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IFPRI Discussion Paper 02060

November 2021

How Much are Multisectoral Programs Worth?

A New Method with an Application to School Meals

Harold Alderman

Elisabetta Aurino

Priscilla Twumasi Baffour

Aulo Gelli

Festus Turkson

Brad Wong

Poverty, Health, and Nutrition Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

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AUTHORS

Harold Alderman (h.alderman@cgiar.org) is a senior research fellow in the Poverty, Health, and Nutrition Division at the International Food Policy Research Institute (IFPRI), Washington DC.

Elisabetta Aurino (e.aurino@imperial.ac.uk) is a research fellow in the Department of Economics and Public Policy at Imperial College London, UK.

Priscilla Twumasi Baffour (ptbaffour@ug.edu.gh) is a senior lecturer in the Department of Economics at the University of Ghana, Accra, Ghana.

Aulo Gelli (a.gelli@cgiar.org)is a senior research fellow in IFPRI's Poverty, Health, and Nutrition Division at the International Food Policy Research Institute (IFPRI), Washington DC.

Festus Turkson (feturkson@ug.edu.gh) is an associate professor in the Department of Economics, University of Ghana, Accra, Ghana.

Brad Wong (brad@copenhagenconsensus.com) is Chief Economist at the Copenhagen Consensus Center, Copenhagen, Denmark.

Notices

Abstract

Social protection programs such as cash or food transfers support current poverty and inequality reduction goals, while at the same time enhance future productivity through human capital investments. Yet, the quantification of their overall productivity and equity benefits is challenging. We address this question utilizing a new methodology that quantifies productivity gains from learning as well as an approach for assessing social protection benefits. We do so by combining data on distributional benefits stemming from current poverty reduction in conjunction with future human capital gains in the context of a large-scale national school feeding program in Ghana. We develop a straightforward approach to map effect sizes from randomized controlled studies into broader economic analyses. In addition, we include the often recognized, but seldom quantified, distributional impacts of multi-sectoral investments. Our methodology is relevant to a broad range of social protection programs that have multidimensional benefits spanning both human capital improvements and equity gains.

Keywords: School feeding; education; program evaluation; redistribution; fiscal policy

JEL Codes: H23 Public Economics; I15 Health, Education and Welfare; I32 Welfare, Well-Being, and Poverty; O15 Income distribution, O22 Project analysis

Acknowledgments

This work was undertaken as part of the CGIAR Research Program on Policies, Institutions, and Markets (PIM) led by the International Food Policy Research Institute (IFPRI). Elisabetta Aurino acknowledges support from an Imperial College Research Fellowship awarded by Imperial College London.

Introduction

School feeding programs are among the most widespread forms of social protection globally; in 2020, 388 million children in 163 countries participated in school meal programs that globally cost between 41 and 43 $ billion (WFP, 2021). Their prevalence reveals the political popularity of such programs, but their economic value both in absolute terms and relative to alternative public programs is often hard to ascertain. In part, this is because school meal programs have diverse benefits, spanning child education, health, and nutrition, as well as social protection contributions to current household poverty reduction and future productivity (Alderman and Bundy, 2012). Which benefits predominate depends, of course, on context and program design, with some programs also having the potential to support local farmers through 'home-grown' food purchases (Gelli et al. 2021). While there is extensive evidence on program effectiveness on different domains (Drake et al. 2017), this multi-dimensionality makes it difficult to assess the benefits of school feeding based on cost-effectiveness. It is unlikely that school meals are cost effective relative to specific sectoral investments in any single dimension, although plausibly the joint benefits may prove comparable or even greater to other investments under a common evaluation metric.

Benefit-cost analysis is a well-known approach to account for multi-dimensional benefits under a common unit, typically currency (Robinson et al. 2019). Benefit-cost analyses have been conducted on school feeding (Verguet et al. 2020; Fernandes and Aurino, 2017; Turkson, Baffour, and Wong 2020). However, these studies included education benefits focusing only on enrolment rather than on learning (a more appropriate driver of future productivity gains) and/or did not include social protection benefits in a way that accounts for social aversion to inequality. The limitations of a focus on enrolment of existing benefit-cost analyses of school feeding is becoming increasingly apparent, as gross primary school enrollment is approaching universal participation. For example, in sub-Saharan Africa enrollment rose from 82% to 98% since 2000 (World Bank, 2021). Thus, while the evidence indicating that school feeding programs increase enrollment is extensive, in many settings that contribution is a declining component of the aggregate benefits of school meal programs in the 21st century; in much of the world, school feeding is no longer primarily about enrollment though access to school for pockets of socially excluded children may still be a concern. Indeed, this a generic issue with the assessment of a wide range of education programs and policies, which are shifting their focus from schooling to learning (Angrist et al. 2020).

This paper addresses this by conducting a benefit-cost analysis using a methodology that address both productivity gains from learning and social protection benefits. We do so by including distributional benefits stemming from current poverty reduction in conjunction with future human capital gains. We use data from a large-scale national school feeding program in Ghana (Gelli et al. 2019; Aurino et al. 2020), but our findings are relevant more broadly to a range of social protection programs (e.g. cash transfers, food assistance) that have multidimensional benefits spanning both human capital improvements and equity gains.

To provide an economic assessment of the observed program impacts we need to address two specific challenges. First, we need to map the effect size of learning improvements stemming from participation in the program into anticipated increased lifetime earnings. Economists have often used Mincer equations to assess the contribution of increased schooling to earnings. However, this approach has limitations (Evans and Yuan 2019; Angrist et al. 2020), and what is often needed is a method to assess the impact of learning, a related but likely more relevant measure of skills driving returns to education, on earnings (Hanushek and Woessmann 2008;

Filmer et al. 2020). We approach this issue by using a perspective presented in Evans and Yuan (2019). Indeed, we explore two conceptually related, but empirically distinct, methods to translate learning impacts to expected growth in wages. While one approach utilized specialized data on skills measured for adults, the other relies on the data collected withing the impact evaluation and commonly available wage regressions. Thus, our results illustrate a broadly applicable empirical technique.

