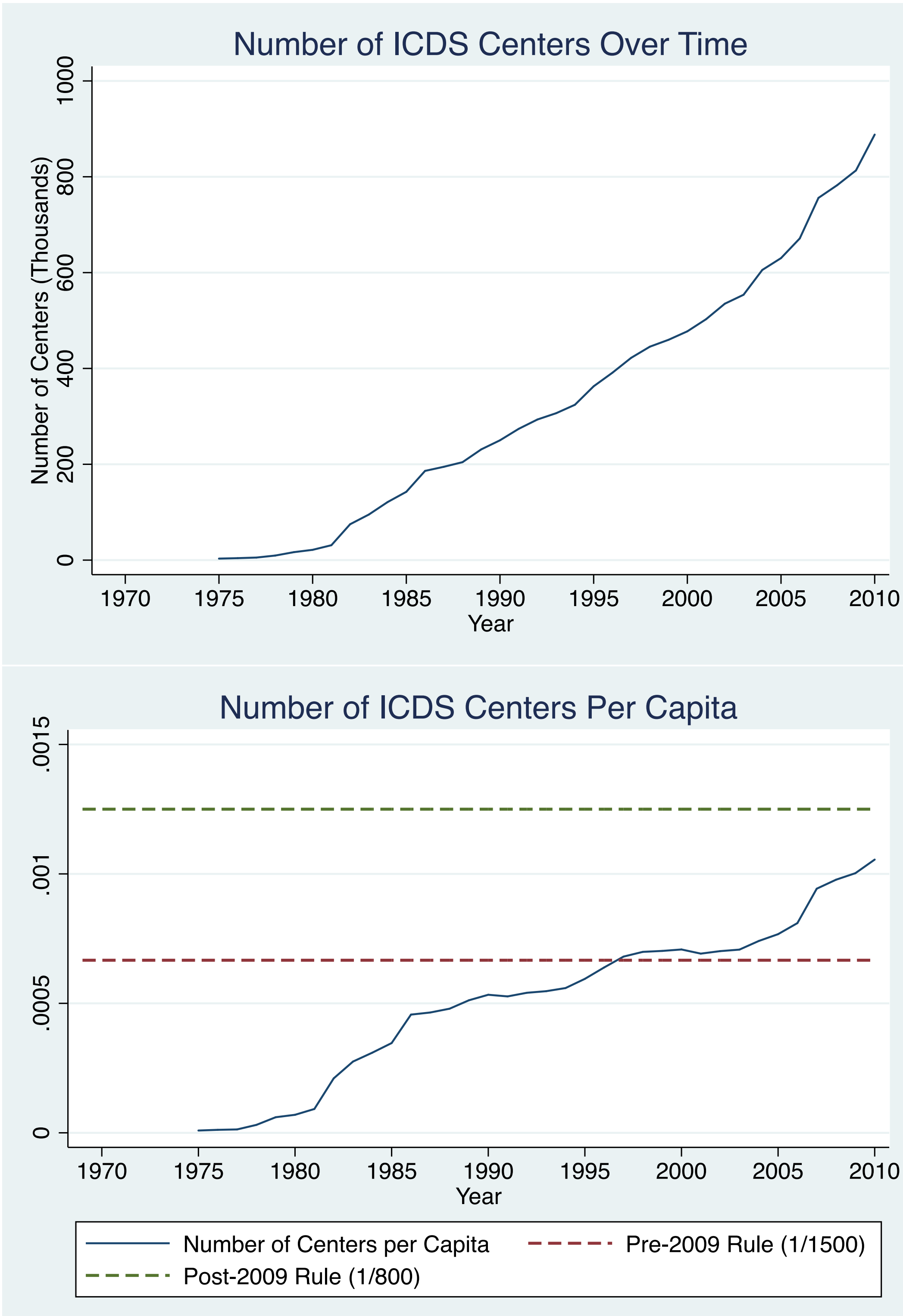
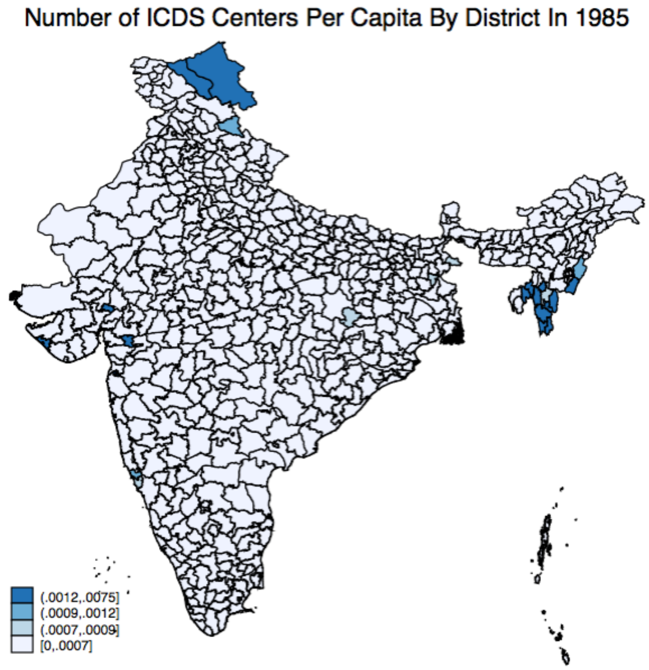


Figure 2: Rollout of the ICDS Program across India over Time



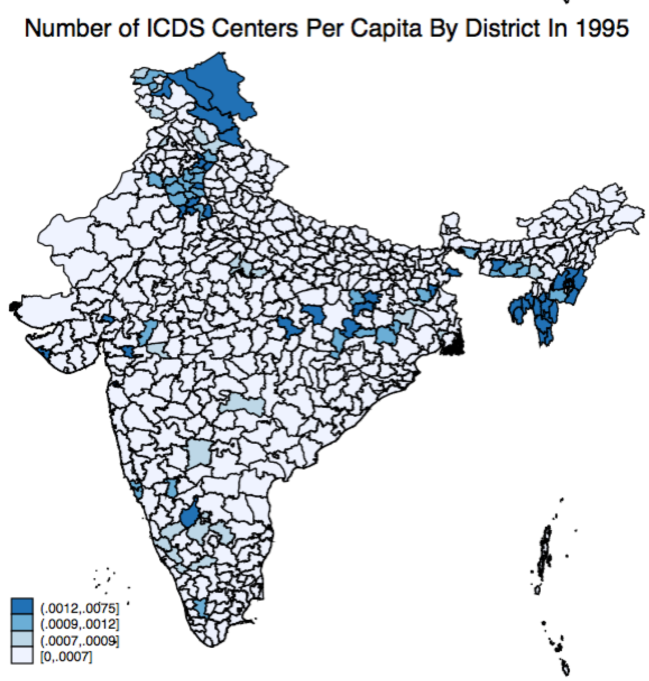


Figure 3: Rollout of ICDS Program across India over Time (continued)

