



Impact of estimation techniques on regression analysis: an application to survey data on child nutritional status in five African countries

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Abstract

This paper illustrates the impact of ignoring survey design and hierarchical structure of survey data when fitting regression models. Data on child nutritional status from Ghana, Malawi, Tanzania, Zambia, and Zimbabwe are analysed using four techniques: ordinary least squares; weighted regression using standard statistical software; regression using specialist software that accounts for the survey design; and multilevel modelling. The impact of ignoring survey design on logistic and linear regression models is examined. The results show bias in estimates averaging between five and 17 per cent in linear models and between five and 22 per cent in logistic regression models. The standard errors are also under-estimated by up to 49 per cent in some countries. Socio-economic variables and service utilisation variables are poorly estimated when the survey design is ignored.

Impact of estimation techniques on regression analysis: an application to survey data on child nutritional status in five African countries

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Introduction

Many studies that analyse data from large surveys often use software designed for simple random samples. Such analyses fail to take into account the impact of the complex sampling design on regression parameter estimates such that the conclusions drawn from these analyses can be misleading. Many of the samples collected under the Demographic and Health Surveys (DHS) programme are drawn using stratified multistage sampling designs, often with over-sampling of smaller domains such as urban areas or some regions of the country (Institute for Resource Development 1987). If the unequal probabilities of selection are ignored, inferences based on the unweighted sample data may be biased since individuals from the over-sampled domains will have greater weight than is the case in the population.

The importance of accounting for the sample design in regression modelling has been widely acknowledged in statistical literature (DuMouchel and Duncan 1983; Korn and Graubard 1995; Pfeffermann and La Vange 1989; Smith 1988; Skinner *et al* 1989). There are three elements of the survey design that may have an effect on the regression estimates based on survey data: the sample weights, stratification, and clustering (Korn and Graubard 1995). The sample weight associated with an individual is the inverse of that individual's probability of being included in the sample, adjusted, if necessary, for non-response (Korn and Graubard 1995). The sample weights in a data

set can therefore be thought of as, approximately, the number of individuals in the population that are represented by the sampled individual. Thus the sample weights act to correct sample data for the unequal selection probabilities and failure to include these in the modelling process can lead to estimates that are seriously biased for their corresponding population quantities.

Stratification can produce gains in precision. That is, a stratified design can lead to smaller standard errors than a simple random sampling design if the observations within strata are similar. If the stratification is ignored in the analysis the standard errors will be too large, hence the confidence intervals will be too wide, giving coverage greater than the nominal coverage. Cluster sampling is often used in national social and demographic surveys, where the clusters are groups of households derived from census enumeration areas or from well-defined communities. Clustering is of both statistical and substantive importance. Individuals who belong to a particular cluster may be more alike than those of different clusters, such that the assumption of independence assumed in ordinary regression techniques is violated. The failure to recognise the clustering of survey data may lead to standard errors that are smaller than the true standard errors, and hence confidence intervals may be too narrow, leading to erroneous model results.

The correlation of outcomes that may arise as a result of clustered data can also be of interest in identifying potential determinants or causes of the outcome under observation. For example, the correlation of mortality risks within a family may indicate genetic frailty among its members. In a data set, there may be many levels at which potential correlation may be expected. For example, children may be nested in households, which are clustered in communities, so that correlation may exist at both levels. The development of software to handle multilevel data has enabled researchers to quantify the correlation of outcomes of interest at various levels of social organisation.

There are several views in the literature on the ways to analyse complex survey data. Some argue for a model-based approach, where the complex design of the sample is accounted for by using auxiliary data in the regression. Examples of such auxiliary data include variables used to construct

the strata in the design phase (Skinner *et al* 1989; Korn and Graubard 1995). In this approach, models are used to mitigate the impact of the complex survey design and regression diagnostics are used to assess the performance of the models. Other statisticians argue for a design-based approach, where the complex design is controlled for explicitly through the use of weighted regression and appropriate software that can handle complex survey designs (Eltinge *et al* 1997). Both approaches have merits and drawbacks. It has been suggested that the model-based approach performs better than the design-based approach when the sample design is inefficient, for example, when very few primary sampling units are selected per strata (Graubard and Casady 1997). Another situation when the model-based approach may be preferred is when the sampling weights vary considerably, or when non-response is a significant problem. This approach requires verification of the model assumptions through diagnostics, and is thus less often used by analysts of large surveys (Eltinge *et al.* 1997).