Second, we address the challenge of including social protection benefits in the context of efficiency gains. While the randomized controlled trial studied shows that the school meal program contributes to economic efficiency by increasing potential lifetime earnings with the gains exceeding the costs (Turkson, Baffour, and Wong, 2020), this may not be the full extent of the social benefits from the program. This is because the objectives of both cash and in-kind transfer programs are often not only to increase human capital investments with implications for future levels and distributions of income but also to alleviate current poverty and reduce current inequality (Das, Do, Özler 2005). Thus, the full extent of the benefits from such programs also depends on the degree of inequality aversion in the social welfare function. The latter, however, is not directly observed. Therefore, we approach this problem by employing plausible simulations based on the distribution of income of the program beneficiaries relative to the national distribution with a parametrized social welfare function (Alderman, Behrman, and Tasneem 2019). We apply this to a school meal program indicating substantial economic gains, primarily from future earnings but also comprised of approximately 10-20% redistribution benefits depending on difference scenarios. This application of distributional gains is an issue that goes beyond the assessment of targeted school meal programs.

Context

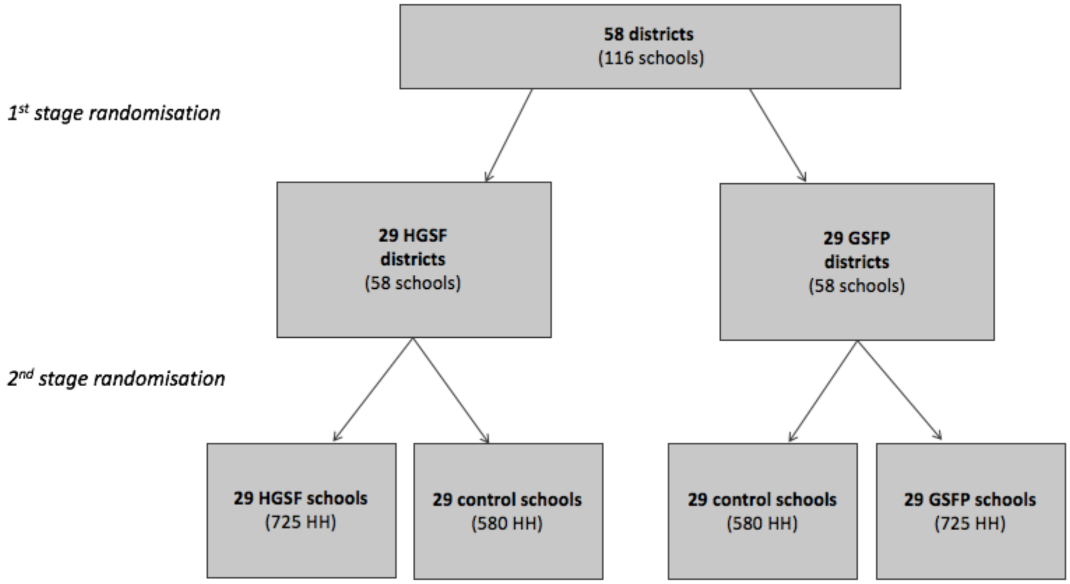
The Ghana School Feeding Program (GSFP) was part of the government's strategy to raise school participation in the wake of the Millennium Development Goals agenda. The program started in 2005 with a four-year pilot, and later it was expanded and integrated to the government annual budget. GSFP coordination and implementation are undertaken by a National Secretariat, with program oversight provided by the Ministry of Gender, Children and Social Protection. The provision of meals is decentralized, with private caterers being awarded contracts by the GSFP to procure, prepare, and serve food to pupils in the targeted schools.

By coordinating with the government's plans to expand the program to new districts, a randomized controlled trial assessed program effects on child learning and nutrition (Aurino et al., 2020; Gelli et al. 2019), and on agriculture outcomes (Gelli et al. 2021). The experiment was designed around the scale-up of the GSFP based on a retargeting exercise conducted in 2012. The decision to retarget the GSFP was driven by evidence that the program overwhelmingly benefited non-poor households, with only 21% of benefits accruing to poor families (World Bank, 2012). The retargeting exercise was guided by the poverty and food insecurity rankings to prioritize districts across the whole of Ghana. Rankings were used to generate district-level indices on the share of national poverty and food insecurity, through which 58 priority districts (out of the country's 170 at the time of this exercise) were identified for the scale-up of GSFP (see Gelli et al., 2016, for details). Analysis of headcount poverty levels after the retargeting show very high levels of consistence between our baseline sample (23%) and the 2012-13 national headcounts (24%) (Ghana Statistical Service 2018). While this speaks to the potential external validity of the findings from the impact evaluation, it also highlights that poverty targeting of the program remained limited even after the retargeting exercise.

The trial focused on assessing the effects of GSFP on children's education and health, as well as on agriculture. To affect these different outcomes, program components were delivered at different administrative levels: the school feeding service (which was hypothesized to affect mostly children's outcomes) was designed to be delivered at the school-level, while the agriculture-related activities were delivered at the district-level, also affecting communities that would not offer school feeding. Given this complexity, a two-step randomization was devised (Figure 1). The first step allocated communities to school feeding or control groups through a restricted randomization procedure that modeled selection using a set of school- and village-level variables (for details, see Gelli et al. 2016). The second stage involved a similar restricted randomization procedure to allocate the school feeding group into two sub-groups (GSFP and home-grown school feeding pilot, HGSF) based on additional variables that characterized the agricultural environment.

With regards to average treatment effects on learning, after two years, the program led to moderate average increases in standardized math (effect size, e.s.: 0.15, $q < 0.1$), literacy (e.s.=0.13, $q < 0.1$) and composite learning scores (e.s.=0.17, $q < 0.05$). The program had larger benefits for girls as well as children from poorest households and regions. The effect size in the improvement in the composite learning score for girls was 0.27 ($q < 0.05$) while it was 0. 33 ($q < 0.01$) for children from poorest households and 0.30 ($q < 0.1$) for children in the northern regions (Aurino et al., 2020). In terms of child nutritional status, exposure to school feeding had no effect on nutritional indicators for the whole sample. However, the GSFP had significant effects on height-for-age z-scores (a marker of chronic malnutrition) of girls (e.s.=0.12, $p < 0.05$) and for young children in households living below the poverty line (e.s.=0.22, $p < 0.05$).

