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Do social protection schemes improve adolescent girls´ schooling and health? Evidence from the implementation of the Sabla scheme in Andhra Pradesh

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Abstract

As part of the ongoing discussion about social protection schemes, this is the first academic study that examines whether the targeted multi-dimensional Sabla scheme in Andhra Pradesh has a positive impact on health and schooling outcomes of adolescent girls. We follow several strategies to produce estimates that deal with non-random program placement, finally using average treatment effects on the treated obtained through Propensity Score Matching and Differences-in-Differences to study the impact of the program. Results suggest that the scheme fails to improve the two studied outcomes and even impacts schooling outcomes negatively. Instead, it has a positive impact on the hours the treated girls spend working.

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1. Introduction

Social protection schemes are becoming increasingly prominent in low-and middle-income countries to address child development with nutrition and schooling, extreme poverty, and vulnerability of households (Banerjee et al., 2022; World Bank, 2018; Borga & D´Ambrosio, 2021). Their presence is growing worldwide as many of these countries are becoming wealthier with substantially larger tax bases. Therefore, increasing attention to the unique challenges in developing social protection schemes is crucial. To design targeted policies and allocate appropriate programs effectively, it is imperative to transition from a holistic view of societies to a nuanced understanding of their distinct subgroups (Banerjee et al., 2022).

One important subgroup which is only scarcely reflected in the literature is that of adolescents[1]. This is particularly important in India as it possesses the largest adolescent population share in the world with 20 percent of the population – an immense group given India's 1.3 billion strong population (United Nations, 2022). Furthermore, India displays significant nutritional and educational deprivation and gender inequalities within an entrenched patriarchal context (Vikram & Chindarkar, 2020). This leads to the fact that around 43 percent of adolescent girls (AG) drop out before the completion of their secondary education due to responsibilities in the household, marriage, or perceived limited relevance of education for employability by the households (United Nations, 2022). Critical interventions in leveraging the potential of AG include various ambitious goals reaching from improving equity in schooling, to nutrition and empowerment.

Several policies and integrated schemes involve multiple inputs and programmatic objectives, but only very little is studied about the effectiveness of the multifaceted nature of those interventions. Most policy evaluations focus only on one input or objective (Delavallade et al.,

[1] Adolescence is referred to ages between 13 and 19 (Himaz, 2018).

2021). In the most recent literature, mainly schemes in the form of conditional cash transfers are studied (Tagliati, 2022).

With this paper, we intend to fill some of these evidence gaps on social protection by studying an integrated scheme specifically targeting *adolescent girls* (AG) which is *multi-dimensional* in terms of its multiple inputs and programmatic objectives. In this approach we study the question: Do multi-dimensional social protection schemes improve AG schooling, health, and empowerment components? Our paper adds to the growing literature which attempts to measure the effectiveness of social policies. It goes beyond assessing the general impact of poverty alleviation programs by focusing on the effects on the specific subgroup of AG in the highly relevant Indian context. Furthermore, we provide evidence on an integrated program in a development country for which evidence is scarce (Vikram & Chindarkar, 2020). Moreover, it is the first analysis in academic literature[2] evaluating the effects of the Rajiv Gandhi Scheme for Empowerment of Adolescent Girls (Sabla) which represents a centrally sponsored scheme aiming to empower AG through nutrition, health care, and life skills education across India.

To uncover evidence on how this scheme affects schooling and health outcomes, as well as empowerment of AG in the medium term[3], we use a rich panel data set from the Young Lives Survey (YL) allowing us to compare the same individual girls over three time periods. To tackle estimation bias and to ensure the robustness of our results, we conduct our quantitative analysis with several distinct models: ordinary least square (OLS), propensity score matching (PSM), difference-in-differences (DID), finally leading us to DID combined with PSM using kernel matching.

[2] To our knowledge, there only exist 3 minor studies on the scheme which all do not use econometric approaches to allow for causal unbiased inference and provide more descriptive insights. Furthermore, the quality of their underlying data sources cannot be assessed due to a lack of transparency.
[3] Referring to 3 years for the Sabla complete scheme treatment variable and to 3-4 years for the nutrition component only variable.

The main estimation results indicate that Sabla fails to produce a positive impact on health and schooling outcomes, while having an ambiguous impact on the empowerment dimension, mainly due to a significant increase in paid work activity. Our findings align with previous research on diverse multi-dimensional integrated social protection schemes, which often fail to demonstrate a positive impact on the desired outcomes (Kandpal, 2011; Lokshin et al., 2005).They differ from findings of studies on other girl-targeting schemes in the form of school-feeding programs or conditional cash transfers which mainly find positive impacts on schooling and health outcomes (Kazianga et al., 2014; Tagliati, 2022). However, it is important to note that the design of these programs differs from that of Sabla. Unlike Sabla, which allows for take-home rations and does not involve conditionalities or cash transfers, these programs are typically provided exclusively within school settings and include a conditional cash component to female decision makers within households.

Based on our findings, several policy implications can be drawn. Firstly, there is potential value in introducing conditionality for the food component of the scheme. Additionally, it may be beneficial to restrict the provision location of the food ration to a specific place. Furthermore, we recommend enhancing the quality of the program provision centers.

2. Literature Review

Nutrition-, Health- and Schooling-Interventions

A rich body of literature surrounds the evaluation of *non-integrated and non-multi-dimensional interventions* targeting improvements in human capital outcomes in the form of health and schooling through income effects. Policies with this targeted aim mainly take the form of conditional or unconditional cash transfers (Banerjee et al., 2022; Borga & D´Ambrosio, 2021). Evidence from cash transfers suggests that especially the imposition of conditions mediates the size of program effects on education and health outcomes (Benedetti et al., 2016). Behrman et al. (2005) find for example that a conditional cash transfer in Mexico stimulates human capital investments conditional on regular attendance of children at school. Thereby it particularly facilitates grade progression during the transition to secondary school and reencourages school entry among those who have dropped out. Furthermore, Sánchez et al. (2020) find that exposure to the same conditional cash transfer in Mexico led to an improvement in nutritional status among children treated during their first years of life.

Evaluations of *multi-dimensional integrated development programs* are much scarcer and provide more mixed evidence regarding their impact on health and schooling. Some research supports their effectiveness studying the Integrated Childhood Development Scheme (ICDS) in India by finding positive impacts of the program on anthropometric outcomes, school enrollment, and increased educational attainment (Vikram & Chindarkar, 2020; Jain, 2015; Nandi et al., 2020; Hazarika & Viren, 2013). Furthermore, Delavallade et al. (2021) find a significant positive effect on especially girls schooling outcomes studying a multi-dimensional education program targeting primary school children in rural India. However, various research studying the ICDS and other integrated development programs suggests that they also often fail to significantly improve child nutrition and schooling (Kandpal, 2011; Lokshin et al., 2005). According to most evaluations of ICDS, implementation issues are commonly identified as the primary cause of the program's ineffectiveness and limited impact (Kandpal, 2011). However, it is worth noting that a study conducted by Stifel and Alderman (2006) on a Peruvian integrated program finds that, despite effective execution, it does not result in significant improvements in child nutrition.

Targeting Gender and Age

Kazianga et al. (2014) find that school-feeding programs are especially successful if only female students receive the ration by alleviating the disadvantage that girls possibly experience at home due to a pro-boy bias in the intra-household allocation of resources. Tagliati (2022) conducted a study emphasizing the significance of the modality of social policies when targeting women or girls. He, on the contrary, finds food transfers to be less effective than cash transfers in increasing female bargaining power and thus in reducing child employment, especially among girls. Furthermore, it is found that targeted transfers can also have long-term impacts relating to inter-generational persistence of outcomes. Musaddiq and Said (2023) find that empowerment, education, and heightened health awareness contribute to a lower probability of early marriage and pregnancy. Additionally, they found that increased utilization of maternal healthcare services has a direct positive impact on the subsequent generation. It is important to note that there is limited literature specifically analyzing health outcomes during adolescence, as the focus primarily centers on young children aged zero to three years (Kandpal, 2011). Himaz (2018) undertook one of the few studies that specifically examines the health of adolescents, particularly focusing on the prevalence of stunting. The study reveals a significant correlation between stunting during adolescence and the likelihood of their offspring also experiencing stunting.

Concluding, we mainly add to this existing body of literature by firstly, providing more evidence on a multidimensional scheme beyond studies about ICDS. Secondly, we specifically add evidence that goes beyond early childhood by studying AG.

3. Program Design and Study Context

Background and Objectives

The Government of India introduced Sabla under the Ministry of Women and Child Development Department. It is a centrally sponsored program, and its objectives include improving AG´s nutrition and health status, facilitating the integration of out-of-school AG into formal or non-formal education, raising awareness about health, hygiene, nutrition, and sexual health, enhancing their life and vocational skills, and providing information and guidance about available public services[4]. Sabla is designed as a targeted in-kind transfer which views AG not

[4] Refer to appendix A1. to see those objectives in a reporting card (called Kishori card) to trace the success in achieving them by consistent monitoring of each AG within the provisioning centers.

only in terms of their current needs but as individuals who become productive members of society in future. It is noteworthy that despite recognizing the importance and desirability of community involvement and awareness building among households to address deeply rooted gender biases, policy makers did not incorporate any specific component within the scheme to directly tackle this issue (GOI, 2010).

