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ORIGINAL ARTICLE

Effects of Long-Term Malnutrition on Education Outcomes in Ghana: Evidence from a Panel Study

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Abstract
Aside the direct effect on GDP at the macro level, the microeconomic impacts of undernutrition are also manifested in lower educational outcomes, reduced productivity and reduced lifetime earnings. This study sought to examine the effect of child malnutrition on learning outcomes by exploiting a nationally representative panel data which allow us to control for child-level unobserved heterogeneity in Ghana. Using a random-effects and Poisson estimations, this study shows that while current malnutrition affects children's learning outcomes negatively, its effect may disappear in the future, especially with the implementation of appropriate interventions. The study concludes that while nutrition matters for learning outcomes, so do other educational inputs. Results are, however, differentiated by individual and household characteristics, including gender and locality. The evidence from this study serves as a useful tool for improving policies and programmes that focus on early feeding practices among pre-schoolers and improved nutrition of children of school-going age.

Keywords Malnutrition · Learning outcomes · Random effects · Cognitive skills · Ghana

Résumé
Outre l'effet direct sur le PIB au niveau macro, les impacts microéconomiques de la sous-nutrition se manifestent également par des résultats scolaires moindres, une productivité réduite et des revenues moindres tout au long de la vie. Cette étude visait à examiner l'effet de la malnutrition infantile sur la capacité d'apprentissage en exploitant des données de panel représentatives au niveau national, ce qui nous

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permet de contrôler la non-hétérogénéité au niveau des enfants au Ghana. En utilisant les estimations du modèle à effets aléatoires et du modèle de Poisson, cette étude montre que si la malnutrition a un effet négatif sur la capacité d'apprentissage des enfants sur le moment, cet effet peut disparaître avec le temps, en particulier grâce à la mise en œuvre d'interventions adaptées. L'étude conclut que si la nutrition est importante pour la capacité d'apprentissage, il en va de même pour les autres facteurs éducatifs. Les résultats sont toutefois différenciés selon les caractéristiques individuelles et celles des ménages, notamment le sexe et la localité. Les données probantes qui émanent de cette étude représentent un outil utile pour l'amélioration des politiques et des programmes qui se concentrent sur les pratiques alimentaires précoces chez les enfants d'âge préscolaire et sur l'amélioration de la nutrition des enfants en âge d'aller à l'école.

Introduction

In spite of the substantial progress made in reducing child malnutrition, recent data suggest that acute malnutrition persists in Ghana. The National Development Planning Commission, NDPC (2016), indicates that almost a quarter of children under the age of 5 years in Ghana are stunted (short for their age). In other words, every one-in-four children in Ghana is in a chronic state of malnutrition. Recent data from the Multiple Cluster Indicator Survey (Ghana Statistical Service 2011) also suggest that about 6% and 13% of children within the ages of 0–5 years in Ghana are, respectively, wasted (low weight for height) and underweight (low weight for age). The same report also shows that about 24% of all child mortalities between 2008 and 2012 were directly associated with malnutrition.

The relatively high rates of malnourishment reflect a very precarious outlook for Ghana, given the negative direct and indirect consequences of undernutrition on the economy. At the macro level, the total economic loss due to malnutrition to the country in 2012 was estimated to be about 6.4% of GDP (NDPC 2016). Its microeconomic impacts are also manifested in lower school attendance (Daniels and Adair 2004) which may lead to lower educational outcomes, reduced productivity and reduced lifetime earnings (Alderman 2006). Specifically, Behrman et al. (2004) suggest that malnutrition may have intergenerational impacts as it reduces lifetime earnings by about 12%. Similarly, it is shown by Schultz-Nielsen et al. (2016) that malnourished children are at an increased risk of lower lifetime earnings, and this further impacts on national productivity in the long run. NDPC (2016), therefore calls for the need for policymakers to prioritise child malnutrition issues to accelerate the socio-economic progress and development in Africa. With respect to its causes, Martínez and Fernández (2007) broadly categorised the main factors associated with malnutrition into three groups, namely; environmental, sociocultural–economic, and political–institutional factors. In Ghana, Yawson et al. (2017) describe the primary causes of malnutrition to include inadequate dietary diversity, poor environment, household and individual hygiene as well as generally poor infant and young child feeding practices.

Malnutrition, especially among children negatively affects the formation of various tissues and organs which interferes with the natural biological processes and may have detrimental consequences on the physiological wellbeing of children. According to Grantham-McGregor (1999) and Martins et al. (2011), the impaired growth associated with malnutrition can lead to poor mental development and learning outcomes as well as behavioural abnormalities. Several cross-sectional studies including Glewwe and Jacoby (1995), Grantham-McGregor and Fernald (1999), Horton and Ross (2003) and Wisniewski (2010) have all examined the relationship between infantile nutritional status and subsequent learning outcomes. However, and as Behrman (1996) argues, most of the studies that have examined this link have measured associations rather than causal relationships. Alderman et al. (2001) also caution that the use of cross-sectional data may lead to biased estimates given that the nature of the data does not allow for the estimations to adequately control for the unobserved characteristics (that require longitudinal data) which may be critical in explaining differences in schooling outcomes among children. Glewwe and Miguel (2008) also make the argument that the way in which child health status was obtained in cross-sectional data previously was through recall. This, as they point out, introduces considerable error and potentially compromises the analysis.

In view of the estimation challenges associated with cross-sectional data in analysing the link between child nutritional status and education outcomes, more recent studies, including Walker et al. (2007) and Belachew et al. (2011), have relied more on longitudinal data and randomised controlled trials (RCTs) to provide less biased estimates for these associations. For instance, in using longitudinal data from South Africa, Glewwe and Miguel (2008) exploited information on siblings within a dynamic framework to examine the effect of nutrition on schooling decision and schooling outcomes such as the age of initial school enrolment, grade repetition and cognitive skills. Using longitudinal data from Philippines and anthropometric measures, Glewwe et al. (2001) show that delayed school enrolment and poor cognitive achievements are significantly associated with child malnutrition. Similarly, using anthropometric measures as proxies for child nutrition and comparing siblings using panel data, Yamauchi (2008) concludes that child health is positively associated with good educational outcomes. Greve et al. (2017) use a natural experiment to show that malnutrition during pregnancy can negatively impact the learning outcomes of children.