Figure 1. Two-level randomization



Notes: this figure provides the study design: first, districts were randomly assigned to pilot (HGSF) and standard (GSFP) school feeding through a first-level randomization; second, within each district, two schools (and related households living within the school catchment areas, which were refer to as "communities") were randomly assigned to school feeding or control. Note that due to the discovery of the GSFP already present in 25 communities at baseline, these were dropped from the original community sample. Two additional communities could not be resurveyed due to local violence at the time of the endline survey. An original third level of randomization was dropped soon after the baseline due to substantial delays in implementation and the limited number of schools still available after the removal of schools that we discovered had school feeding at baseline.

Data

The survey design and data used for the evaluation of the school meal program are described in detail in the papers that present the impacts that we are placing in an economic context (Aurino et al., 2020; Gelli et al. 2019). To briefly reiterate the main features of this data, the impacts were assessed using a baseline survey undertaken in 116 communities between June and September 2013. Implementation in most treatment communities started in the academic year 2014/15. The follow-up survey was conducted in February-March 2016. Given that the academic year in Ghana usually runs from August to May, the program was evaluated after roughly two academic years of implementation. Ninety-two percent of children of target-age and eligible to receive school feeding were reinterviewed in the second round of data collection. This resulted in a longitudinal sample of 3,170 children. Balance tests of baseline covariates found only one difference between the two groups that was statistically significant at 10 percent level, the age of household heads. This single difference indicated that household heads were about one-year-and-a-half older in the school feeding arm than in control communities.

As the school meal program was targeted on poverty levels at district level, albeit imperfectly, the main data source cannot provide a benchmark for assessing the distribution of the benefits within the larger population. Thus, we also utilize the Ghana Living Standards Survey 7 [GLSS-7] collected in 2016-17 to assess how the expenditure levels of the sample of children that received school feeding (N=931) related to that of the general population and to provide information on wages (Ghana Statistical Service 2018). The GLSS is a survey conducted by the Ghana Statistical Service at regular time intervals since 1987 to assess the living conditions and well-being of the Ghanaian population. It is one of the primary tools used to monitor poverty and inequality trends, and includes data on demographics, consumption expenditures, education, employment, and health, among others. The GLSS relies on a nationally representative sample of 140,009 households, which was selected through a two-stage sampling procedure. In the first stage enumeration areas were selected based on the 2010 Population and Housing Census, with probability proportional to number of households, administrative regions, and urban/rural locations. At the second stage, a random number of maximum 15 households were selected by systematic sampling within each of the selected enumeration areas.[1] We inflate all values related to consumption (from both the 2013 impact evaluation data and the 2017 GLSS7) to 2018 using a GDP deflator (2010 = 100; World Bank 2021). Table 1 summarizes the data employed in the analysis.

[1] The response rate was 93.4%. For more information, see: https://catalog.ihsn.org/catalog/7967#metadata-sampling

Table 1 Summary of Data Used

Metric	Value	Units	Source
		Costs	
Cost per pupil (2018 GHS)	1.1	*GHS*	Calculation inflated cost
Extra hours per day spent in school due to school feeding	0.359	*hours*	Aurino et al (2018)
Value of time for 11-13 year olds relative to adults	75%	*%*	Authors' assumption
Pupil teacher ratio primary school	30	#	Ministry of Education supplied data
Pupil teacher ratio junior high school	15	#	Ministry of Education supplied data
Overall PTR for beneficiaries	25	#	Calculation
Monthly teacher salary	800	*GHS*	Authors' estimate
Value of leisure time relative to productive time	50%	*%*	Whittington and Cook (2020)
% of extra time that teachers spend in school that substitutes leisure time	50%	*%*	Authors' estimate
Number of school days in an academic year	200	#	Authors' estimate
		Benefits	
Increase in literacy test scores from exposure to two years of school feeding (sd test scores)	0.13	#	Aurino et al, 2020
Increase in wages per 1 S.D. improvement in test scores	0.178	%	Evans and Yuan (2017)
Increase in wages from exposure to two years of school feeding	0.023	%	Calculation
HH value of 1 meal	1.5	*GHS*	Authors' estimate based on Fernandes et al. and Armenia paper

Metric	Value	Units	Source
Primary income level	5,119	*2016 GHS*	Mincerian analysis results on GLSS7 data
Mean p.c. consumption in national data	3842.66	*2018 GHS*	Analysis of GLSS7 data
Mean p.c. consumption in impact evaluation	3862.932	*2018 GHS*	Analysis of baseline data impact evaluation (2013)
General			
Beneficiaries	931	#	Aurino et al, 2020
Beneficiaries, % poor	27%		Authors' calculation based on Aurino et al (2020)
Low discount rate	3%	%	Robinson et al (2019)
Medium discount rate	5%	%	Discount rate used in other nutrition BCAs, Hoddinott et al. (2013), Wong and Radin (2019)
High discount rate	8%	%	Robinson et al (2019)

Methodology

Returns to education

As noted earlier, some of the benefits of education are more closely associated with learning (Hanushek and Woessmann 2012), while schooling predicts others better (De Neve et al. 2015; Duflo, Dupas, and Kremer 2017). Based on this insight, Filmer et al (2020) proposed a new measure combining years of schooling with a measure of school quality, the learning adjusted years of schooling [LAYS], for international comparisons.[2] The measure was developed by scaling schooling years by its test-score performance relative to a global benchmark. While LAYS was not initially designed for program evaluation, in some cases it is possible to calculate economic returns by either applying estimates of the results indicating the incremental learning attributable to a program, or by estimating equivalent years of schooling by adapting a Mincerian framework (Evans and Yuan, 2019).