Theory of Change, Inputs, and Implementation

Sabla´s theory of change[5] links *nutritional* and *non-nutritional life-skills* and *awareness building* components as complementary *inputs.* The program incorporates various components such as nutrition provision, iron and folic acid supplementation, health check-ups, nutrition and health education, counseling on family welfare, life skill education, guidance for formal school entry or re-entry, and vocational training for girls aged 16 and above. Additionally, an essential aspect of the program's design is facilitating group interaction between both in-school and out-of-school adolescent girls, with the intention of motivating the latter to return to school. The eligibility criteria for the program are designed to encompass all out-of-school girls in the age group of eleven to eighteen and in-school girls aged fourteen to eighteen years[6]. The scheme uses the existing platform of ICDS and is mainly implemented through Anganwadi centers[7] as focal points for service delivery (GOI, 2010; Ministry of Women and Child Development, 2010).

Targeting and Coverage

It was launched in 2010 starting with 200 districts across India based on a composite weighted index, using critical criteria related to AG including drop-out rates of females from school, female literacy rates, and female work participation. To validate the implementation, districts were a combination of good performing, moderate and under-performing ones (GOI, 2010;

[5] Refer to appendix A2. for a compact overview of Sabla´s theory of change.
[6] This is not observed within our sample and in-school AG got access to the Sabla scheme in round 4 with 12 years.
[7] Anganwadi centers are rural childcare centers as part of the ICDS scheme with the aim of providing basic health care and some non-formal schooling and health education and check-up activities especially in villages.

Ministry of Women and Child Development, 2010). One state where Sabla is implemented is Andhra Pradesh, which is the specific state where the surveyed sample used in this paper originates from[8] .

4. Data Description

We use the Indian sample of the YL dataset, an international study of childhood poverty (University of Oxford, 2019). At the beginning of the study in 2002, about 2000 children aged between six and eighteen months were recruited for the younger cohort which we use in our study. AG in this cohort are eligible for the Sabla scheme from 2011 right after the third survey round in 2010 until the last survey round 5 in 2016 when they reach the age of fifteen[9]. Round three, which was conducted in 2009, is used as the baseline as girls were aged eight at that time similar to the approach other studies using YL data (Borga & D´Ambrosio, 2021).

The *sampling strategy* of YL was semi-purposive and all geographical regions of the country were included, alongside with poor and non-poor districts of each region (based on economic, human development, and infrastructure indicators) (Gehrke, 2017; Kumra, 2008). Confirming the validity of this approach, Kumra (2008) concludes that the Indian YL data set offers a comprehensive representation of ethnic, geographic, and socio-economic diversity. It can therefore be regarded as an appropriate tool for analyzing well-being and its dynamics. Attrition rates are very low and 95% of the Younger Cohort children were present up to round four. Nevertheless, we restricted our sample used in this paper to children present in all rounds[10]. Furthermore, our study exclusively focuses on AG, and therefore observations of boys were dropped. We make this deliberate choice to specifically examine the impact of the gender-

[8] Due to privacy protection measures the data points from the sample did not provide precise information on the districts where the children are located. Consequently, it was not possible to determine the exact coverage of the districts involved in the program. Furthermore, this also constrained the method of how the comparison group is constructed later in the paper as using geographical regions with similar characteristics was not possible.
[9] Refer to appendix A3. for a comprehensive timeline relating to key steps along carrying out Sabla in relation to the survey round.
[10] We did this for the sake of having a balanced panel and reducing noise introduced by unit heterogeneity by allowing the observation of the same AG across all rounds.

targeted policy on AG and address their unique challenges [11]. Lastly, we consider AG who accessed the nutritional component of Sabla only in one round, meaning either in round four or round five. We excluded AG who accessed it in both rounds to counteract an upward-biased estimation of treatment effects due to a longer treatment exposure[12].

5. Descriptive Statistics

In appendix A4 we present the *descriptive characteristic*s for the main variables and controls of the treated and non-treated AG for the pre-program implementation round three, to analyze whether the treatment and comparison group were similar in their characteristics[13].

Even though we can observe similarities between the two, like for example their current enrolment status, their general health, having a weak BMI, and the probability of having a brother, they differ in a statistically significant way in other characteristics.

Before the treatment, on average, AG who participate in the scheme differ statistically significantly from the non-treated as a result of residing in poorer and larger households and having less access to sanitation and infrastructure. Furthermore, girls who receive the nutrition component of the scheme spend significantly fewer hours in school. On the other hand, girls who receive the full treatment are more likely to come from rural areas. Despite the statistically significant difference of AG getting the full treatment being enrolled in higher grades than AG in the comparison group, the found pattern indicates that Sabla reaches its main target group of AG from poorer households living in rural areas with less schooling, higher drop-out rates and work participation.

11 The decision to exclude boys as observations was especially guided by the unique situation and challenges AG face in the studied context, as for example their role within the household relevant for empowerment and the patriarchal context and a pro-boy bias within households. This gives boys an advantage over girls and therefore they are not representing an adequate comparison group. This advantage seems also to be present in our sample by comparing some summary statistics, especially the ones related to schooling and empowerment related variables as it can be seen in appendix A5.

12 This adjustment was not necessary for the full Sabla treatment variable as it only included girls who received the treatment since the previous survey round, and we only have data observations for it for the last survey round.

13 For the mean-comparison of the AG characteristics, t-tests were conducted for normally distributed variables and the Wilcoxon rank-sum test for non-normally distributed variables. As a pre-condition for that, normality of the distributions was tested with the Shapiro-Wilk test.

6. Empirical Methods

In addition to the observed differences between the treatment and comparison groups at the baseline, which indicate that program participation was not random, we encounter another challenge that must be addressed to establish causal relationships regarding the effects of Sabla on our desired outcomes: it is not possible to observe what would have happened to the treated AG had the treatment not occurred (counterfactual).

In this section, we outline the underlying identification strategy of this paper trying to overcome these problems. First, we present the applied evaluation methods allowing us to study causal program impacts. Afterwards, we describe the treatment, outcome variables, and indices.

6.1. Identification Strategy

To study the effects Sabla had on AG health and education, we develop our identification strategy through various methods, resulting in the application of robust estimation techniques in a quasi-experimental setup to overcome problems for causal inference. In all the estimations, we control for variables that might be affected by the program and might influence the three different types of outcome variables regarding health, schooling, and other activities of AG. These covariates include individual, household, and community level characteristics of the sample. Furthermore, given the panel design of our data we cluster standard errors at the individual child id level to avoid serial correlation of the individual observations[14]. As a starting point, we conduct an *Ordinary Least Squares regression (OLS)* to examine the basic relationship between the treatment and non-treated. This implied the regression of a treatment dummy variable on the outcome of interest in the following form:

$$Y_i = \alpha_{10} + \alpha_{12} Treatment\ SABLA_i + \delta_1 X_{it} + u_{1it}$$
$$Y_i = \alpha_{20} + \alpha_{22} Treatment\ SABLA\ YL_i + \delta_2 X_{it} + u_{2it}$$

[14] Within panel data residuals in different time periods for a given individual may correlate. This is mainly because traits of the individual observations like its socio-economic background are identical within each round of the panel. We solely did not cluster our standard errors in ii and iii. For this estimation method there is much controversy in determining which standard errors to use, especially whether they should be clustered or bootstrapped or not be adjusted at all (as discussed for example in Abadie & Imbens, (2009).

Afterwards, we implemented quasi-experimental techniques as, in contrast to OLS, they can in theory produce causal estimates of the program impact. In particular, whereas OLS fundamentally relies on the assumption of ignorability (after controlling for observable pretreatment covariates, treatment assignment is independent of the outcome of interest), the following quasi-experimental techniques rely on two different assumptions. We apply the first of these techniques through DID, which compares the changes in outcomes over time between treated and comparison group. Thereby, this method controls for unobserved heterogeneity and allows to correct for any differences between the two groups that are constant over time. The DID estimator provides the average change in outcome in the treatment group minus the average change in outcome in the comparison group. DID implied the following regression model:

$$Y_{it} = \beta_{10} + \beta_{11} Post\ SABLA_t + \beta_{12} Treatment\ SABLA_i + \beta_{13} Post\ SABLA_t * Treatment\ SABLA_i + \varphi_1 X_{it} + v_{1it}$$

where X is a set of control variables, and Y represents for the outcome variables.

$$Post\ SABLA_t = \begin{cases} 1\ if\ Round = 5 \\ 0 \end{cases}$$

$$Treatment\ SABLA_i = \begin{cases} 1\ if\ girl\ i\ is\ given\ the\ treatment \\ 0 \end{cases}$$

$$Y_{it} = \beta_{20} + \beta_{21} Post\ SABLA\ YL_t + \beta_{22} Treatment\ SABLA\ YL_i + \beta_{23} Post\ SABLA\ YL_t * Treatment\ SABLA\ YL_i + \varphi_1 X_{it} + v_{2it}$$

$$Post\ SABLA\ YL_t = \begin{cases} 1\ if\ Round = 4\ or\ 5 \\ 0 \end{cases}$$

$$Treatment\ SABLA\ YL_i = \begin{cases} 1\ if\ girl\ i\ is\ given\ the\ treatment \\ 0 \end{cases}$$

An important underlying condition for the DID estimator to be valid is the parallel trend assumption. This assumption requests that outcome trends are similar in comparison and treatment groups before the intervention and that the only factors explaining differences in outcomes between treated and comparison group are constant over time, apart from the program itself. To validate the plausibility of this assumption, we assess whether the pre-treatment trends were the same between the treatment and the comparison group and documented the results in the appendix A7. and A8. It can be observed in those graphs for some variables this assumption does not fully hold true which is why we use further analysis methods to improve the reliability of our results and do not rely on biased estimates.