The recognition of the complex survey design and the hierarchical structure of the data both make an important difference to the modelling process and it is desirable that a model should be fitted which incorporates both types of effect. Statistical packages for multilevel models such as MLwiN (Institute of Education 2000), while capable of handling many levels of clustering, do not handle weighted data well particularly where the sample weights are not independent of the cluster effect. Pfeffermann *et al.* (1998) proposed methods of weighting in multilevel models but the appropriate software for these methods is still not available.

In this paper, data from DHS programmes conducted in Ghana, Malawi, Tanzania, Zambia, and Zimbabwe between 1992 and 1994 are used to assess the determinants of child nutritional status. Three types of software are used: SPSS version 10 (SPSS Inc. 2000), the standard statistical software commonly used in the social sciences; STATA release 7 (StataCorp 2000), statistical software which includes specialist commands for analysing data from complex surveys; and MLwiN version 1.02.03 (Institute of Education 2000), software for multilevel models. This paper

contrasts four estimation procedures and will argue a case for the eventual inclusion of the survey design and the hierarchical structure of the data in the same modelling process.

Nutritional status of children

A series of demographic and health surveys conducted since 1984 have collected weight and height data for children under five years as well as a wealth of other individual level information about each child, their family and their household. Data from the DHS programme are particularly suitable for comparative studies since they contain a similar core set of information although variations do sometimes occur as countries can choose to omit or add some questions. Of particular importance to this study are the anthropometric measurements of children and their mothers, socioeconomic characteristics of the households, breastfeeding patterns, and morbidity of children.

To measure the nutritional status of the child anthropometric measurements are compared to standard National Health Centre, Centre for Disease Control and World Health Organisation (NCDS/CDC/WHO) reference populations to obtain height-for-age z-scores. For example, a child is regarded as being stunted if his or her height-for-age z-score is less than two standard deviations from the median of the NCHS/CDC/WHO international reference population for the relevant sex and age group. Stunting is an indication of long periods of inadequate dietary intake, often combined with repeated infection. To measure underweight and wasting, weight-for-age and weight-for-height z-scores can be used as indicators.

In this paper, height-for-age z-scores and a binary variable for stunting (1=stunted) are used in the linear regression and logistic regression models, respectively. These nutritional status indicators were chosen for illustrative purposes only but other indicators of nutritional status have been used in the literature (McMurray 1996; Madise *et al* 1999). The percentage of children aged 135 months who were stunted, as defined by the above measure, in the five countries are: 22 in Zimbabwe, 26 in Ghana, 39 in Zambia, 40 in Tanzania and 42 in Malawi (see Figure 1).

[FIGURE 1 ABOUT HERE]

Description of the survey designs

Most DHS surveys use stratified multistage cluster sampling. At the first stage, the country is stratified into subgroups (or strata) that are as similar as possible and in many countries, stratification is based on geographical areas (such as regions or provinces and urban or rural residence). Each stratum is divided into units, which in many cases are census enumeration areas. From these standardised segments of roughly the same size are created (Macro International, 1996). From each stratum, units known as ‘primary sampling units’ (PSUs) are chosen with probability proportional to size, where the size is the number of standardised segments or households. One segment is randomly selected from each PSU. The number of PSUs selected from each stratum is based on proportional allocation, with the same sampling fraction in each stratum to create a self-weighting sample. In some cases varying sampling fractions are used so that some strata are over-sampled or under-sampled. At the second stage, all households in a segment are listed and a fixed number are selected using systematic sampling. All women aged 15-49 years in the selected households are eligible to be included in the interviews.

The Ghana survey used the same sampling fraction in each stratum so that the resulting sample is self-weighting (Ghana Statistical Service and Macro International 1994). In the four remaining surveys, some strata were over-sampled (unequal sampling fractions) so that the samples are not self-weighting. These samples require weighting when making national level estimates. The response rates for the surveys under consideration averaged approximately 95 percent. Full details of the precise numbers of households and women that were selected are reported in the respective DHS country reports.

Methods

Height-for-age z-scores for children aged 1-35 months (continuous outcome) are regressed using the same set of socioeconomic and demographic variables in each country (see Table 1 for a full list of the variables used). The choice of the explanatory variables was determined by earlier work on the determinants of nutritional status among African children (Madise *et al* 1999).

