Early Childhood Malnutrition and the Cummulative Effect of Learning in Academic Achievement: Evidence from Vietnam

Son Nghiem[a], Viet-Ngu Hoang[b] and Binh Vu[a]

[a] Australian Centre for Health Service Innovation
[b] QUT Business School, Queensland University of Technology

Abstract

This paper examines the effects of early childhood malnutrition on academic achievement using data from three waves of the Young Lives Survey in Vietnam. We choose severe stunting (lower 5 percentile of height-for-age Z scores) to represent early childhood malnutrition because the health literature has shown that it is difficult to resevere severe stunting if appearing in the first three years of life. While public health and health economics literature has documented that malnutrition affects academic performance in not only current period but also subsequent periods. However, we argue that these studies fail to take into account of the cumulative effects of learning in the past on the current periods schooling performance; therefore the health impacts in subsequent periods can be overestimated. This study aims to control for this cummulative effect of schooling performance. We use the generalised method of moments (GMM) and conditional mixed process eastimates as alternatives using three waves data of Young Life Survey in Vietnam. Empirical results show that when past academic performance has been controlled for, stunting has no significant direct impact on schooling performance. Instead, stunting affects learning outcomes in the current period, which has long lasting effects in other subsequent periods. Other important determinants of child academic achievements include mother education and access to electricity. Regional inequality also exists but consumption, ethnicity and gender are found to have no statistical relationships with schooling performance.

Key words: Cumulative Effects of Learning, Malnutrition, Stunt, Young Lives Survey, Vietnam

JEL classifications: D12, I12, I24

1 Introduction

Children malnutrition remains high in developing countries. Strong empirical evidence in the field of public health and health economics has shown that malnutrition in early years has severe negative impacts on the academic achievement in school and these impacts can last until they enter labour force (see a recent review by Currie and Vogl, 2013). Recent studies have used instrument variables models to capture various elements of causality and heterogeneity issues. Most previous studies have found positive relationship between child nutrition and school performance, and even post-school productivities (see for example, Glewwe, Jacoby, and King, 2001; Alderman, Hoddinott, and Kinsey, 2006; Duc, 2011). However, to the best of our knowledge, no previous study take into account the impacts of cummulative effects of cognitive skills.

As well argued in education literature, cognitive skills in early years are important for children to perform well in later years, which then contributes to future productivity of labor. Therefore, it is possible that the impacts of malnutrition in early years of life can be due to failture to catch up in latter years simply because they do not have strong knowledge of the previous school years. It is also possible that low performance in early school years affect child esteem which is important for schooling performance in latter years. Therefore, it is reasonable to expect that those empirical studies which do not take into account past knowledge or the cummulative effects of knowledge on school performance would provide biased results, particularly regarding the impacts of malnutrition on schooling performance. In other words, due to the cummulative effects of learning on productivity, it is imporant to examine the relationship between nutrition and health conditions and cognitive development in a dynamic setting.

This study aims to provide more empirical evidences regarding this evolution in knowledge accumulation of children. More specifically we aim to re-examine the relationship bewteen nutrition and schooling performance in Vietnam using the first three waves of the Young Lives Survey in which we take into account the cummulative effect of learning in earlier school years. We also test for the sensitivity of results due to unobserved individual characteristics by using the generalized method of moments (GMM) and conditional mixed process (CMP) estimates as alternatives to IV models as commonly used in the literature.

The remainder of this paper includes a brief review of the literature (Section 2), methodology (Section 3), Data and variable selection (Section 4), results and discussions (Section 5) and Conclusion (Section 6).