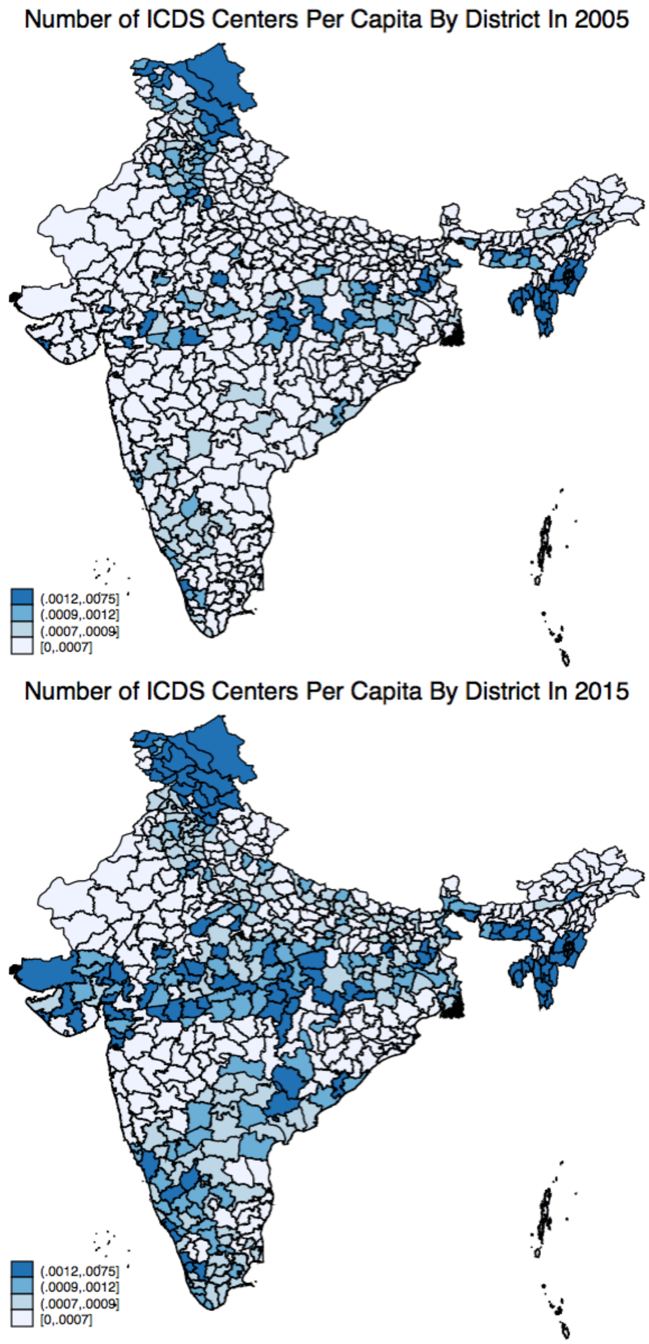


Figure 4: Short-Term Program Impacts

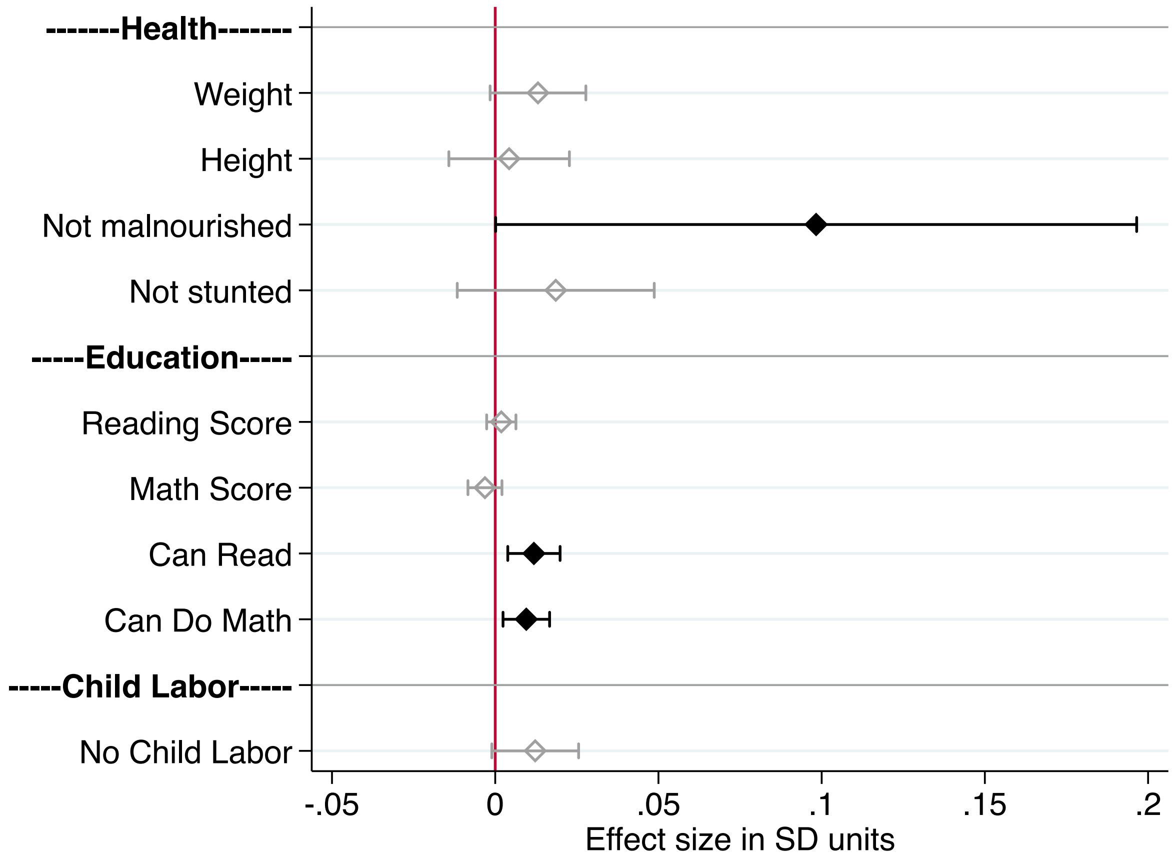


Figure 5: Long-Term Program Impacts

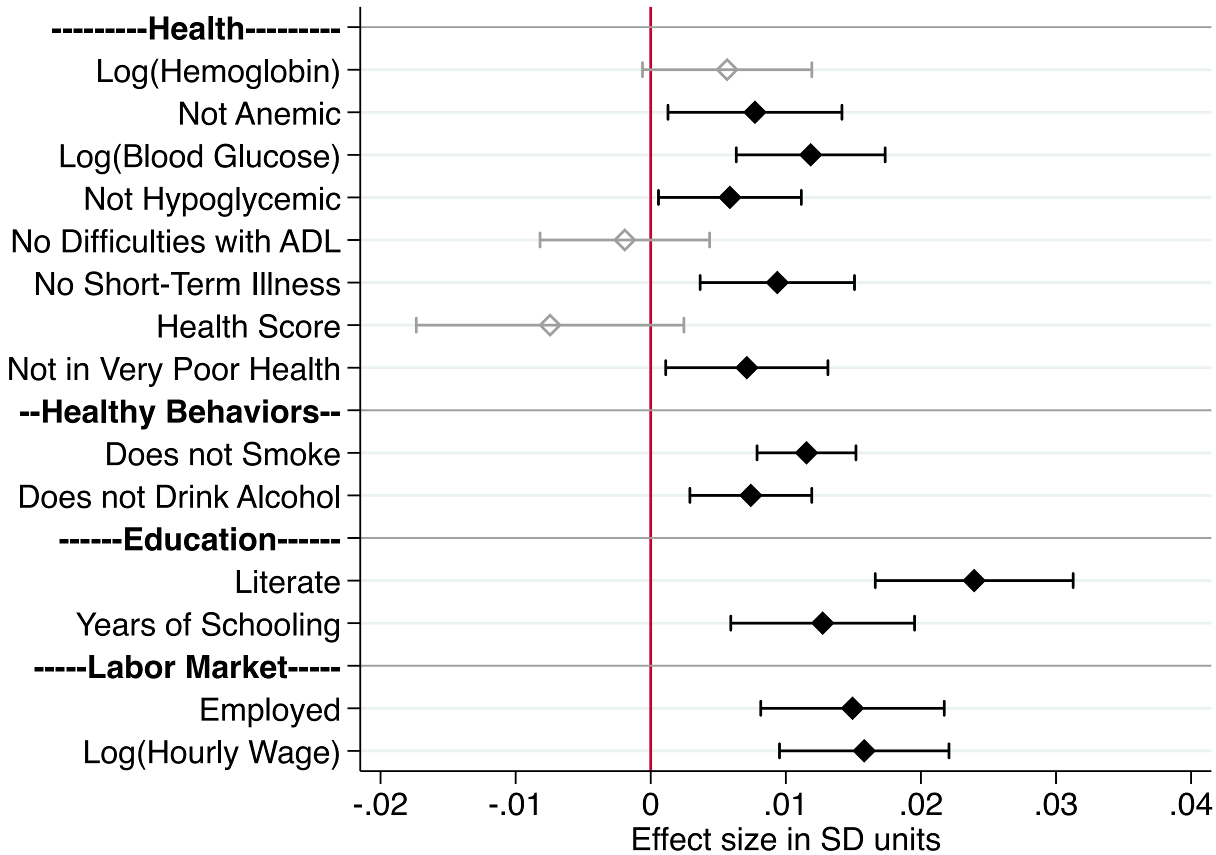


Figure 6: Short-Term Program Impacts: Heterogeneity by Gender

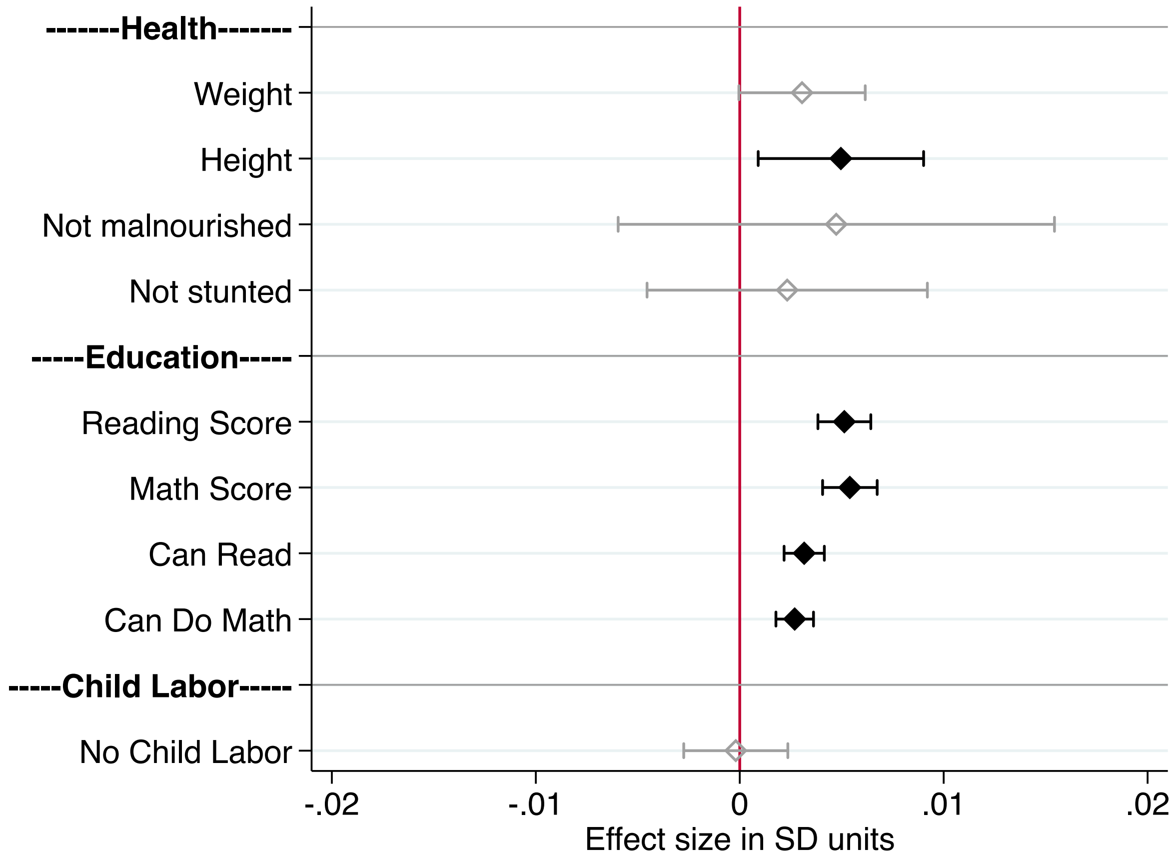


Figure 7: Long-Term Program Impacts: Heterogeneity by Gender

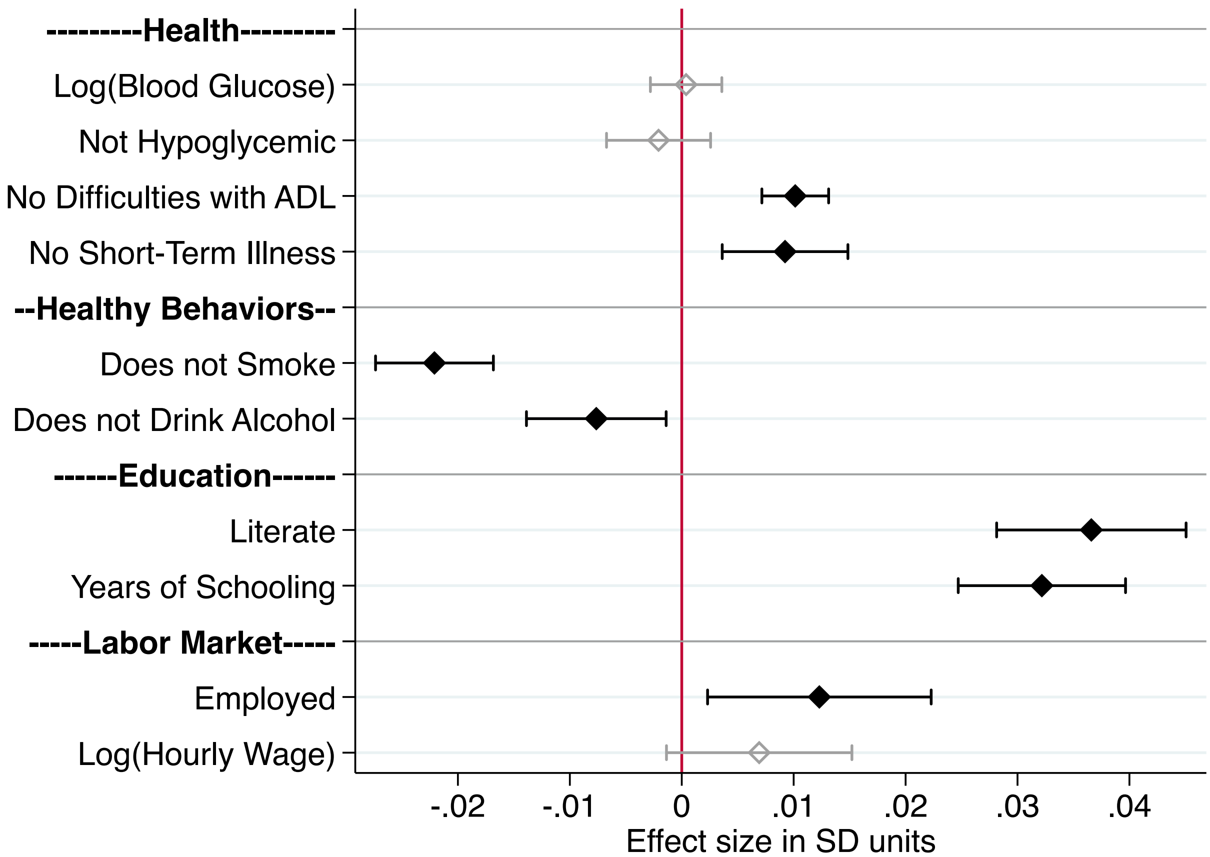