To accomplish this, we employed PSM as a second quasi-experimental technique, with the primary objective of constructing a more credible comparison group. This technique is particularly suitable for mitigating selection bias when the selection process is based on observable characteristics. By matching the treatment and comparison groups on these observables, PSM helps to address this bias. It controls for confounding by matching observations based on their predicted probability of treatment using a set of observable characteristics at baseline which therefore are not to affected by the treatment. The first step consists of constructing a statistical counterfactual by modelling the probability of participating in the program, which represents the propensity score. This propensity score for each AG is estimated using the following formula:

$$PS_i = P(T_i = 1) = \frac{\exp(\theta Z_i)}{1 + \exp(\theta Z_i)}$$

where Z is a set of variables used for generating the propensity scores.

In the case of Sabla treatment was not restricted to AG with a specific set of characteristics, but the rollout was largely based on characteristics critical to female empowerment like the female literacy rate and the development of the areas where at the beginning there was a pro-rural and less developed bias. As a result of incorporating the targeting criteria and reviewing relevant literature, we utilized the following sets of covariates to match participants with non-participants: economic household characteristics, such as wealth, as well as characteristics related to the household members, such as the presence of sons in the household.[15]. Furthermore, we included specific controls regarding female empowerment. An example is whether the household head is female. Additionally, we considered community characteristics

[15] We did this due to the prevalent pro-boy bias observed in India leading to boys being advantaged at all ages when it comes to intra-household resources allocation (Aurino & Morrow, 2018; Jayachandran & Pande, 2015; Deaton & Paxson, 1998).

like the access to infrastructure[16]. For the matching process, we employed the nearest neighbor and Kernel matching techniques. The first one matches pairwise whereas the second uses a weighted average of all non-treated units that are in the region of common support to construct the counterfactual match for each participant. Appendices A11. and A12. show that the common support is complete, meaning for each treated AG, there is a sufficiently high number of close matches from non-participant AG. Further balance checks show that treatment and comparison units have similar characteristics, and the construction of a more credible comparison group was successful, as shown in appendix A9. and A10. The next step involves regressing the propensity score on the outcome variables to estimate the Average Treatment Effect on the Treated (ATT):

$$ATT_{PSM} = E(Y_1|PS, T = 1) - E(Y_0|PS, T = 0)$$

As a final method, we employed a combination of DID and PSM techniques to effectively control for both observed and unobserved characteristics. In this approach, we utilized the calculated propensity score to weight the treatment and comparison samples within the area of common support. By doing so, we were able to address systematic imbalances in the covariates between the treatment and comparison subjects. The application of the kernel propensity score DID estimator helped in obtaining a less biased estimate of the ATT, assuming the unconfoundedness assumption holds[17]. The final estimator provides the average change in the outcome in the treatment group minus the average change in the outcome in the matched comparison group.

6.2. Treatment and Outcome Variables

To study the causal effects of Sabla, YL provides two different variables that we can use as *independent treatment variables*. One of them is related to the whole Sabla scheme (Sabla) with

[16] As the balancing property between treated and comparison groups could not be satisfied with all chosen covariates within the PSM analysis for the Sabla YL variable, living in a rural area and household size were not considered. Afterwards, the balancing property successfully was satisfied as it can be seen in appendix A11.

17 Meaning all variables affecting T and Y are observed and can be controlled for.

all its components and one is only for the nutritional component (Sabla YL) of the scheme. We examine both variables as treatment variables separately, to assess whether the combined approach yielded different outcomes compared to the nutrition component alone. A major advantage of the YL data is its coverage of a wide range of well-being indicators relevant for our work, including health, nutrition, education, and child development indicators (Borga & D´Ambosio, 2021). To best reflect the multidimensionality of our outcomes of interest, we measure them in three different outcome indices, each consisting of several related variables. Indices possess the ability to effectively summarize complex and multifaceted outcomes. Moreover, they enable the interpretation of multiple distinct outcomes in a structured manner by condensing the underlying variables without compromising the information they convey (OECD, 2008). We use a methodological approach for constructing composite indicators, building upon established OECD guidelines (2008) and incorporating insights from Kling (2007) and Borga and D'Ambrosio (2021). Our approach prioritizes transparency and robust statistical methods to ensure reliable and valid composite indicators. We considered Kling's (2007) work to address specific challenges like data limitations and uncertainty, while incorporating Borga and D'Ambrosio's (2021) recent approach for advancements in the field.

Step 1 - Theoretical Framework

In constructing each index, we included multiple components in the form of variables, which we then averaged. We consider advancements in the literature concerning the desired outcomes and multidimensional indexes within the selection of variables. To ensure the relevance of the chosen dimensions in measuring health and education, we consulted research by Borga and D'Ambrosio, Alkire and Seth (2015), and Alkire and Foster (2011). These studies extensively explore the measurement of multidimensional poverty, which includes the outcome indicators under investigation. Notably, their findings highlighted the significance of nutrition as a health component, as well as school attendance and years of schooling as components of schooling.

As a result, the *health index* entails the height-for-age z-score measuring stunting[18], whether the girl has a weak BMI[19], the overall health of the AG and her self-reported health. Secondly, the *education index* consists of whether the AG is enrolled in school, how many hours per day she spends at school and how many for studying and the highest grade she has achieved. Thirdly, to provide a comprehensive assessment, a child activity index was created, encompassing outcome variables primarily associated with the empowerment targeting activities of Sabla. This index included variables such as the number of hours children spent on household activities and the number of hours dedicated to work-related activities [20].

Step 2 - Normalization, Weighting and Aggregation

To ensure consistency and facilitate the interpretation of the indices, we standardized the variables within each index by transforming them into a common scale. This was achieved by calculating their z-scores, which reflect the difference between the variable value and the mean of the comparison group, divided by the standard deviation of the comparison group. By applying this procedure, we can bring all variables onto a standardized scale with a mean of zero and a standard deviation of one. Each index was then derived as the average of these standardized z-scores, with equal weights assigned to each component. This approach follows a widely accepted practice for composite indexes. It is considered a valid weighting procedure when either all variables within the index are deemed equally important or when consensus on an alternative weighting scheme is lacking. In the context of this study, the literature relevant to the outcomes of health and education predominantly supports the use of equal weighting procedures (Borga & D'Ambrosio, 2021; Alkire & Seth, 2018).

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[18] Himaz (2008) found that stunting is not only an important indicator for overall health and nutrition during childhood, but also significant during adolescence as children already stunted may 'catch up' during this period, given appropriate conditions.

[19] This dummy variable was created for the specific context of Sabla, where under-nourished girls are targeted. The monotonic growing variable was therefore preferred for interpretation purposes over a general BMI dummy which considers outlying high BMIs in the same category as outlying low BMIs. Furthermore, for interpretation purposes of the index that all coefficients go in the same direction the weak BMI variable was recoded into strong BMI where the coefficient goes in line with the ones of the other index variables.

20 However, this indicator should be treated cautiously when interpretating it as its variable effects can move in different directions. Whereas more hours spent in household activities are seen negatively in the context of AG´s empowerment by reducing their time spent on gaining education, depending on the type of work, an increase of hours worked can also be interpreted positively.

Step 3 - Multivariate Analysis and Robustness

Lastly, we conducted an exploratory analysis to assess the appropriateness of the variables included in the indices for describing the phenomena under study. Firstly, we examined the percentage of missing values in the data, as these can introduce bias in parameter estimation and limit the generalizability of the findings. Given that the variable with the highest percentage of missing values amounted to 1.7%, which is below the threshold of 5% considered as inconsequential, no imputation or further measures were taken. Secondly, we employed principal components analysis (PCA) to ensure that the dimensions of the phenomenon were well-balanced within the indices, while maximizing variance across components to capture additional information from the variables[21]. By conducting PCA on the same set of variables used in the indices, we assess their correlation with the two weighted-average indices. The aim was to determine if the indices capture similar information. The results revealed a significant correlation between the two, suggesting that we can use the weighted-average indicators for our analysis[22]. They offer a more intuitive interpretation compared to directly utilizing PCA results, as they do not allow for inferences regarding population properties.

7. Econometric Results

In this section, we summarize the main empirical results using our last established estimation method PSM and DID[23]. Our focus lies on these estimates together, as the combination of PSM and DID minimizes the risk of bias in our estimations and provides the most accurate estimate of the counterfactual among the methods we have selected[24]. Table T1 provides the results of PSM and DID estimations for both treatment variables.

21 PCA summarizes a set of individual variables while preserving their maximum possible properties and at the same time not using variables causing multi-collinearity. It does so by finding components z which are linear combinations u of the original variable x that achieve the maximum variance.

22 Refer to appendix A6.to see this correlation illustrated in two scatterplots.

23 Refer to appendices A13. and A14. to see estimation results for all methods.

24 PSM does so by identifying a set of non-treated individuals most similar to the treated based on observable characteristics and DID controls for unobservable characteristics that are constant over time.