2 Literature review

The literature on nutrition and child development is vast; hence we focus on reviewing the most relevant recent studies. Pollitt et al. (1990), Behrman (1996) and Grantham-McGregor and Ani (2001) have reviewed a wealth of literature that supports a significant positive relationship between schooling achievement/cognitive development and childhood health/nutrition. Better health and nutrition in childhood is likely to lead to children enrolling at a younger age, less grade repetition, fewer missed days of schooling, further study being achieved and greater performance on test scores (Behrman, 1996). Among previous studies, the instrumental variable (IV) approach has been widely used. Some IVs used in previous studies include heigh-for-age of older sibling(Glewwe, Jacoby, and King, 2001), sudden changes in prices (Alderman et al., 2001; Wisniewski, 2010), and external shocks such as civil war and drought (Alderman, Hoddinott, and Kinsey, 2006). These studies found a positive correlation between child nutrition and schooling performance regardless of differences in the instrument variables used.

Crookston et al. (2013), Sandjaja et al. (2013) and Duc (2011) are few recent studies that have analysed the relationship between malnutrition and schooling achievement in Vietnam. Crookston et al. (2013) utilised data for Vietnam as well as India, Peru and Ethiopia collected from the Young Lives Survey. The authors show that height-for-age z-scores are inversely associated with achieved grade for age while controlling for the sex of the child, several factors of the parents (i.e. age, the years of schooling), asset index, urban residence, and several community factors (ie.e population, wealth, presence of a community hospital). Although the paper reports that children who had growth recovery from the age of 1 to 8 had better outcomes than those whose growth did not improve, their results are similar to those who experienced growth faltering (an individual who was not growth stunted at the age of 1 but was stunted at the age of 8). These findings suggest that intervention into malnutrition may have positive effects at any age, contrary to findings by Duc (2011).

Sandjaja et al. (2013) empirically analysed the relationship between anthropometric indicators and cognitive performance in Indonesia, Malaysia, Thailand and Vietnam. Using a Raven's Progressive Matrices test it was found that children between the age of 6 and 12 who had a low height-for-age z-score, weight-for-age z score and BMI-for-age z-score are much more likely to have a lower non-verbal IQ level. It was also found that they are likely to have a lower non-verbal IQ score in the presence of severe obesity.

Duc (2011) also utilised a longitudinal Young Liives Survey dataset of 1,200 Vietnamese children to empirically analyse the impact of child malnutrition on cognitive development. Using height-for-age as an indicator the study finds that analysing the impact of early childhood stunting on cognition without controlling for gestational age may lead to significant bias. When controlling for gestational age the height-for-age at age one does not have a significant impact on the cognitive achievement of children aged five. This study however does analyse the effect of growth faltering on educational achievement as done by Crookston et al. (2013), that is, it does not analyse the situation of when the child is not stunted at age one but is stunted at age five.

There are several limitations of these previous studies within Vietnam. First, these studies have not considered the fact that both child health and schooling performance are also affected by household decisions regarding investments on children's human capital. Literature has argued that this type of investment decisions is determined not in isolation with health and schooling performance of the children in the household. Therefore, the model that takes into account changes in investment in children for those of lower birth weight or height or stunt would be interesting. Not controlling for such endogeniety of child health tends to overestimate the impacts of child health on schooling achievement as shown by Khanam, Nghiem, and Rahman (2011). Second, the discussed studies have not controlled for whether the child has a long-term health condition. Therefore, as discussed by Wisniewski (2010), this is likely to cause an upward bias for the effects of stunting on educational achievement when using height-for-age as an indicator for malnutrition. Finally, no previous study examine the relationship between nutrition and child development using the evolution of human capital model and education by Becker (2009). Note that the evolution of knoweldge, more specially the cummulative effects of learning on labour productivity, is important and well acknowledged in the literature; therefore we would like to show that empirical studies which fail to take into account these effects could cause biases to empirical results.

