# THE LONG-TERM COGNITIVE CONSEQUENCES OF EARLY CHILDHOOD MALNUTRITION: THE CASE OF FAMINE IN GHANA

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*We examine the role of early childhood health in human capital accumulation. Using a unique data set from Ghana with comprehensive information on individual, family, community, school quality characteristics and a direct measure of intelligence together with test scores, we examine the long-term cognitive effects of the 1983 famine on survivors. We show that differences in intelligence test scores can be robustly explained by the differential impact of the famine in different parts of the country and the impacts are most severe for children under two years of age during the famine. We also account for model uncertainty by using Bayesian Model Averaging.*

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## 1. Introduction

One of the most notable explanations for the large observed variation in cross-country economic performance has been differences in human capital; see, for example, Mankiw et al. (1992), Barro and Lee (1996), and Kalaitzidakis et al. (2001).[1] Studies have also shown that health is an important determinant of human capital outcomes in developing countries; see the comprehensive survey by Bleakley (2010).[2] In this paper, we are interested in one component of health that is potentially particularly crucial to human capital formation in developing countries – early childhood nutrition – and how it affects cognitive development.[3]

Most of the recent work on the determinants of cognitive development has been carried out in developed countries where data has been more readily available; see, Cunha and Heckman (2009) for a comprehensive survey. This paper contributes to the existing literature by employing a unique survey data set from a sub-Saharan African country, Ghana, that includes test scores for a direct measure of intelligence or IQ (along with scores for English comprehension and mathematics) together with comprehensive information on individual, family, community, and school quality characteristics. Using this data, we exploit a natural experiment; i.e., the 1983 famine that swept across much of West Africa, to examine the long-term effects of early childhood malnutrition on the cognitive development of famine survivors who were between the ages of 0 and 8 at the time of the famine.

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[1] Human capital may also be responsible for sustaining other important growth determinants. Glaeser et al. (2004), for instance, conclude that human capital accumulation leads to improvements in the quality of institutions that then spurs growth and development.

[2] Weil (2005), for example, estimates that almost 10 percent of the differences in per capita GDP across countries can be accounted for by differences in health status.

[3] Cognitive ability has been shown to be a powerful predictor of a wide range of labor market (e.g., wages), educational, and other social (e.g., crime) outcomes. See, for example, Herrnstein and Murray (1994), Murnane, Willett, and Levy (1995), Auld and Sidhu (2005), and Kaestner (2008).

The health literature has yielded many examples where the natural experiment of famine has been used to suggest that early childhood malnutrition has important negative consequences for adult health. The Dutch Famine of 1944-45 has been shown to have had long-term negative impacts on various adult health (Roseboom et al. (2006)), obesity (Lumey et al. (2007)), and epigenetic inheritance (Lumey (1992); Lumey and Stein (1997)) outcomes.[4] Chen et al. (2007) and Meng et al. (2009) report that birth cohorts during the most intense period of the Great Famine of China in 1959-1961 were significantly shorter in adulthood and were also likely to work fewer hours and earn less compared to other birth cohorts[5].

The development literature has also examined the effects of childhood malnutrition on various schooling and labor market outcomes. Glewwe et al. (2007) provides an extensive review of the literature on the long-term impact of child health and nutrition on schooling outcomes in developing countries. A particular concern for researchers has been the effects of early childhood nutrition on cognitive outcomes. The timely development of cognitive functions requires sufficient intake of certain proteins and micro-nutrients like zinc and iron that are crucial for brain development (Grantham-McGregor et al. (1997)). If a child does not get adequate nutrients brain development could be severely impaired.

The literature has been concerned with two key questions. First, in what period of early childhood does the incidence of malnutrition lead to the most severe negative cognitive

[4] Roseboom et al. (2006), for example, show that intrauterine under nutrition caused by reduced calorie intake by pregnant women during the Dutch Famine of 1944-45 resulted in negative health outcomes to such birth cohorts. For example, they were more likely to be glucose intolerant and have reduced insulin concentrations at ages 50 and 58. Other negative adult health outcomes from intrauterine exposure to famine during the early gestation period were increased incidences of coronary heart diseases and greater risks of high blood pressure. These negative health consequences differed for fetus cohorts who experienced malnutrition at different stages of their development in the womb. For instance adult high blood pressure was associated with malnutrition in the third trimester only in their study.

[5] Mu et al. (2011) examined how the impact of famine differs between genders. Females who were exposed to the famine as infants were more likely than males to be illiterate and disabled.

outcomes in later life? Second, are the effects of childhood malnutrition on cognitive development reversible through remedial efforts in later life?

The consensus in the literature is that cognitive abilities are established relatively early on in life – IQ, for example, is known to stabilize by about 10 years of age – and depend crucially on parental and non-parental resources. In examining the long-term effects of early childhood malnutrition, accurate determination of the critical period is crucial[6]. The idea of the critical period is that some needed investments, in this case adequate nutrition and nourishment, should be made in a child's life during this period and failure to do so could result in potentially permanent negative effects. The literature suggests that the critical period for cognitive abilities is up to around 2 years of age. Belli (1971, 1975), citing earlier works, highlighted that brain cell development is fastest within the first two years of a child and then slows down sharply afterward. Most of this growth happens within the first six months and if proteins, which are essential to brain development, are in severe shortage during this period, the brain development could be sub-optimal. Glewwe et al. (2001) with panel data from the Philippines show that children who were malnourished in their second year scored lower on IQ tests at age eight. Alderman et al. (2006) also show that the second year of life is most critical for nutritional investments in children for general health outcomes. Malnourished children from twelve to twenty-four months had lost about 4.6 cm in height-by-age at adolescence.

Nevertheless, there is some evidence that the impact of early childhood malnutrition on health may be partially (though not fully) reversible. For example, Pollitt (1984) suggests that early childhood nutritional shocks that impact cognitive development can be partially reversed

[6] See also Cunha et al. (2010) who build a theoretical model that emphasizes the need for timely investments in children at the "critical period" to optimize skill formation and cognitive achievement.

over time if the nutritional deficiencies are corrected later in childhood. Alderman et al. (2006) explicitly examine the possibility of regaining some or all of the lost height in the aftermath of the Zimbabwean drought of 1983-84. In birth cohorts aged 12 to 24 months during the famine, they conclude that only about a third of the 4.6 cm in lost height is recovered through timely nutritional interventions. Importantly, Cunha and Heckman (2009b) also suggest that there is a "sensitive period" between ages 6 to 8 where investments can make a large impact for cognitive abilities.

Current works in the literature on the effects of childhood malnutrition on cognitive development suffer from two weaknesses. First, even though several studies have recently examined the long-term impact of childhood malnutrition on health, there have been very few studies that have directly examined the impact on cognitive achievement. The reason for this is largely due to the lack of availability of data where direct measures of cognitive achievement (such as IQ scores) have been collected. Instead, researchers have focused on other outcome measures that are only indirectly related to cognition, such as general measures of health or physical development (e.g., height or height adjusted for age), schooling attainment, performance on tests, or various labor market outcomes (e.g., wages or hours worked). Second, when direct measures of IQ scores have been available (such as in the important work of Glewwe et al. (2001)), these scores have been available only for relatively young children. Researchers are therefore not able to definitively answer the question of whether negative impacts on cognitive achievement due to early childhood malnutrition persist into adulthood.

An important exception is Stein et al. (1972). Stein et al. studied the effects of the 1944-45 Dutch Famine on children who were born within 1 year of the famine or who were conceived during the famine (but born after). Their main interest was to evaluate whether there would be significant differences in cognitive outcomes – such as clinically diagnosed measures of severe and mild mental retardation, and also IQ (as measured by scores on a Raven Progressive Matrices test) – between the intrauterine birth cohorts that experienced famine (those who lived in the large cities of Western Holland) through maternal exposure and those that did not (those who lived in cities in the south, east, and north of Holland) by the time the surviving offspring had reached adulthood (age 19[7]). Stein et al. also control for socioeconomic status of the child's family using father's occupation; i.e., whether the father was doing manual or non-manual labor.

Their surprising conclusion was that neither starvation during pregnancy nor early childhood malnutrition appears to have detectable effects on the adult mental performance of surviving male offspring. Stein et al. provide a detailed critique of their methodology and suggest two alternative hypotheses: (1) "selective survival"; that is, only fetuses that were unimpaired by the nutritional deprivations of famine survived, and (2) "compensatory experience"; that is, postnatal education in the period from birth until the time when the individuals were sampled (at military induction) may have (completely, in this case) reversed any early cognitive effects of famine experience. If the compensatory experience hypothesis was true, and the negative cognitive effects of early childhood malnutrition could, in fact, be fully compensated for by subsequent investments, then it would invalidate the "critical period" hypothesis and suggest that more emphasis be placed on establishing the "sensitive period" for childhood investments.

In this paper, we examine the long-term effects of childhood malnutrition that was the consequence of a severe famine in 1983-84 in Ghana on cognitive development in adults 20 years later. In 1982-83 severe droughts and subsequent food shortages plagued most African countries. For example, in 1983, maize, a major food staple, saw a 50 percent drop production

[7] The IQ test was administered as part of a Dutch military recruitment exercise when these birth cohorts were at the age of around 18-19 years. The sample consisted therefore only of males.

from the previous year. In all, there was a food deficit of 361,000 tons and a request was made to the Food and Agriculture Organization (FAO) for assistance much of which was not delivered until late 1984. According to Derrick (1984), there was a significant drop in daily per capita caloric intake to about 1600 kcal in 1983 from 1900 kcal in 1982. Drought-prone northern Ghana, which is mostly rural, was the most affected together with the food-growing areas. The lowest calorie intake was experienced in 1984 for most areas in Ghana. Thus it is expected that birth cohorts within this window should be worst affected by the famine in 1983-84.

Our work differs from the seminal work by Stein et al. in the following ways. First, Stein et al. focused on children between the ages of 0-1 years during the famine because they were primarily concerned with investigating the effects of famine on intrauterine birth cohorts. We focus instead on the question of the effects of famine during early childhood malnutrition on adult cognitive outcomes. Consistent with the literature cited above, we define early childhood as children aged 0-2.[8] We are therefore naturally interested in the question of whether children who experienced famine when they were younger (in the 0-2 age group) as opposed to when they were older (the 3-8 age group, in our case) saw differential impacts in the effects of childhood experience with famine. That is, our study focuses on the long-term cognitive outcomes of children within 2 years of age in 1984 compared with older children (up to 8 years old) at the time of famine.

Stein et al. also only focus on famine *incidence* (i.e., the 7 cities that experienced famine in their treatment group and the 11 cities that did not in their control group), whereas we consider the variation in famine *intensity* across the 10 administrative regions of Ghana. Like Stein et al., but unlike most previous studies on this subject, we exploit a unique survey data set from Ghana

[8] While our data does report the month of birth for some individuals, this information is frequently unreported in the survey, so that there are not sufficient observations for us to properly investigate the intrauterine effects of famine on adult cognitive outcomes.

– the Ghana Education Impact Evaluation Survey (GEIES) in 2003 – that directly measures intelligence or IQ (based on the Raven's Progressive Matrices[9]) – in addition to scores on tests for English comprehension and mathematics – that was administered on adults who had experienced varying degrees of famine intensity as children in 1983-84 20 years earlier, to examine the impact of early childhood malnutrition on adult cognitive development.

Further, unlike Stein et al., the data from Ghana makes it possible for us to control for a large number of individual, family, and community characteristics (and not just family socioeconomic status). Importantly, we are able to control for the cumulative effects of childhood investments in health that can confound the direct effects of the famine on adult cognitive development. Specifically, we use height to proxy for accumulated health status. The data also allows us to control for key schooling quality characteristics such as the quality of schooling infrastructure; i.e., the state of classrooms and the availability of textbooks, and the quality of teachers. We are also able to control for the socio-economic status of the family using parental schooling data. Hence, we are able to investigate the effects of early childhood malnutrition (during the critical period of 0-2 years) on long-term cognitive development after controlling for possible subsequent remedial interventions that fall specifically during the sensitive period of a child's development before her IQ stabilizes (at age 10).

Finally, we also make a methodological contribution. In contrast to previous work in this literature, we explicitly address the issue of model uncertainty in investigating the long-term effects of famine. The term model uncertainty was first coined by Brock and Durlauf (2001) in the empirical growth context to refer to the idea that new growth theories are open-ended, which means that any given theory of growth does not logically exclude other theories from also being relevant. In our context, model uncertainty implies that the role of early childhood malnutrition

[9] The Raven's Progressive Matrices is generally accepted as a good measure of (Carpenter et al (1990)).

in determining IQ does not automatically preclude any of a large number of other possible determinants related to, for example, either nutritional or schooling investments in the sensitive period from being included in the analysis. However, the estimated partial effect of early childhood malnutrition on IQ may vary dramatically across model specifications depending on which other auxiliary variables are included in the regression. How should one deal with the dependence of inference on model specifications?