[TABLE 1 ABOUT HERE]

Ordinary least squares (OLS) regression (which we label Model AI) is applied using the SPSS statistical package. This method treats the data as if they had been sampled using simple random sampling. The variables used during stratification are included as explanatory variables as suggested by Skinner *et al* (1989). The second analysis (Model AII) is a weighted least squares regression, performed using SPSS. This approach produces unbiased parameter estimates but the standard errors are incorrect. In the third approach (Model AIII) we use STATA to account for the unequal sampling probabilities, stratification, and the clustering of individuals within primary sampling units. This approach produces unbiased estimates and appropriate standard errors for the design. The fourth analysis uses MLwiN to fit a three-level model (Model AIV) to account for the hierarchy in the data. The three levels are the primary sampling unit (hereafter called “community”), the family or household, and the child.

Corresponding analyses are performed using a binary dependent variable (stunted or not stunted). Model BI is the standard logistic regression from SPSS, Model BII is the weighted logistic regression, Model BIII is the logistic regression that accounts for the survey design, and Model BIV is the three-level logistic regression model using MLwiN.

Although simple random samples are the simplest to analyse, they are often very expensive and are rarely used for large surveys. Complex designs are often cheaper in comparison but there is a cost in terms of loss of precision. The variances (or standard errors) of the estimates from complex survey designs tend to be larger than those from simple random sampling. A good measure of this

loss of efficiency is the ratio of the standard error of an estimate under the complex design to the standard error of the estimate assuming that the sample was drawn by simple random sampling.

This is known as the *design factor or design effect* (deft), and is estimated using the formula:

$$deft = \sqrt{\frac{\hat{V}_c}{\hat{V}_{srs}}}$$

where \hat{V}_c is the estimated variance of the parameter estimate under the complex survey design (Models AIII and BIII), and \hat{V}_{srs} is the corresponding estimated variance under simple random sampling (Models AI and BI). For example a design factor of two would suggest that the standard error under the complex design is twice that which would have been obtained if simple random sampling had been used. A design factor of less than one would indicate that the complex survey design was more efficient than simple random sampling for estimating the quantity in question.

Finally, the data are clustered (that is children within families, and families within communities) so that it is important to account for this hierarchy (see Table 2). On average, about nine per cent of the households have two or more children in the sample. Similarly, about 40 per cent of the clusters of households have ten or more children, except in Ghana where the percentage is only about seven. The degree of clustering of nutritional status of children within a family can be measured from the multilevel models using the intra-family correlation coefficient. This is the ratio of the family-level variance to the total variance. Similarly, the intra-community correlation coefficient (the ratio of the community-level variance to total variance) measures the homogeneity of nutritional status within communities. For the logistic regression models, the child level variance is assumed to equal $\frac{\pi^2}{3}$ as proposed by Im and Gianola (1988).

[TABLE 2 ABOUT HERE]

Results

As preliminary analyses, 95 percent confidence intervals for the mean height-for-age z-scores were calculated using two approaches: confidence intervals calculated using STATA, which account for aspects of the survey design, and those calculated assuming that the data come from simple random samples (see Figure 2). It can be seen that generally, the confidence intervals that do not account for the survey design are narrower than those that account for the survey design. In particular, the confidence intervals for Malawi do not overlap, indicating that if the design of the survey is ignored, differences may appear more significant than they really are.

FIGURE 2 ABOUT HERE

Parameter estimates for linear models

When the weights are ignored, the parameter estimates may be biased. The degree of the bias can therefore be measured by the difference in the estimates between the model that accounts for the weights and the models that ignore the weights. In this section, we compare for each country, the parameter estimates for Model AI against Model AIII to estimate the degree of bias as a consequence of ignoring the weights. A comparison is also made between estimates from the three-level linear model (Model AIV) and Model AIII. Model AII, the weighted regression, produces unbiased estimates that are identical to those from Model AIII. From Table 3, it can be seen that the degree of bias in the estimates as a consequence of ignoring the sampling weights varies. On average, the bias is highest in Tanzania and Malawi and lowest in Zambia.

[TABLE 3 ABOUT HERE]

For the case of Malawi, treating the data as if they were obtained from a simple random sample (Model AI) result in an overestimation by nearly 100% of the estimate for the father's occupation (non-manual versus manual). This estimate is significant at a five per cent level in Model AI but not significant even at a 10 per cent level in Model AIII. The three-level model (Model AIV) also overestimates this parameter. Another variable with relatively large bias is whether or not the

mother received prenatal care. The estimate for this variable in Model AI is about 25 per cent higher than that from Model AIII. In contrast, the estimate for the size of the baby at birth is underestimated in the models that do not account for the sampling weights.