3 Methodology

Following Glewwe, Jacoby, and King (2001), the malnutrition status of children in the previous period is assumed to affect cognitive development of children in the current period. However, as well argued in the literature of education, the concept of knowledge accumulation is very important for students to perform well in schools and develop cognitive skills. In fact, the concept of cummulative knowledge is the back bone in school circumlum worldwide. Therefore, we apply the concept of knowledge accumulation by Cunha and Heckman (2008) to propose that cognitive outcome of children in the current period is affected by their performance in the past period. Thus, the empirical specification to estimate the relationship between schooling performance and nutrition status is presented as:

$$S_{it} = \alpha_S S_{i,t-1} + \alpha_H H_{i,t-i} + \alpha_X X_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

where S represents schooling performance; H is the nutrition status; X is the set of individual and household characteristics; μ_i is a time-invariant unobserved individual characteristics that can affect both nutrition status and academic outcome; and ε_{it} represents random noise, respectively.

As argued in the litearture, nutrition status can be endogenous in the context of household investment in health and education; hence applying standard regressions can produce biased results. In this study, we address the endogeneity issue by: a) using a comprehensive set of covariates (Gregg et al. (2005)), and b) applying a GMM approach by Blundell and Bond (1998). We can minimise the effects of unobserved individual heterogeneity by controlling for a comprehensive set of observable characteristics that are available in the Young Lives Survey data. The implicit assumption under this approach is that there is a high degree of correlation between observables and unobservables. However, we acknowledge that this approach cannot eliminate all sources of unobserved heterogeneity.

The parameter μ_i in Equation 1 can also be eliminated by applying first-difference but the difference of the lag dependent variable still correlates with the difference of the error term. Arellano and Bond (1991) proposed that using a second lag and higher as instrumental variables, one can estimate the first differenced transformation consistently using a GMM framework (i.e., "difference GMM"). But the time-invariant observable covariates will be eliminated, and lags of level dependent variables are weak instruments. Blundell and Bond (1998) proposed a system GMM estimator that uses both level and lags of additional covariates instrumental variables for differenced endogenous variables ("system GMM"). Results of a Monte Carlo experiment by Blundell and Bond (1998, Table 2) show that the system GMM estimator provided substantial improvement over results by the difference GMM estimator. A potential issue with this estimator is that too many instrumental variables are available, which can lead to over-identification problems (Roodman 2009). A Sargan test can be applied to identify the desirable number of instrumental variables (Bond 2002). Another issue with this estimator is that standard errors of the estimates can be biased downwards, and hence we apply the finite sample correction proposed by Windmeijer (2005) in the analysis.

The GMM estimator is applicable to continuous dependent variable only, thus, we use a conditional mixed-process estimator by Roodman (2011), which estimates equation (1) and the equation (2) as a system[1]. The significant of the correlation coefficient between error terms of equations (1) and (2) are proxied for the endogeneity of child nutrition status.

$$H_{i,t-1} = \beta Z_{i,t-1} + \mu_i + \eta_{i,t-1} \tag{2}$$

4 Data

4.1 Data source and variable selection

We use data from the Young Lives Survey, conducted in four countries: Peru, Ethiopia, Vietnam and Andhra Pradesh (India). The survey covers a total 12,000 children, and hence the sample size in each country is 3000 children. The sample in each country consists of two cohorts, including 2000 young children (aged 6-18 months in 2002) and 1000 older children (aged 7.5-8.5 years in 2002). In this study, we analyse the data collected from Wave 1 (2002), Wave 2 (2006), and Wave 3 (2009). The sample size of Wave 1, 2 and 3 are 3000, 2983 and 2979, respectively. Thus, the average attrition rate is only 0.35%. In this study, we focus on the younger cohort as they're more relevant to examine the effects of stunting during the first three years of life. The sample size for this younger cohort in Wave 1, 2 and 3 are 2000, 1998 and 1987 children, producing a similarly small attrition rate of 3.3%.