Figure 8: Program Impacts on Parental Employment & Wages

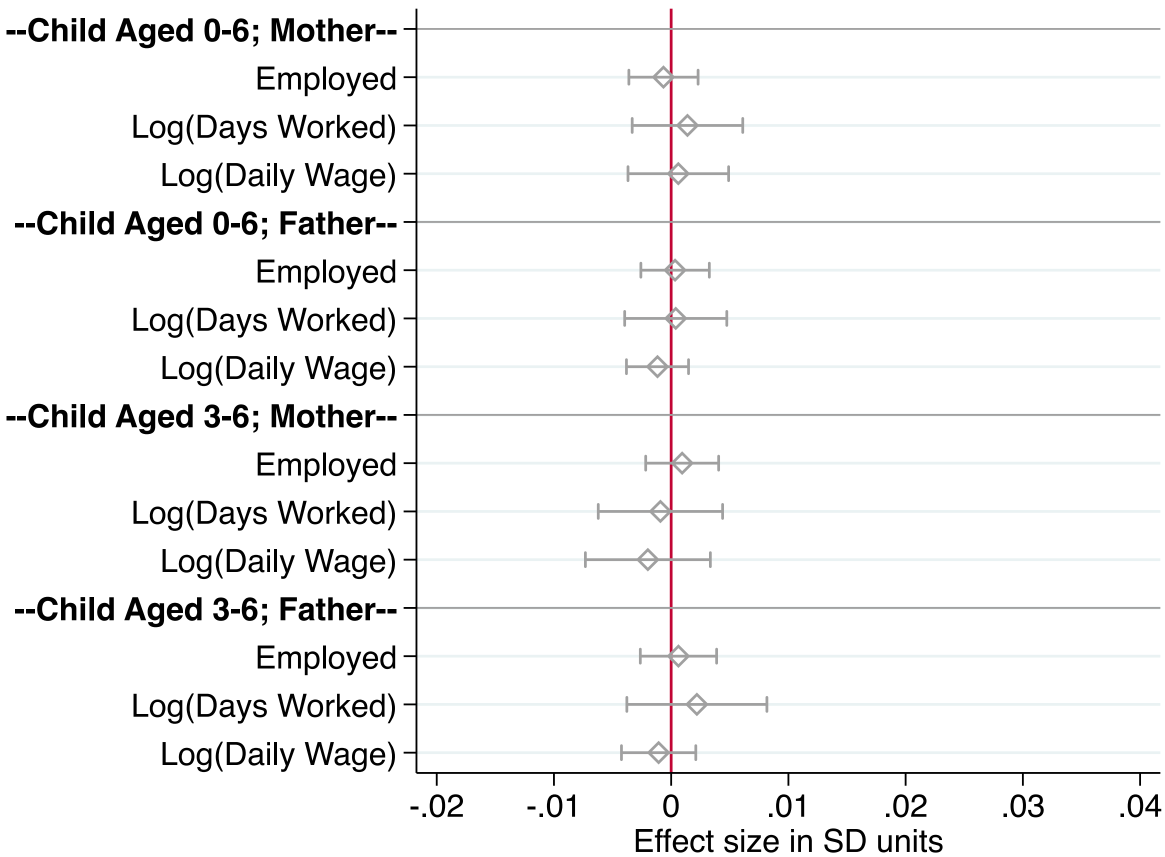
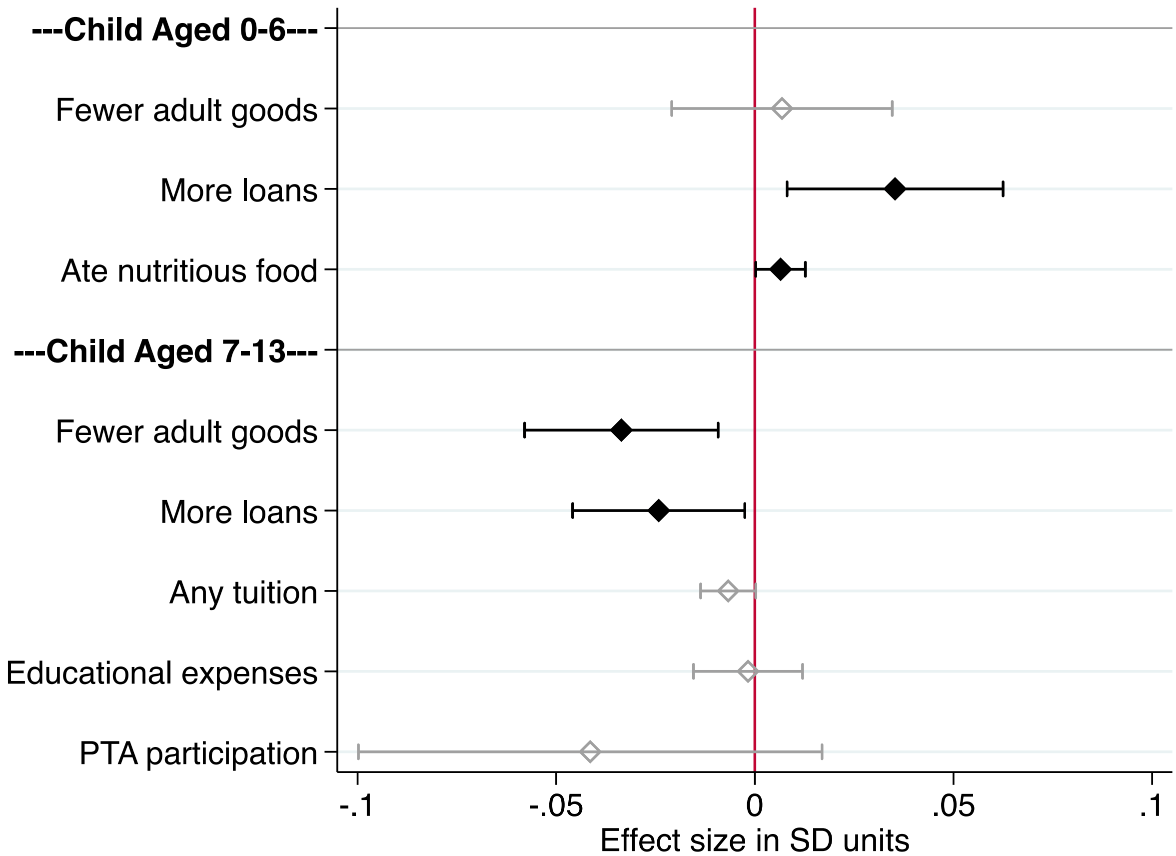
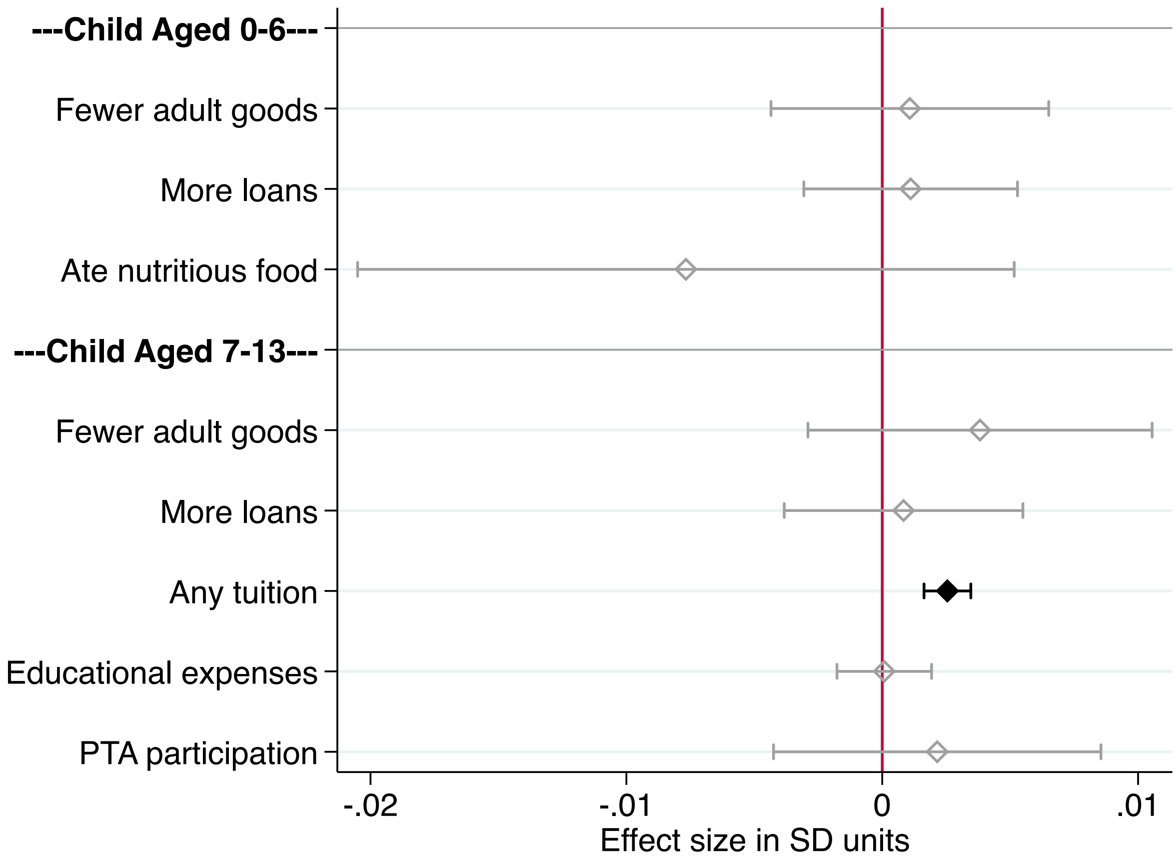


Figure 9: Intertemporal Reallocation of Parental Investments



Notes: 90% Confidence intervals shown for this figure.

Figure 10: Intertemporal Reallocation: Heterogeneity by Gender



Notes: 90% Confidence intervals shown for this figure.