In the linear models, the estimate for the sex of the child for the Tanzania data is underestimated when the weights are not accounted for. The estimate for the parameter for preceding birth intervals of 24 months or longer is significant at a five per cent level in Models AI and AIV but not significant, even at 10 per cent level in Model AIII. The magnitude of the bias is also quite large. The estimates for the place of delivery are larger in magnitude (and therefore more significant) when the sampling weights are ignored.

The difference of the estimates across the models for Zambia and Zimbabwe are generally smaller than those found in the Malawi and Tanzania data. Since the Ghana sample was self-weighting, there were no differences in the estimates across the four models and although the standard errors varied, the significance of the models did not change across the four approaches.

Standard errors for linear models

In this section, comparisons of the standard errors are made between the four models. The ratios of the standard errors under the complex survey design (Model AIII) to the standard errors from ordinary least squares (Model AI) are presented as design factors in Table 5. These design factors, are consistently greater than one, except for Ghana, showing that ignoring the survey design leads to underestimation of the standard errors. On average, the design factors are largest in the Tanzania data, followed by Malawi, and are smallest in Ghana.

[TABLE 4 ABOUT HERE]

When the weighted least squares regression is performed (Model AII) the standard errors produced are generally larger than those obtained from unweighted regression. However, the weighted regression standard errors (Model AII) are not, in general, equal to those obtained from Model

AIII. On average, the standard errors from Models AII and those from Models AIV were smaller than those from Model AIII by about 13 per cent (results not shown). This suggests that if only some components of the survey design (e.g. weights or clustering only) are accounted for in the analysis, the standard errors may still be underestimated. This will result in more significant results than is the case.

Parameter estimates for logistic models

On average, the bias is larger for logistic regression than for the linear models. Again the magnitude of the bias is largest for Tanzania, followed by Malawi and is least in Zambia (see Table 4). The estimates for the length of the preceding birth interval, the place of delivery, household wealth and the father's occupation show greater bias than the rest of the variables.

[TABLE 5 ABOUT HERE]

As with the linear models, some of the parameter estimates are biased when the weights are ignored to the extent that the significance of the parameter is changed. For example, for the Malawi models, the estimate for short preceding birth intervals (< 24 months) is significant at the five per cent level in Model BI but insignificant in Model BIII. Conversely, the estimate for 'medium household wealth' is significant in Model BIII but not Model BI and the degree of the bias is nearly 40 per cent. Again the estimate for father's occupation in the Malawi models shows a high degree of bias when the weights are ignored.

The sex of the child in the Tanzania data is estimated with bias by about 24 percent in the ordinary logistic regression model (Model BI) and by about 20 percent in the three-level logistic regression model. The estimate for preceding birth intervals of 24 months or longer varies greatly between models: from close to zero for Model BIII to 0.15 (significant at a 10 per cent level) for Models BI and BIV. Consequently, the percentage differences are very large. With regards to the place of

delivery, the estimate is overestimated by nearly 100 per cent in Model BI and was highly significant ($p < 0.001$) but not significant in Model BIII. There are also large differences in the estimates for the father's occupation across the models for Tanzania.

For the Zambian models, the largest biases are for estimates of whether or not the mother received prenatal care and the place of delivery. The differences in the parameter estimates across the models for the Zimbabwe data are relatively small except for age-squared and maternal weight but these are based on small values. All the four models for the Ghana data produced similar results.

Standard errors for logistic models

The design factors for the logistic regression models (Model BIII versus Model BI) are presented in Table 6. Across the countries, the general pattern is similar to the linear models. Again, the standard errors from Model BIII are larger than those from Model BI and this is reflected by design factors exceeding one. Some of the design factors are less than one, indicating that the complex survey design is produces more efficient estimates. A comparison was also made between the standard errors of Models BII and BIII and also between BIV and BIII. The results (not shown) indicate that the standard errors from the weighted logistic regression and the three-level logistic regression models are slightly smaller (by about five per cent, on average) than those from the models accounting for the survey design.