In line with the literature, we measure malnutrition via a stunt dummy variable, which is coded as 1 for those having height-for-age Z-score (HAZ) at 2 standard deviation (SD) below the median HAZ and 0 otherwise. The main advantage of this approach is that physical stunting (i.e., having low HAZ) occurs at the first three years of life, where brain develops rapidly and hence would have long-term effects on cognitive development. Stunting is very difficult to reverse and hence stunting children often develop into shorter adults. For sensitivity analysis, we also select a wasting dummy, which is defined as having weight-for-age Z-score (WAZ) at two SD or lower than the median WAZ and

[1] The conditional fixed-effects logit estimator (Baetschmann, Staub, and Winkelmann, 2015) is relevant but it is not applicable in this case because the selected outcome (e.g. enroll school late) did not change it state over time.

0 otherwise, to represent child malnutrition. While stunting can occur due to micronutrient deficiency, wasting is more likely due to food shortages.

The main variables for school performance include the probability of enrolling school late, probability of being able to read, to write, and the score of the Peabody Picture Vocabulary Test (PPVT). The enrollment late dummy was defined as those who current grade is less than their age minus the age of starting school (six years). The richness of the Young Lives Survey allows use to control for characteristics of the child (age, gender, ethnicity and whether the child have any long-term health problem), characteristics of the household (age, gender and education of the household head and the spouse of household head, household size, the proportion of people outside labour force in the households), health inputs (water sources, access to electricity, and the household wealth index).

4.2 Descriptive statistics

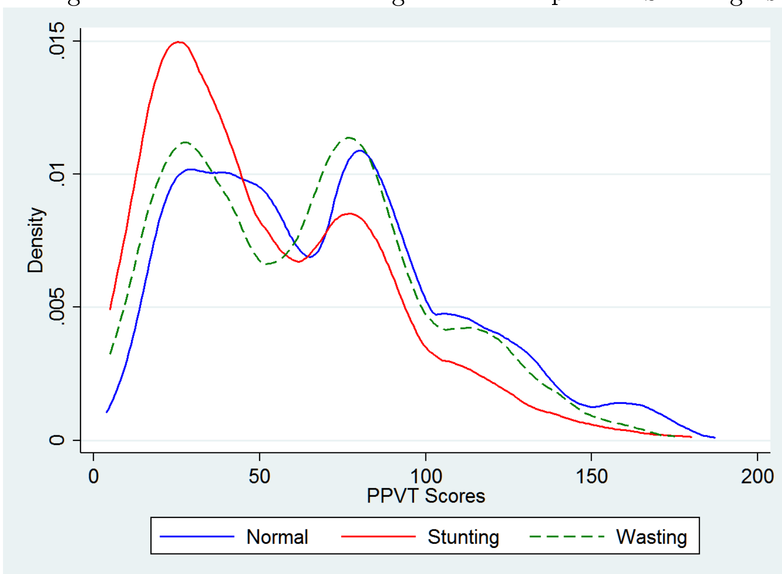
The descriptive statistics show significant differences between stunt (malnourished) and normal children. For example, parents of normal children have higher probability of literate (88% for father and 66% for mother) compared with the respective figure of stunt children (67% for fathers and 64% for mothers). The average level of consumption is also lower among households of stunt children (315 thousand VND) than that of normal children (493 thousand VND). Family of stunt children also have poorer sanitation quality, poorer water quality and lower probability of access to electricity. Stunt children do have lower schooling performance with an average PPTVT scores of 53 while the score of normal children is 70. Stunt children also have lower birth weights (2943 vs 3137 grams) and lower z-scores for BMI-for-age and weight-for-age.

To explore the sensitivity of stunting measurement, we plot the distribution of PPVT scores for normal, stunting and wasting children. It's clearly shown that stunting children have higher frequency of having low scores (less than 50) while having lower frequency of obtaining high score (100 or above). The density plot of PPVT scores for wasting children also shows poorer performance compared with that of normal children but the magnitude of the difference is less substantial. Thus, in the analysis we focus on using the stunt dummy and height-for-age z-score to measure (mal)nutrition.