To do so, we employ Bayesian model averaging (BMA) methods; see, Leamer (1978), Draper (1995), and Raftery et al. (1997), that have been widely applied in other areas of economics, but are novel to this literature. BMA constructs estimates that do not depend on a particular model specification but rather use information from all candidate models. In particular, it amounts to forming a weighted average of model specific estimates where the weights are given by the posterior model probabilities. In particular, we implement BMA in both the linear regression context as well as in the structural context. In the latter case, we use data on regional rainfall variations as an instrument for the degree of severity of famine.

Our main findings are as follows. First, we find that, all else equal, famine intensity only affects the cognitive development of children who were in the 0-2 years age group at the time of famine. The children in the 3-8 age group suffered no direct effects from the famine. Second, after controlling for a large set of characteristics including accumulated health, we find that the magnitude of the effect of famine intensity on cognitive development in children who experienced famine between ages 0-2 is large. For a standard deviation increase in our famine intensity measure, measured IQ falls on average by almost 7 percent for children in this age group. In terms of performance on Math and English tests, this loss of cognitive ability translates on average to a loss that is consistent with a reduction of up to slightly more than half of a year of schooling. Overall, our work suggests that early childhood malnutrition has a large and important direct impact on cognitive performance that persists into adulthood. But, the incidence of the malnutrition needs to be early enough for this effect to take hold.

We proceed as follows: Section 2 describes the empirical strategy and data. We then discuss the results in Section 3. Finally, Section 4 concludes.

## 2. Empirical Strategy and Data

Following Behrman and Lavy (1994) and Glewwe and King (2001), we exploit the differences in famine intensity across Ghana to examine the impact of famine and the resulting malnutrition on survivors. We match data from several sources for the estimation problem at hand. The main data set is the GEIES of 2003 and its precursor the education module of the Ghana Living Standards Survey II of 1988/89. We also use data from the Demographic and Health Survey (DHS) of 1988 and rainfall data from the World Bank's Africa Rainfall and Temperature Evaluation System (ARTES).

The model specification is given by

$$CA_{i,t} = \alpha + \mu_t + \delta_0 DRD_{l,1983} + \delta_1 \left( DRD_{l,1983} * t \right) + x_{i,t}{}'\beta + \varepsilon_{i,t} \qquad (1.1)$$

where $t = 0,1$ denotes the birth cohort (discussed below) to which individual $i$ belongs. The sample consists of individuals of age between 0 and 8 in 1984. Hence, all the individuals in the sample experienced the 1983-84 famine. The first cohort ($t = 0$) is the group of individuals aged 3 to 8 during the famine; i.e., born between the years 1976 and 1981. We refer to this (comparison) group as the *Old Famine* group. The second cohort ($t = 1$) is the group of individuals aged 0 to 2 during the famine; i.e., born between the years 1982 and 1984. We refer to this (treatment) group as the *Young Famine* group.

The reasons for choosing these two cohorts of individuals as comparison-treatment groups are as follows. First, we seek to be consistent with the definition of "early childhood" in the literature. As discussed in the Introduction, the existing literature suggests that the effects of childhood malnutrition should be most severe for the group of children of age 2 years and under. Hence, the aim here is to evaluate the impact of childhood malnutrition on children in this critical age group and to compare them with older children outside of this critical age group who have also experienced the famine. However this concern does not place a natural upper bound on the age of individuals in 1983-84 in the comparison group.

The reason for choosing the upper bound to be 8 years of age in 1983-84 is to yield a comparison group that is likely to have similar schooling inputs as the treatment group. The only other wave of GEIES data (other than the 2003 survey) that is available is the one collected in 1988/89. As we describe below, the GEIES data includes information on school quality at the cluster level[10]. The data does not specify the actual school attended by an individual but in Ghana, students in rural areas typically attend the closest school and this school is usually in the district or the next town. Individuals of primary schooling age who reside in the same cluster would then be enrolled in the same schools. Because both cohorts were in primary (or elementary) school at the same time – the cohort born between the years 1982 and 1984 had just enrolled in primary school in the period 1988/89 while the oldest individual in the 1976-81 cohort would have just graduated from primary school in 1988/89 – this first wave of GEIES

[10] In Ghana the administrative hierarchy is as follows: regions and then districts. Clusters are similar to census tracts in the US and are subdivisions of districts. The survey had 84 clusters in 1989 and 82 of the same clusters were visited in 2003. Two clusters were missing from 2003 because they were no longer inhabited.

data would allow proper control for variations in school quality characteristics across cohorts in (1) above.

The dependent variable, $CA_{i,t}$, in (1.1) is the measure of cognitive achievement for individual $i$. Cognitive achievement for the purpose of this paper refers to IQ test scores. The IQ scores are measured by the Raven's Progressive Matrices (see Appendix A for a sample of the test) which were administered to all respondents between the ages 9 and 55[11] in the 2003 wave of the GEIES. A total of 3582 respondents were tested. For respondents born within the age range of the sample – i.e., those born between 1976 and 1984 inclusive – a total of 611 respondents completed the Raven test. In terms of the effective sample size for the exercises in this paper, after accounting for missing observations in the regressors, the sample size is 560 (233 observations in the *Young Famine* group and 327 in the *Old Famine* group).

We are also interested in the effects of IQ scores (and those of other covariates) on Math and English test scores. For those latter exercises, the regression equation is similar to (1.1); the dependent variable would then be the Math or English test scores while the set of regressors will then consist of IQ test scores and the other independent variables on the RHS of (1.1) above. The Math and English tests administered in the 2003 GEIES come in two flavors. Respondents are first given a *Simple* version of the English reading comprehension and Mathematics tests. Only respondents who scored above 50 per cent were asked to take a second *Advanced* version of the test. We provide samples of all these tests in Appendix A of the paper. The Advanced versions of these tests are substantially more difficult than the Simple versions. For example, the Simple Math test comprised 8 extremely routine arithmetic questions while the Advanced Math test had

[11] All cognitive achievement tests; i.e., the other English and Math tests, were also given to individuals within this age group.

36 questions that are more comparable with standardized tests in the US in terms of difficulty level.

Because there is this process of pre-screening of respondents before they are allowed to take the Advanced tests, we need to address the issue of sample selection. To do so, we always include an inverse Mills ratio (IMR) term, $\lambda\left(0.5 - x'_{i,t}\hat{\theta}\right) = \frac{\phi(0.5 - x'_{i,t}\hat{\theta})}{1-\Phi(0.5 - x'_{i,t}\hat{\theta})}$, to the set of regressors in (1.1) to correct for potential sample selection bias for these exercises; see, Heckman (1979). Here, $\underset{\sim}{x}'_{i,t}\hat{\theta}$ are the fitted values from the corresponding Simple tests regressions (since a 0.5 score on the Simple tests is the selection criteria for taking the Advanced tests) and $\phi(.)$ and $\Phi(.)$ are the Gaussian pdf and cdf, respectively.

The primary focus of our analysis is on the variable $DRD_{l,1983}$; i.e., our measure of famine intensity. We measure intensity of famine following the example of Chen (2007) by proxying it with the under-five mortality rate deviation from an underlying trend. We compute the death rate deviation, $DRD_{l,1983}$, as the difference between under-five mortality rates in the years 1983-84 from the mean for the years 1985-87[12] using data from the DHS of 1988 so that

$$DRD_{L,1983} = DR_{l,1983} - \frac{1}{N}\sum_{n=1985}^{1987} DR_{l,n} \qquad (1.2)$$

where $DR_{l,n}$ is the under-five mortality rate (per thousand) for administrative region $l$ in year $n$. $DRD_{l,1983}$ measures therefore the level of famine intensity experienced by all individuals who resided in region $l$ in 1983-84.

[12] We also tried using alternative trends; i.e., the means for other year ranges such as 1984-1993 and 1984-2005. In all cases, we exclude data from 1988 because the data was collected only in the first part of the year because the survey was administered in March 2003. Our findings are robust to the use of these alternative trends.

The DHS sampled about 3000 families in each round and includes questions on child mortality over the past five years. In the case of the 1988 round it contains information on child births and mortality starting from 1983 thereby making it possible to obtain a measure of famine intensity across administrative regions during the 1983-84 famine period. The mean under-five mortality rate for 1985-87 was chosen as the underlying variable mainly because we did not have similar information prior to the famine in 1983 since the DHS data only starts from 1988. To verify that the 1985-87 trend calculated at the regional level is consistent with the overall trend of the under-five mortality rate for each corresponding region around the 1983-84 period, we first aggregate up the regional data to the national level for the period 1985-87. The World Health Organization (WHO) has data for under-five mortality on Ghana at the national level from 1960 to 1993. We verify that the aggregated up numbers from the DHS sample matches closely to those reported by the WHO for the period 1985-87. The WHO data shows a downward trend in under-five mortality from 1960 to 1993; see Figures 1a and 1b. Figure 1a shows that 1983 had the lowest year-on-year drop in under-five mortality rates compared to the general downward trend of lowering mortality rates between the periods 1960 to 1993. Figure 1b, which is more compressed over time depicts the general downward trend in under-five mortality over the same period.

The set of variables $x_{i,t}$ in (1.1) comprises the set of individual, family and community level characteristics for individual $i$ of cohort $t$ and control for other factors that might affect cognitive achievement. In terms of individual characteristics, we control for the age (in years) of survey respondents in 2003. We also include the square of age to capture possible non-linearity in the effect of age on cognitive achievement scores. We also control for gender as is standard in the literature. We also control for height (in 2003) to isolate the effects of cumulative health status from birth to adulthood. As we discuss above, the negative effects of famine on could be partially or fully reversed when there is a timely intervention to compensate[13] for the inadequate investment during the critical/sensitive period in childhood. In a separate exercise, we also consider the effects of the famine in Ghana on height.

We also control for the effects of school quality in determining IQ; see Heckman (1995). Our aim is to control for any remedial education interventions during the sensitive period before IQ stabilizes at 10 years of age. We do so by including an indicator variable, *Primary School,* for enrolment in primary school.[14] We are also able to include community school characteristics at the cluster level. Thus we are able to control for the quality of the school that students attended. The GEIES and its precursor collected detailed information on classroom conditions. We included in our regressions the state of classrooms – the fraction of classrooms that were unusable at any time of the year. We also included information on the availability of textbooks for Math and English per pupil. A distinguishing feature of the GEIES is the inclusion of teachers' IQ scores which therefore allows us to control for teachers' quality. We also interact the Primary School variable with the set of community schooling characteristics to capture the quality of the primary education received by the child.

It is important to note that the 0-2 age group, born in 1982-1984, were enrolled in primary school in 1988 while the oldest of the 3-8 age group born in 1976-81 were just leaving primary school then. Therefore the school characteristics we consider effectively capture the school quality variables that could potentially affect cognitive achievement scores for both cohorts during the sensitivity period of their cognitive development. For the English and Math

[13] Typical interventions include nutritional and food supplements. We note in the case of Ghana that in late 1984 food aid was delivered by the Food and Agriculture Organization (FAO).

[14] Primary school enrollment in Ghana typically starts at age 6.

tests, we also include the number of years of schooling attained by the individual in 2003 and drop the primary school variable because all the test takers had at least some primary school education. While IQ stabilizes at age 10, an individual's score on English and Math tests may presumably be influenced by her cumulative level of education.

We also consider family characteristics that can influence cognitive achievement scores. We include the *Household Size* during the famine in 1983. In the face of famine and food shortages, household distribution of food can be constrained by the family size. Typically this will mean lower amounts of nutritional intake per person. Importantly, we also include the total schooling of parents[15]. We use parental schooling as a proxy for family income which is known to impact childhood development and subsequently cognitive achievement. We construct the variable *Parental Schooling* as the sum of father and mother's schooling.