[2] See also Gelli et al. 2014.

For the former approach, one needs a measure of learning for a representative sample of the labor market which can be regressed against their earnings. Such regressions have been undertaken for five countries as part of the World Bank's STEP Skills Measurement Program. Using this data, Evans and Yuan (2019) find a 17.8% increase in earnings with a one standard deviation improvement in reading test scores in Ghana. That result is the second lowest of the five similar country estimates reported from STEP surveys and only half of the pooled estimate. Moreover, the result is not statistically significant. Nevertheless, we use this point estimate as a starting point in our calculations of the expected economic returns to the GSFP. An alternative approach, potentially more widely applicable, is an adaptation of the commonly used Mincerian regression:

$$E = b_1 * yrs\_ed \quad (1)$$

where E is the logarithm of earnings and yrs ed is the number of completed years of schooling for the worker. However, yrs_ed is not a good measure of learning adjusted years of education, yrs_ed_LAYS. Ideally, we want to regress

$$E = b_2 * yrs\_ed\_LAYS \quad (2)$$

We would expect that $b_1 < b_2$. In the absence of a direct measure of yrs_ed_LAYS we need to scale the program in terms of years that can be entered into a Mincerian regression. If the program boosts learning compared to that of a counterfactual, normalized as 1, a year of schooling now provides the same learning as *1+n* years had achieved without the program. If the

$$LAYS = \left(\frac{1}{1+n}\right) * yrs\_ed \quad (3),$$

then an estimate of $b_2$is $(1+n) * b_1$ and b_1 can be applied to *n* to get the program impact in terms of expected earnings. This, however, assumes that the increment to learning applies to all years of schooling. However, the project under consideration only covers two years and, thus, we modify years of schooling in an additive manner not as a proportional scaling of years. It is important to indicate that the *LAYS* is relative to the counterfactual derived from the progression of test scores of the control group of the RCT and not the international standardization used in Filmer et al. (2020).

The schooling impacts have benefits that accrue over the student's working lifetime. Everyone is assumed to work from age 20 to age 60, as in Evans and Yuan (2019). There is no consensus rate at which the future stream of benefits is discounted, thus results can be sensitive to the choice of discount rates often with profound implications across generations (Stern, 2008). We follow guidelines for benefit-cost analysis in global health and development (Robinson et al, 2019) and use a constant annual rate of 3 percent in a first scenario that also assumes there is no real income growth. We then model second and third sensitivity analysis scenarios with a higher discount rate of 8 percent noting that Ghana, like many low-and-middle-income countries, has high projected per capita growth rates, warranting higher social discounting under the Ramsey equation (Haacker, Hallett and Atun, 2020). In the second scenario, we continue to exclude income growth. However, as worker productivity increases with capital as well as with the skills of the labor force, it is not uncommon to scale future earnings by an estimate of real economic growth (Hoddinott et al. 2013). Therefore, in the third scenario we also include real per capita income growth rates based on projections of the Shared Socioeconomic Pathway (middle-of-the-road scenario) supplied by the International Institute for Applied Systems Analysis (IIASA) (Riahi *et al.*, 2017).[3] These three scenarios will illustrate the sensitivity of our results to different discount rates and growth assumptions.

[3] IIASA provides country level projections of real GDP and population for every 5th year until 2100. To convert to an annual time series of growth rates, we assume constant GDP and population growth rates between each 5-year interval.

Based on these assumptions, we estimate individual net present values (NPV) of human capital returns from school feeding with the following equation:

$$NPV_i = \sum_{k=20-a_i}^{n=60} \frac{\Delta L * \beta_1 * w_j}{(1+d)^{k+1}} \quad (4)$$

Where:
ΔL =schooling-equivalent treatment effect of school feeding (LAYS)
β_1: estimate from a Mincerian equation of returns to schooling in Ghana
w_j: average wage
k: years between start of work life and age of the child at endline
n: number of years in the workforce
a_i: age at which child i is receiving school feeding
d: discount rate

These values are then summed across children that report receiving school meals in the endline of the impact evaluation (N=931) to get total net present values of human capital returns from school feeding in our sample.

Returns to nutrition

Many of the estimated returns to nutrition are assessed via improved productivity (e.g. Hoddinott et al. 2013). Although improved nutrition may be an underlying contributor to the learning results, we do not include this dimension to avoid potential double counting, as the productivity gains from the program would already be included under learning. Another aspect of nutrition that is implicit in the estimated returns is the expectation that individuals not in the labor force have personal returns that are similar to the returns for an individual with a similar education that earns wages. There is extensive evidence showing that child nutrition improves with the education of the caregiver and that this is mediated by learning (Glewwe 1999). Thus, we assume that the gains to education for women engaged in home production and childcare are equivalent to the gains estimated in the labor force. Furthermore, we assume, along with Schultz (2002), that women and men receive the same percentage increase in their wage rates with additional schooling even if women earn less on average.

Returns to Social Protection

We examine the social protection returns from school feeding by using an additive social welfare function in which social welfare W is summed over individual well-being, x_i , of the N individuals in the society.

$$W = \sum_{i=1}^{N} \frac{x_i^{1-\varepsilon}}{(1-\varepsilon)},\ \varepsilon \neq 1;\ \ln W = \sum_{i=1}^{N} \ln x_i\ ,\ \varepsilon = 1 \quad (5)$$

An important characteristic of this welfare function is that a single distribution parameter, ε, indicates how society values inequality (Atkinson, 1970). If ε = 0, *W* is utilitarian, which means that society places no value on redistribution, while higher ε implies greater inequality aversion. Moreover, this welfare function also has the property that the ratio of marginal social utility of two individuals is the reciprocal of the ratio of their well-being raised to the power of the distribution parameter, ε.

$$\frac{\partial W/\partial x_i}{\partial W/\partial x_j} = (x_j/x_i)^{\varepsilon} \quad (6)$$

When $\varepsilon = 0$ then there is no difference in the marginal social utility across individuals. This is implicit in estimates of benefits from school feeding that assign the same benefit of the transfer to all participants. Since x_j/x_i is greater than one whenever the *ith* individual is poorer than the *jth*, all values of ε > 0 imply that social welfare increases at a faster rate with an increase of consumption for the *ith* individual than an equal increase in consumption for the *jth*. As the redistribution parameter increases, social gain of redistribution from richer to poorer individuals also increases.