Table T1. Impact of Sabla YL and Sabla

Outcome	SABLA_YL	SABLA
	PSM & Diff-in-Diff	PSM & Diff-in-Diff
	(i)	(ii)
	ATT	ATT
HEALTH	**-0.119**	**0.069**
	(0.083)	(0.083)
Weak BMI	0.016	-0.09
	(0.031)	(0.075)
Height-for-Age Z-Score	-0.21	0.189 **
	(0.230)	(0.082)
Self-Reported Health	-0.33	0.066
	(0.290)	(0.261)
Child Overall Health	-0.054	-0.127
	(0.093)	(0.108)
SCHOOLING	**-0.198****	**-0.468****
	(0.085)	(0.198)
Hours/ Day Spent at School	-1.269***	-2.418***
	(0.351)	(0.646)
Currently Enrolled in School	-0.147***	-0.23***
	(0.044)	(0.074)
Highest Grade Achieved at Time of Interview	-0.214	-0.084
	(0.157)	(0.194)
Hours/ Day Spent Studying	-0.148	-0.341*
	(0.163)	(0.195)
ACTIVITIES/ EMPOWERMENT	**0.111**	**0.412****
	(0.105)	(0.180)
Hours/ Day spent in HH Chores	-0.12	0.115
	(0.138)	(0.169)
Hours/ Day Spent in Paid Activity	0.651**	1.58***
	(0.277)	(0.563)
Hours/ Day Caring after other HH members	-0.053	-0.138
	(0.102)	(0.114)
Covariates	Yes	Yes
Matching Algorithm	Kernel	Kernel
Observations	2442	2414

***, **, *: statistically significant at respectively 1%, 5% or 10% significance level.
Robust standard errors in parenthesis, clustered by individual child ID level.
(i) reports the average treatment effects for Sabla_YL. (ii) reports the average treatment effects for the full scheme Sabla treatment variable.
Both estimations include as *controls* parental education, household size, household wealth index, the head of the household being female, presence of a brother in the household, access to electricity and infrastructure and the belonging to a disadvantaged ethnicity group/caste.
Outcome variables are measured as follows: indicators are weighted averages of the z-scores (measured in standard deviation units) of the variables making up the index. Weak BMI is dichotomous assuming 1 if BMI is lower than 18.5, self-reported health and child overall health are measured ordinally with 0 meaning very poor health and 9 and 5 representing very good health respectively. Enrolment is a dichotomous variable and highest grade achieved at school is measured ordinally according to the grade ranging from 0 to 12.

7.1 Nutritional Component – Sabla YL

Firstly, a statistically significant negative estimated program impact on schooling and an insignificant effect on the health indicator suggest a negative program impact. Counterintuitively, the overall estimated effect on the *health indicator* is insignificant for AG who receive the nutritional component of the Sabla scheme. Looking at the estimates of its components directly linked to nutrition, we see a decrease in the height-for-age z-score and a slightly higher likeliness of AG to have a weak BMI, however both estimates are not statistically significant. Estimated effects of the nutritional part of the scheme continue to be statistically insignificant for both, self-reported and objective health of the AG. In conclusion, we can say that the nutritional part of the scheme did not have any statistically significant effect on any of the health outcome variables. Continuing with the *schooling indicator*, in contrast, estimated effects are negative and statistically significant (a finding at the 5% level). The policy had a negative impact on both, the extensive margin (enrolment) and the intensive margin (hours per day spent at school) of schooling in a highly statistically significant way (at the 1% level). These negative estimates continue for the highest grade achieved and the hours per day spent studying, however for these two they do not differ from the comparison group in a statistically significant way. They also do not differ significantly from the comparison group for the *index of activities related to empowerment* on which the treatment overall has a positive effect. Within this index, there is however one variable on which Sabla YL has a highly statistically significant positive effect, namely the hours an AG spends in a paid activity per day. On the contrary the hours treated AG spend in household activities decrease, but the estimated coefficients are not statistically significant.

7.2 Total Scheme – Sabla

Analogously to the results of the prior treatment variable, also when combining nutritional with educational and empowerment inputs in the full treatment, we observe a highly statistically significant negative effect on schooling outcomes and a statistically insignificant effect on the health outcome. Among *health outcome variables*, for the full Sabla treatment we can observe a statistically significant estimated effect on the height-for-age z-score, meaning that AG are less likely to be impaired in growth due to bad nutrition or disease[25]. Our estimates suggest that the estimated effect on self-reported health is positive, however statistically insignificant. This statistical insignificance remains for the other two outcome variables of having a weak BMI

[25] Stunting is the impaired growth and development that children experience from poor nutrition, repeated infection, and inadequate psychosocial stimulation. Children are defined as stunted if their height-for-age is more than two standard deviations below the WHO Child Growth Standards median (WHO, 2015).

and objective overall health comparable to the nutrition component Sabla treatment. Within the *schooling indicator* our estimates for the full Sabla scheme possess a similar pattern as well. We find a highly statistically significant and even stronger negative program effect on enrolment and the hours per day spent at school (at the 1% level). Additionally, for this treatment variable estimated effects of Sabla on the hours per day a treated AG spends studying are negative in a statistically significant way. Only the estimated effect on the treatment impact on the highest grade achieved seems to be negligible and statistically insignificant. The estimated effect on the *index of activities related to empowerment* is positive and statistically significant mainly due to a highly statistically significant increase in the hours per day in a paid activity (at the 1% level). The estimated effect for the full treatment is even larger in comparison to the other treatment variable. Lastly, we cannot observe any statistically significant effects on the two other variables related to empowerment, namely the hours per day spent in household chore or caring activities.

Taken together, our findings demonstrate that participating in both, the full Sabla scheme or the nutritional component of it, firstly, *has negative estimated effects on schooling outcomes of AG* especially in terms of enrolment and hours per day spent at school. Secondly, it *has a highly statistically significant positive effect on their time spent working in a paid activity*. Thirdly, *estimated effects on health and time spent in household activities are statistically insignificant*.

8. Discussion Of Results

In this section, our aim is to delve into the previous key findings and understand the reasons behind the negative impact of Sabla on schooling outcomes and its lack of significant effect on health outcomes. Additionally, we seek to examine the significant impact of the program on the hours AG spent in paid activities. As our study is the first to analyze the Sabla scheme, direct comparisons to findings from other studies are not feasible. However, to gain insights, we mainly focus on existing studies that have examined the multi-dimensional ICDS as Sabla´s implementation is fully based on its set-up. By comparing our results to these studies, we can identify differences between them and gain a better understanding of the potential factors contributing to our estimated results, which suggest a failure of the Sabla scheme.

Age Group Relevance for Nutritional Health Improvements

In contrast to our negative estimated impact of Sabla on schooling, for ICDS Jain (2015), Nandi (2020) and Vikram & Chindarkar (2020) find positive effects on enrolment and educational attainment. Nandi finds when studying long-term effects that adult women and men who were exposed to ICDS during the first three years of their lives complete 0.1-0.3 additional grades compared to a comparison group where children were exposed to the scheme three years later. These could indicate that a reversal of bad health and anthropometric outcomes is difficult during the years of adolescence and therefore, policies targeting the first three years of live are more successful than Sabla´s approach with adolescents. Hoynes et al. (2016) support this argument by highlighting the crucial role of early-life nutrition and stimulation in achieving positive schooling effects for adolescent girls. Similarly, Jain (2015) estimates positive health and nutrition effects of ICDS on girls who received the nutritional component, particularly if they received it before the age of two.

Inefficiency of Providing Centers

However, Jain (2015) highlights that the positive effects of ICDS can only be achieved if children receive the program's treatment on a regular daily basis. Unfortunately, this is often not the case due to inefficiencies in the providing Anganwadi centers. Kandpal (2011) and Vikram and Chindarkar (2020) also identify the inefficiency of these centers as a significant reason for the program's failure in ICDS. Their research reveals that workers at the centers are often overburdened and lack the necessary skills to deliver services effectively. Additionally, there is a lack of appropriate infrastructure, and food leakages occur regularly within the system. Since the Sabla program utilizes the same centers for the distribution of its services, these inefficiencies could contribute to the negative and insignificant estimated effects observed in our study.

Non-Holistic Take-Up of the Scheme

Another factor that may contribute to the failure of Sabla in achieving its intended outcomes is its nature as a multi-dimensional integrated scheme. These types of schemes are designed to operate holistically, with interrelated inputs that work in tandem. However, if these schemes are only utilized partially, it becomes problematic and may hinder their effectiveness. Consistent with our findings that a larger proportion of adolescent girls access only the nutritional component of the Sabla program, Kandpal (2011) identifies a similar pattern in the implementation of ICDS. This selective utilization of specific components is identified as an important driver for the lack of significant program impacts.

Intra-Household Redistribution

Another potential explanation for the lack of significant impact on health outcomes is that AG may not receive the treatment themselves, but rather other household members do. This is particularly relevant in the context of strong patriarchal norms in India, which often result in a pro-boy bias within households. Given that the nutrition component of Sabla can be accessed as a take-home ration, it is possible that brothers or other household members receive the food instead of the targeted AG, due to a redistribution of the food ration based on household preferences. Nandi et al. (2020) address this issue when evaluating the take-home food component of ICDS and find insignificant effects on health outcomes. This finding aligns with studies that have examined the positive effects of girls-targeting in-school feeding programs. Such programs ensure that the intended recipient receives the food ration, reducing the likelihood of intra-household reallocations. This ensuring component of targeted feeding programs could play a vital role in their success (Kazianga et al., 2014). Therefore, the lack of significant impact on health outcomes in Sabla could be attributed to the possibility of food redistribution within households, driven by prevailing patriarchal norms and biases.

Missing Conditionality

Additionally, *missing conditionality* could be a reason for the non-improvement of schooling outcomes. In contrast, several studies point out the relevance of conditionality within policy design like Gitter & Barham (2008) who find that conditionality is decisive for a policy to have positive effects on schooling outcomes. Premand and Barry (2022) find that conditionality especially matters for the increase in schooling by inducing a change in parents´ decision making which is not achieved through the transfer itself, but by tying it to sending their children to school. Furthermore, the condition directly ties the transfer to schooling and thereby offsets the opportunity costs of not sending children to school (Behrman et al., 2005). Within Sabla the food component can be accessed by AG without any condition linked to it which is why it especially does not induce a behavioral change in parents decision making by linking the transfer to the desired behavior of sending AG to school.