In accordance with standard practice, we dropped all observations with missing data for both parents' schooling – out of the 611 respondents in the age range who were tested in the 2003 GEIES, 167 observations fell into this category. Of the remaining observations, only 322 had reported years of schooling for both parents. We are therefore left to consider the two cases where schooling information is missing for one parent. It turns out that for the cases where only the father's schooling information was missing, the fathers were not living at home at the time of the survey. For the cases where only the mother's schooling information was missing, the mother was actually also surveyed in the 2003 GEIES, but the respondent imputed a missing value for the mother's years of schooling. We also check in these cases that the mother's response to her own years of schooling information was also missing. In these cases therefore we assumed that

[15] The GEIES 2003 data collected information on income and annual family expenditures in 2002-3. However these are not appropriate since we are interested in family characteristics during the famine and not after.

the respondents were simply confused by the question and that a missing value denotes zero (or minimal) years of actual schooling. We therefore imputed zero for the cases where either father or mother's (but not both) years of schooling information was missing. As a robustness check therefore we also carried out exercises where we dropped *Parental Schooling* from the set of regressors. Our findings are robust (stronger) when we do so.

Finally, we include the type of locality, whether rural or urban, to capture the differential location effects of the famine and the cluster's proximity to the nearest district capital. Tables 1.1 and 1.2 provide summary statistics and full descriptions for the variables discussed above.

In terms of equation (1.1), the statement that (only) early childhood malnutrition has negative effects on cognitive development that persist into adulthood then translates into the hypothesis that $\delta_0 = 0$ and $\delta_1 < 0$. We address two concerns with the identification of these parameters. One worry we might have is that families in regions that experience more severity in terms of famine might migrate to other areas. Migration is in no way restricted in Ghana and therefore there could potentially be migration to less famine-stricken areas. If this was in fact the case, then estimates for $\delta_0$ and $\delta_1$ may be biased. Surprisingly, there was very little migration during this period. We use data from the Ghana Living Standards Survey (GLSS) of 1988[16] to determine the migration pattern. The survey asked questions on the length of stay in a region, the reasons for moving and the number of times a person has changed residence since age 3 months. 56 percent of the survey respondents lived away from their original birth regions. If famine stricken households and individuals migrated, the period 1983-84 should see increased movements compared to periods immediately before and after. However, this was not the case as

[16] The GLSS II is a national representative survey taken every 5 years and samples over 4000 households with over 10,000 individuals in each round. We pick the GLSS II because the survey period is closer to the famine years.

shown in Figure 2[17]. It shows how many respondents had lived in their present regions since the years given on the x-axis. Even though there is an upward trend (from right to left), the migrations in 1983-84 are not unusual. There was a general upward trend in migration from 1979 and the numbers for 1983-84 follow the trend – about 5 percent and 4.5 percent migrated in 1983 and 1984 respectively, higher than previous years but less than the period 1986 – 1988.

In any case, we attempt to address the issue of the possible endogeneity of our famine intensity variable ($DRD_{l,1983}$) by instrumenting it using rainfall data. Specifically, we compute the rainfall deviation, $RainD_{l,1983}$ as the deviation of 1982-83 average annual rainfall from the average of 1985 to 1991[18] using data from ARTES which collected daily sub-national rainfall and temperature for all regions in Ghana (and other African countries) from 1948 to 2001, so that

$$RainD_{l,1983} = Rain_{l,1983} - \frac{1}{N}\sum_{n=1985}^{1991} Rain_{l,n} \qquad (1.3)$$

where $Rain_{l,n}$ is the average annual rainfall for the year *n* for region *l.* Since the deviation of rainfall from trend is presumably random, it should be exogenous and is therefore presumably uncorrelated with the individual idiosyncratic innovation. However, since the famine in Ghana was caused by drought, we expect to see a significant partial correlation of the rainfall deviation with famine intensity. We therefore carry out exercises in both the linear regression as well as the structural (2SLS) context.

Finally, we also address the important issue of model uncertainty when deriving estimates for $\delta_0$ and $\delta_1$ . We turn to this issue in the next sub-section.

[17] We used the GLSS II of 1992 which specifically has data on migrants who return to places of origin. Few migrated in 1983 and returned and even fewer migrated because of drought.
[18] We also worked with deviations from alternative trends: 1) the deviation from the 1948-2001 rainfall mean, and 2) the deviation from the 1971 – 1981 rainfall mean, and got similar results.

*2.1 Bayesian Model Averaging*

One important issue that researchers face in uncovering the effect of early childhood malnutrition on cognitive outcomes is that of model uncertainty. The standard approach for reporting results in the literature is to run a preferred regression for a given cognitive outcome variable on a well-chosen set of covariates and then to take the coefficient estimates and significance levels for that regression as the benchmark values. The researchers may then report the results of an ad hoc series of robustness exercises that either include some additional controls or drop some variables from the benchmark model to show that the qualitative findings of the benchmark model are upheld by the robustness exercises. An alternative approach is simply to consider the largest "kitchen sink" model; i.e., the one that includes the largest set of covariates, on the basis that the coefficient estimates for such a model would be consistent if not efficient because of the presence of irrelevant variables.

In both instances, what researchers have highlighted is the substantial model uncertainty that goes into these exercises due to the lack of specific guidance from theory[19]. Theory suggests (see Cunha and Heckman (2008); Cunha et al. (2010); Heckman (2000, 2008)), for instance, that cognitive outcomes are likely to be influenced by individual characteristics, family characteristics, and community-level characteristics, and these are, in fact, the types of characteristics that most analyses control for. However, in practice, a large number of variables fall into each of these categories. In this paper, for example, we found a total of 14 such variables (with sufficient observations for them in the data set to make them feasible). If we are concerned with the effect of one such variable, say, childhood malnutrition (measured in this case by the

[19] The issue of model uncertainty has been shown to be a concern in many areas of economics including economic growth (see, for example, Brock and Durlauf (2001), Sala-i-Martin and Doppelhofer, (2004), Fernandez et al. (2001)), macroeconomic policy (Brock et al. (2003)), law and economics (Cohen-Cole et al. (2009)), and religion and economics (Durlauf et al. (2011)) amongst others.

intensity of famine), on cognitive outcomes, one cannot know from an a priori basis whether the estimated effect would change dramatically or be fragile (in the sense of Leamer (1983)) depending on which particular auxiliary variables are included or excluded in the regression equation. There is therefore a need to systematically account for model uncertainty in order to obtain coefficient estimates that are robust to it.

Bayesian model averaging (BMA; see Hoeting et al. (1999)) is one popular method of obtaining such robust estimators[20]. BMA starts by defining a model space that is generated from the set of plausible explanatory variables for the dependent variable. A model is simply a particular permutation of the set of explanatory variables. BMA accounts for model uncertainty by considering the evidentiary weight for each possible model in the model space given the data, and then obtaining the posterior distribution of the parameter of interest (e.g., the effect of childhood malnutrition on cognitive outcomes) by averaging across the set of models in the model space using these evidentiary weights. Formally, let the effect of interest be $\beta_z$. The posterior distribution of this parameter is

$$P(\beta_Z|D) = \sum_{k=1}^{K} P(\beta_Z|M_k, D)P(M_k|D) \tag{3.1}$$

where $$P(M_k \mid D) = \frac{P(D \mid M_k)P(M_k)}{\sum_{l=1}^{K} P(D \mid M_l)P(M_l)} \tag{3.2}$$

and where $$P(D \mid M_k) = \int P(D \mid \theta_k, M_k)P(\theta_k \mid M_k)d\theta_k \tag{3.3}$$

[20] We use the BMS software developed by Zeugner (2011) to implement BMA in this paper. We refer the reader to Zeugner (2011) for a detailed discussion of model and parameter prior specifications and choices.

where $\theta_k$ is the vector of parameters of $M_k$, $P(\theta_k \mid M_k)$ is the prior density of $\theta_k$ under the model $M_k$, $P(D \mid \theta_k, M_k)$ is the marginal likelihood, and $P(M_k)$ is the prior probability that $M_k$ is the true model.

With this information, the posterior mean and variance can be determined as follows:

$$E\left[\beta_z \mid D\right] = \sum_{k=1}^{K} E\left[\beta_z \mid M_k, D\right] P\left(M_k \mid D\right) \tag{3.4}$$

$$Var\left[\beta_z \mid D\right] = \sum_{k=1}^{K} Var\left[\beta_z \mid M_k, D\right] P\left(M_k \mid D\right) + \sum_{k=1}^{K} \left(E\left[\beta_z \mid M_k, D\right] - E\left[\beta_z \mid D\right]\right)^2 P\left(M_k \mid D\right) \tag{3.5}$$

As is standard in the literature, we take the posterior mean to be our model-averaged coefficient estimate and the square root of the posterior variance as the corresponding standard error. We also report the posterior inclusion probability (PIP) for each regressor. The PIP of a regressor is given by the sum of the model posterior probabilities of models that include that variable. It is meant to give a sense of the (posterior) probability that the regressor is in the true model.

In terms of implementation, we set the model prior to be uniform. The uniform model prior implies that the prior probability of a growth regressor being in the true model is set to 0.5. In terms of priors over parameters, we report results for g priors that are estimated using Empirical Bayes (see Liu, (2008)).[21] In terms of the settings for the MCMC stochastic search

[21] We also considered various alternative specifications for Zellner's g priors such as the unit information prior that sets $g = N$; i.e., the total number of observations, as well as the benchmark priors suggested by Fernandez et al (2001) that set $g = \max\left(N, K^2\right)$ where $K$ is the size of the model. The results in this paper are robust to these prior alternatives.

algorithm, we use a burn-in phase of 50,000 draws, and then calculate posterior probabilities based on 1 million successive draws. After 1 million draws, the correlation of posterior model probabilities is 0.9972 indicating that the 500 most successful models have converged over the million draws.

In addressing model uncertainty in the structural context, we follow Durlauf et al. (2008) who propose a 2SLS model-averaging (2SLS-MA) estimator. Durlauf et al.'s 2SLS-MA estimator essentially makes use of the BIC-approximation BMA strategy proposed by Raftery, (1995). Raftery showed, in the linear regression case, that the posterior probability of each model can be approximated by the exponential of the Bayesian information criterion (BIC). The BIC approximation is justified when a unit information prior for parameters is assumed; see (Kass and Wasserman, (1995)). A BMA estimator for the parameter of interest is then a BIC-weighted average of model-specific MLE estimators. In considering the structural case, Durlauf et al. proposed to replace the model-specific MLE estimators with the model-specific 2SLS estimators for the case of just-identification (which is the relevant case in our context). The 2SLS-MA estimator turns out to be a special case of the IVBMA estimator independently proposed by Eicher et al. (2009).[22]

## 3. Results

### *3.1 Results for Raven (IQ) Scores*

[22] Eicher et al.'s IVBMA significantly extends Durlauf et al.'s approach by allowing for over-identification, and allowing for both uncertainty in the set of instrumental variables (model uncertainty in the first stage) and for the set of regressors in the reduced form equation (model uncertainty in the second stage). Koop et al. (2011) have recently proposed a fully Bayesian implementation of model averaging in the structural equation context that does away with the BIC approximation and allows for direct specification of priors (like in the case of BMS). However, software to implement Koop et al's approach is currently still under development and therefore we could not implement their approach in this paper. We do not, however, expect our results to change substantially given our experience with the linear regression case where we have compared results obtained via BMS and results obtained using Raftery's BIC approximation approach.

We now turn to a discussion of the results. We first present our findings for IQ (i.e., Raven scores) in Table 2. We start with a discussion of our least squares estimation results. Column (1) of Table 2 presents the OLS results for the largest model in the model space (i.e., the "kitchen sink" model). Since this model is likely to contain irrelevant variables, the coefficient estimates are inefficient although they should remain consistent. Furthermore, the "kitchen sink" model is not one of the top five models in terms of posterior model probability. As it turns out, the posterior model probabilities taper off considerably after the top two models[23], so that it is clear that the "kitchen sink" model is not one that is well supported by the data. Column (3) of Table 2 presents the estimation results of our least squares BMA (LS-BMA) analysis while column (2) presents the corresponding posterior inclusion probability (PIP) for each regressor. Finally, column (4) shows the results for the posterior mode (best) model. The posterior mode model is of interest to researchers who prefer model selection to model averaging. Since this model is the one for which there is the highest posterior evidence for being the true model, it would be the model in the model space that is selected.

Our least squares results provide strong evidence for the hypothesis that early childhood malnutrition has an important and significant negative impact on cognitive development. In terms of equation (1), our results do in fact affirm that $\delta_0 = 0$ and $\delta_1 < 0$. Famine intensity (as measured by the Death Deviation in 1983; i.e., $DRD_{l,1983}$) is found to have no significant effect on the group of older children in 1983-84 (*Old Famine* group) in the "kitchen sink" and LS-BMA exercises. It is also not a variable that is found to be included in the posterior mode (best) model. On the other hand, the PIP for the Death Deviation in 1983 variable interacted with the *Young Famine* cohort dummy – corresponding to $\left(DRD_{l,1983} * t\right)$ in equation (1.1) – is 0.99

[23] The posterior probabilities for the top five models are 0.119, 0.115, 0.074, 0.041, 0.038.

suggesting that there is very strong evidence that famine intensity is an important determinant of IQ losses in children in the *Young Famine* group (the age 0-2 in 1983-84 cohort). Famine intensity is found to have a significant negative impact on IQ in all three exercises. It is significant at the 5% level in the “kitchen sink” specification and at the 1% level for both LS-BMA and the posterior mode model.