Figure 11: Dynamic Complementarities with Rainfall Shocks

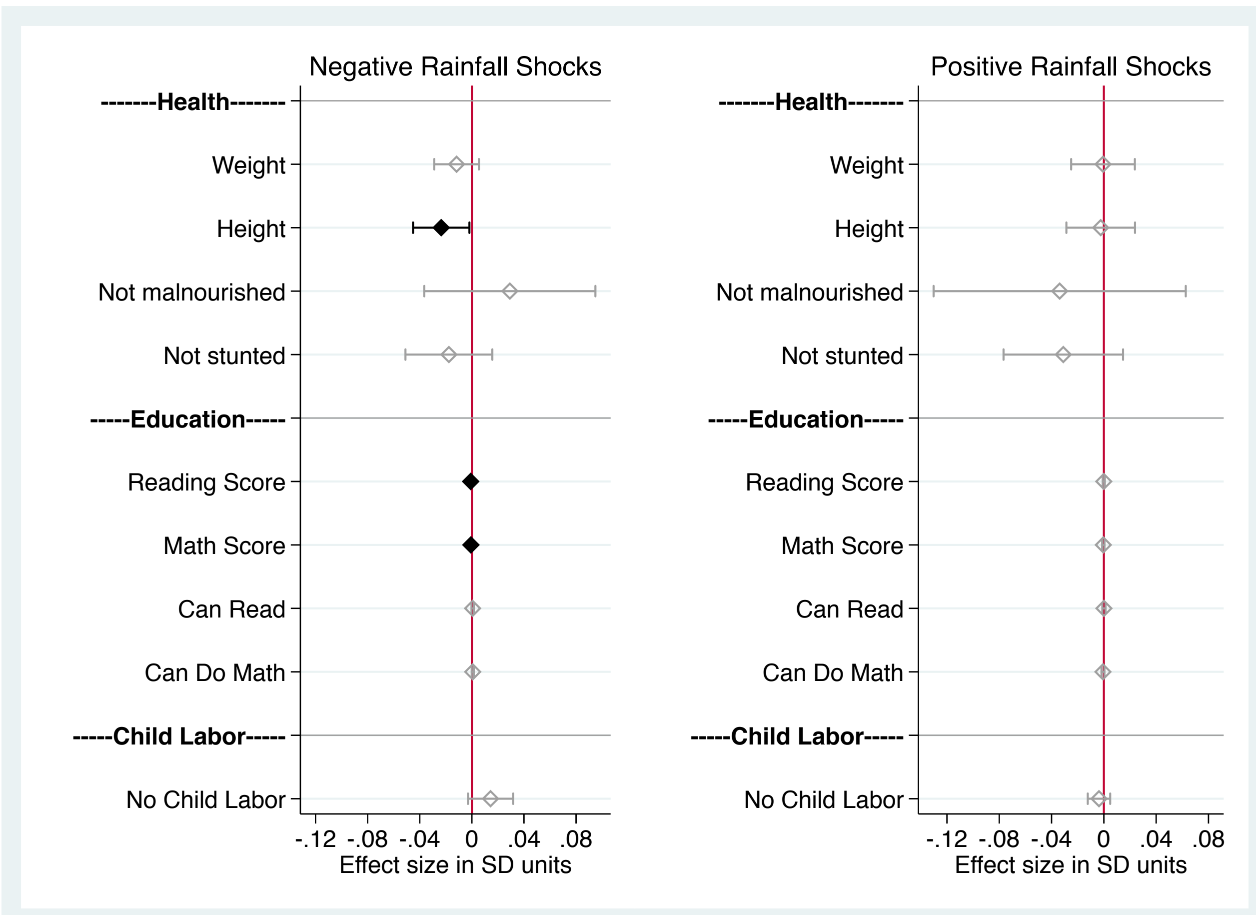


Figure 12: Intra-household Reallocation of Investments

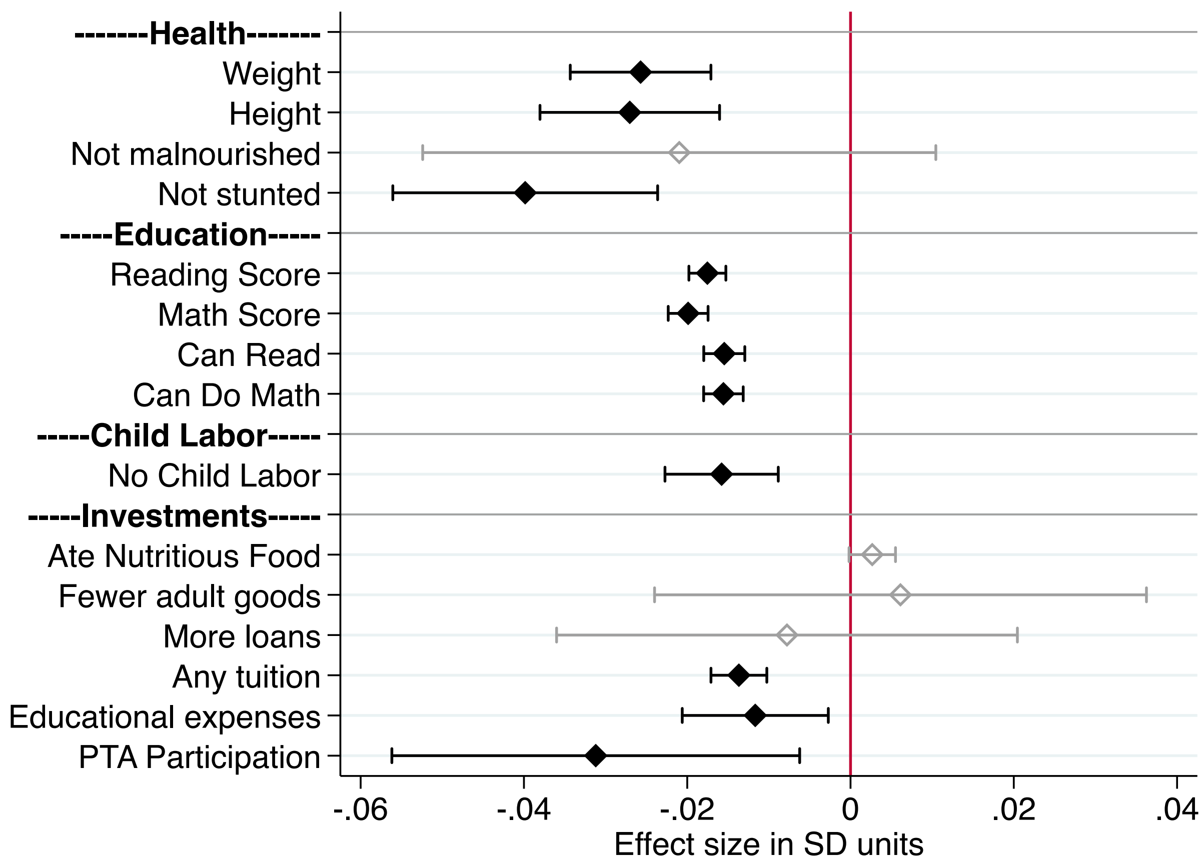


Figure 13: Intra-household Reallocation of Investments: Heterogeneity by Gender

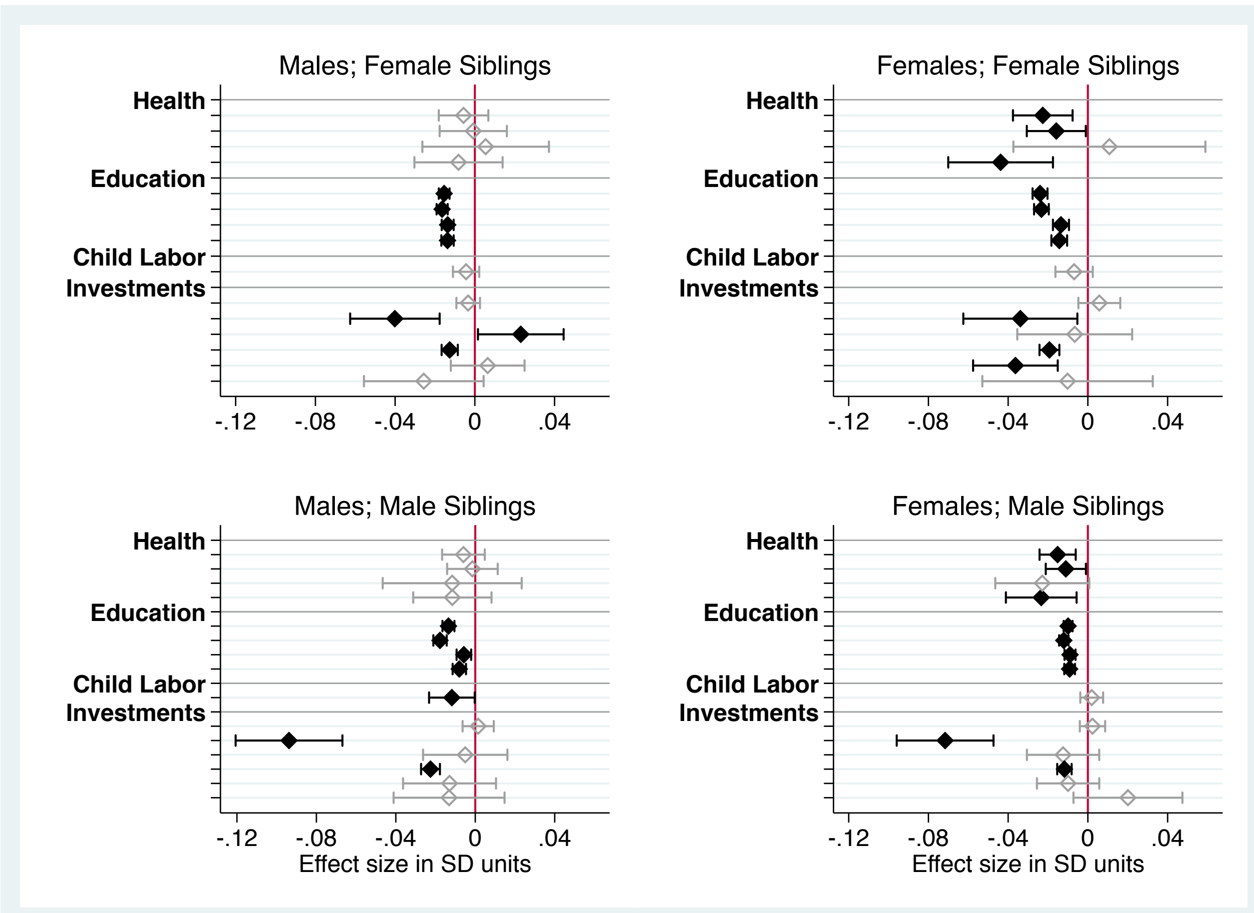


Figure B.1: Placebo Test: Malnutrition

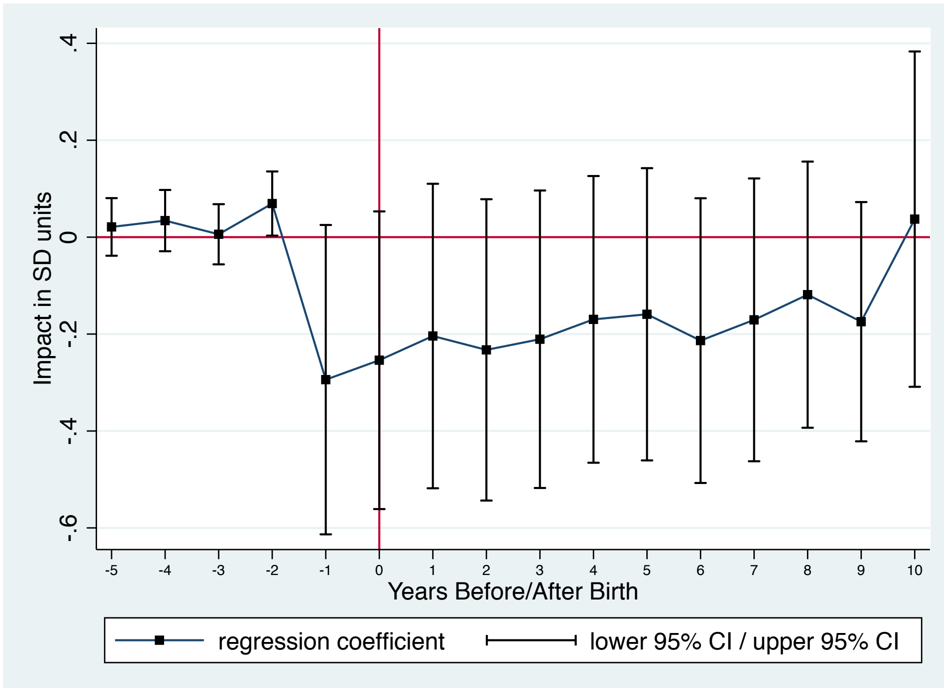


Figure B.2: Placebo Test: Can Read

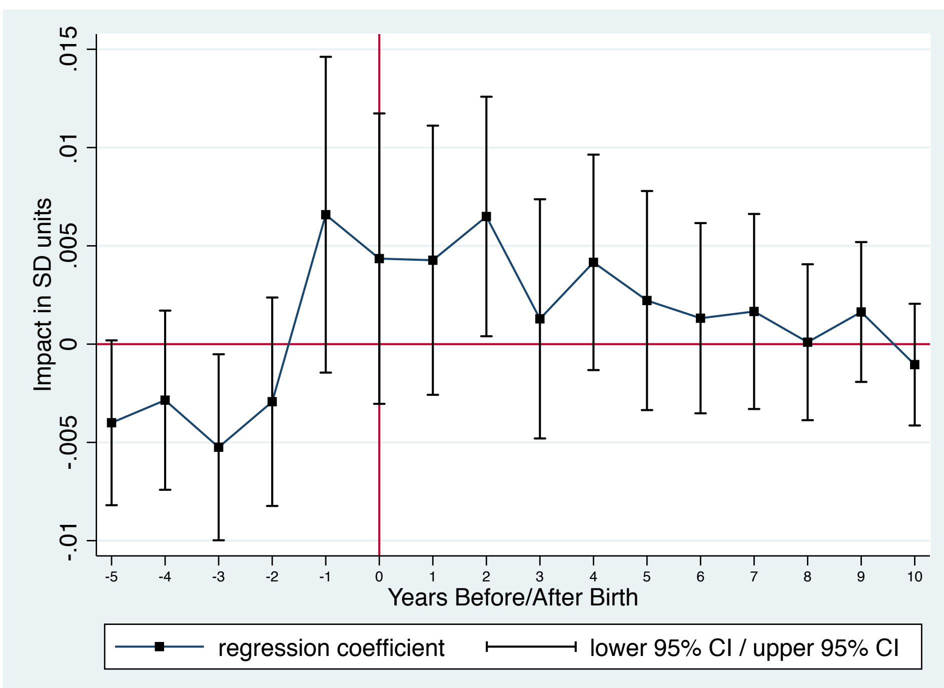


Figure B.3: Placebo Test: Can Do Math

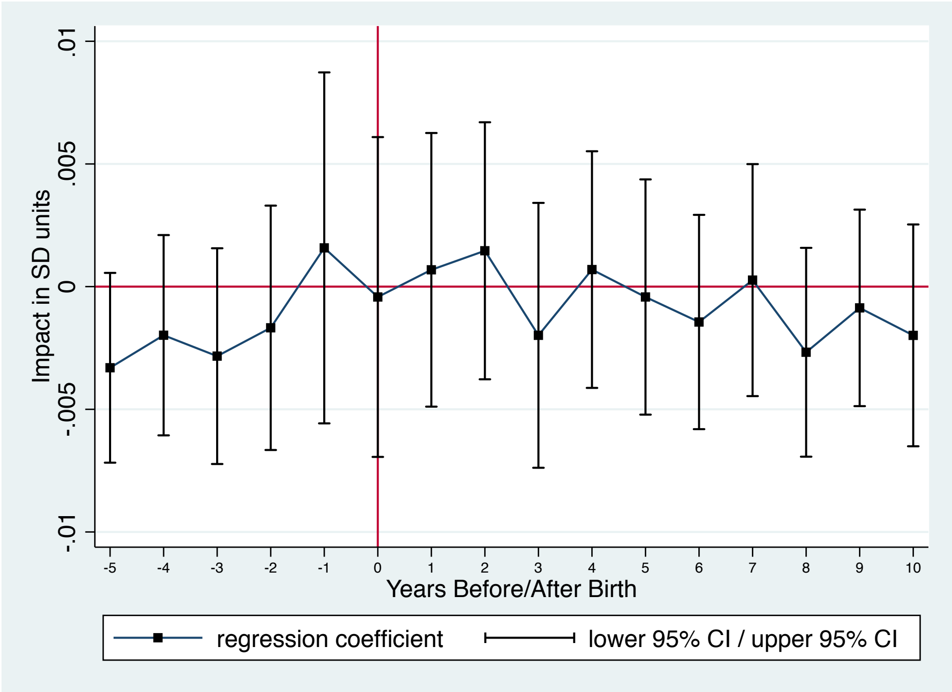


Figure B.4: Placebo Test: Anemic

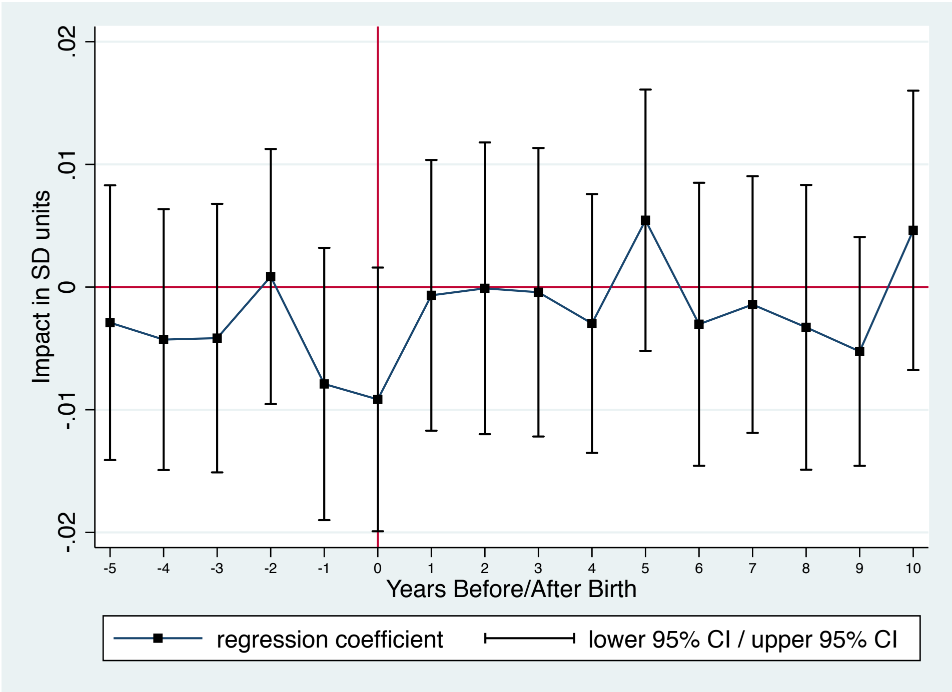


Figure B.5: Placebo Test: Log(Blood Glucose)