Modality of the Transfer

But Sabla does not only have no effect on schooling outcomes, it also impacts them in a negative way leading to negative estimates on enrolment and hours per day spent at school. One potential explanation for this observation can be found by comparing our results to those of Tagliati (2022), who examines the importance of transfer modality. He finds that transfers specifically targeted at women have a greater empowering effect when provided in cash rather than in-kind transfers. Cash transfers are more likely to enhance female bargaining power within the household compared to in-kind transfers. This increased bargaining power enables women's participation in household decision-making, particularly regarding the allocation of household income towards child schooling (Tagliati, 2022; Almås et al., 2018). The underlying reason for this effect can be derived from several studies suggesting that income controlled by women is more likely to be spent on children compared to income controlled by men (Lundberg et al., 1997; Macours et al., 2012). Therefore, the negative impacts on schooling outcomes and the positive impact on working hours could potentially stem from a lack of increased intra-household bargaining power for women, hindering their ability to make decisions regarding the AG time allocation.

Job Types AG are Engaged in

Furthermore, it is important to note that it is not possible for us to assess whether the increase in hours spent working is favorable for AG or not[26]. The limitation arises from the fact that our dataset does not provide information on the specific nature of the work undertaken by AG. On one hand, it is plausible that the increase in hours spent working could be beneficial for AG if they are engaged in skilled jobs that offer vocational training opportunities. On the other hand, if the increase in hours spent working primarily involves low-skilled jobs that do not require or provide vocational training or valuable skills, it would not be favorable for them. Consequently, the observed increase in hours worked among the AG cannot be attributed to the influence of vocational training provided by Sabla. Knowing the quality of jobs in which AG work would be additionally beneficial as Jensen (2012) finds in rural India that if parents believe there are opportunities within more skilled and salient jobs for their daughters, they will increase their human capital investments in them. In our context this could point towards the problematic of only including the AG themselves in the program and not their parents. This does not allow for increasing their awareness about future job opportunities of their daughters and the corresponding importance of prior education. Concluding, this missing knowledge could be another driver of the negative impact on schooling and the positive impact on hours worked instead.

Inclusion of other Household Members

[26] It is crucial to consider that AG included in our study were 15 years old during the last round of data collection, indicating that they had not yet participated in the vocational training component of the Sabla program.

Lastly, another potential reason for Sabla´s failure in improving schooling and health outcomes is closely related to intra-household decision making and the modality of the scheme. It is represented by its missing integration of other household members. Delavallade et al. (2021) find that one key component of their studied multi-dimensional program to increase enrollment rates is conducting door-to-door enrolment drives. These drives directly inform households about the importance and benefits of education. In contrast, Sabla does only address AG directly by giving them isolated information sessions at the program centers and through mixed group interactions with in-school AG. It does not incorporate any component specifically focused on raising awareness within the community or household.

9. Concluding Remarks

This paper represents the first one that aims to provide causal evidence on how the age- and gender-targeted in-kind social protection scheme Sabla affects multiple outcomes for AG in India in the medium-term. To accomplish this, the study utilizes a panel data set of YL in Andhra Pradesh. We conducted several quasi-experimental methods finally leading us to employ PSM combined with DID to interpret our results. They suggest that the policy fails to improve health and schooling outcomes of its recipients and instead significantly increases the hours they spend in a paid activity. As a result, the overall impact on adolescent girls' empowerment is ambiguous. The estimated effects on empowerment-related outcomes regarding household tasks are not statistically significant, and the influence of the increased hours worked in paid activities on empowerment remains unknown. This limitation arises from our dataset, as it does not provide information on the specific type of work in which AG engage. To fully understand the impact of their engagement, it is essential to distinguish whether the AG are involved in skilled work that provides vocational training or in unskilled work without such training.

Therefore, there is a need for follow-up research with data providing information about the type of work participants are conducting. Furthermore, it would be interesting to study the long-term impacts of Sabla on women´s empowerment, especially related to the timing of marriage, childbirth, and maternal health care as attending school and proper nutrition during adolescence are not the finish line for girls' empowerment. A last more general need for future research lies within exploring additional policies targeting AG beyond Sabla, enabling comprehensive comparisons of different modalities and policy designs. This would contribute to a more nuanced understanding of the factors that may have a significant impact on relevant outcomes for AG.

Finally, with our results we can draw some policy recommendations to potentially improve the impacts of Sabla on its intended outcomes. To enhance the results in health and schooling, a policy option could be to introduce conditionality of the nutritional component on attendance of the providing centers. Thereby it could be ensured that the targeted group of AG are truly its recipients instead of facing the risk of other household members receiving it. Furthermore, one could make the food component conditional on schooling to lower the associated costs of it and thereby potentially improving its effects on schooling. The modality of the program could be reassessed in general as other ways of delivery could be more supportive in achieving the desired outcomes. As an example, the inclusion of a conditional cash transfer component could be considered as its success within the girl-targeting context is often presented in the literature. Additionally other members of the household despite AG themselves could be included in the program to increase awareness of household decision makers about the benefits of AG´s schooling. Finally, improving the capacity and quality of the providing centers could be another key area of improvement. In this regard, a better education of workers or minimizing the services provided by the centers and instead focusing on a thorough delivery of each component could be considered.

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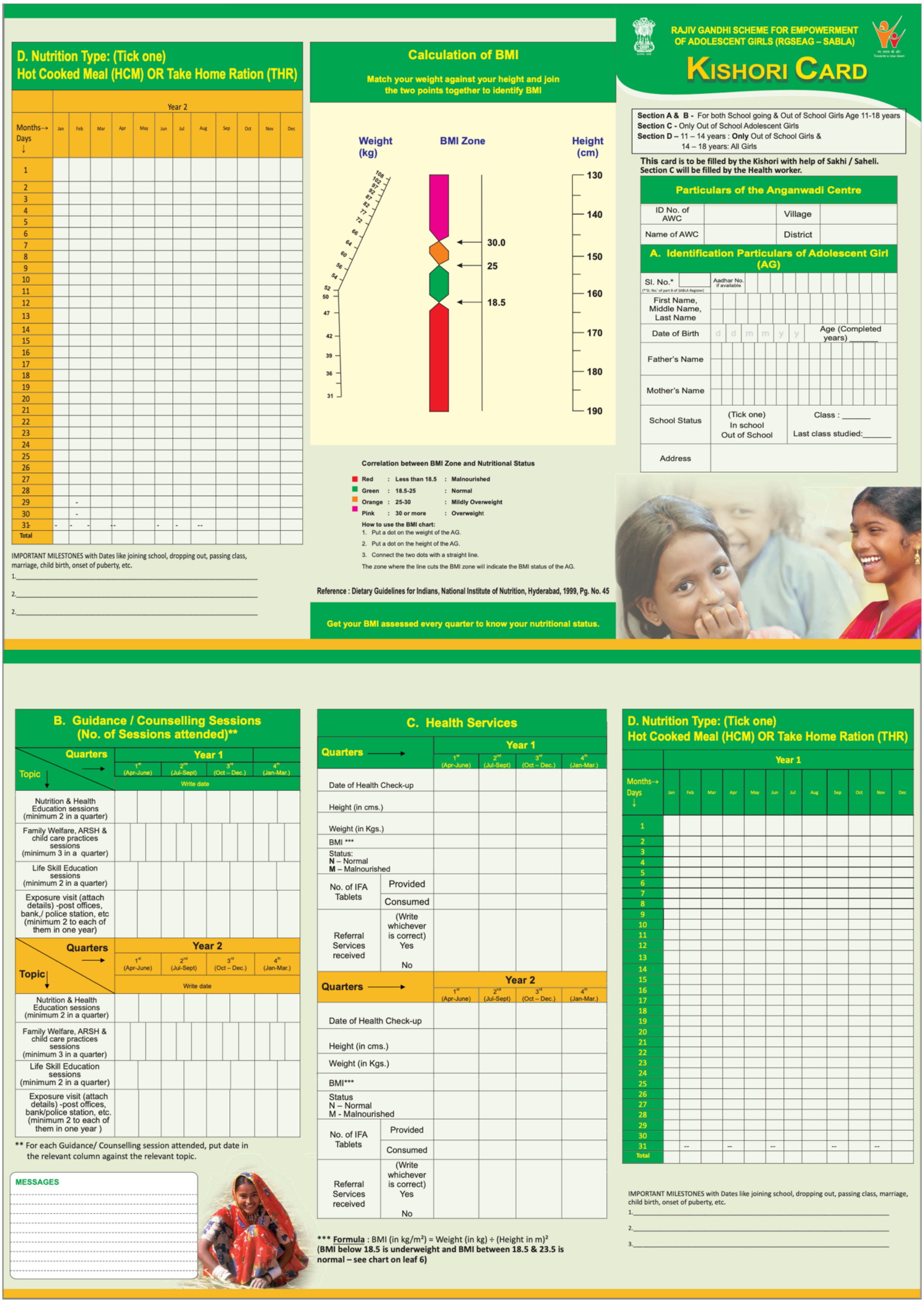
Appendix

<u>Appendix A1.</u> **Kishori Card** (Ministry of Women and Child Development, 2010)



This figure shows a Kishori card, which is distributed to each AG participating in Sabla, to facilitate tracking and monitoring of targeted outcomes and participation. Thereby, it provides a visual overview of the targeted objectives of the scheme.