[TABLE 6 ABOUT HERE]

Family and community level clustering of nutritional status

The three-level models (Models AIV and BIV) allow for the estimation of the correlation of nutritional status between children of the same family and also between children of the same community. The results from the linear models showed that there was significant correlation of nutritional status of children within families. The intra-family correlation coefficients were 0.24 for

Malawi, 0.28 Tanzania for, 0.30 for Zimbabwe and 0.33 for Zambia. Only in Ghana was this intra-family correlation not significant. At the community level, the correlation was smaller, averaging about three per cent. From the logistic regression models, the intra-family effects were much weaker, ranging between four per cent in Tanzania to about 14 per cent in Zimbabwe. The intra-community correlation coefficients averaged about two per cent.

Discussion

Many researchers have demonstrated the pitfalls of ignoring the survey design when analysing data (Chambers 1986; Skinner *et al* 1988; Brogan 1998; Eltinge *et al* 1997) but few have performed multi-country comparisons (Lê and Verma 1997). The impact of complex designs on regression modelling is now a subject of interest among social scientists since statistical software for properly handling complex survey designs is available. Many social and demographic surveys use stratified multistage sampling and commonly use the regions and/or the place of residence to stratify the population. Such designs tend to be informative for many health outcome variables such as nutritional status, mortality, and fertility so that inferences based on analyses that ignore the design of the survey can be misleading.

These results have demonstrated that care needs to be taken when analysing data from complex survey designs since regression estimates may differ in magnitude and significance depending on the estimation procedure and software used. In particular, the use of statistical packages that account for sample weights, stratification, and clustering produce different results compared to those obtained from standard software.

The comparative analyses, using data from five different countries, have produced important similarities. The bias when the sample weights are ignored appears larger for socio-economic variables such as the father's occupation, and also for health service utilisation variables such as receiving prenatal care and the place of delivery. Since the distribution of children according to socio-economic status and health care variables can vary by region of residence, it is clear that

when some regions are over-sampled, the weighted and unweighted samples will be different, leading to different estimates. The consequence is that the association between these variables and nutritional status appears stronger than it really is.

Other variables with relatively large bias are the length of the preceding birth interval. It is not immediately apparent why the estimates of these variables should differ between the models that account for the survey design and those that do not. However, it is possible that when other factors are controlled, the distribution of children by these variables differs in the weighted and unweighted samples.

The inclusion of the survey design variables as explanatory variables in ordinary least squares regression models ameliorates to some extent the bias in the parameter estimates as has been suggested by the model-based approach proponents. For example, further analysis (not shown) of the bivariate association between the age of a child and his/her height-for-age z-score in Malawi showed systematic bias when the sample weights were not accounted for. The bias was reduced when the survey design variables were included in model even without accounting for the sample weights. However, from the results it is clear that inclusion of the survey design variable does not eliminate all the bias totally.

Our results also confirm that the magnitude of the bias is related to the variability in the sample weights (Eltinge *et al* 1997). This indicates that samples with survey weights that vary considerably are more vulnerable to estimation bias if the weights are ignored in the analysis. The results have also confirmed that ignoring stratification and clustering in data analysis can produce standard errors that are incorrect. Generally, the standard errors from standard statistical software and from MLwiN were smaller compared to those from STATA. The implication of this is that ignoring the survey design may lead to more significant results and narrower confidence intervals than is the case.

The statistical package that was used to account for the survey design (STATA) accounts for clustering at one level (the community level). The package does not, at present, allow multilevel modelling with more than two levels. However, our results have shown that the degree of clustering at family level is stronger and more significant than clustering at the community level, thus both levels need to be accounted for in analysis using DHS data. Further, Lê and Verma (1997) have shown that part of the design factor in many estimates that use child-level data from DHS samples can be attributed to the clustering effects at the household or family level. Clearly, when hierarchical data are collected using complex survey designs, there are many factors that can lead to biased estimates if the design and data structures are ignored.

Conclusion

The Demographic and Health Survey programme has created a wealth of data which continue to be analysed by many scientists globally. However, many ignore the survey design and treat the data as if there were collected by simple random sampling. The consequences of ignoring the survey design on regression estimates have been demonstrated in this paper using four different approaches. Ignoring the survey weights leads to biased estimates and not accounting for other aspects of the survey design such as stratification and clustering of areas can lead to inaccurate standard errors.

The hierarchical structure of the data is also important and our results show that clustering of children within families or households is important and that ignoring this extra level in the data can lead to misleading results. Hence it is desirable that the design of the survey, as well as the hierarchy in the data are taken into account when analysing DHS datasets to produce robust results in regression modelling.