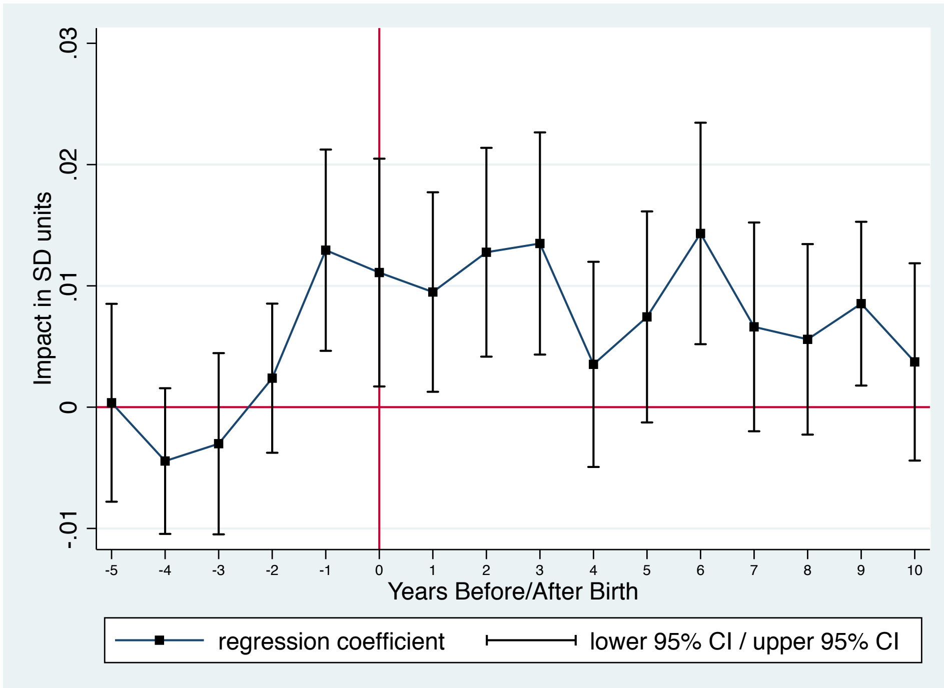


Figure B.6: Placebo Test: Hypoglycemia

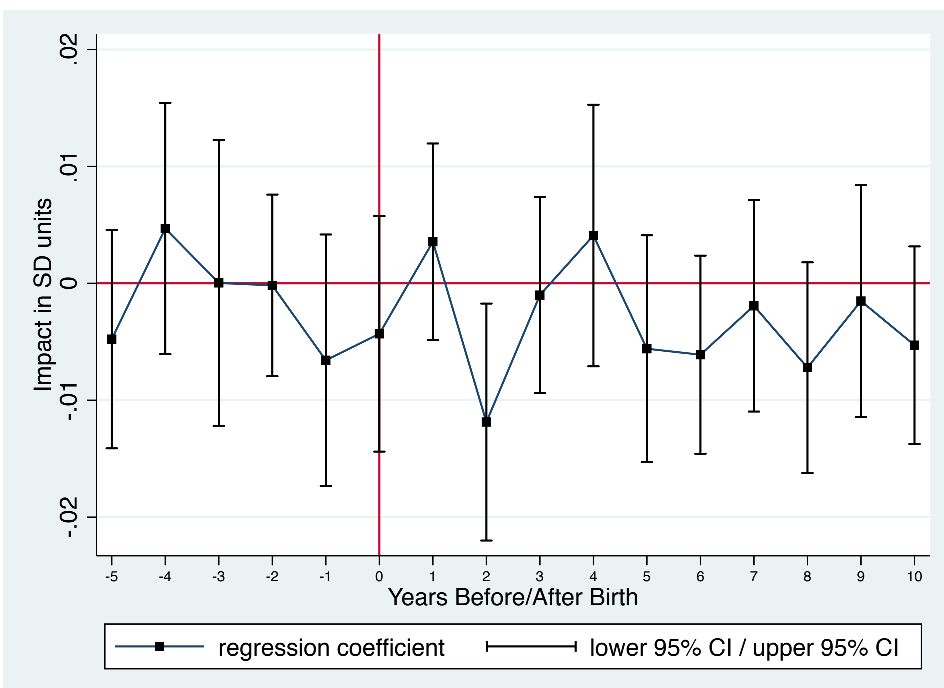


Figure B.7: Placebo Test: Any Short-Term Illness

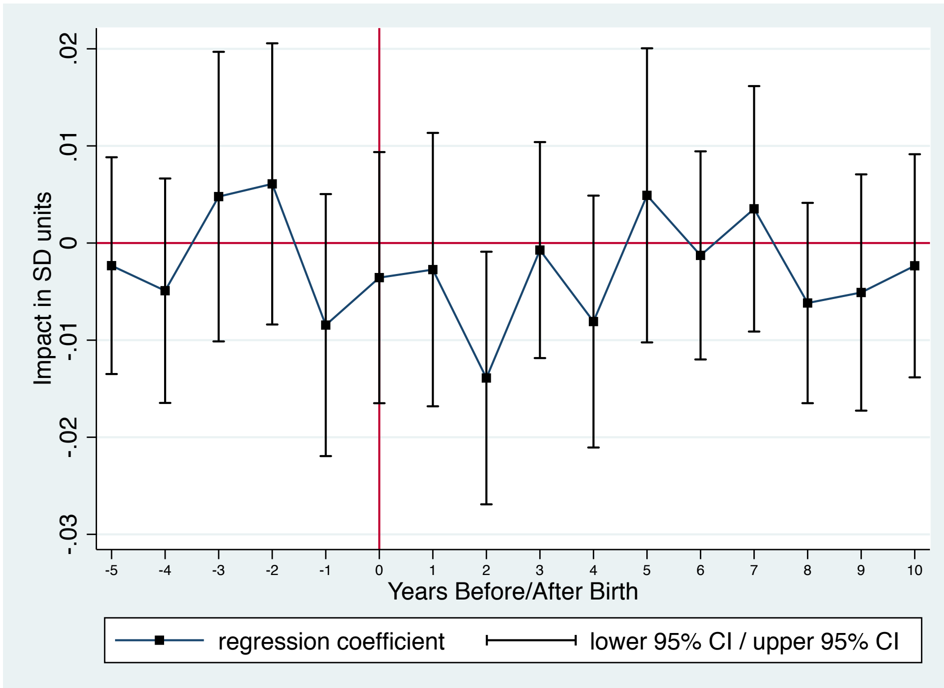


Figure B.8: Placebo Test: Smokes or Consumes Tobacco

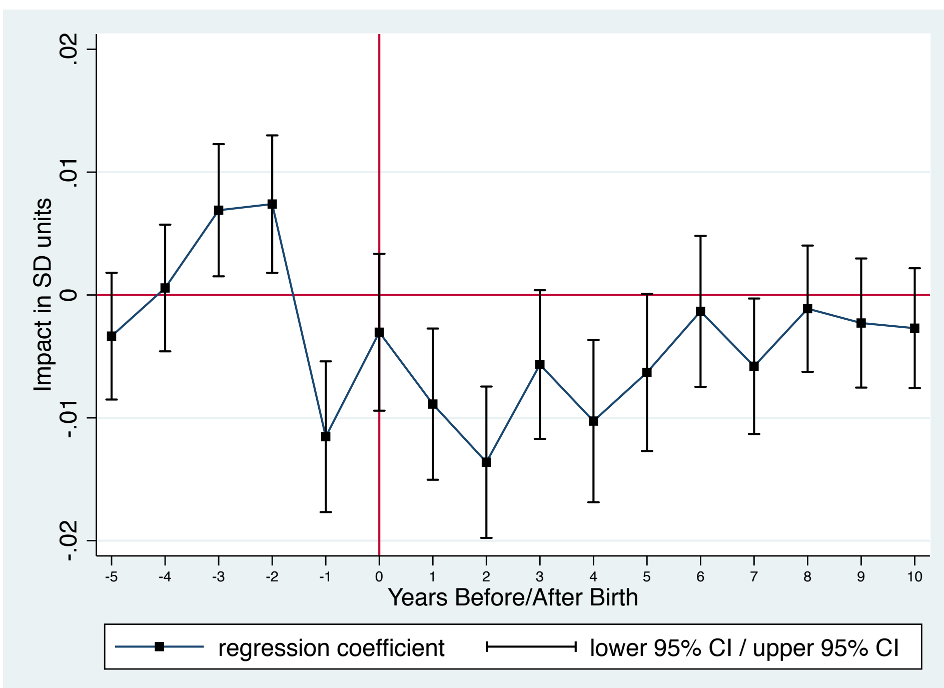


Figure B.9: Placebo Test: Consumes Alcohol

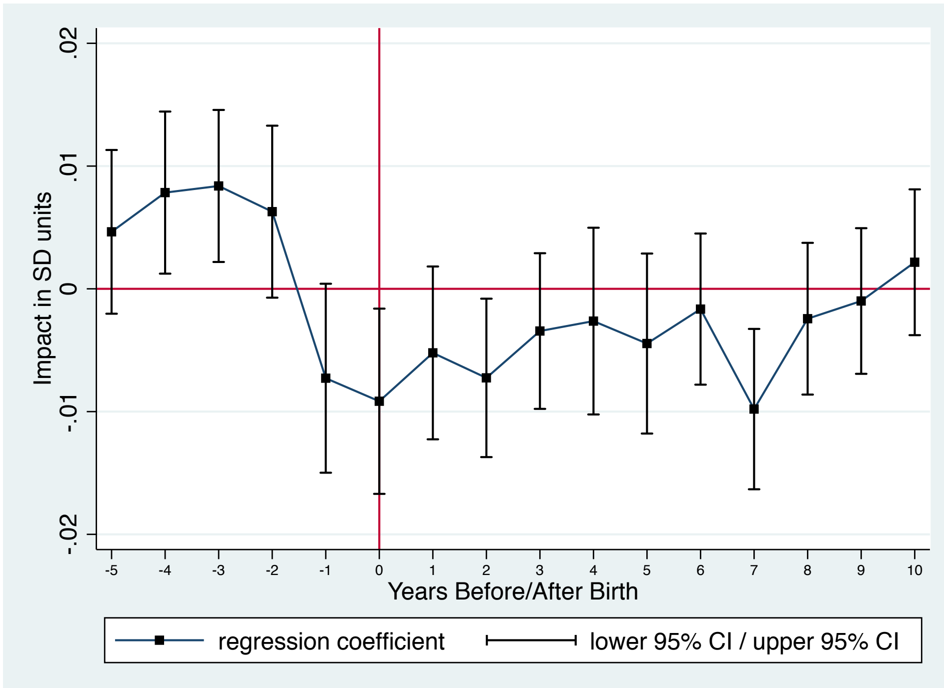


Figure B.10: Placebo Test: Literate

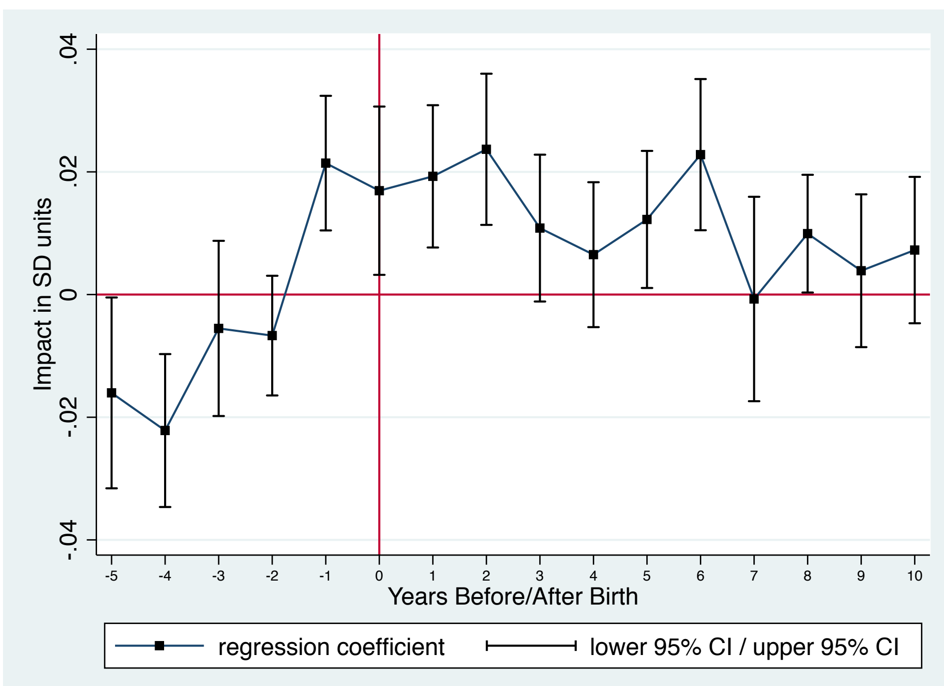


Figure B.11: Placebo Test: Years of Education

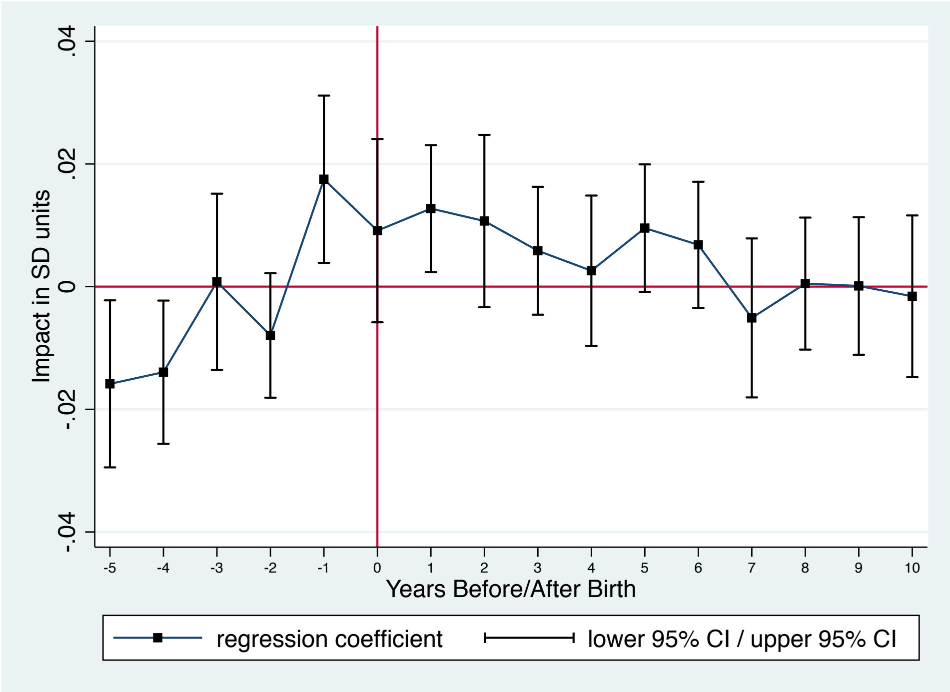


Figure B.12: Placebo Test: Unemployed

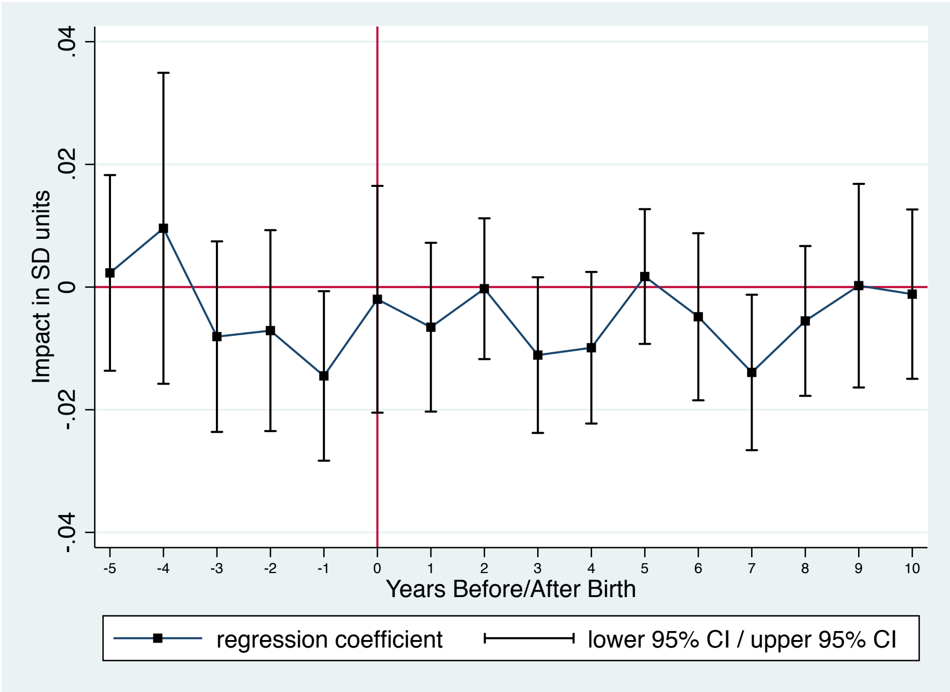


Figure B.13: Placebo Test: Log(Hourly Wage)