Equation 6 is often applied to assess the redistributive effects of fiscal policies (Deaton 1997; Coady and Skoufias, 2004). Skoufias and coauthors (2010) employed the constant relative social welfare function from eq. 5 to measure the distributional characteristics of transfer programs. They parameterize eq. 6 with ε = 2, thus placing a relatively high value on redistribution compared to other studies in the literature. This, then, goes to a limitation of the social welfare function in that this key parameter is not directly observed. However, a reluctance to assign a positive value to ε ignores the fact that zero is also a number and one that is inconsistent with the design of targeted transfer programs. Behrman and Birdsall (1988) tackle this limitation by estimating the parameter from the revealed behavior of public educational investments in Brazil, obtaining an estimate of 0.7. We consider this as a reasonable value and we use this as our main value of ε, but offer a range of simulations to assess the sensitivity of such choice.

While many papers employing social welfare functions focus on relative inequality, to aggregate with the benefits from education we require a cardinal rather than ordinal measure. This necessitates additional assumptions. Following Alderman, Behrman, Tasneem (2019) we set x_j to mean per capita consumption and then also set $\delta W/\delta x_j = 1$. This, then, allows us to generate values for $\delta W/\delta x_i$ for any given value of ε.

Benefits are estimated based on

$$D = \sum_{i=1}^{N} v_i (x_j/x_i)^{\varepsilon} \quad (7)$$

where v is the transfer value, whereas values of per capita consumption from the baseline impact evaluation data provide the values of x_i from while the mean from the GLSS7 provides the value for x_j.

When calculating benefits, we consider a transfer value at GHS 1.5 per day based on insights from Fernandes et al (2017) in Ghana as well as a similar observation in Bakhshinyan et al. (2019) in Armenia, whereby households tend to value school feeding at a higher value than its budgetary costs. For instance, Bakhshinyan et al. (2019) show that households that have access to school meals report budget savings above the cost to the government for provision. Additionally, in those households where a student was not eligible for a school meal the median reported daily cost of meals purchased exceeded what the program cost with the median of both reported household savings and out of pocket costs being identical.[4]

Program costs

The GFSP budget was based on GHS 1.1 per child per day in direct costs paid to caterers over 400 hypothesized feeding days over the two years of the evaluation[5]. We also compute opportunity costs, as students and teachers spend more time at school – roughly 20 min per day on average due to school feeding. Half of the extra teacher time is assumed to substitute for teaching responsibilities valued at the full wage rate of GHS 800 per month, while the remainder is assumed to substitute leisure time valued at 50% of the wage rate (Whittington and Cook, 2019). Following Turkson, Baffour, and Wong (2020), we do not value the opportunity costs of children below the age of 10 due to uncertainties around these costs for young children and their caregivers. However, for children older than 11 receiving the intervention at endline (45% of the sample), we value time at the implied wage rate of primary school graduates which equals GHS 5,119 per year and apply a 75% factor to account for age, leading to an average yearly wage of GHS 3,839. Thus, we estimate total economic costs of the intervention to be GHS 1.12 per child per day, for a total of GHS 418,224 for the endline intervention sample over the two years (US 68,956.97).

Results

We start our analysis by converting program impacts on learning into lifetime economic returns. As noted, one approach derives from the direct product of the program impact on learning and the coefficient of learning reported in Evans and Yuan, leading to a 2.3% increase in earnings after

[4] This may also reflect a convenience yield and a reallocation of time in household tasks distinct from the transfer value and which might partially explain the popularity of programs where food security is not a major policy concern.

[5] This is a likely overestimation of actual financial costs as the program faced disbursement challenges during the implementation period.

two years exposure to the program. This is the product of the 0.13 effect size increase of literacy test scores from Aurino et al. (2020) and the 17.8% increase in wages per SD of literacy for Ghana reported by Evans and Yuan (2019). We focus on literacy test scores to be consistent with the results reported by these authors.[6]

However, there are only a handful of studies that have data for a similar approach due to lack of data that directly map learning to wages. Thus, we compare this approach to the estimation of learning adjusted years of schooling (LAYS), which is a more generalizable approach as it would rely on data that are more commonly found in impact evaluations and school surveys. The underlying Mincerian equation from the GLSS, adjusted for sample selection for inclusion into wage employment (Heckman, 1979), is reported in Table 2.

[6] If we would apply the treatment effect coefficient on the composite learning score (e.s.=0.17), we would have an estimate of increased future earnings of 3.1% after being exposed to the program.

Table 2: Mincerian Equation- Earnings Effect of Schooling

Years of Education	0.074***
	(0.003)
Potential Labor Market Experience	0.032***
	(0.005)
Potential Labor Market Experience^2	-0.001***
	(0.000)
Selection Variable (Inverse Mills Ratio)	-0.564***
	(0.060)
Services	
Total Working Hours (Weekly)	
Female Worker	
Urban Location	
Constant	5.339***
	(0.087)
Number of Observations	**4,539**
R-squared	**0.191**

Notes: Estimates based on GLSS 7 2016/17 Database.
*Bootstrap standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Earnings only include values from wage employment due to lack of self-employment earnings in the GLSS 7 data.*

To adjust these Mincer results for the program impact we need first to estimate the improvement in learning that occurs in the absence of the program, a ‘business-as-usual’ scenario. Table 3 reports estimates of the changes in the literacy and composite test scores in the control group over a two-year period. Column 1 indicates the composite index of standardized math and literacy test scores as a function of grade attained (as per the OLS approach of Evans and Yuan), controlling for child gender, age, whether her family was below the poverty line at baseline, and region fixed effects. Column 2 builds on this model by including baseline test scores. Columns 3 and 4 present the same models by focusing on only endline literacy test scores. Results presented in Model 1 shows that in a business-as-usual scenario, each additional year of school contributes to an increase of 0.21 of a SD in learning. Thus, it takes 4.76 years to increase learning by a standard deviation. This estimate of learning-adjusted years of schooling is in line with the 4.4 yrs_ed_LAYS Evans and Yuan report. Hence, the treatment effect of school feeding translates into an increase of 0.81 years of learning-adjusted years of school (treatment effect from impact evaluation*effect size in EYOS=0.17*4.76).