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Figure 1 Percentage children aged 1-35 months who are stunted in 5 African countries

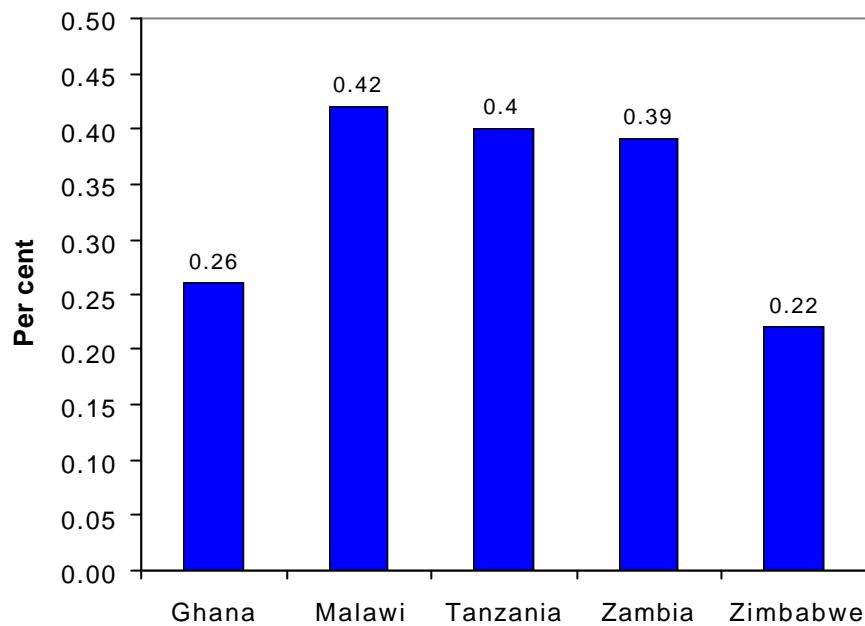
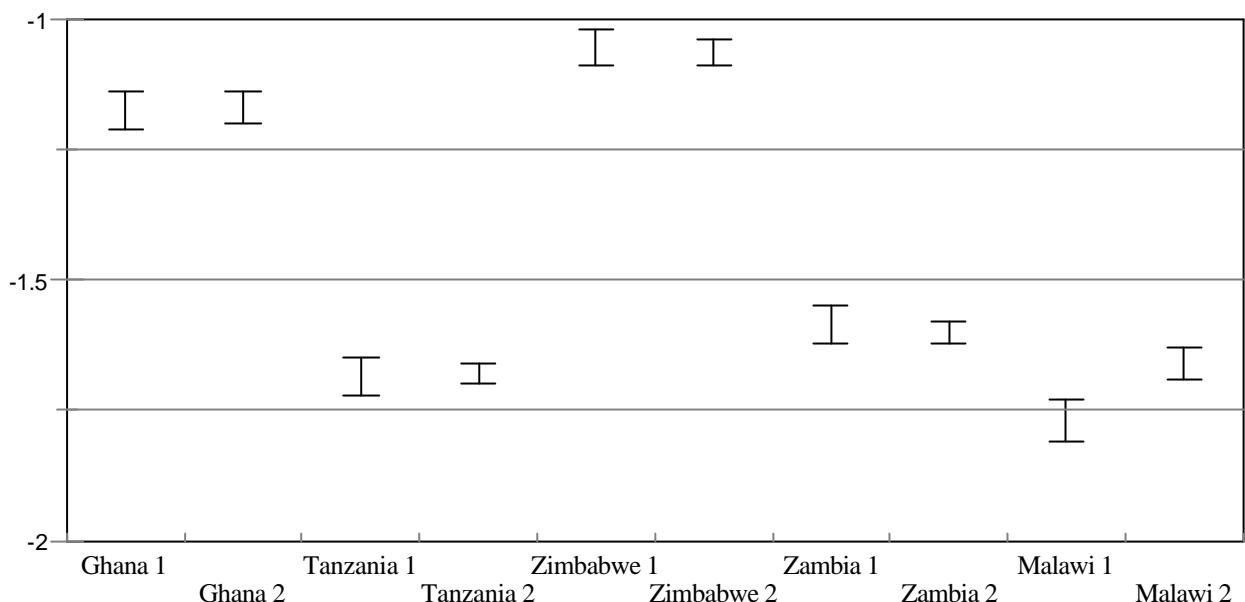


Figure 2. 95% Confidence Intervals for the mean height-for-age z-scores



1 = Accounting for survey design

2 = Not accounting for survey design

Table 1. Independent variables used in the modelling of height-for-age z-scores.