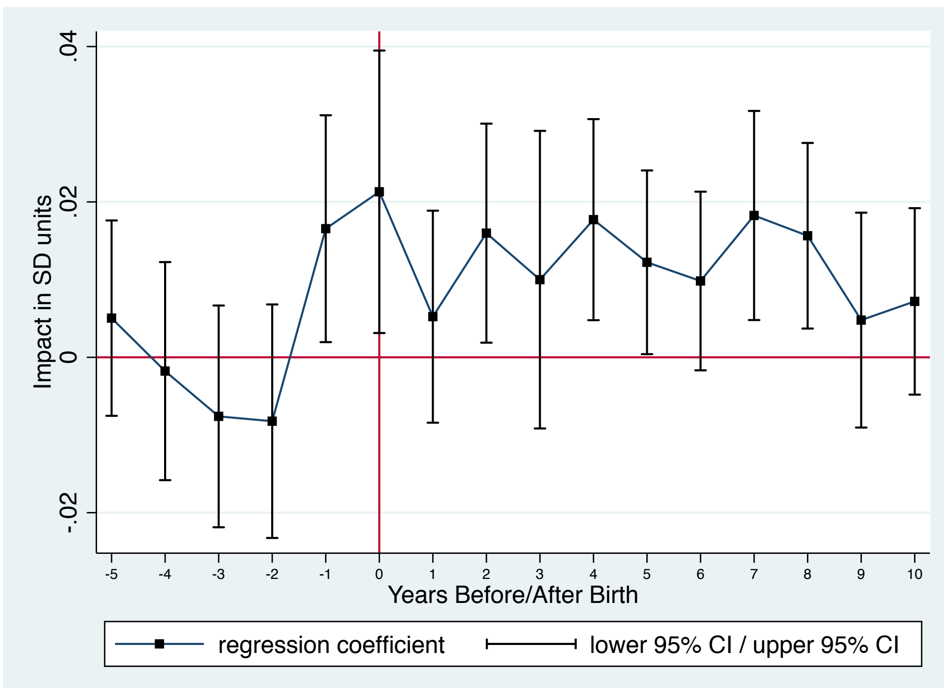


Figure C.1: Short-Term Impacts; Mid-Day Meal Controls

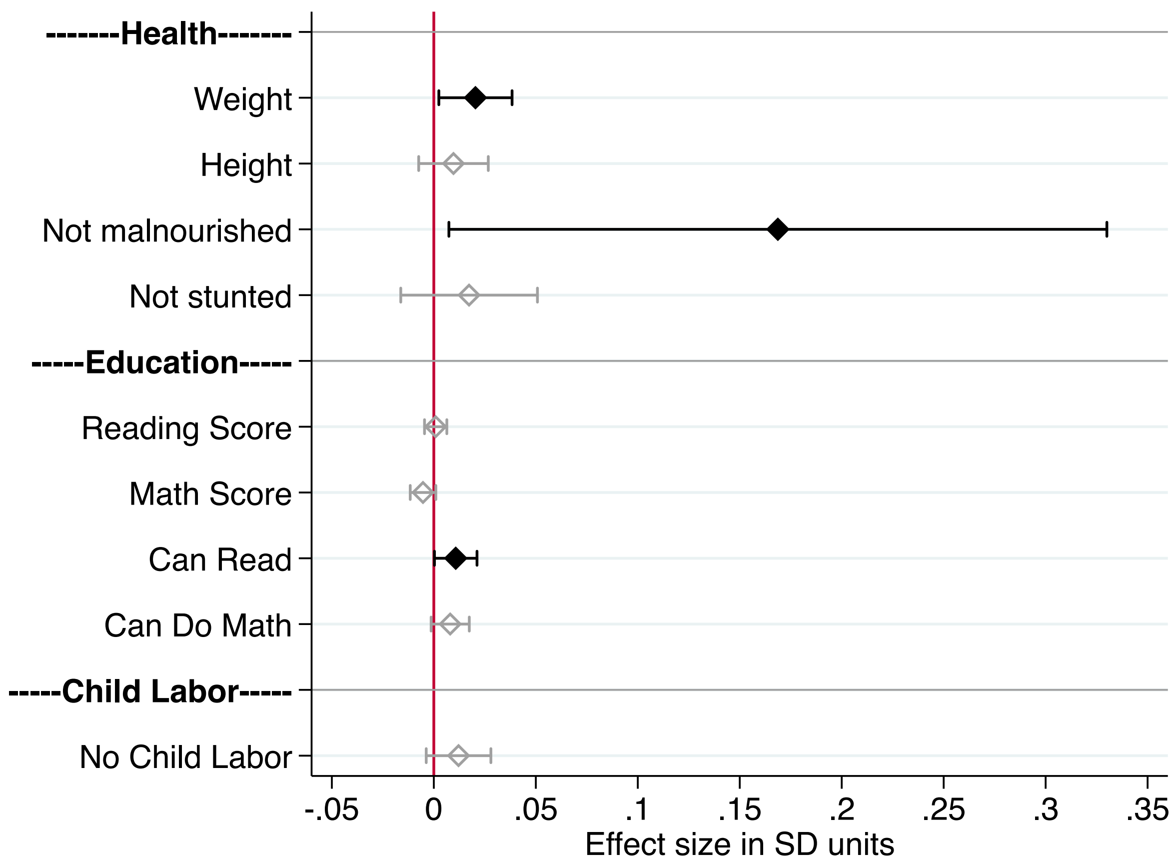


Figure C.2: Long-Term Impacts; Mid-Day Meal Controls

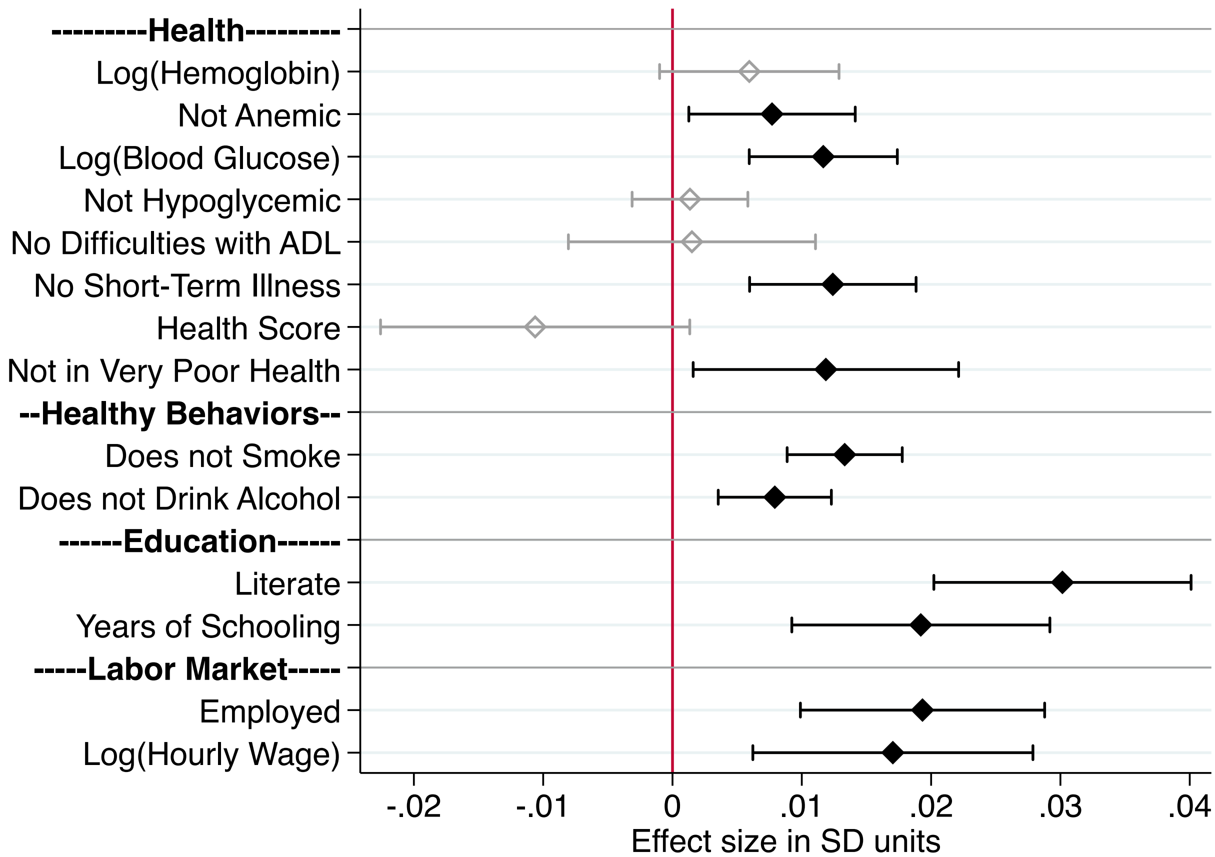


Figure C.3: Intertemporal Reallocation; Mid-Day Meal Controls

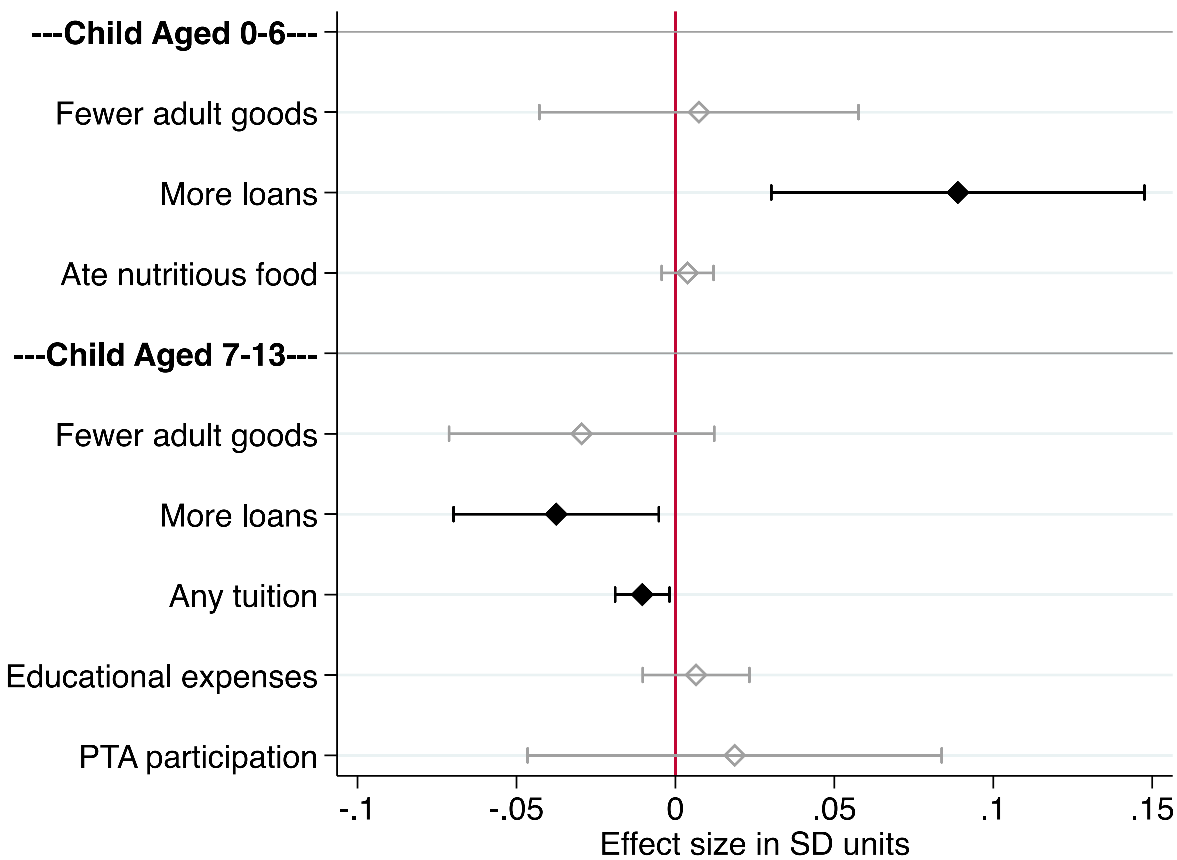


Figure C.4: Intra-household Reallocation; Mid-Day Meal Controls

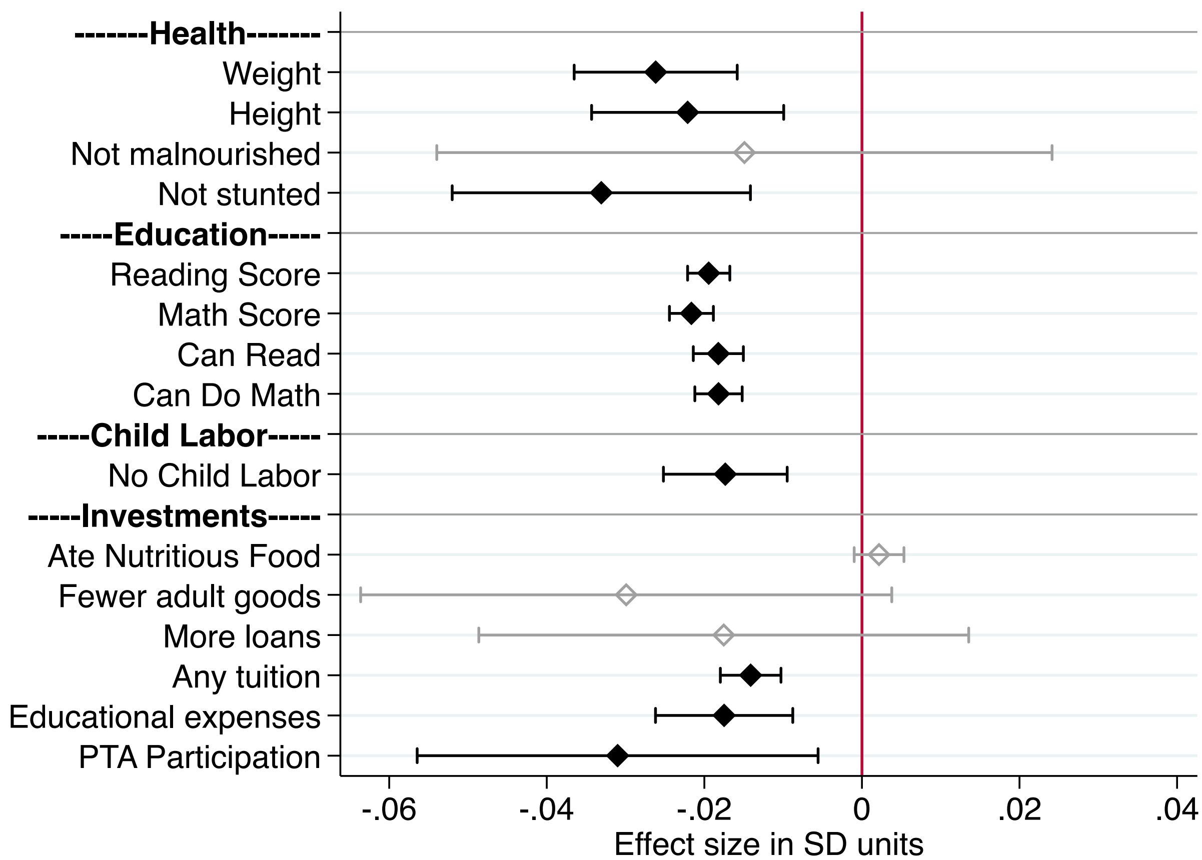


Table 1: Guidelines on Time Allocation During Operational Hours

Daily Tasks	Expected Time
Preschool Education	2 Hours
Preparation and Distribution of Supplementary Nutrition	30 Minutes
Treatment of Common Childhood Illnesses & Referral	30 Minutes
Filling up Records and Registers	30 Minutes
Total	**3.5 Hours**

Source: Handbook for Anganwadi Workers, National Institute for Public Cooperation and Child Development (2006).

Table 2: Summary of Key Datasets Used

Dataset	Years Covered	Geography Covered	Key Variables
ICDS Administrative Data	1975 - 2016	Rural + Urban	Location of centers, date of opening
National Family Health Survey (NFHS) Rounds 1, 2, and 4	1992 - 2016 (with gaps)	Rural + Urban	Health, healthy behaviors
India Human Development Survey (IHDS) Round 2	2011 - 2012	Rural + Urban	Education, health, wages, employment
National Sample Survey (NSS) Employment Rounds 55, 60, 61, 62, 64, 66, 68	1999 - 2012 (with gaps)	Rural + Urban	Parents' employment, child labor
National Sample Survey (NSS) Education Expenditure Rounds 64, 71	2007 - 2014 (with gaps)	Rural + Urban	Education expenditure
Annual Status of Education Report (ASER)	2006 - 2014	Rural only	Test scores
Census of India	1901 - 2016	Rural + Urban	Population
University of Delaware Rainfall Data	1900 - 2014	Rural + Urban	Rainfall

Table 3: Summary Statistics

Category	Variable	Mean	Std. Dev.	N
Panel A: Child Outcomes				
Health	Weight, Age 7-17 (kg)	32.85	11.8	34,032
	Height, Age 7-17 (m)	1.38	0.19	33,989
	Malnourished	0.32	0.47	12,604
	Stunted	0.31	0.46	33,989
Education	Reading test score (0-4)	2.66	1.44	4,709,681
	Math test score (0-4)	2.47	1.36	4,688,733
	Can read	0.89	0.31	4,709,681
	Can do math	0.89	0.31	4,688,733
Labor	Any child labor	0.02	0.13	493,894
Panel B: Adult Outcomes				
Health	Blood hemoglobin (g/dL)	11.77	1.66	182,930
	Anemic	0.12	0.33	182,929
	Blood glucose (mg/dL)	103.26	25.95	254,532
	Hypoglycemic	0.02	0.13	254,532
	Any difficulties with ADL	0.07	0.26	117,414
	Any short-term illness	0.14	0.35	117,414
	Subjective health score (1-5)	2.08	0.84	34,092
	Very poor health	0.004	0.061	34,092
Healthy Behaviors	Drinks alcohol	0.11	0.31	272,039
	Smokes or uses tobacco	0.21	0.4	272,036
Education	Literate	0.67	0.47	117,267
	Years of education	6.09	5.14	117,244
Labor	Hourly wage (Rs.)	25.14	30.8	45,298
	Unemployed	0.02	0.14	111,396
Panel C: Parental Investments				
Monetary	Child ate nutritious food	0.83	0.38	182,202
	Annual educational expenses (Rs.)	12,561	30,023	186,675
	Any tuition	0.18	0.39	3,260,790
Time	Parents participated in PTA	0.43	0.5	13,023
Panel D: Parental Employment				
Mother	Mother employed	0.31	0.46	220,712
	Mother weekly days worked	1.72	2.73	220,712
Father	Father employed	0.97	0.17	209,283