Table 1: Descriptive statistics

Variables	Normal	Stunt	P-value
Child's gender (1=male)	0.50	0.57	0.00
Child's ethnic group (1=Vietnamese)	0.92	0.64	0.00
Long-term health problem (1=yes)	0.09	0.10	0.09
Child's age (months)	57.12	57.38	0.81
Gender of household head (1=male)	0.86	0.87	0.59
Father's age (years)	33.95	32.87	0.00
Father is literate (1=yes)	0.88	0.67	0.00
Mother's age (years)	30.92	30.35	0.00
Mother is literate (1=yes)	0.86	0.64	0.00
Housing quality index	0.64	0.54	0.00
Consumer durables index	0.47	0.34	0.00
Real consumption (thousand VND/person/month, 2006 prices)	493	315	0.00
Access to electricity (1=yes)	0.16	0.05	0.00
Sanitation quality index	0.94	0.84	0.00
Drinking water quality index	0.59	0.39	0.00
Household size (people)	4.67	4.92	0.00
Face advert events (1=yes)	0.30	0.29	0.53
PPVT Scores	70.09	53.07	0.00
Enroll school lates (1=yes)	0.17	0.25	0.00
Birthweight (grams)	3137	2943	0.00
Height-for-age Z-score	-0.75	-2.69	0.00
Weight-for-age Z-score	-0.74	-2.14	0.00
BMI-for-age Z-score	-0.43	-0.55	0.00

Figure 1: Malnutrition and cognitive development: Stunting vs Wasting



5 Results and Discussion

The results show that when the lag of outcome (PPVT scores) is taken into account, stunt in the previous period has no significant effect on the school performance (PPVT scores) of children in the current period (see GMM column in Table 2). In fact, the past performance (lag of PPVT scores) is the strongest predictor of the current school performance. Other factors affecting schooling performance of children include, age of the child, parents' education level and infrastructure. In particular, PPVT scores improves with age of the child, *ceteris paribus*. Children of literate mother has PPVT scores higher by 8%[2] compared with children of mothers with difficulties of reading and writting. Also, children of families with access to electricity have PPVT scores higher by 9% compared with those without access to electricity. The correlation coefficient (ρ) between error terms of equations (1) and (2) is statistically significant, suggesting that there are some unobserved factors that affect both malnutrition and schooling performance. This implies that standard estimators of equation (1) would produce biased results.

[2]we have take the logarithm of PPVT, and hence the parameter of dummy variable like stunt is interpreted as change in % of PPVT

Table 2: Effects of malnutrition on cognitive development

Independent variables	GMM		CMP	
	Coef.	Std. err	Coef.	Std. err
Lag of outcome	***0.37	0.09		
Stunt in the previous period	-0.03	0.03	***-0.161	0.031
Red River Delta	***0.09	0.02	-0.001	0.020
Phu Yen	0.06	0.04	***-0.206	0.020
Da Nang	-0.01	0.03	**0.057	0.022
Mekong River Delta	*0.06	0.03	***-0.161	0.020
Child's gender (male=1)	0.01	0.01	-0.001	0.012
Child's age (months)	**0.01	0.003	***0.029	0.000
Child's ethnic group (Vietnamese=1)	0.03	0.04	***0.172	0.026
Gender of household head (male=1)	-0.03	0.02	**-0.042	0.020
Age of household head (years)	-.0002	0.001	-0.0002	0.001
Father is literate	-0.01	0.03	***0.089	0.021
Mother is literate	***0.08	0.02	***0.071	0.021
Access to electricity	*0.09	0.05	***0.212	0.037
Consumption per capita	0.02	0.02	***0.114	0.013
Household size	0.0004	0.01	-0.003	0.005
Dependent ratio	-0.03	0.03	-0.023	0.028
Long-term health problem (1=yes)	0.02	0.02	-0.006	0.018
Log of birth weight	-0.004	0.02	-0.016	0.021
Constant	***2.33	0.21	***0.710	0.091
ρ			***0.151	0.042

The main difference between our empirical specification and previous studies is that we take into account the cumulative effects of past schooling. In order to examine the robustness of our results, we also applied a conditional mixed process (CMP) estimates to equations (1) and (2) without the presence of past schooling performance. The CMP model presented similar results with previous studies in the literature: being stunt in the previous period is associated with 16.1% reduction in the PPVT scores of the current period (see CMP column of Table 2). These results are important for several reasons. First, it highlights the important role of past knoweldge in children cognitive performance; therefore it favours policies that help enhance schooling performance in early years.