If we focus on the estimates from Model 2 instead, where baseline test scores are controlled for, a business-as-usual year of schooling contributes to only 0.14 SD of learning, which implies it takes 7.1 years to increase learning by one SD. As the value-added estimates of model 2 imply the program impact is equivalent to more years in the Mincer equation than the results in model 1, we focus on the estimates from the first model, as they provide a more conservative scenario. We have broadly similar results when we focus on treatment effects on the literacy test scores (see columns 3 and 4 of Table 3). Yet, we prefer using the estimates based on the composite score, rather than literacy, as the former is likely to be more predictive of the type of skills that are valued on the labor market[7]. To summarize, we use the product of the learning adjusted years of schooling and the Mincer coefficient [0.81*0.074] for our core earning increment, which we then apply to wages perceived between 20 and 60 years to estimate lifetime earning returns stemming from increased human capital from exposure to the program. This 5.9% increase is larger than that implied by the direct application of the STEM data, a point we return to in the discussion.

[7] As participating in the program leads to an improvement of 0.13 SD in the literacy scores, the program would translate into an effect of 0.62 learning-adjusted years of schooling in the Mincer results.

Table 3. Estimates of grade attainment on endline composite test scores index and literacy scores

	(1)	(2)	(3)	(4)
	Composite of literacy and math		Literacy	
Grade attained	0.208***	0.138***	0.193***	0.128***
	(0.0339)	(0.0377)	(0.0305)	(0.0326)
Baseline test scores		0.199***		0.245***
		(0.0407)		(0.0510)
Poor household	-0.204**	-0.171*	-0.172**	-0.122
	(0.0813)	(0.0850)	(0.0834)	(0.0838)
Child is male	0.120**	0.112*	0.0983**	0.0744
	(0.0567)	(0.0576)	(0.0460)	(0.0460)
Age in years	-0.127***	- 0.0789***	-0.126***	- 0.0834***
	(0.0198)	(0.0252)	(0.0192)	(0.0221)
Constant	0.268	-0.0107	0.300	0.0662
	(0.266)	(0.313)	(0.279)	(0.319)
Observations	1,059	1,003	1,057	990
R-squared	0.141	0.152	0.135	0.143
Estimated EYOS	**4.8**	**7.1**	**5.3**	**7.7**

*Notes: *** p<0.01, ** p<0.05, * p<0.1 This model regresses a composite index of endline standardized math and literacy test scores (models 1 and 2) and endline standardized literacy scores for the control group of the school feeding evaluation, as a function of grade attained, and other child characteristics. Estimates also control for region fixed effects. Standard errors are clustered at the community level.*

Table 4 presents lifetime human capital returns to school feeding under three scenarios. As mentioned earlier, the first and the second scenarios relate to income levels that are fixed at the average wage of primary school leavers[8] over the lifetime under the assumption of no real national income growth and a discount rate of 3% and 8%, respectively. Under the first scenario, in which there is a relatively high weight assigned to future productivity (in keeping with a relatively low

[8] This is a conservative assumption as most children in Ghana usually transition to junior secondary schools after primary school.

discount rate), the individual NPV amounts to GHS 5361.8 (equivalent to current USD 883[9]), which leads to a total NPV of GHS 4.9 million (USD 806,974) for the sample of school feeding beneficiaries in the impact evaluation (N=931). When the discount rate rises to 8%, the individual NPV decreases to GHS 1786 (USD 294), and the total NPV to GHS 1.66 million (USD 273,383). In the third scenario, we add real income growth over time based on projections of the Shared Socioeconomic Pathway middle-of-the-road scenario by IIASA (Riahi et al., 2017). Keeping the discount rate of 8%, the NPV of school feeding returns from enhanced human capital over an individual working lifetime is GHS 2900 (USD 478)[10]. For the full sample, benefits amount to GHS 2.7 million (USD 444,659).

Table 4 also presents redistributive benefits at different preferences for redistribution, and total benefits for the sample of endline beneficiaries.

Table 4. Benefit-cost ratios at different scenarios and values for redistribution for the endline intervention sample (Panel A) and for retargeting sample (Panel B)

Panel A; Endline impact evaluation school feeding beneficiaries										
		Scenario 1 d=3%, no growth			Scenario 2 d=8%, no growth			Scenario 3 d=8%, income growth		
ε	Redistributive benefits	NPV of human capital investment	Total benefits	BCR	NPV of human capital investment	Total benefits	BCR	NPV of human capital investment	Total benefits	BCR
0	0.27	4.9	5.2	12.4	1.7	1.9	4.6	2.7	3.0	7.1
0.5	0.30	4.9	5.2	12.4	1.7	2.0	4.7	2.7	3.0	7.2
0.7	0.32	4.9	5.2	12.5	1.7	2.0	4.7	2.7	3.0	7.2
1	0.36	4.9	5.3	12.6	1.7	2.0	4.8	2.7	3.1	7.3
1.3	0.41	4.9	5.3	12.7	1.7	2.1	4.9	2.7	3.1	7.4
2	0.63	4.9	5.5	13.2	1.7	2.3	5.5	2.7	3.3	8.0

[9] Based on an exchange rate of 0.16 per Ghanaian cedi, as per October 20th, 2021.