	Father weekly days worked	6.43	1.5	209,283

Table 4: Short-Run Program Impacts on Children

Panel A: Child Health (IHDS)	(1) Weight (Z-Score)	(2) Height (Z-Score)	(3) Malnourished (Z<-2)	(4) Stunted (Z<-2)
Program Intensity	0.0131*	0.00425	-0.0453**	-0.00872
	(0.00746)	(0.00940)	(0.0230)	(0.00722)
	[0.159]	[0.901]	[0.100]	[0.416]
Adjusted R^2	0.681	0.624	0.072	0.068
District sub-division FEs	Yes	Yes	Yes	Yes
Cohort x State FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	0	0	0.306	0.329
Observations	31,538	31,506	11,815	31,506

Panel B: Test Scores (ASER)	Reading Score (Z-Score)	Math Score (Z-Score)	Can Read	Can Do Math
Program Intensity	0.00187	-0.00315	0.00345***	0.00279***
	(0.00228)	(0.00265)	(0.00119)	(0.00106)
	[0.574]	[0.346]	[0.006]	[0.014]
Adjusted R^2	0.451	0.442	0.201	0.186
District sub-division FEs	Yes	Yes	Yes	Yes
Cohort x State FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	0	0	0.906	0.905
Observations	4,459,291	4,440,879	4,459,291	4,440,879

Panel C: Child Labor (NSS)	Any Child Labor
Program Intensity	-0.00167*
	(0.000925)
	[0.071]
Adjusted R^2	0.053
District sub-division FEs	Yes
Cohort x State FEs	Yes
Mean in district sub-divisions without program	0.019
Observations	346,963

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses and clustered by district sub-division.

P-values adjusted for multiple hypothesis testing via Bonferroni-Sankoh procedure in brackets.

Notes: Sample consists of children aged 7-17. Program intensity is measured as number of ICDS centers per 1,000 children aged 0-6. All regressions include controls for gender, birth order, gender x birth order interaction, quadratic population polynomial, caste, religion, and mother's education.

Table 5: Program Impact on Adult Health & Healthy Behaviors

Panel A: Biomarker Data (NFHS)	(1) Log (Hemoglobin)	(2) Anemic	(3) Log(Blood Glucose)	(4) Hypoglycemic
Program Intensity	0.000894*	-0.00244**	0.00269***	-0.000737**
	(0.000505)	(0.00104)	(0.000638)	(0.000339)
	[0.246]	[0.065]	[0.003]	[0.087]
Adjusted R^2	0.063	0.033	0.086	0.024
District sub-division FEs	Yes	Yes	Yes	Yes
Cohort x State FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	4.767	0.112	4.635	0.016
Observations	174,329	174,329	241,478	241,478
Panel B: Self-Reported Data (IHDS)	Any Difficulties with ADL	Any Short-Term Illness	Health Score	Very Poor Health
Program Intensity	0.000577	-0.00335***	-0.00653	-0.000460**
	(0.000961)	(0.00104)	(0.00442)	(0.000198)
	[0.797]	[0.002]	[0.260]	[0.040]
Adjusted R^2	0.222	0.085	0.227	0.018
District sub-division FEs	Yes	Yes	Yes	Yes
Cohort x State FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	0.101	0.151	2.106	0.004
Observations	113,807	113,807	29,613	29,613
Panel C: Healthy Behaviors (NFHS)	Smokes or Uses Tobacco	Consumes Alcohol		
Program Intensity	-0.00514***	-0.00255***		
	(0.000831)	(0.000793)		
	[0.002]	[0.002]		
Adjusted R^2	0.376	0.264		
District sub-division FEs	Yes	Yes		
Cohort x State FEs	Yes	Yes		
Mean in district sub-divisions without program	0.273	0.138		
Observations	258,408	258,411		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses and clustered by district sub-division.