Variable	Definition
<i>Child-level variables</i>	
Sex, age	
Size of the baby at birth	Based on mother's report, a proxy for the baby's birth weight
Still breastfeeding	Whether or not the child was still breastfeeding
Preceding birth interval	Length of preceding birth interval (none, < 24 months, 24 months or longer)
Prenatal care	Whether or not the mother received prenatal care during the pregnancy of the index child
Hospital delivery	Index child was delivery at hospital or other place.
<i>Mother-level variables</i>	
Maternal anthropometry	Height in centimetres and weight-for height percentage of the reference median based on the World Health Organisation standard
Father's occupation	Manual or non manual occupation of the father or mother's partner
Household wealth	Based on a score of whether or not the household possessed amenities such as electricity, piped water, bicycle etc. Coded as 0-2, 'low'; 3-5, 'medium'; and 6+, 'high'.
<i>Community/Area variables</i>	
Region of residence	Geographical /administrative area. All the five surveys used region as one of the variables in stratification.
Place of residence	Most commonly classified as 'rural' or 'urban' but sometimes as 'city', 'town' or 'village' (also used as a stratifying variables).

Table 2. Description of the 5 Demographic and Health Survey Data sets

Characteristic	Ghana 1993	Malawi 1992	Tanzania 1991/92	Zambia 1992	Zimbabwe 1994
Number of children	1803	2050	4083	3237	2043
Number of Clusters (Communities)	388	225	349	261	230
Number of strata	183	6	168	5	18
<i>% Families with 2+ children in sample</i>	<i>6.5</i>	<i>9.6</i>	<i>9.8</i>	<i>10.9</i>	<i>7.4</i>
<i>% Communities with</i>					
<i>< 10 children</i>	<i>92.5</i>	<i>57.8</i>	<i>43.8</i>	<i>39.1</i>	<i>60.7</i>
<i>10 – 19</i>	<i>7.5</i>	<i>40.4</i>	<i>45.6</i>	<i>46.7</i>	<i>34.9</i>
<i>20+</i>	<i>-</i>	<i>1.8</i>	<i>10.6</i>	<i>14.2</i>	<i>4.4</i>
Range of survey weights	0	1.39	7.20	0.71	1.67

Numbers in italics are percentages.

Table 3. Percentage difference in parameter estimates between ordinary least squares regression (Model AI), linear regression accounting for survey design (Model AIII) and 3-level linear models (Model AIV).

Parameter Estimate	Models	Malawi		Tanzania		Zambia		Zimbabwe	
		<i>AI vs AIII</i>	<i>AIV vs AIII</i>						
Child's age		2.00	6.67	8.06	8.19	2.22	1.48	8.96	7.46
Age squared		0.00	0.00	0.00	0.00	0.00	3	18.30	16.29
Sex-female		0.68	2.39	15.63	14.38	8.77	7.60	6.12	9.18
Size of baby at birth		20.54	20.16	1.43	5.14	3.06	6.66	0.33	1.16
Still breastfeeding		10.58	12.98	7.32	3.41	4.69	4.15	10.95	13.43
Preceding interval (< 24 months)		1.25	3.75	ns	ns	ns	ns	14.52	13.17
Preceding interval (24+months)		0.44	4	58.23	75.35	12.24	11.56	ns	ns
No prenatal care		25.52	22.73	ns	ns	5.63	ns	ns	ns
Place of delivery – home		0.00	4.11	45.33	20.00	9.63	3.38	0.77	5.02
Maternal height		3.92	1.96	4.00	2.00	1.92	3.85	2.44	2.44
Maternal weight		16.67	16.67	0.00	11.11	5.24	2.05	0.00	16.67
Medium Household wealth		ns	ns	ns	ns	4.05	16.76	1.77	14.16
High household wealth		11.84	7.89	13.81	0.95	5.06	17.30	ns	ns
Father's occupation-non manual		98.81	79.76	15.97	11.34	2.72	3.40	13.76	12.39
Average		14.79	14.08	15.61	13.81	5.01	6.77	7.08	10.12
Range		98.81	79.76	58.23	75.35	12.24	15.82	18.30	15.51

ns – not significant at a 10% level for all three models . All four Ghana models not very different.

All models are adjusted for region and place of residence.