Appendix A2. **Sabla Theory of Change** (Illustration by the Authors)

Problem

Multi-dimensional disadvantage of AGs due to lack in access to proper nutrition and education leading to
- under-nourished AGs with bad health-status
- a lack in education/ schooling
- a lack of independence within households and society/ early marriage
- long-lasting problems also in womanhood and inter-generational transmission of problems

→

Intervention

Nutrition Component
- Meal provision
- Iron and folic acid supplementation

Non-Nutrition Component
- Health checkups
- Nutrition and health education
- Life skill education
- Guidance of out-of-school girls to re-enter formal schooling
- Vocational training for girls aged 16 and above

→

Outcomes

Mitigating disadvantages of AGs by
- improvement in nutrition and health status,
- mainstream out of school AGs into formal/non formal education
- improvement in health and hygiene knowledge
- improvement in empowerment and independence by upgrading life skills and vocational skills

Appendix A3. **Timeline of Sabla Implementation and Survey Data** (Illustration by the Authors)

2009
- Round 3 survey of the YL study serving as baseline
- Age of AG: 8 years

→

2010
- Launch of the Sabla scheme in 200 districts within the country based on composite weighted index using criteria targeting AG´s health and education

→

2013
- Round 4 survey of the YL study
- Age of AG: 12 years

→

2016
- Round 5 survey of the YL study
- Age of AG: 15 years

Appendix A4. Descriptive Statistics at Baseline

Characteristics at Baseline - Round 3

	SABLA YL			SABLA		
	(i) Treatment	(ii) Comparison	(iii) T-C	(iv) Treatment	(v) Comparison	(vi) T-C
AG Individual Characteristics						
Health in General	3.870	3.944	-0.074	3.833	3.943	-0.110
	(0.726)	(0.622)		(0.537)	(0.635)	
Hours/ Day spent in HH Chores	0.652	0.433	0.219***	0.476	0.449	0.027
	0.638	(0.639)		(0.594)	(0.643)	
Hours/ Day Spent in Paid Activity	0.116	0.004	0.112	0.000	0.013	-0.013
	(0.963)	(0.079)		0.000	(0.288)	
Hours/ Day Spent at School	7.290	7.643	-0.353*	7.405	7.625	-0.220
	(1.741)	(1.036)		(1.270)	(1.101)	
Currently Enrolled in School	0.928	0.961	-0.034	0.952	0.959	-0.007
	(0.261)	(0.193)		(0.216)	(0.198)	
Highest Grade Achieved at Time of Interview	1.986	1.798	0.188*	2.143	1.793	0.349***
	(0.157)	(0.935)		(1.026)	(0.951)	
Weak BMI	0.971	0.986	-0.015	1.000	0.984	0.016
	(0.169)	(0.116)		0.000	(0.124)	
Hours/ Day Caring after other HH members	0.362	0.243	0.119	0.167	0.256	-0.090
	(0.766)	(0.573)		(0.377)	(0.600)	
Household Characteristics						
Wealth Index	0.451	0.512	-0.061***	0.423	0.512	-0.089***
	(0.163)	(0.177)		(0.141)	(0.177)	
Male Child in HH	0.652	0.598	0.054	0.571	0.604	-0.033
	(0.480)	(0.491)		(0.501)	(0.489)	
Disadvantaged Group	0.899	0.808	0.09*	0.881	0.812	0.069
	(0.304)	(0.394)		(0.328)	(0.391)	
Household Size	5.942	5.421	0.521***	6.071	5.433	0.638***
	(2.093)	(2.369)		(2.029)	(2.362)	
Community Characteristics						
Urban Area	0.174	0.249	-0.075	0.119	0.249	-0.13*
	(0.382)	(0.433)		(0.328)	(0.433)	
Access to Services / Sanitation	2.087	2.267	-0.18***	2.048	2.264	-0.216***
	(0.535)	(0.568)		(0.439)	(0.572)	
Number of Observations	69	803		42	831	

*** p<0.01, **p<0.05, *p<0.1.
Standard deviations in parenthesis.
The table reports the descriptive characteristics for both treatment variables (Sabla YL and Sabla) in the baseline period round 3. The means of each variable are presented correspondingly, followed by the standard deviation in parenthesis. Furthermore, columns iii and vi report the differences between the treatment and the comparison groups with their corresponding significance levels.

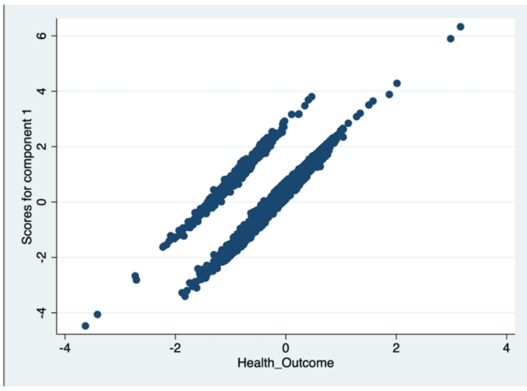
Appendix A5. **Support for Analysis Based on Only Girls in Comparison Group: Comparison of Boys and Girls in the Data Set**

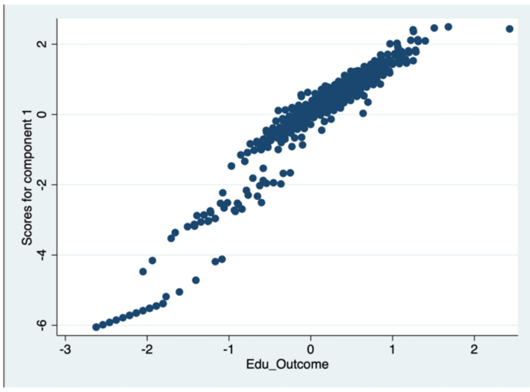
Comparison to Boys

	(i) Girls	(ii) Boys	(iii) G-B
AG Individual Characteristics			
Health in General	3.852	3.881	-0.029
	(0.698)	(0.675)	
Hours/ Day spent in HH Chores	0.968	0.645	0.323***
	(0.976)	(0.719)	
Hours/ Day Spent at School	7.736	7.920	-0.184**
	(2.183)	(2.051)	
Hours/ Day Caring after other HH members	0.231	0.126	0.105**
	(0.631)	(0.408)	
Number of Observations	2618	3054	

*** p<0.01, **p<0.05, *p<0.1.
Standard Deviations in parenthesis.
The table reports the descriptive characteristics for boys and girls in the data set for all the 3 rounds.The means of each variable are presented correspondingly, followed by the standard deviation in parenthesis. Furthermore, column iii reports the differences between boys and girls within the variables with their corresponding significance levels.

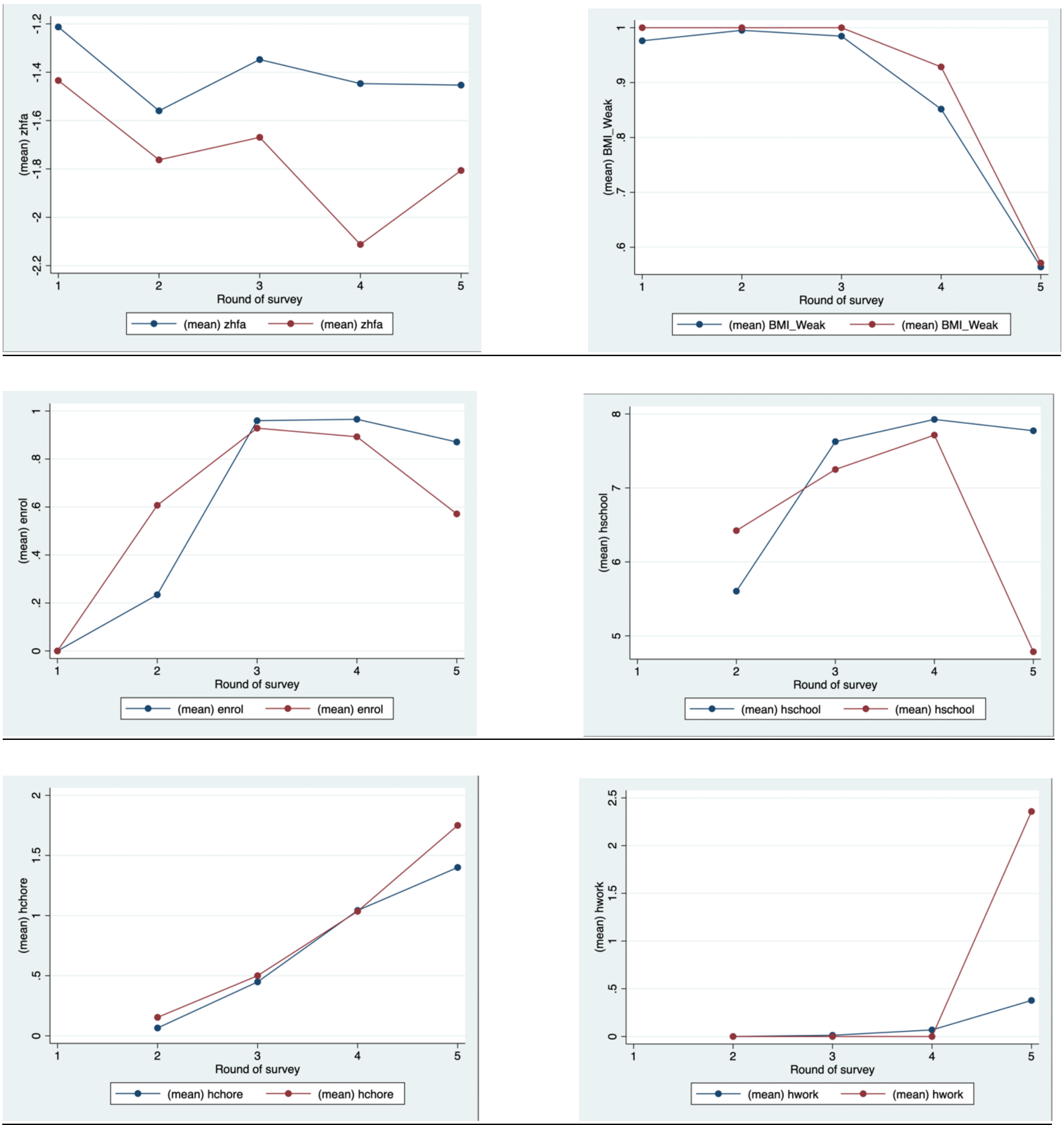
Appendix A6. **Robustness Check for Constructed Indices with PCA: Scatterplots Showing Correlation**