[10] These estimates of net present values fall around the median of the range of net present values estimated by other interventions assessed by Evans and Yuan (2019). For instance, a Gambia school grant and remedial classes in China lead to USD40 and USD274 in increase in lifetime earnings, while structured pedagogy in Kenya and a computer-assisted program in Ecuador let to increases of around USD 1,338 and 3,093, respectively.

Panel B: Retargeting to 50% poor

		Scenario 1 d=3%, no growth			Scenario 2 d=8%, no growth			Scenario 3 d=8%, income growth		
ε	Redistributive benefits	NPV of human capital investment	Total benefits	BCR	NPV of human capital investment	Total benefits	BCR	NPV of human capital investment	Total benefits	BCR
0	0.27	9.2	9.5	22.6	3.1	3.4	8.1	5.0	5.3	12.6
0.5	0.35	9.2	9.5	22.8	3.1	3.4	8.2	5.0	5.3	12.8
0.7	0.38	9.2	9.6	22.9	3.1	3.5	8.3	5.0	5.4	12.9
1	0.46	9.2	9.7	23.1	3.1	3.6	8.5	5.0	5.5	13.1
1.3	0.56	9.2	9.8	23.3	3.1	3.7	8.8	5.0	5.6	13.3
2	0.99	9.2	10.2	24.4	3.1	4.1	9.8	5.0	6.0	14.3

Notes: this table computes benefit-cost ratios from school feeding by summing redistributive and human capital returns for the sample of endline recipients (N=931) at different values of ε, d, and with/without economic growth (Panel A). Panel B presents results for a new sample based on a retargeting scenario where 50% of the children are below the poverty line. Transfer size is GHC 1.5 per child per day at 200 hypothesized school feeding days. Economic growth projections are based on IASSA estimates. All values are in million GHC. Aggregate costs are 0.42 m GHC.

Figure 2 shows the ratio of the redistributive benefits as a share of total benefits under the three different scenarios related to the estimation of NPV of human capital support. The figure highlights the role of current increased consumption of the households of children participating into the program. Even when societies do not value redistribution (ε =0), the transfer contributes to 5-11% of total school feeding benefits, depending on the different assumptions related to preferences for future productivity and whether projected real growth is accounted for. When ε =0.7, the distributional benefits are appreciable, ranging between 6% at a 3% discount rate, to 16% when the discount rate is high and there is no real economic growth since only human capital benefits are discounted. At very high levels of redistributive preferences, the relative contribution of current equity gains ranges between 11% (at a discount rate of 3%) and 19% (discount rate =8%, with no growth).

Figure 2. Share of equity benefits over total benefits, inclusive of NPV of human capital support

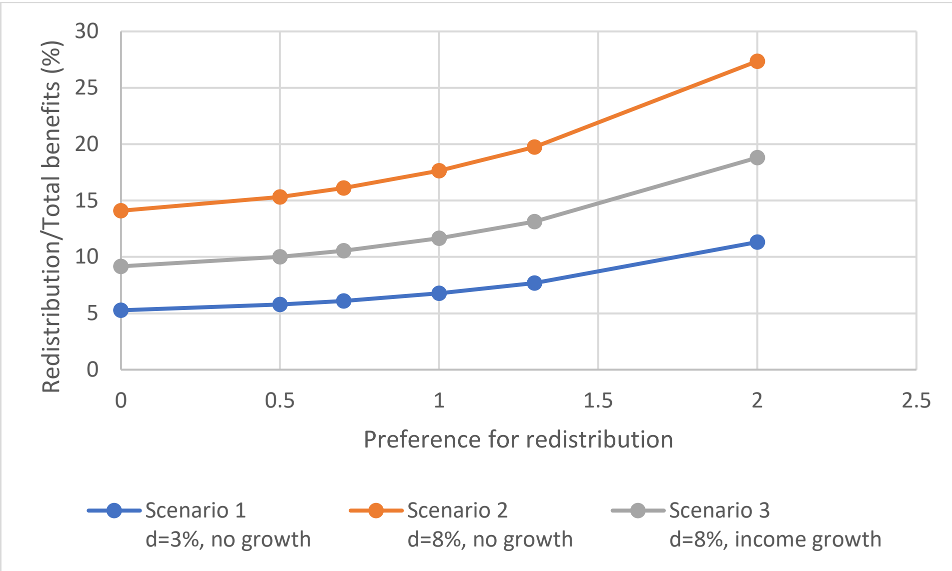


Table 4 Panel A also presents a summary of all benefits (in million GHS), including equity and human capital (based on the Mincerian results), with varying values for ε, and discount rates for a transfer valued at GHS 1.5, and total benefit cost ratios (BCRs), with benefits including both redistributive and NPV of human capital, along the three different scenarios. Again, we focus on a transfer value of 1.5 GHS. Once the present value from increased consumption is taken into account BCRs range from 4.6 in the most conservative scenario where there is no societal preference for redistribution and the stringent discount and growth assumption (scenario 2), to 13.2, where discount rates are low and the preference for redistribution is high (scenario 1). We recall that costs are estimated to be 0.4m GHS.

Retargeting simulation

As indicated, the GSFP was retargeted, albeit imperfectly, prior to the impact evaluation. Thus, the distribution of benefits reflects the program as implemented. However, the research design included subgroup analysis, which showed greater impacts for poorer households as well as within the more deprived northern regions. We use this information to explore a scenario under which the targeting is improved. As it is unlikely that an improved targeting criterion can be explicitly based on locale, gender, or school characteristics, we assume that the most likely potential targeting strategy is based on local poverty. We thus hypothesize that the program will be delivered in the same areas but assuming that 50% of the population is under the poverty line (N=465). Under this scenario there can be both efficiency improvements as well as equity gains as the learning and nutrition results differ by poverty.

We start by estimating human capital effects. Following the first approach proposed by Evans and Yuan (2019), the one based on the World Bank's STEP database, there would be an increase in lifetime earnings by 4.1 for the poor, based on estimated treatment effects of 0.23 from the literacy score for children under the poverty line (Aurino et al. 2020) and the increase in wages with each standard deviation of learning of 17.8% from Evans and Yuan (2019). By including the impact on the non-poor, the overall increase of wages following a retargeted program would be 3.2%.