Using the summary information in Table 1.1, we find that the point estimates suggest that a one standard deviation increase in the Death Deviation in 1983 leads to a 1.31 loss in Raven points for the *Young Famine* group in the “kitchen sink” model. The effect is even stronger when we account for model uncertainty by averaging across models. The LS-BMA results suggest that a one standard deviation increase in the Death Deviation in 1983 results in a loss of 1.5 Raven points. The corresponding loss for the posterior mode model is 1.8 Raven points. As we will describe later when we discuss our findings for the Math and English scores, a reduction of Raven points of these magnitudes implies potentially economically significant outcomes.

Our results for the negative impact of famine intensity (i.e., early childhood nutrition) on IQ are particularly strong because we also control for the cumulative effects of childhood nutritional status on IQ using Height. As Table 2 shows, IQ scores are significantly impacted by the cumulative health and nutritional status of children (Height). The PIP for Height is at 1 suggesting that this variable is very likely to be in the true model. The point estimate for the “kitchen sink” model suggests that a one standard deviation decrease in height leads to a loss of between 1.6 to 1.9 IQ points across groups. The magnitude of the effects is similar under LS-BMA and the posterior mode model. We also note that the magnitude of the negative effects of cumulative health on IQ is comparable to our findings for those associated with early childhood malnutrition above.

A natural question is whether famine intensity (i.e., early childhood malnutrition) has irreversible cumulative health effects, and therefore could constitute an indirect effect on IQ via its effect on Height. We examine this possibility, similar to test scores, by using Height as the dependent variable. We consider three different birth cohorts in this exercise. Children aged 0-2 during the famine, those between 3 and 5 years during the famine, and those aged 6-8 during the famine. The results are shown in Table 8. We find no significant effects of famine on Height. It is likely that lost height as a result of the famine may have been reversed (see, Alderman (2006)) through subsequent interventions since food aid from the international community started arriving in late 1984.

Our results therefore affirm existing findings in the literature on the importance of cumulative health on cognitive development. However, our findings also suggest that early childhood malnutrition (particularly for the 0-2 age group) is of equal importance, and that its negative effects on cognitive development persist into adulthood.

In terms of other determinants of IQ, we find that there is strong evidence that attending primary school is beneficial to IQ. The PIP for Primary School is 0.99 and the coefficient estimate under BMA is strongly significant and positive. There is also some weaker evidence that the quality of the infrastructure of the primary school (in terms of the usability of classrooms) also plays some role in improving IQ.

In terms of the effects of other individual, family, and community characteristics on IQ, we find that socio-economic status (as measured by Parental Schooling) is a significant and positive determinant of IQ in the “kitchen sink” model, under BMA, and also for the posterior mode model. In the BMA case, a standard deviation increase in years of Parental Schooling leads to a 0.7 and 0.8 point gain in IQ for the *Young Famine* and *Old Famine* cohorts respectively. The

PIP is also very high at 0.94. The effects are slightly larger for the "kitchen sink" and posterior mode models. There is also strong evidence that a child who lived in an urban area at the time of the famine performed better on the Raven test than one living in a rural area. The former child scores about 2.74 points higher on the Raven test that the latter child with similar characteristics, according to the BMA results. This finding contrasts with that of Neelsen (2011), but is similar to that found in Chen (2007).

As discussed in Section 2 above, we also address the issue of the endogeneity of famine intensity by instrumenting $DRD_{l,1983}$ with rainfall deviation, $RainD_{l,1983}$. We report our 2SLS results for the "kitchen sink" model, for 2SLS-MA (as described in Section 2 above), and for the posterior mode (best) model under 2SLS-MA in columns (5) to (8) of Table 2. Finally, Column (9) of Table 2 reports the first stage results for the "kitchen sink" model.

These results illustrate that rainfall deviation is not a weak instrument as it has a highly significant (at the 1% level) partial correlation with famine intensity. The 2SLS results affirm the conclusions of the least squares exercises reported above. We focus our attention on our primary variables of interest; i.e., famine intensity ($DRD_{l,1983}$) and famine intensity interacted with the *Young Famine* cohort dummy $\left(DRD_{l,1983} * t\right)$. As in the case of least squares, the coefficient to $DRD_{l,1983}$ is always found to be insignificant. However, we see some differences in results for the interaction term. The point estimate for the "kitchen sink" model in the structural case is higher than the least squares case (in absolute value), but now, the point estimate is only significant at the 10% level. When we account for model uncertainty, we also find that the point estimate for the interaction term is now significant at the 10% level for the 2SLS-MA (as opposed to 1% previously, although the PIP remains very high at 0.93. The results for the posterior mode model in the structural case, however, remain in agreement with the least squares case. We also perform a standard Hausman test for correct specification. The Chi square test statistic has an associated p-value of 0.99. We therefore do not reject the null of correct specification and prefer the efficient least squares findings.

Overall our findings confirm the main hypothesis in this paper: childhood malnutrition experienced before the age of 2 has a large and significant direct effect on long-term cognitive development even after controlling for individual and family characteristics, and for possible subsequent nutritional and educational remediation efforts.

*3.2 Results for Math and English Tests Scores*

Tables 3-6 examine the impact of Raven (IQ) scores on other cognitive achievement tests – Mathematics and English reading comprehension. Tables 3 and 4 describe results for the Simple and Advanced Math tests, respectively, while Tables 5 and 6 present the corresponding results for the Simple and Advanced English tests. As in the case of the Raven score regressions in the previous section, we present results for OLS and 2SLS estimation for the "kitchen sink" model (columns (1) and (5), respectively, in each Table), as well as LS-BMA and 2SLS-MA results for PIP, point estimates, and standard errors (columns (2)-(3) and (6)-(7), respectively, for each case). We also show results for the posterior mode model under LS-BMA in column (4) of the respective Tables[24].

The results we obtained for cognitive achievement tests turned out to be surprisingly similar across tests. We therefore discuss all the results jointly and point out the main differences. A key finding is that IQ (Raven scores) plays an important role in an individual's

[24] We do not report the corresponding model for 2SLS-MA because, in all cases, the posterior mode model turned out to be the same as under LS-BMA and it did not include the endogenous famine intensity variable

performance on cognitive achievement tests. Across all tests, Raven scores turn out to have highly significant (at the 1% level in virtually all cases) positive effects on cognitive achievement test scores. The second key finding is that once Raven scores are controlled for, the only other variables that appears to be consistently important in determining cognitive achievement test scores is years of schooling. Surprisingly, other measures of schooling quality, such as the quality of classrooms, the number of textbooks available per student, or even average teachers' IQ scores, do not matter once we control for the individual's IQ and schooling. Both these key findings are true whether or not we explicitly account for model uncertainty. They are also true regardless of whether we instrument for famine intensity.

In terms of the magnitude of the effects, as we noted in the subsection above, after accounting for model uncertainty, a one standard deviation increase in the famine intensity variable is associated with a loss on average of 1.5 Raven points. The effect of such a loss on cognitive achievement test scores translates on average to a corresponding loss of slightly more than one half of a year of schooling with the larger effects applying to the mathematics tests. Further, our results for the cognitive achievement tests also suggest that there is virtually no evidence that famine intensity has a direct effect on cognitive achievement test scores once we control for IQ and other covariates and account for model uncertainty. We conclude therefore that early childhood malnutrition has a severe impact on learning and human capital accumulation (as measured by performance in cognitive achievement tests) but the channel through which this effect takes place is via the serious negative consequences that early childhood malnutrition imposes on cognitive development (IQ).

*3.3 Falsification Tests*

We check the validity of our difference-in-difference method and results by running the same analysis on birth cohorts that did not experience famine as well as the entire sample from 1976-1987 that includes children who have experienced famine and those who have not. These exercises constitute falsification tests since we should not expect famine intensity to have any effect on birth cohorts born after the famine. This is especially true since we know that food aid started arriving in substantial quantities in Ghana from 1985. Table 7 shows the regression results for the falsification tests using the two samples. Columns (1) to (6) show the results for OLS and LS-BMA exercises for the entire sample (children born in 1976-1987). In both the OLS (column (1)) and LS-BMA (column (3)) cases, the interaction of the birth cohort 1982-1984 (i.e., our *Young Famine* group) show a significant loss of Raven (IQ) scores compared to no significant effects for the other two birth cohorts (the *Old Famine* group and the group of children who were born after the famine). As with Table 2, the 2SLS results in the falsification tests are insignificant. In columns (7) – (12), we present corresponding results for only the birth cohort that experienced no famine – born in 1985-1987. Again we see no impact of famine intensity on Raven scores for this cohort. These results are precisely what we should expect to find.

## 4. Conclusion

In this paper, we investigate the impact of early childhood (children between 0 to 2 years of age) malnutrition resulting from widespread famine in Ghana on cognitive development. A novel feature of our analysis is that we explicitly control for model uncertainty in our estimation. We find a direct, negative, and significant impact of early childhood malnutrition on the cognitive development of famine survivors. These effects persist well into adolescence and adulthood. In turn, this loss of cognitive ability results in poorer performance on cognitive achievement tests (in English reading comprehension and mathematics). Our findings suggest that the magnitude of the costs to famine survivors from early childhood malnutrition is large.

A surprising finding of our analysis is the limited impact of schooling infrastructure – such as the availability of textbooks and the quality of classrooms – has on cognitive and academic achievement once the cumulative effect of early nutrition and overall health status are accounted for. The data for this paper was motivated by a significant injection of resources by the World Bank into education in Ghana over a 15 year period. Much of these resources went into education infrastructure such as textbooks, teacher training, and other classroom resources. However, our results also suggest that, at least for the case of Ghana during this period, targeted investments at improving children's health, and especially, at alleviating early childhood malnutrition, may have led to potentially larger social welfare payoffs than direct investments in improving the quality of the physical infrastructure of schools.[25]

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[25] Since famine is an ongoing issue in the developing world – the recent 2011 Horn of Africa drought, for example, is estimated to have affected about 9.5 million people – our work advocates for more and continued attention to the need for early intervention in alleviating hunger and malnutrition.

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## Tables and Figures

**Table 1.1 Summary Statistics by Famine Group**

| | Young Famine | | | Old Famine | | | |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Obs. | Mean | SD | Obs. | p-value |
| Raven | 21.543 | 8.104 | 233 | 21.979 | 7.797 | 327 | 0.53 |
| Male | 0.511 | - | 233 | 0.419 | 0.494 | 327 | - |
| Years of Schooling | 8.583 | 2.434 | 163 | 9.231 | 2.727 | 216 | 0.187 |
| Simple Math | 6.221 | 1.528 | 163 | 6.102 | 1.573 | 216 | 0.2873 |
| Simple Reading | 6.544 | 1.924 | 125 | 6.321 | 2.172 | 165 | 0.2789 |
| Advanced Math | 13.495 | 6.953 | 93 | 15.293 | 7.518 | 99 | 0.4751 |
| Advanced Reading | 16.136 | 6.005 | 103 | 16.897 | 5.801 | 97 | 0.0443 |
| Primary School | 0.852 | 0.356 | 233 | 0.823 | 0.383 | 327 | 0.357 |
| Height | -0.018 | 0.991 | 233 | 0.041 | 1.004 | 327 | 0.498 |
| Age | 18.969 | 0.84 | 233 | 23.596 | 1.773 | 327 | 0 |
| Household Size 1983 | 2.915 | 1.947 | 233 | 2.755 | 1.819 | 327 | 0.333 |
| Parental Schooling | 4.973 | 7.144 | 233 | 6.979 | 8.029 | 327 | 0.002 |
| Urban* | 0.552 | - | 233 | 0.587 | 0.493 | 327 | - |
| Average Teacher Raven | 25.437 | 9.102 | 233 | 24.981 | 9.46 | 327 | 0.57 |
| Distance to District Capital | 0.74 | 1.21 | 233 | 0.725 | 1.093 | 327 | 0.881 |
| Poor Classrooms | 0.08 | 0.119 | 233 | 0.059 | 0.089 | 327 | 0.029 |
| Average Math Textbooks Per Student | 0.632 | 0.29 | 233 | 0.643 | 0.3 | 327 | 0.686 |
| Average English Textbooks Per Student | 0.342 | 0.2 | 233 | 0.398 | 0.309 | 327 | 0.721 |
| Death Deviation 1983 | 0.053 | 0.045 | 233 | 0.05 | 0.042 | 327 | 0.548 |
| Rainfall Deviation 1983 | -33.047 | 6.571 | 233 | -33.112 | 5.931 | 327 | 0.906 |

* The numbers reported describe the proportion of respondents with the corresponding characteristic.