There is ample empirical literature from randomised controlled trials which have examined the effect of child nutrition on schooling outcomes using interventions such as school feeding programmes (Kazianga et al. 2009; Alderman et al. 2012) and nutrient supplement programmes. Aside from the desired expected educational outcomes of such interventions, another goal of these programmes have been to improve the nutritional status of children, and thereby prevent both short-term and long-term malnutrition.

Despite the popularity of randomised controlled trials as a robust strategy for establishing the causal link between child malnutrition and learning outcomes, studies such as Buttenheim et al. (2011) have raised concerns about the efficacy of such interventions in completely offsetting early childhood nutritional deficits.

These studies argue that given that the first two years are very critical for the development of the child's brain, it is less likely that any micronutrient supplementation at school age can reverse the harmful effects caused by the deficiency in earlier ages. These concerns may perhaps explain the mixed results from this strand of the literature.

Existing research on the causal relationship between child malnutrition and education outcomes in Ghana is scanty. Our review of the literature points to two main studies by Glewwe and Jacoby (1995) and Ampaabeng and Tan (2013). In the dated Glewwe and Jacoby (1995) study, the authors use instrumental variables and cross-sectional data to deal with possible endogeneity in children's nutritional status as it examined the relationship between child malnutrition and education outcomes. Using multiple sources of cross-sectional data, Ampaabeng and Tan (2013) exploit the 1983 famine that was experienced in the country as a natural experiment while using Bayesian Model Averaging methods to account for model uncertainty as they examined the long-term effects of child malnutrition on cognitive abilities. After accounting for different econometric problems associated with their respective data, both studies find robust negative impacts of early childhood malnutrition on learning outcomes.

We contribute to the literature on the relationship between child nutrition and educational outcomes in three ways. First, this study is able to independently examine the effect of malnutrition on learning outcomes by controlling explicitly for children's cognitive abilities. Cognitive abilities of children are measured using the digit span tests, which are believed to be robust measures of cognitive skills in the context of a developing country like Ghana. Second, the panel data used for the study allow us to directly control for the impact of previous nutritional status of children on current period learning outcomes. Third, and to the best of our knowledge, no study has been able to explore this empirical relationship using a nationally representative panel data for Ghana. From a policy perspective, findings from this study will contribute to the current debates around issues of childhood malnutrition and its implication for educational outcomes.

The current study uses a nationally representative panel survey data (the first of its kind in Ghana) covering the period 2010 to 2014. The paper is structured as follows: "Theoretical Framework" section reviews the theoretical underpinnings related to child nutrition and educational outcomes. "Data" section describes the data for the analysis followed by "Empirical Strategy" section, which explains the empirical strategies employed. "Results and Discussion" section presents and discusses the results, and "Conclusion and Recommendations" section concludes with a summary of the main findings and some policy recommendations.

Theoretical Framework

Aside from other factors, the learning outcomes of children are influenced by their capacity to process and respond to stimuli (Levinger 1992). As this capacity improves, so does the child's learning efficiency, which increases the likelihood that the child's innate cognitive abilities are fully developed. Poor nutrition often delays the development of the child's capacity to progress in school. A malnourished child may not be able to fully take advantage of instructional resources to ensure positive learning outcomes.

The theoretical underpinnings through which malnutrition may lead to poor learning outcomes are based on the analytical framework of Glewwe (2005). In examining this relationship, the author describes three periods. The first period, which begins from conception and ends at age 2, is found to be critical for a child's cognitive development; the second period begins from ages 2 to 6 when the child is eligible to enrol in school; and the third period, is from ages 6 to 11 when the child is of primary school age. The relationship between child health and schooling outcomes in the third period (SO_3) is modelled by a basic production function which measures the effect of variables including health inputs in all three periods (H_1, H_2, H_3), parents' provision of education inputs which includes school supplies such as books, toys and time spent by parents with their children ($\mathrm{PEI}_1, \mathrm{PEI}_2, \mathrm{PEI}_3$), school and teacher characteristics (ST), household resources (Y), the child's innate abilities (β), and years of schooling (YS). The function is represented as follows:

$$\mathrm{SO}_3 = f(Y, H_1, H_2, H_3, \mathrm{PEI}_1, \mathrm{PEI}_2, \mathrm{PEI}_3, \beta, \mathrm{ST}, \mathrm{YS}). \tag{1}$$

From Eq. 1, the impact of a child's health on education outcomes can be measured directly through the specified variables in all three periods. The above equation, therefore, represents a structural equation as it captures how all the specified variables directly affect the learning outcomes of children at any point in time. Glewwe (2005) further asserts that other indirect effects ought to be considered in estimating the impact of child health on learning outcomes. Glewwe (2005) argues that some variables such as parent's provision of educational inputs may be endogenous as parents' decision to provide the requisite inputs and environment may be a reflection of parents' preferences for healthy and more educated children. These preferences, according to the study, is further determined both by household characteristics such as income or child characteristics. For instance, parents' incentive and decision to provide education inputs is influenced by the child's health. However, a child's health may also be influenced by parental characteristics and parental education inputs which are not entirely exogenous in Eq. 1. This points to endogeneity in the decision regarding investments to promote child health and household or parental characteristics, which are both likely to impact learning outcomes.