Second, it shows that those models which do not take into account the cumulative effects of schooling could produce biased results. We do not argue that our model specification is more appropriate than past models but we argue that the missing of such an important variable as the past schooling performance would cause models misspecified; consequently empirical results could be misleading. In no way the insignificance of stunting on school performance in subsequent periods in our empirical study suggests that it is not important to address the issue of stuning. In fact, our empirical results support a mechanism through which stunting can effect future productivity of human labour: that is it has severe impacts on schooling performance in early years and these negative impacts of stunting have lasting effects on schooling performance in future. Therefore, our empirical study provides further evidence to support those policies those not only prevent stunting in early years of life in an indirect maner but also promote further support on schooling for those children get caught in stunting.

Third, we suggest that more empirical studies looking at the effects of health on the cummulation of knoweldge, rather than the congitive performance in single periods are needed to shed more lights on the relationship between health and skills of the human capital.

Without controlling the effects of past knowledge, child gender, father education and consumption per capital are strongly correlated with schooling performance. However, when the effects of past knowlege is accounted for, such relationships do not exist anymore. However, good infrastructure such as access to electricity and mothers' education are important determinants of child school performance. In fact, if we do not controlling for past knoweldge, access to electricity has the highest magnitude, creating a 21.2% increase in PPVT scores while its magnitude in the model with the presence of past knowedge is only 0.09. We also estimated several the IV models, however we could not find any significant instrument variables. This shows that if we use instrument variable approach, one needs to be very careful in choosing the instruments. Also, we suggest the use of the GMM approach could provide an useful alternative in which second lags and higher moments are used as internal IVs. In fact, these internal IVs can be more suitable in the context of the cummulative effect of schooling as they are correlated with the past and not the current IV. Nevertheless, we suggest analysts need to be more careful in model specifications in empirial studies as misspecified models can provide inaccurate results.

6 Conclusions

This paper has examined the effects of malnutrition on the cognitive development of children using the human capital theory by Cunha and Heckman (2008). We found that when past schooling performance is controlled for, severe stunting has no significant effects on the cognitive outcome of children in subsequent school years. While this empirical finding is different from past studies, it presents several interesting implications. First, the important role of cummulative effects in school performance is reinforced by our empirical results. In fact, school performance in the past period is the most substantial factor that explains current period school performance. Second, failing to take into account of this cumulative effects in schooling performacne may cause the mispecification problem of empirial models. Third, empirial results present one mechanism through which the health conditions in early years of life can affect human producitvity, not directly through its long lasting impacts on acquisition of cognitive skills but indirectly through low performance in early years that has long lasting effects. In other words, health conditions in the early years of life is more important as it affects the concurent school performance which then have effects in subsequent periods. Therefore children in early years of life should receive good levels of investment both in health and in schooling. This finding favours policies that can address special atentions in improving the school performance of stunts. In addition, our empirical results show regional inequality in school performance across Vietnam in which children in Mekong and Red river delta regions performed better in coginitive tests. Interestingly, we do not find empirical evidence of gender and ethnicity inequality as reported in previous studies after the effects of past knowledge are controlled for. However, the role of mother's education and access to eletricity remain important factors.

While we cannot find good instruments in the dataset used, we argue that the use of GMM approch could provides an useful alternate estimate. However, the use of GMM approach is not free of problems; therefore future studies could improve on this. Furthermore results could be very specific to data used; therefore we suggest more studies using international datasets or datasets of other countries could provide more empirical results in the debate of the relationship between health and cummulative effects of skill acquisition of human capital.

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