**Table 1.2 Data Appendix**

| Variable | Description | Source/Year Collected |
|---|---|---|
| Raven | IQ score of individual using Raven's Progressive Matrices. | GEIES (Household)/2003 |
| Simple Math | Simple math test score. Test included simple arithmetic operations on integers. This served as screening for the advanced math test. | GEIES (Household)/2003 |
| Simple Reading | Simple reading score. Also used to screen respondents for the advanced reading test. Only those scoring above 50% take the advanced test. | GEIES (Household)/2003 |
| Advanced Math | A more advanced math test in areas such as geometry. Only those who score above 50% in the simple math test take this test. | GEIES (Household)/2003 |
| Advanced Reading | Advanced reading comprehension tests. | GEIES (Household)/2003 |
| Height For Age | Height of observation adjusted for age in 2003. | GEIES (Household)/2003 |
| Years of Schooling | Number of years of school completed as of 2003. | GEIES (Household)/2003 |
| Primary School | Whether observation has had at least a year of primary school. | GEIES (Household)/2003 |
| Age | Age in 2003 | GEIES (Household)/2003 |
| Male | Gender of observation; 1=Male, 0=Female | GEIES (Household)/2003 |
| Parental Schooling | Sum of years of schooling of parents. | GEIES (Household)/2003 |
| Household Size 1983 | Total size of household during famine. | GEIES (Household)/2003 |
| Urban | Locality of observation. 1=Urban, 0=Rural | GEIES (Household)/2003 |
| Average Teachers' Raven | Average Teacher IQ in community in 1989 | GLSS IWE (1988/89) |
| Distance to Public Health Facility | Distance of community to nearest public health facility in 1989. | GLSS IWE (1988/89) |
| Distance to District Capital | Distance of community to nearest district capital. | GLSS IWE (1988/89) |
| Poor Classrooms | Fraction of schools in 1989 with classrooms unusable at any time of the year. | GLSS IWE (1988/89) |
| Average Math Textbooks Per Student | Average number of math textbooks per pupil in 1989. | GLSS IWE (1988/89) |
| Average English Textbooks Per Student | Average number of English textbooks per pupil in 1989. | GLSS IWE (1988/89) |
| Death Deviation 1983 | Deviation of Under-five mortality in 1983 from the 1985-1987 average at the administrative regional level. | DHS 1998 |
| Rainfall Deviation 1983 | Deviation of average annual rainfall in 1983 from mean annual rainfall from 1985-1991 at the administrative regional level. | ARTES (World Bank) |

**Table 2 - Raven**

| | (1) LS | (2) PIP | (3) LS-BMA | (4) Best Model | (5) 2SLS | (6) PIP | (7) 2SLS-MA | (8) Best Model | (9) 1st Stage |
|---|---|---|---|---|---|---|---|---|---|
| Constant | 11.7042 | 1.00 | 22.701 | 23.0785*** | 19.1595 | 1 | 21.4619*** | 21.3826*** | 0.1062 |
| | (33.5296) | | (22.0871) | (1.9726) | (32.0185) | | (4.8256) | (1.7886) | (0.0933) |
| Male | 0.2963 | 0.31 | 0.0646 | -- | 0.1824 | 0.02 | 0.00534 | -- | -0.0004 |
| | (0.7706) | | (0.403) | | (0.7349) | | (0.103) | | (0.0021) |
| Height | 1.7943*** | 1.00 | 1.6215*** | 1.9052*** | 1.7055*** | 1 | 1.7291*** | 1.6801*** | 0.0001 |
| | (0.3876) | | (0.321) | (0.321) | (0.3701) | | (0.3123) | (0.3039) | (0.0011) |
| Age | 0.8671 | 0.57 | -0.1258 | -- | 0.1241 | 0.17 | -0.0582 | -- | -0.0095 |
| | (2.8670) | | (1.065) | | (2.7386) | | (0.3268) | | (0.008) |
| Age Square | -0.0291 | 0.58 | -0.0053 | -0.0106*** | -0.0117 | 0.71 | -0.0067 | -0.0094** | 0.0002 |
| | (0.0619) | | (0.023) | (0.0032) | (0.0591) | | (0.0082) | (0.003) | (0.0002) |
| Primary School | 5.9637 | 0.99 | 4.8854** | 4.7359*** | 6.7699* | 1.00 | 4.682*** | 4.964*** | 0.0027 |
| | (3.7135) | | (1.886) | (0.9107) | (3.5397) | | (1.0912) | (0.8638) | (0.0104) |
| Parental Schooling | 0.1274*** | 0.94 | 0.0991** | 0.1145*** | 0.1198** | 0.49 | 0.053 | -- | -0.0001 |
| | (0.0441) | | (0.047) | (0.0419) | (0.0421) | | (0.0615) | | (0.0001) |
| Household Size | 0.3254* | 0.69 | 0.2122 | -- | 0.3356* | 0.19 | 0.0621 | -- | 0.0008 |
| | (0.1797) | | (0.196) | | (0.1715) | | (0.1483) | | (0.0005) |
| Urban | 2.9655*** | 1.00 | 2.7431*** | 3.4788*** | 2.6242*** | 1 | 3.4571*** | 3.5932*** | -0.0104*** |
| | (0.7326) | | (0.707) | (0.6687) | (0.6992) | | (0.7051) | (0.6288) | (0.0022) |
| Distant to District Capital | -0.5203 | 0.64 | -0.3092 | -- | -0.536* | 0.16 | -0.0865 | -- | -0.0007 |
| | (0.3183) | | (0.328) | | (0.3035) | | (0.2326) | | (0.0009) |

**Table 2 – Raven (Continued)**

| | (1) LS | (2) PIP | (3) LS-BMA | (4) Best Model | (5) 2SLS | (6) PIP | (7) 2SLS-MA | (8) Best Model | (9) 1st Stage |
|---|---|---|---|---|---|---|---|---|---|
| Avg. Teacher Raven | 0.0238 | 0.32 | 0.0019 | -- | 0.035 | 0.02 | -0.0002 | -- | 0.0005* |
| | (0.1053) | | (0.043) | | (0.1016) | | (0.005) | | (0.0003) |
| Primary School * Avg. Teacher Raven | -0.0318 | 0.34 | -0.0117 | -- | -0.0616 | 0.02 | -0.0004 | -- | -0.0003 |
| | (0.1092) | | (0.047) | | (0.1042) | | (0.0059) | | (0.0003) |
| Poor Classrooms | 1.7210 | 0.33 | 0.1801 | -- | 2.1393 | 0.02 | -0.0576 | -- | -0.0148 |
| | (4.1615) | | (2.278) | | (3.9944) | | (0.7587) | | (0.0116) |
| Primary School * Poor Classrooms | -7.0808* | 0.68 | -3.976 | -7.4035** | -6.3623 | 0.47 | -3.4036 | -8.0816* | -0.0205* |
| | (4.0742) | | (3.911) | (3.3274) | (3.8862) | | (4.2458) | (3.1544) | (0.0115) |
| Math Books Per Student | -1.2058 | 0.56 | -1.0321 | -- | -1.1339 | 0.13 | -0.3088 | -- | 0.0034 |
| | (2.6730) | | (1.584) | | (2.5608) | | (0.9209) | | (0.0083) |
| Primary School * Math Books Per Student | -1.0185 | 0.50 | -0.7939 | -2.3215** | -1.0938 | 0.26 | -0.6008 | -- | -0.0109 |
| | (2.9451) | | (1.688) | (1.0978) | (2.813) | | (1.1556) | | (0.0077) |
| Age 0-2 During Famine | -0.3274 | 0.32 | -0.0372 | -- | -0.7432 | 0.03 | 0.0262 | -- | -0.1053*** |
| | (1.6254) | | (0.772) | | (1.7189) | | (0.2977) | | (0.0103) |
| Death Deviation 1983 | -7.7686 | 0.34 | -1.6484 | -- | -5.474 | 0.05 | -0.8188 | -- | -0.0003 |
| | (10.3812) | | (5.883) | | (14.0529) | | (4.6907) | | (0.0002) |
| Age 0-2 During Famine * Death Deviation 1983 | -29.2343** | 0.99 | -33.0689*** | -39.129*** | -22.8503 | 0.93 | -35.0165* | -40.3924*** | -0.0046*** |
| | (14.7375) | | (11.5258) | (9.7938) | (21.038) | | (18.0338) | (9.3945) | (0.0003) |

*** 1 % significance, ** 5% significance, * 10% significance. Heterskedasticity robust standard errors are in parentheses. Posterior inclusion for the best models for the LS-BMA and 2SLS-MA are, respectively , 0.147 and 0.33

**Table 3 - Simple Math**

| | (1) LS | (2) PIP | (3) LS-BMA | (4) Best Model | (5) 2SLS | (6) PIP | (7) 2SLS-MA |
|---|---|---|---|---|---|---|---|
| Constant | 10.757 | 1 | 3.6007 | 4.357*** | 7.5083 | 1 | 3.4437*** |
| | (6.7472) | | (3.5130) | (0.5728) | (7.3828) | | (1.0287) |
| Raven | 0.0612*** | 1 | 0.0676*** | 0.0695*** | 0.0581*** | 1 | 0.067*** |
| | (0.0102) | | (0.01) | (0.0092) | (0.0114) | | (0.0102) |
| Male | 0.2175 | 0.07 | 0.0108 | -- | 0.1356 | 0.06 | 0.0084 |
| | (0.1617) | | (0.0537) | | (0.1832) | | (0.0488) |
| Height | -0.0771 | 0.04 | -0.0011 | -- | -0.0269 | 0.02 | 0.0001 |
| | (0.0858) | | (0.0156) | | (0.0962) | | (0.0098) |
| Age | -0.6587 | 0 | -0.0255 | -0.068*** | -0.4351 | 0.32 | -0.0203 |
| | (0.5851) | | (0.0804) | (0.0248) | (0.6387) | | (0.0578) |
| Age Square | 0.013 | 0.28 | -0.0003 | -- | 0.008 | 0.22 | -0.0003 |
| | (0.0127) | | (0.0018) | | (0.0139) | | (0.0012) |
| Years of Schooling | 0.2247*** | 1 | 0.1832*** | 0.1881*** | 0.2214*** | 1 | 0.1914*** |
| | (0.033) | | (0.0304) | (0.0276) | (0.0378) | | (0.0353) |
| Parental Schooling | -0.0043 | 0.04 | -0.0001 | -- | -0.0009 | 0.02 | 0 |
| | (0.0092) | | (0.0017) | | (0.01) | | (0.0011) |
| Household Size | 0.0142 | 0.04 | 0.0008 | -- | 0.0168 | 0.02 | 0.0005 |
| | (0.0394) | | (0.0085) | | (0.0415) | | (0.0062) |
| Urban | 0.1258 | 0.13 | 0.0316 | -- | 0.0694 | 0.12 | 0.0283 |
| | (0.1588) | | (0.0973) | | (0.1739) | | (0.0941) |
| Distant to District Capital | -0.1161 | 0.20 | -0.0266 | -- | -0.12982 | 0.22 | -0.0324 |
| | (0.0772) | | (0.0616) | | (0.0851) | | (0.074) |

**Table 3 - Simple Math (Continued)**

| | (1) LS | (2) PIP | (3) LS-BMA | (4) Best Model | (5) 2SLS | (6) PIP | (7) 2SLS-MA |
|---|---|---|---|---|---|---|---|
| Avg. Teacher Raven | -0.0045 | 0.1 | -0.0002 | -- | -0.0015 | 0 | -0.0001 |
| | (0.0078) | | (0.0017) | | (0.0066) | | (0.0012) |
| Poor Classrooms | 0.3788 | 0 | 0.0048 | -- | -0.3745 | 0 | -0.024 |
| | (0.745) | | (0.1563) | | (0.9659) | | (0.2202) |
| Math Books Per Student | 0.0674 | 0 | -0.0001 | -- | 0.0245 | 0 | -0.003 |
| | (0.2592) | | (0.0523) | | (0.2668) | | (0.0494) |
| Age 0-2 During Famine | 0.0407 | 0.2 | 0.05 | -- | -0.073 | 0.1 | 0.026 |
| | (0.335) | | (0.1338) | | (0.3642) | | (0.0994) |
| Death Deviation 1983 | 1.2716 | 0 | -0.0207 | -- | -0.7185 | 0 | -0.0277 |
| | (2.3413) | | (0.3702) | | (3.1634) | | (0.3983) |
| Age 0-2 During Famine * Death Deviation 1983 | -2.7894 | 0.1 | -0.0369 | -- | -0.8683 | 0 | 0.0062 |
| | (3.2029) | | (0.6305) | | (4.1776) | | (0.6572) |