In resolving this problem, Glewwe (2005) suggests that parental educational input is modelled as a function of child health in the previous period, parental preferences for healthy children, parental preferences for educated children, prices of school inputs and health inputs. Parental education inputs in all three periods can, therefore, be expressed as follows.

$$\mathrm{PEI}_1 = f(Y, \mathrm{ME}, \mathrm{FE}, \mathrm{HE}_1, \mathrm{ST}, p_{\mathrm{s}}, \mathrm{ph}_1, \gamma, \rho, \beta), \tag{2}$$

$$\mathrm{PEI}_2 = H_1, Y, \mathrm{ME}, \mathrm{FE}, \mathrm{HE}_2, \mathrm{ST}, p_s, \mathrm{ph}_2, \gamma, \delta, \beta), \tag{3}$$

$$\mathrm{PEI}_3 = f(H_1, H_2, Y, \mathrm{ME}, \mathrm{FE}, \mathrm{HE}_3, \mathrm{ST}, p_s, \mathrm{ph}_3, \gamma, \delta, \beta). \tag{4}$$

Equation 2 expresses parental education input in period one as a function of household resources (Y), mother and father's education (ME, FE), respectively, the general health environment in period one (HE_1), school and teacher characteristics (ST), prices of school inputs (p_s) which is assumed to be constant over time, prices of health inputs in period one (ph_1), parental preferences for healthy children (γ), preferences for education for children (δ) and child innate abilities (β). In period 2, parental educational input (PEI_2) is a function of the health status of the child in period 1 (H_1), the general health environment in period two (HE_2), the prices of health inputs in period 2 (ph_2), household resources, school and teacher characteristics, parental preferences for education and health for children and child's innate abilities as discussed earlier. Similarly, the parental education inputs in period three (shown in Eq. 4) is expressed as a function of the health status of children in the previous two periods, household resources, parental education, general health environment, school and teacher characteristics, prices of health inputs in period three, prices of school inputs, parental preferences for a child's education and health as well as child innate abilities. Years of schooling (YS) in period three can also be expressed as a function of health inputs in the previous two periods and the same variables as shown below as:

$$\mathrm{YS} = H_1, H_2, Y, \mathrm{ME}, \mathrm{FE}, \mathrm{HE}_3, \mathrm{ST}, p_s, \mathrm{ph}_3, \gamma, \delta, \beta. \tag{5}$$

Substituting Eqs. 2 to 5 into 1 gives a new Eq. 6 that captures both the direct and indirect effects of child health on learning outcomes.

$$\mathrm{SO}_3 = f(Y, H_1, H_2, H_3, \mathrm{ME}, \mathrm{FE}, \mathrm{HE}_3, \mathrm{ST}, p_s, \mathrm{ph}_1, \mathrm{ph}_2, \mathrm{ph}_3, \gamma, \delta, \beta). \tag{6}$$

Based on the model as discussed above, Glewwe (2005) conjectures that more household resources will enable parents to purchase more educational inputs which will lead to better learning outcomes. Similarly, parental education may yield a positive impact on learning outcomes because highly educated parents may be better placed to help their children with school work and also use educational inputs more effectively to ensure better learning outcomes.

The literature documents different mechanisms through which child health is likely to affect learning outcomes negatively. One strand of the literature is about the lack of essential micronutrients. Studies such as Pollit (1990), Grantham-McGregor and Walker (1998) and Rosso and Marek (1996) have argued that the lack of protein energy ultimately results in child absenteeism in school, and increases the likelihood of grade repetition as well as the propensity of dropping out of school. The lack of essential micronutrients such as iron, iodine and vitamin A may have dire consequences on the health of children. Horton and Ross (2003) and Grantham-McGregor (2005) all provide evidence to show that the lack of these nutrients often leads to poor attention in class and low motivation to attend school. Lack of iron, for instance, has been proven to lead to general body weakness, poor physical growth and a compromised immune system which reduces the body's ability to fight infections.

This paper tests four key hypotheses which are implicit in the theoretical framework developed by Glewwe (2005) and discussed in the next section.

(a) Malnourished children have lower learning outcomes.
(b) Child's innate abilities have positive impacts on learning outcomes.
(c) Both previous and current health status of children have significant impacts on a child's learning outcomes.
(d) Parental education and other household characteristics moderate the effects of child malnutrition on their educational outcomes.

Data

The analysis relies on the first two waves of the Ghana Socio-economic Panel Survey (GSPS) data. These panel data were a collaborative effort between the Economic Growth Centre (EGC) at Yale University and the Institute of Statistical, Social and Economic Research (ISSER), at the University of Ghana. The survey follows individuals over time with the primary objective of providing opportunities to analyse the short to medium term dynamics of various economic and development related issues. The first wave of the data was collected on about 5010 households in 2010, and the second wave in 2014. In the second wave, about 5484 households were to be surveyed. This included the 5010 at baseline, plus an additional 475 from split households. Data were, however, obtained from 4774 households containing 16,356 household members.

The survey adopted a two-stage stratified sample design where stratification was based on the regions of Ghana. In the first stage of the sampling, 334 enumeration areas were sampled from a master sampling frame based on the 2000 Ghana Population and Housing Census. The clusters were randomly selected based on a simple random sampling technique. In the second stage, 15 households from the selected clusters were randomly selected for interview.

Using household and community questionnaires, detailed information was collected on demographic characteristics of households, Education, Health, Employment, Migration, Land Information, Agricultural Production Input, Livestock and Household Tools, Non-farm Enterprise, Housing Characteristics of Household, Financial Assets, Psychological Measures, Risk Preference, Social Status and Responsibilities.

This dataset was particularly unique for the current study as it contained important information on test scores for both mathematics (arithmetic) and English tests as well as the digital span tests which are widely relied upon to measure children's cognitive abilities. Thus, aside demographic and other socio-economic characteristics, the dataset afforded us the opportunity to test for the independent effects of malnutrition as we controlled for the cognitive abilities of children in the sample over time. The primary dependent variables in this study are the mathematics and English scores which are used as proxy variables for educational outcomes. A total of eight questions were asked for each subject. This suggests that the maximum accurate responses that a child obtained for the mathematics and English test were eight.