**Table 4. Design Effects for linear regression Models
(Ratio of standard errors of Model AIII to Model AI)**

Parameter Estimate	Malawi	Tanzania	Zambia	Zimbabwe	Ghana
Child's age	1.19	1.12	1.15	1.03	1.04
Age squared	1.15	1.13	1.12	1.01	1
Sex-female	1.05	1.20	1	1.13	1
Size of baby at birth	1.16	1.00	1.11	1.12	0.95
Still breastfeeding	1.18	1.42	1	1.03	0.96
Preceding interval (< 24 months)	1.13	1.45	1.1	1.1	0.9
Preceding interval (24+months)	1.05	1.09	1.07	1	1
No prenatal care	1.19	1.09	1.2	1.11	1
Place of delivery – home	1.24	1.20	1.09	1.11	1.04
Maternal height	1.16	1.10	1.12	1.17	0.91
Maternal weight	1.16	1.36	1.05	1.02	1.12
Medium Household wealth	1.11	1.30	1.14	1.04	1.09
High household wealth	1.09	1.08	1.06	1.12	1.09
Father's occupation-non manual	1.06	1.25	1.07	1.28	1
Average	1.14	1.20	1.09	1.09	1.01

Table 5. Percentage difference of the parameter estimates between ordinary logistic regression (Model BI), logistic regression accounting for survey design (Model BIII) and 3-level logistic regression models (Model BIV).

Parameter Estimate	Malawi		Tanzania		Zambia		Zimbabwe		
	Model	BI vs BIII	BIV vs BIII	BI vs BIII	BIV vs BIII	BI vs BIII	BIV vs BIII	BI vs BIII	BIV vs BIII
Child's age		3.60	10.8	5.38	7.17	1.07	5.14	1.90	8.89
Age squared		7.44	2.56	0.00	0.00	0.00	0.00	16.67 ^b	16.67 ^b
Sex-female		3.52	8.57	24.64	21.17	6.61	6.70	ns	ns
Size of baby at birth		4.21	9.71	0.28	2.61	3.09	1.06	2.44	10.00
Still breastfeeding		8.76	18.65	3.95	7.39	3.89	3.87	ns	ns
Preceding interval (< 24 months)		42.32	43.07	ns	86.84	ns	ns	18.24	17.68
Preceding interval (24+months)		13.66	16.30	100 ^a	100 ^a	ns	ns	ns	ns
No prenatal care		9.95	7.99	ns	ns	16.76	ns	ns	ns
Place of delivery – home		16.24	20.51	94.08	79.29	10.00	16.48	0.68	4.60
Maternal height		8.33	19.44	4.74	5.99	4.00	1.00	0.00	5.06
Maternal weight		ns	ns	15.34	20.25	0.00	3.33	4.90	20.02 ^b
Medium Household wealth		37.98	18.82	ns	ns	ns	ns	ns	ns
High household wealth		8.75	0.81	20.06	2.19	2.79	5.54	ns	ns
Father's occupation-non manual		64.42	76.07	53.83	46.97	2.68	3.55	11.08	9.42
Average		17.63	19.49	22.23	25.44	4.63	4.67	6.99	11.54
Range		60.90	75.26	94.08	86.84	16.76	16.48	18.24	15.42

ns – not significant at a 10% level. ^aPercentage difference very large but based on small values. ^bBased on small values. All four Ghana models not very different.
All models are adjusted for region and place of residence

**Table 6. Design Effects for logistic regression models
(Ratio of standard errors of Model BIII and BI)**

Parameter Estimate	Malawi	Tanzania	Zambia	Zimbabwe	Ghana
Child's age	1.16	1.42	1.08	1.05	1.04
Age squared	1.1	1.38	1	1.1	1.04
Sex-female	1.14	1.40	1.06	1.12	1.03
Size of baby at birth	1.16	0.97	0.98	1.16	0.93
Still breastfeeding	1.17	1.14	1.07	1.01	0.96
Preceding interval (< 24 months)	1.23	1.51	1.09	1.03	1
Preceding interval (24+months)	1.13	1.26	1.06	1.05	0.97
No prenatal care	1.18	1.12	0.86	1.23	0.98
Place of delivery – home	1.15	1.27	1.05	1.06	1
Maternal height	1.17	1.12	1.04	1.07	0.98
Maternal weight	1.12	1.37	0.96	1.08	1
Medium Household wealth	1.21	1.29	1.19	0.99	1.09
High household wealth	1.06	1.07	1.07	1.08	1.04
Father's occupation-non manual	1.09	1.36	1	1.05	0.99
Average	1.15	1.26	1.04	1.08	1.00