*** 1 % significance, ** 5% significance, * 10% significance. Heterskedasticity robust standard errors are in parentheses. Posterior inclusion for the best models for the LS-BMA and 2SLS-MA are, respectively, 0.34 and 0.43

**Table 4 - Advanced Math**

| | (1) LS | (2) PIP | (3) LS-BMA | (4) Best Model | (5) 2SLS | (6) PIP | (7) 2SLS-MA |
|---|---|---|---|---|---|---|---|
| Constant | -58.1113 | 1 | 0.6867 | 1.6243 | -56.1256 | 1 | -0.8808 |
| | (53.5753) | | (0.7832) | (1.6729) | (53.9636) | | (3.8026) |
| Raven | 0.3996*** | 1 | 0.3745*** | 0.4652*** | 0.4035*** | 1.00 | 0.394*** |
| | (0.0952) | | (0.0772) | (0.0639) | (0.0972) | | (0.0738) |
| Male | 2.8533* | 0.29 | 0.5937 | -- | 2.8821* | 0.36 | 0.7792 |
| | (1.4613) | | (1.0962) | | (1.4782) | | (1.2197) |
| Height | -0.5499 | 0.08 | 0.0107 | -- | -0.5657 | 0.05 | 0.0055 |
| | (0.7338) | | (0.2062) | | (0.7368) | | (0.1531) |
| Age | 4.2043 | 0.08 | 0.0229 | -- | 4.0749 | 0.05 | 0.0055 |
| | (4.52331) | | (0.3976) | | (4.5451) | | (0.1264) |
| Age Square | -0.0869 | 0.07 | -0.0001 | -- | -0.0841 | 0.05 | 0.0001 |
| | (0.0983) | | (0.0087) | | (0.0988) | | (0.0029) |
| Years of Schooling | 0.5689* | 0.60 | 0.36217 | -- | 0.5634* | 0.82 | 0.5214* |
| | (0.3252) | | (0.3475) | | (0.3264) | | (0.313) |
| Parental Schooling | -0.0124 | 0.07 | 0.0018 | -- | -0.0101 | 0.04 | 0.0009 |
| | (0.0660) | | (0.018) | | (0.0666) | | (0.0121) |
| Household Size | -0.6747** | 0.44 | -0.2381 | -- | -0.6671** | 0.58 | -0.3277 |
| | (0.2709) | | (0.3143) | | (0.2750) | | (0.3629) |
| Urban | 1.5942 | 0.13 | 0.1631 | -- | 1.5957 | 0.03 | -0.0007 |
| | (1.1446) | | (0.5594) | | (1.1475) | | (0.1043) |
| Distant to District Capital | 0.3913 | 0.07 | -0.0006 | -- | 0.3642 | 0.04 | 0.0037 |
| | (0.6444) | | (0.144) | | (0.6503) | | (0.0491) |

**Table 4 - Advanced Math (Continued)**

| | (1) LS | (2) PIP | (3) LS-BMA | (4) Best Model | (5) 2SLS | (6) PIP | (7) 2SLS-MA |
|---|---|---|---|---|---|---|---|
| Avg. Teacher Raven | 0.2011 | 0.07 | 0.0067 | -- | 0.17977 | 0.07 | -0.3604 |
| | (0.2834) | | (0.0694) | | (0.2961) | | (1.9662) |
| Poor Classrooms | -8.6322 | 0.09 | -0.3937 | -- | -8.2033 | 0.03 | -0.0028 |
| | (6.7418) | | (2.155) | | (6.8939) | | (0.3016) |
| Math Books Per Student | 1.0492 | 0.07 | 0.0017 | -- | 1.0352 | 0.04 | 0.0641 |
| | (1.8766) | | (0.4282) | | (1.8929) | | (1.5777) |
| Age 0-2 During Famine | 1.7431 | 0.07 | -0.0076 | -- | 1.4097 | 0.03 | -0.0073 |
| | (2.6980) | | (0.3608) | | (3.1406) | | (0.2121) |
| Death Deviation 1983 | -16.1665 | 0.08 | -0.7479 | -- | -15.9118 | 0.04 | 0.0767 |
| | (19.0051) | | (4.4882) | | (30.6059) | | (3.6617) |
| Age 0-2 During Famine * Death Deviation 1983 | 7.7040 | 0.07 | -0.1523 | -- | 13.9756 | 0.03 | -0.0182 |
| | (25.2117) | | (4.0444) | | (41.1783) | | (3.46) |

*** 1 % significance, ** 5% significance, * 10% significance. Heterskedasticity robust standard errors are in parentheses. Posterior inclusion for the best models for the LS-BMA and 2SLS-MA are, respectively, 0.18 and 0.40

**Table 5 - Simple Reading**

| | (1)<br>LS | (2)<br>PIP | (3)<br>LS-BMA | (4)<br>Best Model | (5)<br>2SLS | (6)<br>PIP | (7)<br>2SLS-MA |
|---|---|---|---|---|---|---|---|
| Constant | -6.1203 | 1 | 3.13 | 4.0915*** | -6.3295 | 1 | 3.8832 |
| | (9.9358) | | (3.0343) | (0.3635) | (9.6956) | | (4.6739) |
| Raven | 0.0647*** | 1 | 0.0634*** | 0.0554*** | 0.0657*** | 1 | 0.068*** |
| | (0.0144) | | (0.0139) | (0.0118) | (0.0149) | | (0.0152) |
| Male | 0.428* | 0.30 | 0.0942 | -- | 0.4232* | 0.12 | 0.0356 |
| | (0.2354) | | (0.1877) | | (0.2381) | | (0.1219) |
| Height | -0.1849 | 0.21 | -0.0261 | -- | -0.1932 | 0.06 | -0.0057 |
| | (0.1235) | | (0.0759) | | (0.1228) | | (0.0375) |
| Age | 0.9757 | 0.53 | 0.157 | -- | 1.0051 | 0.39 | 0.074 |
| | (0.8588) | | (0.5357) | | (0.8462) | | (0.4242) |
| Age Square | -0.0255 | 0.68 | -0.0071 | -- | -0.0262 | 0.72 | -0.0053 |
| | (0.0186) | | (0.012) | | (0.0187) | | (0.0097) |
| Years of Schooling | 0.2153*** | 1 | 0.201*** | 0.1546*** | 0.2071*** | 1 | 0.213*** |
| | (0.0426) | | (0.041) | (0.0352) | (0.0475) | | (0.0473) |
| Parental Schooling | 0.0001 | 0.14 | 0.0001 | -- | 0.0007 | 0.02 | 0 |
| | (0.0132) | | (0.0046) | | (0.0126) | | (0.0016) |
| Household Size | 0.0559 | 0.24 | 0.0148 | -- | 0.0535 | 0.10 | 0.0068 |
| | (0.056) | | (0.0363) | | (0.0581) | | (0.0264) |
| Urban | -0.0459 | 0.14 | 0.0012 | -- | -0.0532 | 0.03 | 0.0009 |
| | (0.2348) | | (0.0865) | | (0.2237) | | (0.0413) |
| Distant to District Capital | -0.2902** | 0.80 | -0.221 | -0.2216** | -0.2919** | 0.79 | -0.2328 |
| | (0.1171) | | (0.1443) | ( 0.0918) | (0.1407) | | (0.1709) |

**Table 5 - Simple Reading (Continued)**

| | (1) LS | (2) PIP | (3) LS-BMA | (4) Best Model | (5) 2SLS | (6) PIP | (7) 2SLS-MA |
|---|---|---|---|---|---|---|---|
| Avg. Teacher Raven | -0.0018 | 0.15 | -0.0005 | -- | 0.0014 | 0.03 | -0.0001 |
| | (0.0112) | | (0.0042) | | (0.0101) | | (0.0016) |
| Poor Classrooms | -0.3087 | 0.15 | -0.0747 | -- | -0.3418 | 0.03 | -0.0199 |
| | (1.5027) | | (0.5953) | | (1.9262) | | (0.352) |
| Eng. Books Per Student | -0.0173 | 0.14 | -0.0048 | -- | -0.004 | 0.02 | -0.0014 |
| | (0.455) | | (0.1622) | | (0.465) | | (0.0676) |
| Age 0-2 During Famine | 0.0882 | 0.17 | -0.0236 | -- | -0.0604 | 0.04 | -0.0088 |
| | (0.484) | | (0.1848) | | (0.4272) | | (0.0896) |
| Death Deviation 1983 | -2.3075 | 0.26 | -0.77 | -- | -5.4628 | 0.10 | -0.4825 |
| | (3.1806) | | (1.7947) | | (4.2091) | | (1.7941) |
| Age 0-2 During Famine * Death Deviation 1983 | -1.7171 | 0.28 | -1.16 | -- | 1.591 | 0.15 | -0.889 |
| | (4.4768) | | (2.6189) | | (6.2043) | | (2.9531) |

*** 1 % significance, ** 5% significance, * 10% significance. Heterskedasticity robust standard errors are in parentheses. Posterior inclusion for the best models for the LS-BMA and 2SLS-MA are, respectively, 0.39 and 0.46

**Table 6 - Advanced Reading**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | LS | PIP | LS-BMA | Best Model | 2SLS | PIP | 2SLS-MA |
| Constant | -62.9122 | 1 | 1.7951 | 1.066 | -67.5805* | 1 | 1.5593 |
| | (39.0350) | | (2.0451) | (1.9113) | (40.0062) | | (4.798) |
| Raven | 0.2876*** | 1.00 | 0.2742*** | 0.3048*** | 0.2692*** | 1 | 0.2875*** |
| | (0.0734) | | (0.0571) | (0.0527) | (0.0757) | | (0.0566) |
| Male | 0.7184 | 0.07 | 0.0186 | -- | 0.9846 | 0.04 | 0.0087 |
| | (1.0654) | | (0.2286) | | (1.1119) | | (0.1627) |
| Height | -0.1851 | 0.07 | -0.007 | -- | -0.1413 | 0.03 | -0.003 |
| | (0.5389) | | (0.115) | | (0.5508) | | (0.0776) |
| Age | 5.7729* | 0.08 | 0.0566 | -- | 6.0826* | 0.06 | 0.0189 |
| | (3.3308) | | (0.6057) | | (3.407) | | (0.3643) |
| Age Square | -0.1268* | 0.08 | -0.0015 | -- | -0.13434* | 0.06 | -0.0007 |
| | (0.0727) | | (0.0136) | | (0.0743) | | (0.0084) |
| Years of Schooling | 0.8432*** | 0.99 | 0.7247*** | 0.7779*** | 0.85801*** | 1.00 | 0.756*** |
| | (0.2424) | | (0.2052) | (0.1778) | (0.2488) | | (0.1953) |
| Parental Schooling | 0.0280 | 0.10 | 0.0041 | -- | 0.0301 | 0.05 | 0.0022 |
| | (0.0513) | | (0.0197) | | (0.0526) | | (0.0146) |
| Household Size | -0.4669** | 0.25 | -0.0846 | -- | -0.4587** | 0.32 | -0.1186 |
| | (0.2114) | | (0.1758) | | (0.2168) | | (0.2042) |
| Urban | 1.8632** | 0.25 | 0.369 | -- | 1.8826** | 0.05 | 0.0136 |
| | (0.8817) | | (0.7535) | | (0.8998) | | (0.1264) |
| Distant to District Capital | 0.5407 | 0.07 | 0.0168 | -- | 0.6439 | 0.03 | -0.0002 |
| | (0.5416) | | (0.1441) | | (0.5553) | | (0.036) |