The main independent variable of interest is stunting. Other measures of child health, namely wasting and underweight, were also considered in this paper. However, due to minimal variation in the values for this variable, the paper only focused on stunting. This variable is constructed based on height-for-age measures (HAZ), where HAZ score of less than -2 standard deviation of the reference median is termed stunting. Stunting is argued to be the overall best indicator of child malnutrition, and it is the most prevalent form of child malnutrition worldwide (De Onis and Branca 2016). In this study, stunting is a binary variable that takes on a value of 1 if the HAZ scores are less than -2 SD and 0 otherwise. According to WHO (2008), stunting reflects a long-term measure of malnutrition as it manifests the cumulative effects of undernourishment and infections since and even before birth. Stunted children are, therefore associated with retarded growth due to poor nutrition or recurrent infections. Such long-term deprivation results in delayed cognitive and intellectual capacity, which in turn results in poor school performance as shown by Hoddinott et al. (2013) and Prendergast and Humphrey (2014).

To control for the cognitive ability of children in the analysis, the study makes use of digit span tests. These tests, according to Wechsler (1991), are the most widely used measure of cognitive ability. The test is administered using two variants—forward digit span and backward digit span tests. These tests are used to measure the cognitive skills of the children in the sample. Each variant is meant to capture a different dimension of cognitive ability. The forward digit span test primarily taps into the short-term memory by requiring the child to do a simple verbatim recall of a list of digits. Some studies such as Bull et al. (2008) have used the forward digit span test as a predictor of reading skills.

On the other hand, the backward digit span test measures the child's ability to manipulate verbal information while still in temporary storage. It then requires test takers to reproduce a given list of digits in the reverse order. Bull et al. (2008) have discussed its use as a predictor of math achievement. Forward and backward digit span tests are therefore used to measure short-term and working memory of children, respectively. In the data used for this study, the two tests are administered only to children within the ages of 5 to 15 years. Accounting for cognitive abilities independent of malnutrition measures restricts the sample to children within this age bracket. In the data, each test consists of eight questions.

The study also includes relevant controls such as education of both mother and father. As discussed earlier, parental education has been established to have important impacts on children learning outcomes. According to Glewwe (2005), educated parents are more likely to make efficient use of educational inputs and are in a better position to help their children with school work. Also, the study controls for the presence of both parents within the household. Other household-level demographic characteristics such as household expenditure, household size and household location are also controlled for in the analysis. To account for household resources, the study makes use of the adult equivalence expenditure as a proxy for household wealth. This variable which was used as a measure of poverty by Osberg and Xu (1999), is constructed from household expenditure values adjusted for household size and composition. In its construction, different weights are assigned to different individuals within the household based on the caloric needs of different age groups. Higher values indicate more household resources and vice versa. Child-level characteristics such as gender, age, health status of the child in the past two weeks, and access to learning materials are also included in the analysis. The analysis is restricted to children who are between the ages of 5 and 15 years because cognitive tests were available only for this age bracket in the data.

Table 1 shows the variables used in the analysis and their summary statistics for the two waves of the data. The same table shows the statistical differences in the

Table 1 Descriptive statistics

Study variables	2009/2010		2013/2014		Difference	*t*-value
	Mean	SD	Mean	SD		
Mathematics test scores	4.646	2.2	2.56	2.71	2.086***	−33.96
English test scores	3.548	3.03	2.102	2.71	1.446***	−21.05
Child is stunted	0.116	0.32	0.109	0.31	0.0076	−1.07
Mother present in the household	0.748	0.43	0.817	0.39	−0.069***	−7.48
Father present in the household	0.62	0.49	0.649	0.48	−0.0292**	−2.67
Child is healthy (in the last 2 weeks)	0.956	0.21	0.91	0.29	0.0455***	−7.87
Forward digit span test	3.669	2.21	2.544	1.65	1.124***	−26.06
Backward digit span test	1.536	1.45	1.211	1.34	0.325***	−10.36
Child is male	0.59	0.49	0.552	0.5	0.0385***	−4.43
Household size	2.685	1.58	4.676	2.9	−1.991***	−48.33
Age of child (years)	11.91	1.99	9.813	3.12	2.097***	−34.31
Household is in the urban locality	0.332	0.47	0.287	0.45	0.0450***	−4.31
Father has at least primary education	0.283	0.45	0.235	0.42	0.0483***	−6.18
Mother has at least primary education	0.146	0.35	0.131	0.34	0.0149*	−2.4
Child has at least basic education	0.992	0.09	0.845	0.36	0.147***	−22.02
Child has access to textbook	0.927	0.26	0.882	0.32	0.0445***	−6.05
HH consumption expenditure	220.049	181.63	241.61	195.04	−21.56***	−6.30
Western Region	0.091	0.29	0.083	0.28	0.0078	−1.57
Central Region	0.077	0.27	0.076	0.27	0.000834	−0.18
Greater Accra Region	0.107	0.31	0.094	0.29	0.0127*	−2.41
Volta Region	0.089	0.29	0.079	0.27	0.0106*	−2.17
Eastern Region	0.121	0.33	0.11	0.31	0.0113*	−2.00
Ashanti region	0.185	0.39	0.166	0.37	0.0189**	−2.83
Brong-Ahafo Region	0.1	0.3	0.106	0.31	−0.00619	1.16
Northern Region	0.139	0.35	0.182	0.39	−0.044***	−6.79
Upper East Region	0.052	0.22	0.06	0.24	−0.00816*	−2.02
Upper West Region	0.04	0.19	0.044	0.2	−0.004	−1.14
Observations	6317		6701			

t-statistics in parenthesis

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

variables over the two waves. Concerning mathematics and English scores, the data show a reduction in the average test scores of children for both subjects from 2010 to 2014. Between the two periods under consideration, mathematics scores reduced from an average of about 5 to about 3. A similar reduction was recorded for English test scores, where the average for 2010 was 3.5, and that for 2014 was about 2.1. The differences in both mathematics and English scores over the two periods are statistically significant. Similarly, there are significant differences in the digit span tests for the two waves. For the forward digit span test, the average scores declined from 3.7 in 2010 to about 2.5 in 2014. This indicates that children were able to accurately repeat more numbers after it was read to them in the first wave compared to the second wave. In the more challenging backward digit span test which required children to repeat numbers in the reverse order, the accurate average numbers in both years are low. However, the average score obtained in 2010 is relatively higher (1.5) compared to the average score of 1.2 in 2014. As shown, this difference is statistically significant. From the low average correct responses for both periods, it can be inferred that in general children in the sample have low capacities in manipulating verbal information.