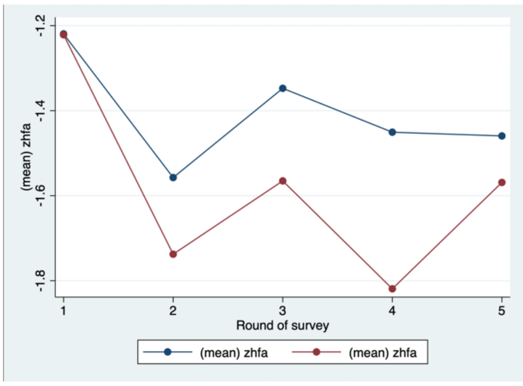
These scatterplots provide visual representation of the correlation between the constructed indices using simple averages and those obtained through PCA. By observing this correlation, we establish the robustness of using simple averages in creating the health and schooling outcome indices. The first plot shows the correlation of the health outcome index, whereas the second graph shows the correlation of the schooling outcome index.

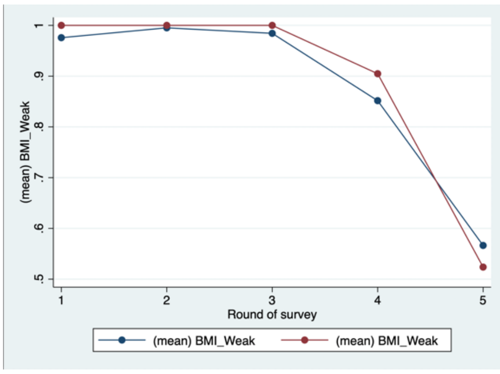
Appendix A7. Parallel Trend Graphs SABLA_YL

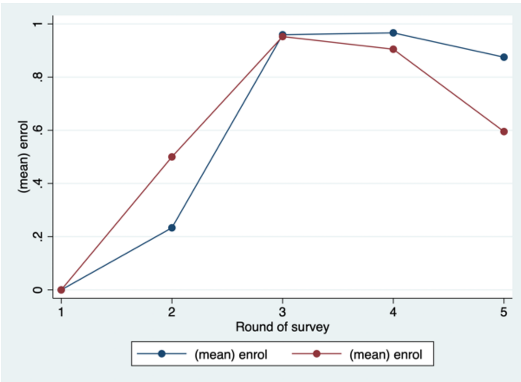


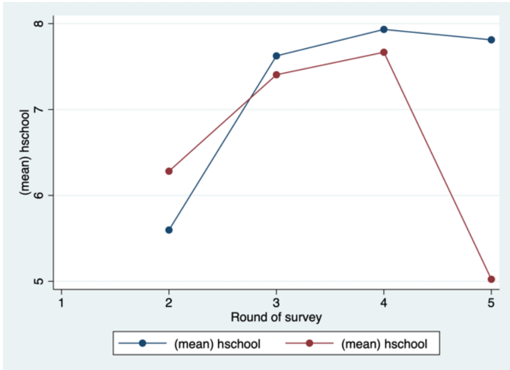
These graphs show the trends within several outcome variables by treatment status for the Sabla YL treatment variable. The treatment group is represented in red, while the comparison group is represented in blue.

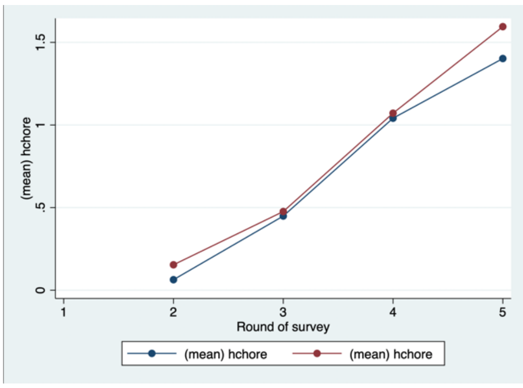
Appendix A8. Parallel Trend Graphs SABLA

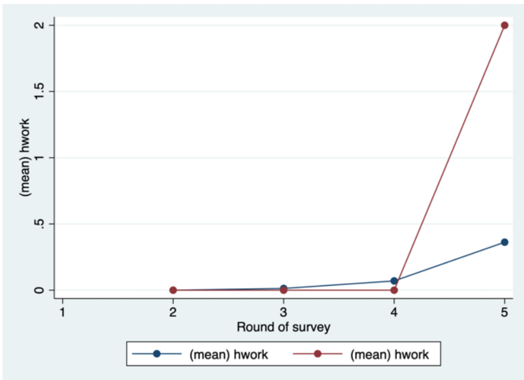












These graphs show the trends within several outcome variables by treatment status for the Sabla treatment variable. The treatment group is represented in red, while the comparison group is represented in blue.

Appendix A9. Propensity Score Matching: Test of Differences in Means SABLA_YL

SABLA YL

Covariate	Matched	Mean (i) Treated	Mean (ii) Control	T-Test (iii) t	T-Test (iv) p > t
Education Father	U	6.189	6.292	-0.190	0.847
	M	6.189	6.059	0.160	0.870
Education Mother	U	4.740	4.418	0.630	0.532
	M	4.740	4.272	0.570	0.571
Wealth Index	U	0.447	0.515	-4.200	0.000
	M	0.447	0.463	-0.790	0.427
Household Head Female	U	0.016	0.027	-0.740	0.460
	M	0.016	0.019	-0.190	0.850
Brother in Household	U	0.654	0.600	1.180	0.239
	M	0.654	0.652	0.030	0.973
Access to Infrastructure & Sanitation	U	2.063	2.270	-3.960	0.000
	M	2.063	2.112	-0.710	0.480
Disadvantaged Group (Ethnicity/Caste)	U	0.890	0.809	2.240	0.025
	M	0.890	0.876	0.330	0.740

This table reports the results of the t-tests between treated and control units with the variables used to calculate the propensity score. The p-values reported in column iv reveal that within the matched sample there are not statistically significant differences between treated and control units, which means that the matching was successful.

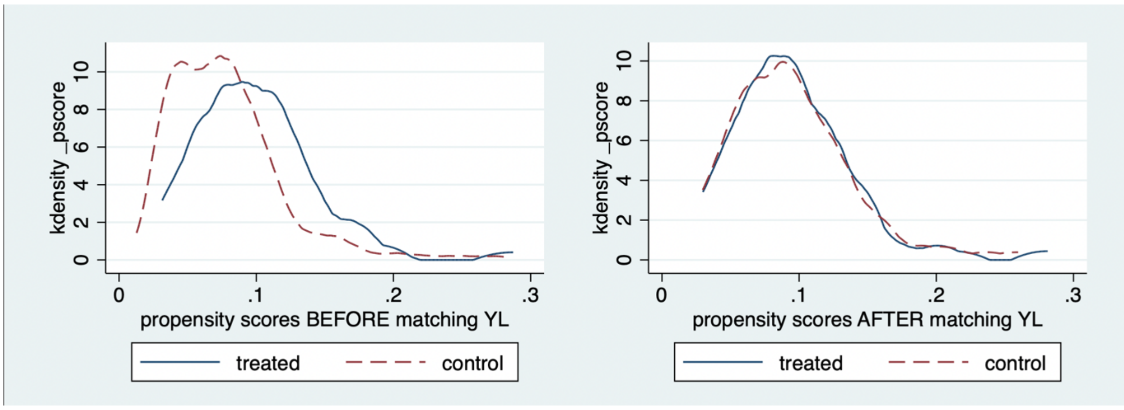
Appendix A10. Propensity Score Matching: Test of Differences in Means SABLA

SABLA

Covariate	Matched	Mean (i) Treated	Mean (ii) Control	T-Test (iii) t	T-Test (iv) p > t
Education Father	U	6.854	6.268	0.630	0.529
	M	6.854	7.805	-0.530	0.596
Education Mother	U	5.073	4.401	0.750	0.452
	M	5.073	2.951	1.360	0.179
Household Size	U	6.122	5.509	1.610	0.108
	M	6.122	6.439	-0.510	0.613
Wealth Index	U	0.421	0.514	-3.300	0.001
	M	0.421	0.433	-0.340	0.736
Household Head Female	U	0.024	0.023	0.040	0.969
	M	0.024	0.000	1.000	0.320
Brother in Household	U	0.561	0.608	-0.600	0.548
	M	0.561	0.537	0.220	0.827
Access to Infrastructure & Sanitation	U	2.049	2.264	-2.370	0.018
	M	2.049	2.195	-1.310	0.193
Rural Area	U	0.098	0.250	-2.220	0.026
	M	0.098	0.122	-0.350	0.728
Disadvantaged Group (Ethnicity/Caste)	U	0.878	0.816	1.000	0.318
	M	0.878	0.951	-1.180	0.241