**Table 6 - Advanced Reading (Continued)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | LS | PIP | LS-BMA | Best Model | 2SLS | PIP | 2SLS-MA |
| Avg. Teacher Raven | -0.0729 | 0.07 | -0.0007 | -- | -0.0626 | 0.04 | -0.0563 |
| | (0.2142) | | (0.0506) | | (0.2273) | | (0.9498) |
| Poor Classrooms | -3.1571 | 0.07 | -0.1137 | -- | -4.2644 | 0.13 | -0.3314 |
| | (5.2303) | | (1.3205) | | (5.4207) | | (1.069) |
| Eng. Books Per Student | -2.5087 | 0.14 | -0.324 | -- | -2.4514 | 0.08 | 0.4869 |
| | (1.9288) | | (1.0396) | | (1.9719) | | (2.3808) |
| Age 0-2 During Famine | 2.7561 | 0.08 | 0.0574 | -- | 5.1073** | 0.06 | 0.0367 |
| | (2.0166) | | (0.375) | | (2.3890) | | (0.2668) |
| Death Deviation 1983 | 6.2088 | 0.07 | 0.19501 | -- | 32.2337 | 0.02 | 0.1776 |
| | (14.38) | | (2.6263) | | (23.2068) | | (2.6124) |
| Age 0-2 During Famine * Death Deviation 1983 | -7.3985 | 0.07 | 0.2705 | -- | -54.8122* | 0.03 | 0.2666 |
| | (18.9731) | | (3.2463) | | (31.18332) | | (3.1528) |

*** 1 % significance, ** 5% significance, * 10% significance. Heterskedasticity robust standard errors are in parentheses.
Posterior inclusion for the best models for the LS-BMA and 2SLS-MA are, respectively, 0.18 and 0.41

**Table 7 - Falsification Test**

| | ALL Cohorts | | | | | | Post Famine | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| | LS | PIP | LS-BMA | 2SLS | PIP | 2SLS-MA | LS | PIP | LS-BMA | 2SLS | PIP | 2SLS-MA |
| Constant | -25.6348 | 1 | -20.2015 | -25.5763 | 1 | 14.0853 | 101.8224 | 1 | 24.1476 | 103.3466 | 1 | 9.7364 |
| | (20.6785) | | (18.0932) | (19.4115) | | (8.7895) | (87.7397) | | | (82.3197) | | (12.9102) |
| Male | 1.6296** | 0.91 | 1.4157** | 1.6195*** | 0.76 | 1.2920 | 2.2194*** | 0.80 | 1.41349 | 1.9404* | 0.57 | 1.0899 |
| | (0.5881) | | (0.7126) | (0.5765) | | (0.8786) | (0.8159) | | (0.955) | (0.7667) | | (1.0995) |
| Height | 1.1287*** | 0.99 | 1.0682*** | 1.1403*** | 1 | 1.2820*** | 0.7998* | 0.58 | 0.4279 | 0.7744* | 0.61 | 0.588 |
| | (0.3236) | | (0.3489) | (0.3115) | | (0.3174) | (0.4661) | | (0.4873) | (0.437) | | (0.59) |
| Age | 3.9367** | 0.88 | 3.76048* | 3.9305** | 0.05 | 0.1570 | -11.5836 | 0.52 | -1.6784 | -11.5783 | 0.27 | 0.0889 |
| | (1.7317) | | (2.1949) | (1.6469) | | (0.8934) | (10.8995) | | (5.7928) | (10.2315) | | (1.5348) |
| Age Square | -0.1078** | 0.94 | -0.0987* | -0.1076*** | 0.05 | -0.0040 | 0.3968 | 0.55 | 0.07246 | 0.3917 | 0.32 | 0.0117 |
| | (0.0409) | | (0.0526) | (0.0382) | | (0.023) | (0.3494) | | (0.18614) | (0.328) | | (0.05) |
| Primary School | 5.3449 | 0.42 | 0.721 | 6.0008 | 0.06 | -0.2987 | 2.5152 | 0.63 | 2.7802 | 1.8829 | 0.82 | 4.0519* |
| | (10.8022) | | (3.6684) | (9.6253) | | (1.9367) | (19.4055) | | (5.409) | (18.1953) | | (2.2887) |
| Parental Schooling | 0.0717* | 0.51 | 0.0323 | 0.0734* | 0.11 | 0.0085 | 0.0637 | 0.35 | 0.0203 | 0.0653 | 0.05 | 0.0037 |
| | (0.0392) | | (0.042) | (0.0407) | | (0.0277) | (0.0653) | | (0.0437) | (0.0612) | | (0.0212) |
| Household Size | 0.2746* | 0.53 | 0.1291 | 0.2773** | 0.08 | 0.0183 | 0.0937 | 0.28 | 0.0074 | 0.0775 | 0.02 | 0 |
| | (0.1485) | | (0.1618) | (0.1226) | | (0.0731) | (0.2499) | | (0.1155) | (0.2343) | | (0.0256) |
| Urban | 2.269*** | 1.00 | 2.438*** | 2.2772*** | 1.00 | 2.91298*** | 3.6545*** | 1.00 | 3.1954 | 3.2616*** | 1 | 3.7111*** |
| | (0.6112) | | (0.6039) | (0.6002) | | (0.5872) | (0.9234) | | (0.8419) | (0.8713) | | (0.8243) |
| Distant to District Capital | -0.5553** | 0.68 | -0.3505 | -0.5705 | 0.15 | -0.0770 | -0.622 | 0.48 | -0.2547 | -0.6289* | 0.26 | -0.166 |
| | (0.2634) | | (0.3167) | (0.2192) | | (0.2038) | (0.4033) | | (0.3577) | (0.3788) | | (0.3146) |

**Table 7 - Falsification Test (Continued)**

| | ALL Cohorts | | | | | | Post Famine | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| | LS | PIP | LS-BMA | 2SLS | PIP | 2SLS-MA | LS | PIP | LS-BMA | 2SLS | PIP | 2SLS-MA |
| Avg. Teacher Raven | 0.26 | 0.38 | 0.0731 | 0.2592 | 0.08 | 0.01981 | -0.1212 | 0.29 | -0.02666 | -0.1226 | 0.02 | -0.0012 |
| | (0.3318) | | (0.1424) | (0.2916) | | (0.0778) | (0.6016) | | (0.1717) | (0.5661) | | (0.0286) |
| Primary School * Avg. Teacher Raven | 0.0339 | 0.77 | 0.1541 | 0.0139 | 0.99 | 0.19748** | 0.0968 | 0.53 | 0.0666 | 0.11386 | 0.18 | 0.0268 |
| | (0.3563) | | (0.1306) | (0.3134) | | (0.0723) | (0.6307) | | (0.1813) | (0.5913) | | (0.068) |
| Poor Classrooms | 1.1192 | 0.24 | -0.2114 | 1.432 | 0.02 | -0.05433 | 7.5406 | 0.32 | 1.04418 | 7.084 | 0.02 | 0.0176 |
| | (3.4493) | | (1.6744) | (2.7341) | | (0.5547) | (5.3456) | | (3.0818) | (5.0216) | | (0.5319) |
| Primary School * Poor Classrooms | -4.4652 | 0.48 | -2.1564 | -4.4118 | 0.24 | -1.31799 | -6.329 | 0.37 | -1.5745 | -6.655 | 0.06 | -0.2176 |
| | (3.344) | | (2.9781) | (3.0628) | | (2.6926) | (4.8222) | | (3.17951) | (4.5236) | | (1.2851) |
| Math Books Per Student | -2.4258 | 0.42 | -0.7095 | 1.0502 | 0.06 | -0.0896 | 0.0036 | 0.39 | -0.4863 | 0.0735 | 0.06 | -0.148 |
| | (2.8526) | | (1.2556) | (2.3466) | | (0.4265) | (5.008) | | (1.9441) | (4.6982) | | (0.6739) |
| Primary School * Math Books Per Student | 0.9702 | 0.32 | -0.2663 | -2.587 | 0.12 | -0.23489 | -2.237 | 0.41 | -0.748 | -2.3691 | 0.09 | -0.2058 |
| | (2.6553) | | (0.9858) | (2.567) | | (0.7392) | (4.7772) | | (1.8696) | (4.486) | | (0.8347) |
| Death Deviation 1983 | -11.4062 | 0.42 | -5.6902 | -12.4375 | 0.94 | -24.2932** | -15.6201 | 0.41 | -4.7847 | -11.53484 | 0.08 | -1.4264 |
| | (12.07) | | (9.4372) | (16.872) | | (11.355) | (10.9172) | | (8.327) | (13.8655) | | (6.1541) |
| Age 0-2 During Famine | -1.4178 | 0.27 | -0.2175 | -2.0219 | 0.01 | -0.00342 | -- | | -- | -- | | -- |
| | (1.5202) | | (0.8743) | (1.6789) | | (0.0843) | | | | | | |
| Age 0-2 During Famine * Death Deviation 1983 | -30.0228* | 0.92 | -32.9499** | -19.2518 | 0.06 | -1.50113 | -- | | -- | -- | | -- |
| | (16.554) | | (15.2939) | (24.0053) | | (8.0096) | | | | | | |
| Born After Famine | -2.1506 | 0.36 | -0.7469 | -2.4223 | 0.02 | -0.00746 | -- | | -- | -- | | -- |
| | (2.2006) | | (1.5628) | (2.3852) | | (0.1306) | | | | | | |
| Born After Famine * Death Deviation 1983 | -8.7003 | 0.48 | -8.7511 | -3.8215 | 0.03 | -0.68033 | -- | | -- | -- | | -- |
| | (16.0393) | | (12.4891) | (22.3004) | | (4.8168) | | | | | | |

*** 1 % significance, ** 5% significance, * 10% significance. Herterskedasticity robust standard errors are in parentheses. Posterior inclusion for the best models for the LS-BMA and 2SLS-MA are, respectively, 0.18 and 0.31 for post-famine cohort and 0.19 and 0.24 for all cohorts

**Table 8 - Height**

| | (1) LS | (2) PIP | (3) LS-BMA | (4) 2SLS |
|---|---|---|---|---|
| Constant | -8.2317** | 1 | -1.1643 | -8.1017** |
| | (3.8415) | | (1.3459) | (3.86119) |
| Male | 1.1017*** | 1 | 1.1101*** | 1.0999*** |
| | (0.0702) | | (0.07051) | (0.0704) |
| Age | 0.6082* | 0.42299 | 0.03082 | 0.5985* |
| | (0.3361) | | (0.09221) | (0.3368) |
| Age Square | -0.0116 | 0.33971 | 0.00002 | -0.011 |
| | (0.0076) | | (0.002) | (0.0076) |
| Household Size 1983 | 0.008 | 0.05545 | 0.0012 | 0.01 |
| | (0.0191) | | (0.0068) | (0.0192) |
| Parental Schooling | -0.0103** | 0.18798 | -0.0017 | -0.0104** |
| | (0.0047) | | (0.0041) | (0.0047) |
| Urban | 0.1311* | 0.07107 | 0.0067 | 0.1324* |
| | (0.0761) | | (0.0309) | (0.0767) |
| Distant to District Capital | 0.0289 | 0.04295 | 0.0006 | 0.028 |
| | (0.0339) | | (0.0074) | (0.0339) |
| Death Deviation 1983 | 3.7272 | 0.14271 | -0.2301 | 3.7503 |
| | (11.795) | | (0.659) | (12.6082) |
| Age 0-2 During Famine | 0.2998 | 0.07106 | -0.00367 | 0.3384 |
| | (0.8633) | | (0.0515) | (0.917) |
| Age 0-2 During Famine * Death Deviation 1983 | -4.7433 | 0.05658 | -0.0471 | -5.5777 |
| | (11.8636) | | (0.4323) | (12.7586) |
| Age 3 - 5 During Famine | 0.0545 | 0.03594 | -0.0014 | -0.0099 |
| | (0.8609) | | (0.02757) | (0.9156) |
| Age 3 - 5 During Famine * Death Deviation 1983 | -5.5092 | 0.0568 | -0.072 | -4.1815 |
| | (11.886) | | (0.44923) | (12.8027) |
| Age 6 - 8 During Famine | 0.0397 | 0.06381 | 0.00144 | 0.0668 |
| | (0.8791) | | (0.0535) | (0.9349) |
| Age 6 - 8 During Famine * Death Deviation 1983 | -6.267 | 0.10347 | -0.2308 | -6.5897 |
| | (-11.9018) | | (0.8510) | (12.8800) |

*** 1 % significance, ** 5% significance, * 10% significance. Heterskedasticity robust standard errors are in parentheses. Posterior inclusion for the best models for the LS-BMA 0.24