The proportion of children who were stunted was about 12% and 11% in 2010 and 2014, respectively. The prevalence of stunting appears to be similar across the two waves. However, the disaggregated data by regions show marked variations in the incidence of stunting as shown in Fig. 1. According to the data, Volta region recorded the most significant improvement in stunting. Between 2010 and 2014, the proportion of stunted children had declined significantly from 26% to about 9%. Similarly, Brong-Ahafo and Upper West regions also recorded significant improvement in children health status as the proportion of stunted children reduced from 14 to 6% and from 10 to 4%, respectively. On the contrary, the Northern and Greater Accra regions recorded an increased prevalence of malnutrition. The proportion of stunted children in Greater Accra increased from 9.8 to 14.2% while the proportion of stunted children in the Northern region increased from 13.1 to 19.3%. The proportion of children who had obtained primary education or more reduced significantly from 99% in 2010 to about 85% in 2014.

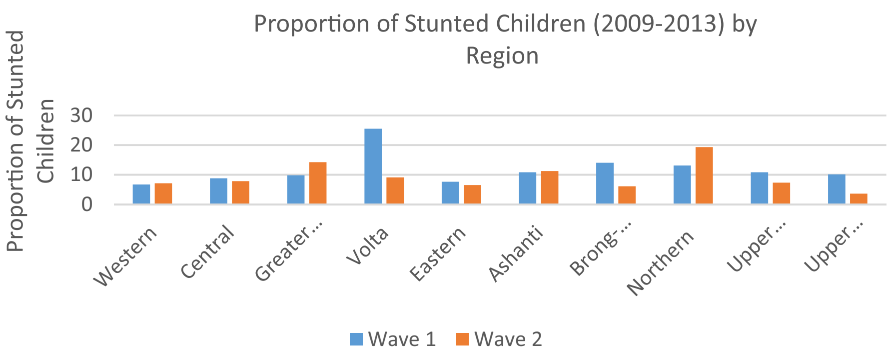

Fig. 1 Prevalence of stunting in Ghana. *Source* based data from Ghana Socio-Economic Panel Survey (2009/2010–2012/2013)

The average age of children in the study in the first wave was about 12 years, while the average age in the second wave was about 10 years. The sample is almost equally represented with respect to gender as slightly more than half of the sample (59% in wave 1 and 55% in wave 2) were male.

Concerning access to learning materials, the data show that about 92% of children in the sample indicated that they had access to textbooks to aid in their studies although this proportion reduced to about 88% in the second wave.

The data show that the average household size increased significantly from 3 persons in wave 1 to 5 persons in wave 2. To capture the importance of parental education on learning outcomes, the study includes the educational status of both mother and father. Both variables are constructed as dummy variables taking on the value of 1 if the father or mother has at least primary education and 0 if there have no education. In the two periods, the proportion of fathers with at least primary education was about 28 and 24%, respectively. For mother's education, the proportion marginally reduced from 14% in the first wave to about 13% in the second.

Concerning parental presence in the household, the data show that in wave one, about 75% of mothers in the sample indicated that they were present within the household. By wave 2, the proportion had increased significantly to about 82%. In both waves, about two-thirds (62% in wave 1 and 65% in wave 2) of fathers were present within the households. The results point to the fact that more mothers appear to be present compared to fathers within households. We also note that about a third (33% in wave 1 and 29% in wave 2) households reside in the urban areas. For household resources, the data suggest a significant difference in consumption expenditure between the two periods. In 2010, adult equivalence real expenditure increased from GHS 220 (USD 44) in wave 1 to about GHS 240 (USD 48) in wave 2.

Empirical Strategy

The study exploits the panel structure of the dataset by estimating a random-effects model following Glewwe and Miguel (2008). This directly tests the relationship between children's malnourished status and learning outcomes. The study estimates the equation below:

$$Y_{it} = \alpha_i + \beta_i X_{it} + \delta_i + \varepsilon_{it}, \tag{7}$$

where Y_{it} represents Math or English scores of individual i at time t; X_{it} refers to the explanatory variables for individual i at period t; β_i measures the average effects of the various explanatory variables; and δ_i reflects unobserved individual heterogeneity that is likely to cause differences in learning outcomes. The specification is based on the premise that some unobserved variables such as the child's innate healthiness, parental preference for educated and healthy children, school quality, general education, and healthy environment, do not change over time and that these unobserved characteristics do not vary in any systematic manner. To test for the second hypothesis, the study includes a measure of the child's ability (proxied by the digit span tests) as an explanatory variable in Eq. 6.

To test for the third hypothesis, the study estimates a cross-sectional model which accounts for the health status of children in previous and current periods. This is represented in Eq. 7.

$$Y_i = \alpha_i + \beta_1 X_i + \beta_2 \mathrm{CH}_i + \beta_3 \mathrm{CH}_{i(t-1)} + \varepsilon, \tag{8}$$

where Y_i presents mathematics or English test scores at the current period and CH_i and$\mathrm{CH}_{i(t-1)}$ represent child's health status in the present and previous periods, respectively. X_i refers to other individual and household characteristics that are likely to affect learning outcomes, including child's age, gender, parental education, parental presence, household income, location of households, and access to textbooks. The control for the location of children was done to capture the differences in educational infrastructure and a healthy environment that are likely to affect learning outcomes.