Alternatively, in keeping with the results based on the Mincer equations, we employ the 'business-as-usual' approach based on learning among control children from poorest households estimated from the interaction between grade and being from a household below the poverty line (Appendix Table 1). Every additional year of school increases the composite score by 0.15 SD [0.23-0.083], translating to an estimate of EYOS for poor children of 6.6 years. The learning-adjusted treatment effect for poor children participating in the intervention is thus 2.18 additional years of school [0.33*6.6], leading to an average effect of 1.5 additional learning-adjusted years for the whole retargeted sample. Appendix Table 2 presents individual and aggregate NPVs for the poor, and total benefits from human capital accumulation (including benefits for the group of non-poor children) under the three different scenarios. We add to these the benefits from redistribution, which are reported in Table 4, Panel B, together with the new CBRs for this hypothetical retargeted sample. When societies do not value redistribution, the redistributive benefits do not change based on a different poverty headcount. As soon as ε increases, redistributive benefits increase as well, together with the CBRs from the program. But as schooling benefits also increase with retargeting, the share of total benefits from redistribution is lower under retargeting than in the current program.

Discussion and Conclusions

We illustrate that under a range of assumptions the learning gains attributed to a government-led school feeding program at scale in Ghana greatly exceed the program costs. We also note that while redistributive benefits add to the total welfare returns of the program, they contribute a substantial but minority share of the total. Taking these redistributive benefits alone, under observed poverty targeting only when the redistributive parameter, ε , is 1.3 or above do these benefits exceed the program cost by themselves. With plausible improved targeting (and assuming that the retargeting is a fixed and not a variable cost) the benefit:cost ratio will exceed 1 when ε is slightly below 1, within the range of distributional studies (Skoufias et al. 2010).

There is little question that the effect size of learning stemming from the program is appreciable. The challenge, however, is to map this improvement in learning to a more conventional metric for program design. This requires yet additional assumptions. The logic of converting improved learning to expected increasing in wages is readily apparent. We have, however, two plausible empirical approaches to applying this logic, both reliant on the assumption that the improvements recorded in primary school result in similar benefits when the student enters the labor force. We have illustrated this calculation both using STEM data available for Ghana as well as using Mincerian wage estimates which are far more readily obtainable. We focus on the more accessible Mincerian approach but note that in the current program it results in higher estimates of future wages. Nevertheless, it should be readily apparent from Table 4 that even if one halves our estimates of the NPV from the contribution to learning attributed to the school feeding program, the program still results in favorable BCRs under each scenario.

There are, in additional, other assumptions that may affect the overall results, hopefully only at the margin. For example, the GLSS data does not allow us to clearly distinguish the impact of schooling on self-employment in the Mincerian estimates. Both the magnitude and even the sign of any bias from the assumption that the gain in earnings from better schooling for self-employed is the same as for low wage earners is unknown. We also have subsumed all gains from the observed improvements in nutrition for poor individuals under education when, in fact, there are additional documented impacts via health including on the next generation (Chakrabarti et al. 2021). While not dismissing the potential gains from narrowing such uncertainties, we consider the main contribution of this analysis to be the illustration of a straightforward approach to utilize effect sizes from randomized controlled studies in broader economic analyses as well as the inclusion in such analyses of often recognized, but seldom quantified, distributional impacts of sectoral investments.

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Appendix Table 1. Estimates of grade attainment on endline composite test scores index and literacy scores for the group of the poor

	Composite literacy and math		Literacy	
Grade attained	0.231***	0.160***	0.215***	0.149***
	(0.0308)	(0.0362)	(0.0291)	(0.0312)
Grade attained*Poor household	-0.0830*	-0.0732	-0.0770*	-0.0714
	(0.0419)	(0.0443)	(0.0410)	(0.0432)
Poor household	0.0458	0.0542	0.0595	0.0977
	(0.121)	(0.138)	(0.117)	(0.128)
Baseline test scores		0.194***		0.241***
		(0.0400)		(0.0496)
Child is male	0.121**	0.114*	0.0994**	0.0769
	(0.0577)	(0.0584)	(0.0470)	(0.0469)
Age in years	-0.131***	-0.0839***	-0.130***	-0.0879***
	(0.0190)	(0.0244)	(0.0186)	(0.0213)
Constant	0.223	-0.0416	0.258	0.0340
	(0.267)	(0.311)	(0.279)	(0.319)
Observations	1,059	1,003	1,057	990
R-squared	0.146	0.156	0.140	0.147
Estimated EYOS for poor children	**6.67**	**11.1**	**6.9**	**12.7**

*Notes: *** p<0.01, ** p<0.05, * p<0.1 This model regresses a composite index of endline standardized math and literacy test scores (models 1 and 2) and endline standardized literacy scores for the control group of the school feeding evaluation, as a function of grade attained, and other child characteristics. Estimates also control for region fixed effects. Standard errors are clustered at the community level. EYOS for the poor are estimated first based on the difference of the coefficient for grade and the interaction between grade and being in a poor household. Then, we divide 1 for this difference.*

Table Appendix 2. NPVs for the retargeting scenario

Scenario 1a d=3%, no growth, 50% sample poor			Scenario 2a d=8%, no growth, 50% sample poor			Scenario 3a d=8%, income growth, 50% sample poor		
Individual NPV, poor (GHC)	Total NPV, poor (m GHS)	Total NPV (poor + non-poor), m GHC	Individual NPV poor (GHC)	Total NPV poor (m GHS)	Total NPV (poor + non-poor), m GHC	Individual NPV poor (GHC)	Total NPV poor (m GHS)	Total NPV (poor + non-poor), m GHC
14430.5	6.7	9.2	4806.9	2.2	3.1	7807.4	3.6	5

Notes: This table provides the individual and total Net Present Values (NPVs) from increased human capital for the sample of poor children, and total NPVs for the whole sample in a retargeting scenario where half of the population is below the poverty line.

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Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org