*Figures*

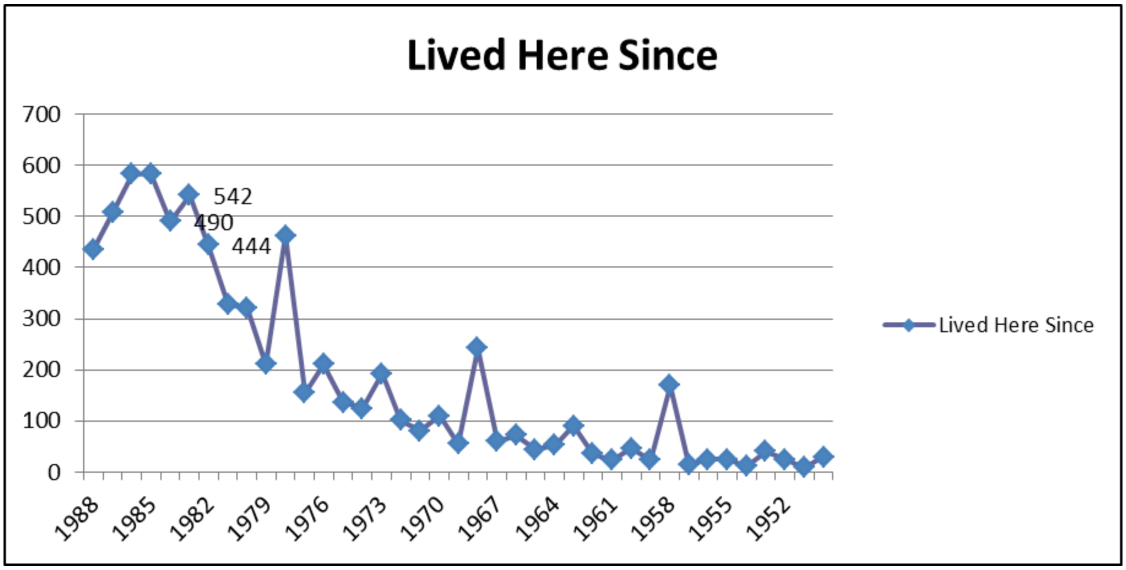



**Figure 1a**

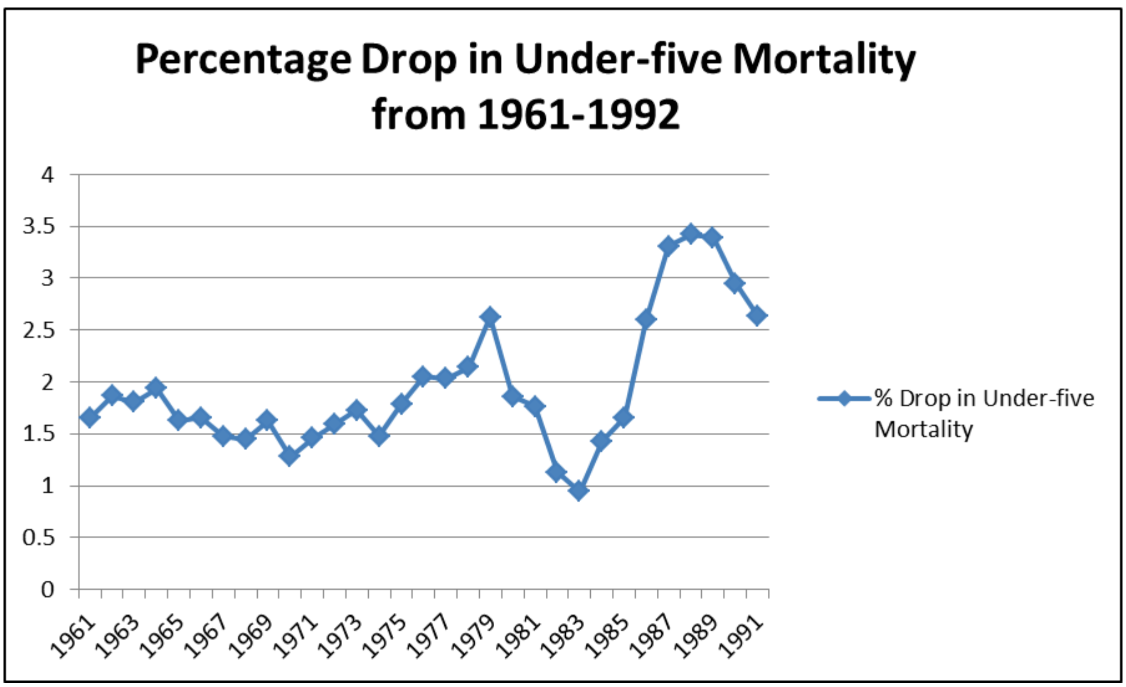



**Figure 1b**

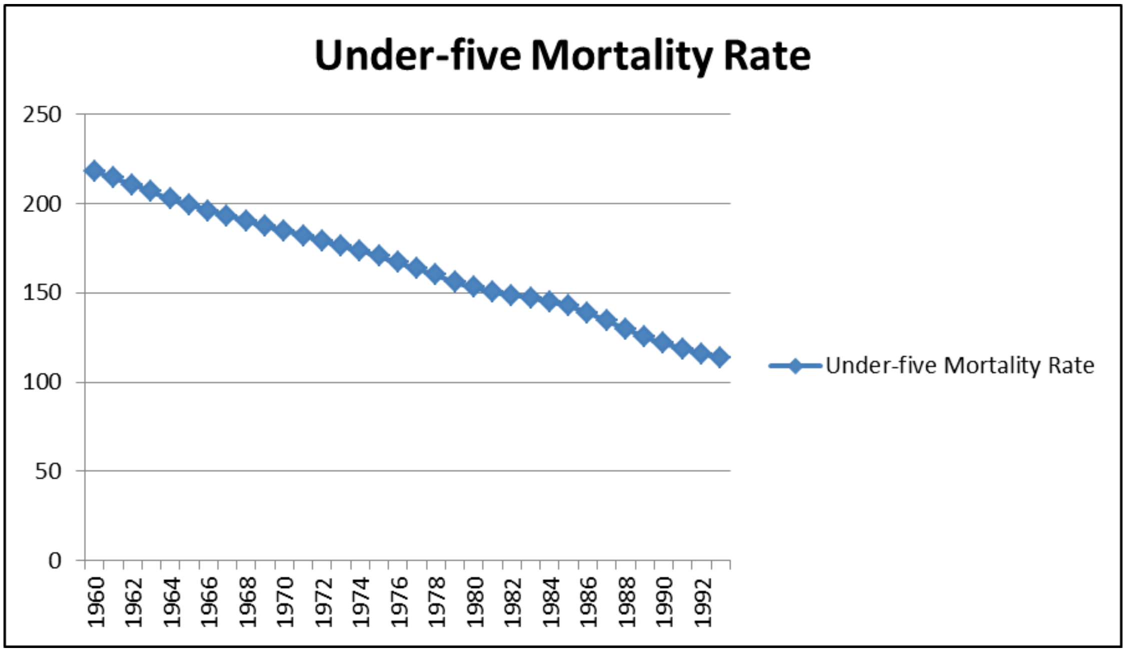

Under-five Mortality Rate
250
200
150
100
50
0
1960
1962
1964
1966
1968
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
Under-five Mortality Rate

**Figure 2**

# Appendix A

Sample Raven Test

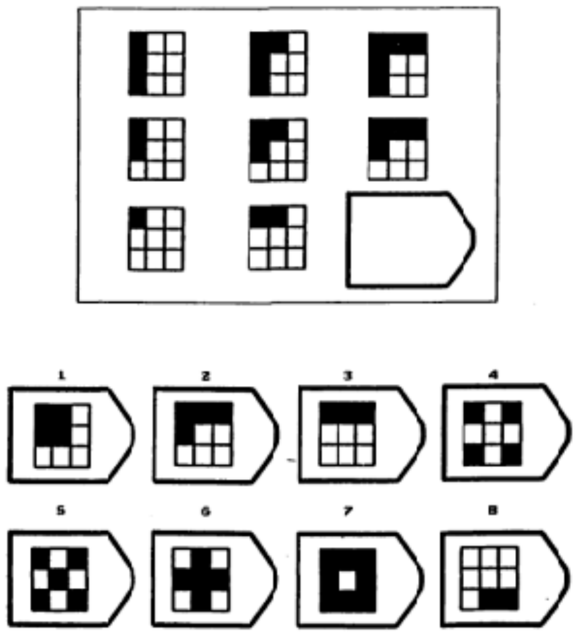



Figure 4a. A problem to illustrate the quantitative pairwise progression rule. The number of black squares in the top of each row increases by one from the first to the second column and from the second to the third column. The number of black squares along the left remains constant within a row, but changes between rows from three to two to one. (The correct answer is #3)

*Short Math Test*

1. $1 + 2 =$

2. $5 - 2 =$

3. $2 \times 3 =$

4. $10 \div 5 =$

5. $24 + 17 =$

6. $33 - 19 =$

7. $17 \times 3 =$

8. $41 \div 7 =$

*Short English Reading Test*

John is a small boy. He lives in a village with his brothers and sisters. He goes to school every week. In his school there are five teachers. John is learning to read at school. He likes to read very much. His father is a teacher, and his parents want him to become a school teacher too.

1. Who is John?

   (A) An old man
   (B) A small boy
   (C) A school teacher
   (D) A school

2. Where does John live?

   (A) In a village
   (B) In a city
   (C) In a school
   (D) In a forest

3. What does John do every week?

   (A) Works with his father
   (B) Plays with his friends
   (C) Helps his brothers and sisters
   (D) Goes to school

4. How many teachers are there at John's school?

   (A) One
   (B) Three
   (C) Five
   (D) Six

5. What is John doing at school?

   (A) Helping the teacher
   (B) Talking with his friends
   (C) Learning to read
   (D) Teaching the class

6. Who is a school teacher?

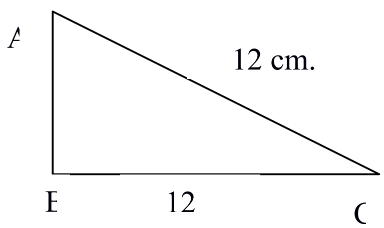
   (A) John
   (B) John's father
   (C) John's brother
   (D) John's mother

7. What do John's parents want him to do?

   (A) Go to school
   (B) Learn to read
   (C) Obey his teachers
   (D) Become a teacher

8. The best title for this story is

   (A) John Learns to Read
   (B) Why Reading is Important
   (C) John's Village
   (D) Schools in Ghana




Note: figure not drawn to scale

13. If the perimeter of the triangle ABC is 30 centimetres, what is the length, in centimetres of side AB?

(A) $2\frac{1}{2}$

(B) 3

(C) 6

(D) 18

---

14. Two cities are 12 kilometres apart. Each day, a bus makes 3 round trips between these cities. How many kilometres does the bus travel each day?

(A) 72

(B) 36

(C) 1

(D) 4

---

15. A meal costs 1500 Cedis. If a 10% service charge is to be added to the bill, what would the total charge be?

(A) 1510 Cedis

(B) 1600 Cedis

(C) 1650 Cedis

(D) 2500 Cedis

---

16. An island has an area of about 300 square miles. The government reports that one third of the island is not suitable for cultivation. About how many square miles of this island are suitable for cultivation?

(A) 50

(B) 100

(C) 150

(D) 200

---

| | Highest | Lowest |
|---|---|---|
| Elderet | 23.6 ° | 9.5 ° |
| Magadi | 34.9 ° | 23.1 ° |
| Nakura | 26.4 ° | 10.1 ° |
| Narok | 24.4 ° | 8.3 ° |

17. The chart above shows the average (mean) high and low temperatures for four cities in a certain year. In which of the cities was there the greatest difference between the average high and the average low?

(A) Eldoret

(B) Magadi

(C) Nakura

(D) Narok

Directions: For questions 10-15, read the passage below. Each line of the passage has a number. In each line, there is a box with four possible choices. Pick the choice that best completes the sentence in each numbered line. Mark the letter (A, B, C, or D) of the choice on your answer sheet.

| | | | |
|---|---|---|---|
| 10. | Sound is something we | (A) hears.<br>(B) hearing.<br>(C) heard.<br>(D) hear. | It comes to your |

| | | |
|---|---|---|
| 11. | (A) Eyes<br>(B) nose<br>(C) ears<br>(D) mouth | in different ways. It might be pleasant, |

| | | | |
|---|---|---|---|
| 12. | like the voice of a friend, | (A) when<br>(B) as<br>(C) or<br>(D) since | unpleasant, like the yelp of a |

| | | | |
|---|---|---|---|
| 13. | dog that has been struck by a | (A) horn.<br>(B) car.<br>(C) road.<br>(D) bridge. | Some sounds are loud, |

| | | | |
|---|---|---|---|
| 14. | and some are soft; some are high, and some are | (A) full.<br>(B) low.<br>(C) quite.<br>(D) big. | Sound is |

| | | | |
|---|---|---|---|
| 15. | very | (A) importance<br>(B) importantly<br>(C) important<br>(D) import | to us because it is the basic means of |

communication.