To test for the fourth hypothesis, the study estimates Eq. 6 with interaction terms as additional regressors to capture the possible heterogeneity in effects as predicted in the discussion under the theoretical model that underpins this study.

The discrete nature and distribution of the main variables of interest (mathematics and English test scores) as shown in Fig. 2 violates the normal distribution assumption and as such the traditional linear models were deemed not applicable. Indeed in such instances, and as suggested by McCullagh and Nelder (1989), Agresti (2002) and Cameron and Trivedi (2013), generalised linear models, which extend to other data types such as count or discrete data, can be constructed by choosing an appropriate link function and response probability distribution. For count responses, Poisson or Negative Binomial distributions are the best-known models (Lindsey 1995; Agresti 2002) where their link functions are modelled as the log of the mean. The log link is mostly attractive for Poisson or Negative Binomial regressions because it ensures that all the predicted values are non-negative.

The Poisson estimation assumes mean–variance equality of the dependent variable. However, in cases where this assumption is violated, it produces small standard errors and inconsistent variance estimates (Barron 1992) which suggests that the Poisson estimation may also not be appropriate due to over-dispersion. Given that the variance of the two dependent variables (as shown in Table 1) is almost four

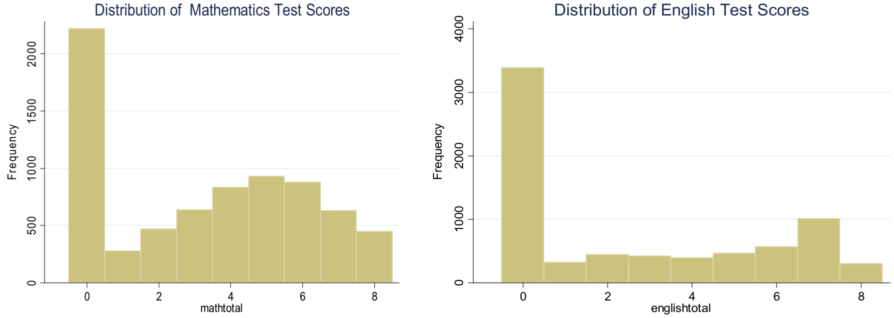

Fig. 2 Distribution of Mathematics and English scores

times their means, it suggests over-dispersion in the data. The formal test of over-dispersion discussed by Cameron and Trivedi (1998) tests the equality of the mean and variance as restricted by the Poisson distribution against the alternative hypothesis that the variance exceeds the mean. Results, from this test (shown in Table 2), provide evidence of over-dispersion in the dependent variable. Both the Deviance and the Pearson goodness of fit statistics (using the Poisson regression) were significant, indicating that the Poisson model was inappropriate.

Moreover, the Likelihood Ratio test (using the negative binomial regression) was significant and provided evidence that the negative binomial was more appropriate. This evidence supports claims by Agresti (2002) that to avoid the over-dispersion problems associated with estimating the Poisson model; the negative binomial regression is an alternative strategy. Other alternatives of dealing with over-dispersion according to Agresti (2002) is to run the Poisson regression but correct for the standard errors and test statistics, although Allison (1999) argues that doing this may produce coefficients that lack efficiency. The study estimated the Poisson models with robust standard errors given that the estimated negative binomial models failed to converge.

Results and Discussion

Estimations from the random-effects Poisson models (shown in Table 3) suggest a negative and significant relationship between child malnutrition and learning outcomes. Specifically, the result shows that children who are stunted are expected to have a rate ratio of mathematics scores that are 0.93 times lower compared to children who are not stunted, holding other explanatory variables in the model constant. The negative relationship between children's long-term malnutrition and learning outcomes is consistent with findings from other studies from Ghana, such as Ampaabeng and Tan (2013) who found that poor nutrition compromises the development of cognitive skills. Deficiencies in essential micronutrients such as iron, vitamin A, zinc, iodine and folate may retard critical growth functions of children and may lead to adverse learning outcomes (Feyrer et al. 2017). Ross (2010) also explained that malnourished children often get fatigued easily due to rapid loss of

Table 2 Goodness of fit tests for Poisson and Negative Binomial regression (based on pooled regression analysis)

Test criteria	Mathematics scores	English scores
Deviance	Value = 8071	Value = 12,349.12
	DF = 5423	DF = 5423
	Prob > $\chi^2(5423) = 0.0000$	Prob > $\chi^2(5423) = 0.0000$
Pearson	Value = 7027	Value = 11,055.06
	DF = 5423	DF = 5423
	Prob > $\chi^2(5423) = 0.0000$	Prob > $\chi^2(5423) = 0.0000$
Log-likelihood test of $\alpha = 0$	30.71	1843.70

Table 3 Incident rate ratios from negative binomial regression model with random effects

Variable	Mathematics scores		English scores	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Child characteristics				
Child is stunted	0.93**	−2.96	0.93	−1.36
Forward digit span test	1.06***	10.30	1.09***	8.56
Backward digit span test	1.05***	7.36	1.14***	9.85
Child is male	1.03**	1.87	1.00	0.16
Child's age (years)	1.18***	38.95	1.24***	32.88
Child has at least basic education	4.28***	10.58	2.97***	9.43
Child has textbooks	1.10**	2.72	1.35***	4.55
Child is healthy in the past 2 weeks	1.06*	1.76	1.04	0.67
Household characteristics				
Household size	0.98***	−4.87	0.99*	−1.71
Mother is present	1.02	0.80	1.06	1.48
Father is present	1.00	0.12	0.96	−1.07
Father has at least basic education	1.01	0.35	1.02	0.60
Mother has at least basic education	1.02	0.62	1.01	0.30
Adult equivalence expenditure	1.00	0.76	1.00	1.60
Household location				
Residential type is urban	1.14***	6.75	1.41***	11.19
Western Region	1.04	1.13	0.95	−0.81
Central Region	0.95	−1.27	0.90	−1.54
Volta Region	0.98	−0.55	0.82***	−2.98
Eastern Region	1.01	0.30	0.90*	−1.75
Ashanti Region	1.09**	2.63	1.09*	1.71
Brong-Ahafo Region	1.02	0.63	0.80***	−3.59
Northern Region	0.99	−0.24	0.83**	−2.96
Upper East Region	1.17***	3.82	1.06	0.75
Upper West Region	0.86**	−2.64	0.59***	−5.99
Log-likelihood	−10,677.67		−10,480.09	
Observations	5399		5399	