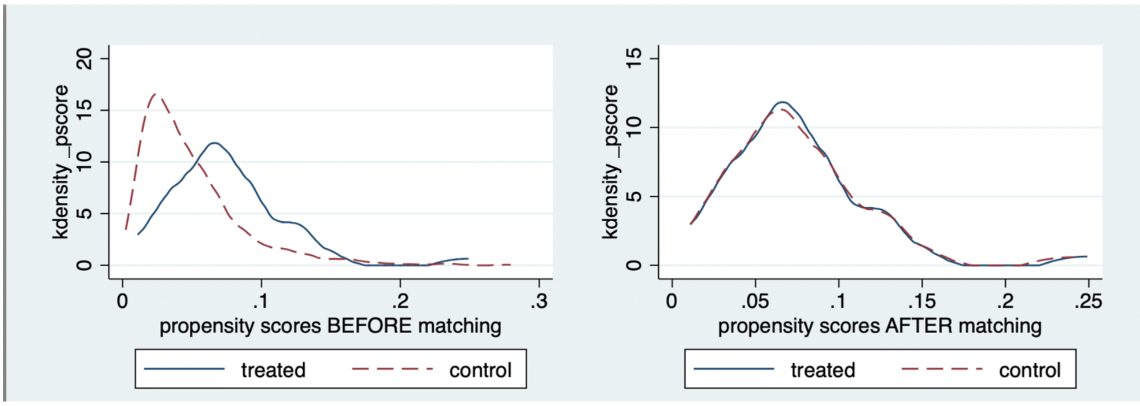
This table reports the results of the t-tests between treated and control units with the variables used to calculate the propensity score. The p-values reported in column iv reveal that within the matched sample there are not statistically significant differences between treated and control units, which means that the matching was successful.

<u>Appendix A11.</u> Propensity Score Matching: Area of Common Support Graphs SABLA_YL



These graphs depict the distribution of propensity scores in the treatment and comparison group before and after matching for the Sabla_YL treatment variable. The overlapped zone corresponds to the area of common support between the two groups.

<u>Appendix A12.</u> Propensity Score Matching: Area of Common Support Graphs SABLA



These graphs depict the distribution of propensity scores in the treatment and comparison group before and after matching for the Sabla treatment variable. The overlapped zone corresponds to the area of common support between the two groups.

Appendix A13. **Total Estimation Methods Results: SABLA_YL**

	SABLA_YL				
	OLS	PSM		Diff-in-Diff	PSM & Diff-in-Diff
Outcome	(i)	(ii)	(iii)	(iv)	(v)
	OLS	ATT	ATT	ATT	ATT
HEALTH	**-0.067**	**0.183****	**-0.105***	**-0.132**	**-0.119**
	(0.085)	(0.086)	(0.057)	(0.085)	(0.083)
Weak BMI	-0.016	-0.11*	0.013	0.050	0.016
	(0.044)	(0.063)	(0.041)	(0.042)	(0.031)
Height-for-Age Z Score	-0.081	-0.085	-0.137	-0.221	-0.210
	(0.130)	(0.205)	(0.116)	(0.241)	(0.230)
Self-Reported Health	-0.306**	0.111	-0.287**	-0.237	-0.330
	(0.130)	(0.236)	(0.126)	(0.295)	(0.290)
Child Overall Health	-0.065	0.071	-0.081	-0.041	-0.054
	(0.076)	(0.112)	(0.074)	(0.082)	(0.093)
SCHOOLING	**-0.328*****	**-0.219****	**-0.32*****	**-0.259*****	**-0.198****
	(0.093)	(0.100)	(0.092)	(0.090)	(0.085)
Hours/ Day Spent at School	-1.642***	-1.961***	-1.645***	-1.423***	-1.269***
	(0.386)	(0.389)	(0.337)	(0.359)	(0.351)
Currently Enrolled in School	-0.814***	-0.242***	-0.178***	-0.518**	-0.147***
	(0.155)	(0.043)	(0.039)	(0.246)	(0.044)
Highest Grade Achieved at Time of Interview	0.018	-0.211	-1.374***	-0.291	-0.214
	(0.226)	(0.470)	(0.400)	(0.178)	(0.157)
Hours/ Day Spent Studying	-0.379***	-0.291*	-0.391***	-0.199	-0.148
	(0.139)	(0.170)	(0.123)	(0.170)	(0.163)
ACTIVITIES/ EMPOWERMENT	**0.259*****	**0.465*****	**0.27*****	**0.105**	**0.111**
	(0.095)	(0.107)	(0.094)	(0.103)	(0.105)
Hours/ Day spent in HH Chores	0.118	0.283*	0.072	-0.104	-0.120
	(0.114)	(0.154)	(0.099)	(0.145)	(0.138)
Hours/ Day Spent in Paid Activity	0.693***	0.969***	0.73***	0.623**	0.651**
	(0.252)	(0.248)	(0.251)	(0.287)	(0.277)
Hours/ Day Caring after other HH members	0.050	0.189**	0.082	-0.060	-0.053
	(0.070)	(0.083)	(0.068)	(0.107)	(0.102)
Covariates	Yes	Yes	Yes	Yes	Yes
Matching Algorithm	-	Nearest Neighbor	Kernel	-	Kernel
Observations	1558	1626	1626	2370	2442

***, **, *: statistically significant at respectively 1%, 5% or 10% significance level.
Robust standard errors in parenthesis, clustered by individual child ID level.
Each cell reports a different estimation of the treatment effect. (i) reports the results of the OLS estimation. (ii) And (iii) report the average treatment effect on the treated estimated through the PSM method. (ii) Shows the results of nearest neighbor matching and (iii) of kernel matching. Column (iv) report the results of the difference-in-differences method. Column (v) shows the ATT calculated through DID with PSM.
Controls and measures of the outcome variables are the same as described in table T1.

Appendix A14. Total Estimation Methods Results: SABLA

Outcome	SABLA				
	OLS	PSM		Diff-in-Diff	PSM & Diff-in-Diff
	(i)	(ii)	(iii)	(iv)	(v)
	OLS	ATT	ATT	ATT	ATT
HEALTH	**-0.039**	**0.183****	**-0.105***	**0.116**	**0.069**
	(0.079)	(0.126)	(0.095)	(0.095)	(0.083)
Weak BMI	-0.183	-0.195*	-0.090	-0.071	-0.090
	(0.213)	(0.107)	(0.081)	(0.079)	(0.075)
Height-for-Age Z Score	0.122	0.077	-0.054	0.313	0.189 **
	(0.137)	(0.222)	(0.181)	(0.136)	(0.082)
Self-Reported Health	-0.402*	-0.341	-0.43*	0.076	0.066
	(0.222)	(0.306)	(0.222)	(0.267)	(0.261)
Child Overall Health	-0.153	-0.39***	-0.173	-0.052	-0.127
	(0.111)	(0.150)	(0.125)	(0.114)	(0.108)
SCHOOLING	**-0.567****	**-0.595*****	**-0.516*****	**-0.554****	**-0.468****
	(0.185)	(0.228)	(0.187)	(0.198)	(0.198)
Hours/ Day Spent at School	-2.338***	-3.024***	-2.475***	-2.365***	-2.418***
	(0.681)	(0.747)	(0.676)	(0.676)	(0.646)
Currently Enrolled in School	-0.795***	-0.293***	-0.247***	-0.659**	-0.23***
	(0.226)	(0.091)	(0.078)	(0.325)	(0.074)
Highest Grade Achieved at Time of Interview	0.401**	-2.146**	-1.803*	-0.024	-0.084
	(0.173)	(0.470)	(0.968)	(0.199)	(0.194)
Hours/ Day Spent Studying	-0.494**	-0.7561**	-0.534**	-0.296	-0.341*
	(0.191)	(0.314)	(0.211)	(0.196)	(0.195)
ACTIVITIES/ EMPOWERMENT	**0.309***	**0.502****	**0.352***	**0.371****	**0.412****
	(0.184)	(0.213)	(0.190)	(0.184)	(0.180)
Hours/ Day spent in HH Chores	0.092	0.293	0.087	0.090	0.115
	(0.175)	(0.221)	(0.177)	(0.173)	(0.169)
Hours/ Day Spent in Paid Activity	1.291**	1.683***	1.4**	1.492**	1.58***
	(0.577)	(0.585)	(0.562)	(0.571)	(0.563)
Hours/ Day Caring after other HH members	-0.151**	-0.122	-0.125	-0.139	-0.138
	(0.067)	(0.146)	(0.092)	(0.086)	(0.114)
Covariates	Yes	Yes	Yes	Yes	Yes
Matching Algorithm	-	Nearest Neighbor	Kernel	-	Kernel
Observations	766	774	774	2370	2414

***, **, *: statistically significant at respectively 1%, 5% or 10% significance level.
Robust standard errors in parenthesis, clustered by individual child ID level.
Each cell reports a different estimation of the treatment effect. (i) reports the results of the OLS estimation. (ii) And (iii) report the average treatment effect on the treated estimated through the PSM method. (ii) Shows the results of nearest neighbor matching and (iii) of kernel matching. Column (iv) report the results of the difference-in-differences method. Column (v) shows the ATT calculated through DID with PSM.
Controls and measures of the outcome variables are the same as described in table T1.