P-values adjusted for multiple hypothesis testing via Bonferroni-Sankoh procedure in brackets.

Notes: Sample for columns (3) - (4) of panel B consists only of adult women. Program intensity is measured as number of ICDS centers per 1,000 children aged 0-6. All regressions include controls for quadratic population polynomial, caste, and religion.

Table 6: Program Impact on Education & Labor Market Outcomes

	(1) Literate	(2) Years of Schooling	(3) Unemployed	(4) Log(Hourly Wage)
Program Intensity	0.0117***	0.0646***	-0.00194***	0.0115***
	(0.00182)	(0.0176)	(0.000449)	(0.00233)
	[0.002]	[0.002]	[0.002]	[0.002]
Adjusted R^2	0.339	0.429	0.064	0.382
District sub-division FEs	Yes	Yes	Yes	Yes
Cohort x State FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	0.604	5.193	0.017	2.952
Dataset	IHDS	IHDS	IHDS	IHDS
Observations	113,690	113,669	108,002	43,834

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses and clustered by district sub-division.

P-values adjusted for multiple hypothesis testing via Bonferroni-Sankoh procedure in brackets.

Notes: Program intensity is measured as number of ICDS centers per 1,000 children aged 0-6. All regressions include controls for gender, quadratic population polynomial, caste, and religion.

Table 7: Impact on Parental Employment & Wages

	Mother			Father		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Child Aged 0-6 (NSS)	Employed	Log(Days Worked)	Log(Daily Wage)	Employed	Log(Days Worked)	Log(Daily Wage)
Program Intensity	-0.000310	0.000571	0.000533	0.0000581	0.0000760	-0.000974
	(0.000713)	(0.000988)	(0.00191)	(0.000259)	(0.000433)	(0.00113)
Adjusted R^2	0.193	0.197	0.376	0.031	0.069	0.431
District sub-division FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cohort x State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	0.341	1.663	4.505	0.969	1.89	5.24
Observations	190,290	59,456	22,391	180,054	174,530	85,879
Panel B: Child Aged 3-6 (NSS)	Employed	Log(Days Worked)	Log(Daily Wage)	Employed	Log(Days Worked)	Log(Daily Wage)
Program Intensity	0.000450	-0.000374	-0.00171	0.000107	0.000426	-0.000899
	(0.000760)	(0.00110)	(0.00233)	(0.000286)	(0.000591)	(0.00136)
Adjusted R^2	0.202	0.195	0.371	0.031	0.072	0.431
District sub-division FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cohort x State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	0.36	1.668	4.479	0.969	1.89	5.25
Observations	133,259	44,131	16,722	125,704	121,898	58,964

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses and clustered by district sub-division.

Notes: Program intensity is measured as number of ICDS centers per 1,000 children aged 0-6. All regressions include controls for gender, birth order, gender x birth order interaction, quadratic population polynomial, caste, religion, and dummies for the quarter of the year in which the survey was conducted, to account for seasonality in employment.

Table 8: Intertemporal Reallocation of Investments

Panel A: Adult Goods Consumption and Debt				
	Child Aged 0-6:		Child Aged 7-13:	
	(1)	(2)	(3)	(4)
	Log(Per Capita Consumption on Adult Goods)	Any Loan in Past Five Years	Log(Per Capita Consumption on Adult Goods)	Any Loan in Past Five Years
Program Intensity	-0.00675	0.0176**	0.0322**	-0.0121*
	(0.0166)	(0.00824)	(0.0142)	(0.00656)
Adjusted R^2	0.301	0.188	0.301	0.217
District sub-division FEs	Yes	Yes	Yes	Yes
Cohort x State FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	3.765	0.521	3.765	0.521
Dataset	IHDS	IHDS	IHDS	IHDS
Observations	15,679	23,239	16,742	25,301

Panel B: Direct Measures of Investment				
	Child Aged 0-6:	Child Aged 7-13:		
	Child Ate Nutritious Food and Drink	Any Tuition	Log(Educational Expenditure)	Parents Participated in PTA
Program Intensity	0.00242*	-0.00250**	-0.00239	-0.0206
	(0.00142)	(0.00120)	(0.0116)	(0.0176)
Adjusted R^2	0.192	0.225	0.683	0.294
District sub-division FEs	Yes	Yes	Yes	Yes
Cohort x State FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	0.833	0.158	7.678	0.447
Dataset	NFHS	ASER	NSS	IHDS
Observations	177,116	3,105,805	93,884	12,102

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses and clustered by district sub-division.

Notes: Program intensity is measured as number of ICDS centers per 1,000 children aged 0-6. All regressions include controls for gender, birth order, gender x birth order interaction, quadratic population polynomial, caste, religion, and provision of any free textbooks, stationery, meals, or education.

Table 9: Dynamic Complementarities - Negative Rainfall Shocks

Panel A: Impact on Child Health				
	(1) Weight (Z-Score)	(2) Height (Z-Score)	(3) Malnourished (Z<-2)	(4) Stunted (Z<-2)
Program Intensity	0.116*	0.0597	-0.356**	-0.0781
	(0.0604)	(0.0725)	(0.180)	(0.0567)
Program Intensity ∗	-0.0117	-0.0235*	-0.0134	0.00828
Negative Rainfall Shock	(0.0104)	(0.0131)	(0.0184)	(0.00951)
Adjusted R^2	0.681	0.624	0.072	0.068
Mean in district sub-divisions without program	0	0	0.306	0.329
Observations	31,538	31,506	11,815	31,506

Panel B: Impact on Test Scores				
	Reading Score (Z-Score)	Math Score (Z-Score)	Can Read	Can Do Math
Program Intensity	0.00247	-0.00241	0.00321***	0.00256**
	(0.00228)	(0.00265)	(0.00120)	(0.00107)
Program Intensity ∗	-0.000878**	-0.000735*	0.000175	0.000196
Negative Rainfall Shock	(0.000392)	(0.000414)	(0.000158)	(0.000145)
Adjusted R^2	0.451	0.442	0.201	0.186
Mean in district sub-divisions without program	0	0	0.906	0.905
Observations	4,459,291	4,440,879	4,459,291	4,440,879

Panel C: Impact on Child Labor	
	Any Child Labor
Program Intensity	-0.0126*
	(0.00726)
Program Intensity ∗	-0.00196
Negative Rainfall Shock	(0.00144)
Adjusted R^2	0.053
Mean in district sub-divisions without program	0.019
Observations	346,963

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses and clustered by district sub-division.

Notes: All regressions include district sub-division fixed effects and cohort x state fixed effects. Program intensity is measured as number of ICDS centers per 1,000 children aged 0-6. All regressions include controls for gender, birth order, gender x birth order interaction, quadratic population polynomial, caste, religion, and mother's education.

Table 10: Dynamic Complementarities - Positive Rainfall Shocks

Panel A: Impact on Child Health				
	(1) Weight (Z-Score)	(2) Height (Z-Score)	(3) Malnourished (Z<-2)	(4) Stunted (Z<-2)
Program Intensity	0.104*	0.0350	-0.368**	-0.0764
	(0.0608)	(0.0772)	(0.185)	(0.0593)
Program Intensity $*$ Positive Rainfall Shock	-0.000647	-0.00243	0.0156	0.0146
	(0.0148)	(0.0159)	(0.0270)	(0.0130)
Adjusted R^2	0.681	0.624	0.072	0.068
Mean in district sub-divisions without program	0	0	0.306	0.329
Observations	31,538	31,506	11,815	31,506

Panel B: Impact on Test Scores				
	Reading Score (Z-Score)	Math Score (Z-Score)	Can Read	Can Do Math
Program Intensity	0.00187	-0.00300	0.00344***	0.00287***
	(0.00228)	(0.00267)	(0.00121)	(0.00108)
Program Intensity $*$ Positive Rainfall Shock	-0.0000686	-0.000414	0.0000175	-0.000207
	(0.000509)	(0.000539)	(0.000221)	(0.000205)
Adjusted R^2	0.451	0.442	0.201	0.186
Mean in district sub-divisions without program	0	0	0.906	0.905
Observations	4,459,291	4,440,879	4,459,291	4,440,879

Panel C: Impact on Child Labor	
	Any Child Labor
Program Intensity	-0.0139*
	(0.00746)
Program Intensity $*$ Positive Rainfall Shock	0.000510
	(0.000712)
Adjusted R^2	0.053
Mean in district sub-divisions without program	0.019
Observations	346,963

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses and clustered by district sub-division.

Notes: All regressions include district sub-division fixed effects and cohort x state fixed effects. Program intensity is measured as number of ICDS centers per 1,000 children aged 0-6. All regressions include controls for gender, birth order, gender x birth order interaction, quadratic population polynomial, caste, religion, and mother's education.

Table 11: Intra-household Reallocation - Impact on Child Outcomes

Panel A: Impact on Child Health	(1) Weight (Z-Score)	(2) Height (Z-Score)	(3) Malnourished (Z<-2)	(4) Stunted (Z<-2)
Average Program Intensity of Siblings	-0.0256***	-0.0269***	0.00981	0.0187***
	(0.00438)	(0.00560)	(0.00738)	(0.00390)
	[0.002]	[0.002]	[0.364]	[0.002]
Adjusted R^2	0.693	0.636	0.074	0.092
District sub-division x Cohort x Age FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	0	0	0.306	0.329
Observations	28,708	28,678	10,834	28,678

Panel B: Impact on Test Scores	Reading Score (Z-Score)	Math Score (Z-Score)	Can Read	Can Do Math
Average Program Intensity of Siblings	-0.0175***	-0.0199***	-0.00450***	-0.00456***
	(0.00115)	(0.00124)	(0.000373)	(0.000362)
	[0.002]	[0.002]	[0.002]	[0.002]
Adjusted R^2	0.488	0.486	0.270	0.271
District sub-division x Cohort x Age FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	0	0	0.906	0.905
Observations	3,751,115	3,735,251	3,751,115	3,735,251

Panel C: Impact on Child Labor	Any Child Labor
Average Program Intensity of Siblings	0.00216***
	(0.000483)
	[0.000]
Adjusted R^2	0.192
District sub-division x Cohort x Age FEs	Yes
Mean in district sub-divisions without program	0.019
Observations	335,066

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses and clustered by district sub-division.

P-values adjusted for multiple hypothesis testing via Bonferroni-Sankoh procedure in brackets.

Notes: Average program intensity of siblings is measured as number of ICDS centers per 1,000 children aged 0-6. All regressions include controls for gender, birth order, gender x birth order interaction, quadratic population polynomial, caste, religion, and mother's education.

Table 12: Intra-household Reallocation - Impact on Parental Investments

Panel A: Adult Goods Consumption and Debt				
	Child Aged 0-6:		Child Aged 7-13:	
	(1) Log(Per Capita Consumption on Adult Goods)	(2) Any Loan in Past Five Years	(3) Log(Per Capita Consumption on Adult Goods)	(4) Any Loan in Past Five Years
Average Program Intensity of Siblings	-0.00604	-0.00388	0.0188*	-0.00436
	(0.0151)	(0.00717)	(0.0100)	(0.00441)
	[0.904]	[0.831]	[0.118]	[0.542]
Adjusted R^2	0.292	0.181	0.299	0.214
District sub-division x Cohort x Age FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	3.765	0.521	3.765	0.521
Dataset	IHDS	IHDS	IHDS	IHDS
Observations	11,849	17,639	15,302	23,351

Panel B: Direct Measures of Investment				
	Child Aged 0-6:	Child Aged 7-13:		
	Child Ate Nutritious Food and Drink	Any Tuition	Log(Educational Expenditure)	Parents Participated in PTA
Average Program Intensity of Siblings	0.000994*	-0.00499***	-0.0185***	-0.0155**
	(0.000541)	(0.000636)	(0.00657)	(0.00632)
	[0.066]	[0.000]	[0.005]	[0.014]
Adjusted R^2	0.182	0.244	0.714	0.285
District sub-division x Cohort x Age FEs	Yes	Yes	Yes	Yes
Mean in district sub-divisions without program	0.833	0.158	7.678	0.447
Dataset	NFHS	ASER	NSS	IHDS
Observations	105,238	2,579,242	61,193	11,114

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses and clustered by district sub-division.

P-values adjusted for multiple hypothesis testing via Bonferroni-Sankoh procedure in brackets.

Notes: Average program intensity of siblings is measured as number of ICDS centers per 1,000 children aged 0-6. All regressions include controls for gender, birth order, gender x birth order interaction, quadratic population polynomial, caste, religion, and provision of any free textbooks, stationery, meals, or education.

Table 13: Cost-Benefit Analysis

	Cost (Rs.)	Direct Benefit (Rs.)	Indirect Costs (Rs.)	IRR (Direct Impact Only)	IRR (Direct & Indirect Impacts)
Retirement at Age 50	4,554	7,746	610	8.1%	7.3%
Retirement at Age 55	4,554	8,068	636	8.2%	7.4%
Retirement at Age 60	4,554	8,321	656	8.3%	7.5%

Notes: A discount rate of 5% is used to value the direct and indirect impacts of the program.