*$p<0.05$, **$p<0.01$, ***$p<0.00$

energy which often results in difficulties in concentrating in school and non-participation in learning activities. Undernourished children are most likely to have a compromised immune system, thereby making them more susceptible to infections. The increased infection levels may lead to reduced school attendance which may, in the long term, have adverse effects on learning outcomes.

Our results indicate that cognitive skills significantly influence children's learning outcomes. Estimations on both forward and backward test show a positive and significant influence on both the mathematics and reading skills. Specifically, estimations on the forward digit span test indicate that ability to keep information in the short-term memory significantly increases the rate ratio of mathematics test scores by about by about 1.06 times. Similarly, a unit increase in the average score of the backward digit span test, which is meant to capture the working memory abilities of children increases the rate ratio of mathematics test scores by about 1.05 times. The influence of the forward and backward digit span test is positive and significant for English test scores. Particularly, a unit increase in both digit span tests increases the rate ratio of English test scores by 1.09 and 1.14 times, respectively. These results suggest that the ability of children to hold information in short memory, as well as their ability to manipulate and work on information received, have important implications for their learning outcomes.

As expected, the educational level of children determines their ability to obtain higher test scores. Children with at least basic education are associated with math scores that are about 4.3 times higher than children who have less than basic education and about three times higher for English scores than children with less than basic education. All things being equal, the older the child is, the higher the likelihood of obtaining higher test scores. An additional year in age increases the rate ratio of mathematics scores and English scores by about 1.2 times. This may be because older children are more likely to have received more arithmetic training and reading training from their education compared to younger children who are likely to be in lower school grades and might have had fewer opportunities to develop such skills.

Interestingly, the results suggest that gender plays a significant role in explaining the variation in mathematics scores but not English test scores. Male children, according to the estimates, are associated with a rate ratio which is 1.03 times higher for mathematics scores than female children. The estimation results also provide evidence to support the claim that children's access to textbooks is important for improved learning outcomes. For both mathematics and English test scores, access to test books plays a significant role. Children who reported having access to text books are associated with ratios of mathematics and English scores that are, respectively, 1.1 times and 1.3 times higher than scores of children who did not have access to textbooks.

The estimates also point to the importance of household size in the learning outcomes of children. The negative and significant estimates suggest that children who come from large households are associated with lower test scores. If a household were to increase by one person, the rate ratios of mathematics and English scores of children from such households are found to decrease by 0.98 and 0.99 times, respectively. This may be because, in larger households, resources may not be enough to provide all the needed educational inputs to ensure better learning outcomes.

As expected, children from urban areas are associated with better learning outcomes. For mathematics scores, children who reside in urban areas were found to have rate ratios of mathematics scores that are 1.3 times higher compared to children who live in rural areas. Similarly, for urban children, their rate ratios for English scores were found to be about 1.4 times higher compared to children from rural areas. These differences in learning outcomes in the two locations may be due to the marked differences in educational infrastructure and inputs between schools in the urban and rural areas of the country. All things being equal, the health condition of a child appears to contribute significantly to learning outcomes. Interestingly, the effect is only significant for mathematics scores but not for English scores.

The regional disparities in the socio-economic development of Ghana may be the primary reason for the differences in the regional and locational inequalities in the educational outcomes found in this study. Learning outcomes are a function of several factors including the school environment, which is dictated by the school infrastructure and teacher's attitude towards work. Disparities in educational infrastructure and human resources are biased in favour of urban areas and some regions in Ghana. For instance, urban areas such as Accra, Kumasi, Tamale, and Cape-Coast among others are more likely to have highly qualified teachers, have access to more textbooks, as well as have more access to other teaching and learning materials compared to rural areas. These differences are likely to reflect on the learning outcomes for children.

In interpreting these results, however, it is important to note a key challenge with respect to the estimates which has to do with the robustness of the model implemented. As discussed earlier, the diagnostic tests suggested that the negative binomial was the preferred model; the Poisson model implemented with robust standard errors is equally appropriate. Unfortunately, we were unable to check for robustness of the results, as the negative binomial model failed to converge.

To test the third hypothesis of this study, which seeks to examine the claim that both past and present health status of children have significant implications for current learning outcomes, the Poisson model was estimated. This was done by including lagged stunting measures in the estimation. Table 4 shows the incidence rate ratios from these estimations. Results suggest that after controlling for other relevant covariates, the stunting status of children in previous periods does not significantly affect current learning outcomes, although the sign is negative as expected. This finding suggests that the adverse effect of malnutrition does not linger once appropriate initiatives are implemented. In the study context, the implementation of interventions such as the school feeding programme which was scaled up in the country in 2011 may be a plausible explanation for the dissipation of the malnutrition effect as children get access to food in school.

To test for heterogeneity in the effects of malnutrition on learning outcomes, the study estimated interaction effects between stunting and parental education as well as household and individual child characteristics. The study makes use of the linear combination option to capture the actual effect of the interaction terms accurately. Table 5 shows the incidence rate ratios for the interaction terms.

While results from Table 3 suggest an overall negative and significant effect of stunting on learning outcomes, the effects may be differentiated based on parental education and household characteristics which may affect the learning environment of children as predicted by Glewwe (2005). Results from Table 4 indicate that the effect of stunting on learning outcomes is moderated by factors such as access to textbooks, location of household residence, household size and gender of the child. However, the estimations provide weak evidence to support the claim that parental education moderates the impact of malnutrition on children's learning outcomes.

Table 4 Incidence rate ratios from Poisson estimation

Variable	Mathematics achievement		English achievement	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Child characteristics				
Child is stunted in current period	0.94	−1.01	0.96	−0.66
Child is stunted in previous period	0.99	−0.13	0.96	−0.49
Forward digit span test	1.04**	2.37	1.05**	2.89
Backward digit span test	1.06***	3.74	1.10***	6.00
Child is male	1.03	0.85	1.01	0.33
Child's age (years)	1.06***	4.15	1.09***	5.48
Child has at least basic education	1.25*	1.79	1.15	1.09
Child has textbooks	0.97	−0.36	1.02	0.26
Child is healthy in the past 2 weeks	0.97	−0.52	1.07	0.89
Household characteristics				
Household size	−0.99	−0.49	1.00	0.14
Mother is present	1.02	0.43	0.92	−1.49
Father is present	0.93*	−1.63	0.94	−1.37
Father is educated	1.05	0.95	1.02	0.38
Mother is educated	1.01	0.20	1.01	0.20
Adult Equivalence Expenditure	1.00	0.70	1.00	1.46
Household location				
Residential type is urban	1.05	1.15	1.20***	4.01
Western Region	0.91	−1.16	0.87	−1.53
Central Region	0.96	−0.38	0.99	−0.15
Volta Region	0.90	−1.19	0.97	−0.28
Eastern Region	0.96	−0.44	0.98	−0.28
Ashanti Region	0.99	−0.06	0.96	−0.49
Brong-Ahafo Region	0.95	−0.56	0.80**	−2.44
Northern Region	0.95	−0.65	0.91	−1.09
Upper East Region	1.13	1.42	1.08	0.89
Upper West Region	0.48***	−5.26	0.63***	−3.47
Observations	619		619	
Pseudo R^2	0.053		0.080	

t-statistics in parenthesis

*$p<0.05$, **$p<0.01$, ***$p<0.00$

Conclusion and Recommendations

The problem of child malnutrition is widespread in many developing countries in sub-Sahara Africa, including Ghana. Using nationally representative panel data, the study provides robust empirical evidence on the effect of child malnutrition over time. The results suggest that children's current nutritional status, measured by height-for-age scores, is significantly associated with lower scores in mathematics.

Table 5 Measuring interaction effects (IRR)

Interaction terms	Linear combination test (mathematics scores)	Linear combination test (English scores)
Stunting * Access to Textbook	0.93** (− 2.51)	0.92 (− 1.47)
Stunting * household size	0.90** (− 2.55)	0.94 (− 0.81)
Stunting * Male	0.92** (− 2.45)	0.90* (− 1.63)
Stunting * Father's Education	0.90* (− 1.76)	0.96 (− 0.34)
Stunting * Mother's Education	0.92 (− 0.93)	1.01 (0.06)
Stunting * Urban	0.89** (− 2.40)	0.87 (− 1.57)

*$p < 0.05$, **$p < 0.01$, ***$p < 0.00$

The negative relationship is established even after controlling for cognitive abilities of children. This suggests that independent of cognitive skills of children, prolonged nutrient deficiency is likely to result in unfavourable learning outcomes, particularly for mathematics. Results from the study provide no evidence that past nutritional health status influences learning outcomes.

The results are indicative of the significance of good feeding and nutritional practices from early stages (which is what stunting captures) which are likely to result in enhanced long-term nutritional outcomes, superior cognitive skills and better learning outcomes. Findings from the study suggest that child characteristics such as age and education level are critical in promoting positive learning outcomes. The size of the household and gender of the child appears to be important in explaining the variation in the learning outcomes for children.

Findings from the study confirm that learning materials such as textbooks are imperative in promoting positive learning outcomes. Based on the results from the interaction effects models, the study concludes that learning outcomes are reinforced by educational inputs such as textbooks or other household and individual characteristics such as gender and location. Although these results are largely similar to other findings in the literature, the findings are still relevant in the Ghanaian context where the prevalence of child malnutrition is high with a quarter of all child mortalities related to malnutrition. Moreover, the panel nature of the data enabled us to show the cause–effect relationship between malnutrition and education outcomes, which in this context, is moderated by investments in learning materials such as textbooks. Also, the findings suggest that the adverse effect of malnutrition may not necessarily linger on and may disappear especially when appropriate initiatives are pursued. Overall, the study concludes that although nutrition matters, so do other educational inputs in determining children's education outcomes.

Based on these findings, the study makes the following policy recommendations. First, there is a need for programmes and policies that promote early childhood nutrition to be developed to ensure improved schooling outcomes. Policies and programmes that focus on early feeding practices among pre-schoolers may be considered to mitigate the possible harmful effects on learning outcomes when these children start schooling. Second, given that household size plays a role in ensuring positive learning outcomes among children, it suggests that reducing household size may have some desired impacts. Given this, families may be encouraged to have fewer children (a number that household resources can adequately support) to ensure that they can provide good learning environments as well as relevant educational inputs for improved learning outcomes of their children. Third, given the importance of access to textbooks in achieving positive learning outcomes, it may be prudent to put programmes and policies in place to ensure that children have access to learning materials. Fourth, findings from the study suggest the need to formulate more targeted policies that will provide the required infrastructure and favourable learning environments, particularly in deprived rural areas and in the various regions to deal with the unfavourable learning outcomes.

Given the limited data on wages in the data, the current study used consumption aggregates as a proxy for household poverty. With the availability of data, future studies may consider using more robust measures of poverty in examining these relationships. Moreover, with a more extended panel, future studies may be able to explicitly control for parental preferences for healthy and educated children based on households' decisions on education investment through the provision of health and education inputs in the previous stages of children's development.

Compliance with Ethical Standards

Conflict of interest On behalf of the authors, the corresponding author states that there is no conflict of interest.

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