Journal of Official Statistics, Vol. 26, No. 2, 2010, pp. 341–359

# District-level Estimates of Institutional Births in Ghana: Application of Small Area Estimation Technique Using Census and DHS Data

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The Ghana Health Service functions under a decentralised approach; however, the lack of district level statistics implies that local authorities are faced with difficulties in making policy decisions without relevant statistics. The Ghanain Demographic and Health Surveys provide a range of invaluable data at the regional/national level; they cannot be used directly to produce reliable district-level estimates due to small sample sizes. This article uses small area estimation techniques to derive model-based district-level estimates of institutional births in Ghana by linking data from the 2003 GDHS and the 2000 Population and Housing Census. The models indicate considerable variability in the estimates, with institutional births ranging between 7% and 27% in the districts of the Northern region, compared to 78% and 85% in the districts of the Greater Accra Region. The diagnostic measures indicate that the model-based estimates are reliable and representative of the district to which they belong.

*Key words:* Institutional births; demographic and health surveys; Census; small area estimates; districts; Ghana.

## 1. Introduction

The demand for small area statistics has grown tremendously in recent years, especially in the context of decentralised approaches to population planning and resource allocation. This is particularly the case in less developed countries, for example in Sub-Saharan Africa where there are considerable spatial inequalities with regard to the distribution and use of health resources (WHO 2000; UN-HABITAT 2004). In many African settings small area statistics are almost nonexistent, except for census data which provide restricted data on socioeconomic and population indicators. Moreover, population censuses in these countries tend to be less regular due to high costs involved in the production of such data. For instance, since independence Ghana has had only

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**Acknowledgments:** The authors gratefully acknowledge the constructive comments from the referees and the editor.

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four censuses, in 1960, 1970, 1984 and 2000, which indicates that they are becoming less frequent over the period of time.

In contrast, cross-sectional surveys, such as the Demographic and Health Surveys (DHS), have become more regular and they collect a substantial amount of nationally representative data. Ghana has had four rounds of DHS in the years 1988, 1993, 1998 and 2003. Whilst the DHS can provide reliable national and regional level estimates of important demographic and health indicators, they cannot be used to derive reliable direct estimates at the district level owing to small sample sizes which lead to high levels of sampling variability (Pfeffermann 2002; Rao 2003). A solution to this problem is to consider small area estimation (SAE) techniques. SAE is based on model-based methods. The idea is to use statistical models to link the variable of interest with auxiliary information, e.g., census and administrative data, for the small areas to define model-based estimators for these areas. In other words, if the area-specific direct estimators do not provide adequate precision, then in making estimates for small area quantities it is necessary to employ model-based estimators that "borrow strength" from other areas. The small areas defined in our study are the districts[5] of Ghana.

Small area models can be classified into two broad types:

i) area level random effect models, which are used when auxiliary information is available only at area level. They relate small area direct estimates to area-specific covariates (Fay and Herriot 1979),
ii) nested error unit level regression models, proposed originally by Battese, Harter and Fuller (1988). These models relate the unit values of a study variable to unit-specific covariates.

We adopt the area level model since covariates are available only at the district level. The application of SAE techniques is well acknowledged in public health and epidemiological research (Qiao 2005; Jia et al. 2004; Twigg and Moon 2002; Malec, Davis, and Cao 1999) and also in other fields of social sciences (Elbers et al. 2003) but has not been explored with demographic data from sub-Saharan Africa.

This article uses SAE techniques to derive model-based district level estimates of institutional births in Ghana by linking data from the 2003 Ghanian DHS (GDHS) and the 2000 Population and Housing Census (GPHC). Our aim is to derive district-level estimates of the proportion of births in health institutions. This research provides a detailed illustration of how the GDHS and census data can be combined to derive robust small area estimates for a policy-relevant maternal health care indicator. An understanding of local (district) area variations in the distribution of institutional births is pertinent especially in the Ghanaian context where both maternal and infant mortality are high (GSS, NMIMR, and ORC Macro 2004; Mills and Bertrand 2005; Thaddeus and Maine 1994). Evidence from previous studies shows that the type of delivery care, especially that involving the attendeance of health professionals with midwifery skills

[5] The districts in this study refer to the 110 districts created as part of the political decentralisation of Ghana in 1988 and adopted for the 2000 Ghana Population and Housing Census.

who can perform normal deliveries, diagnose, manage and treat delivery complications, has an effect on maternal and child survival (Koblinsky et al. 2006; Mills and Bertrand 2005; Ronsmans et al. 2002; Ronsmans and Graham 2006; Marsh et al. 2002). Home births in sub-Saharan Africa, unlike in most European countries, are predominantly attended by unskilled persons and take place in unhygienic environments where access to emergency obstetric care is limited and the needed referral services are usually not available (Geller et al. 2005; Kyomuhendo 2003; Ramarao et al. 2001; Wall 1998). A higher proportion of these births are associated with complications, in some cases leading to maternal and child deaths (Geller et al. 2005; Ramarao et al. 2001; Sule-Odu 2000). Increasing skilled attendants at delivery within districts was one of the primary goals enunciated in the Ghana Health Services and Teaching Hospitals Act 525 and it was further stressed in the Millennium Development Goals framework (Kumi-Kyereme et al. 2006; Crawford 2004).

Ghana, with a population of 18,912,079 is divided into ten regions and 110 administrative districts (Ghana Statistical Service 2002). The three northern regions account for 17.5% of the population (Northern – 9.6%, Upper West – 3.0%, Upper East – 4.9%) and are the most poorly developed regions in terms of extreme poverty incidence (World Bank 2003; Vanderpauye-Orgle 2002). They are characterized by low levels of education, high fertility rates, short birth intervals, high infant and child deaths and poor access to health services (GSS, MoH and ORC Macro 2003; GSS, NMIMR and ORC Macro 2004). Estimates from the Ghana Living Standards Survey (2000) show that the mean annual per capita income is ¢210,000 for the Northern region, ¢206,000 for the Upper West and ¢321,000 for the Upper East, compared to ¢932,000 for the Greater Accra region and ¢622,000 for the Ashanti region (Ghana Statistical Service 2000). The Greater Accra region, which constitutes 15.4% of the national population, is the most urbanised region in the country and is made up of a conglomeration of economically vibrant districts including major ports, harbours, industries and political and commercial headquarters. The Ashanti, Brong Ahafo and Eastern regions, which are the prime cocoa, timber and mineral producing areas, constitute 19.1%, 9.6% and 11.1% of the population, respectively. The Western region, which borders Côte d'Ivoire, has a vibrant harbour and is characterised by numerous small and large-scale gold mines. In recent times, the Greater Accra and Ashanti regions have experienced a high influx of migrants from rural areas resulting in the growth of slum communities and urban poverty in these regions (Ghana Statistical Service 2002). The Volta region constitutes 8.6% of the population and is made up of agriculture and fishing communities with 4 out of every 5 people being self-employed (Ghana Statistical Service 2002). The Central region constitutes 8.4% of the population. Fishing and agriculture are the main economic activities in this region.

## 2. Data

As described in the previous section, this article uses an area level model to derive the district level estimates. In general, two types of variables are required for this analysis. The dependent (or target) variable for which small area estimates are required is drawn from the 2003 GDHS and the auxiliary variables (covariates) known for the entire population are drawn from the 2000 GPHC. Our main variable of interest is the place of childbirth. That is, the proportion of institutional births recorded in the 2003 GDHS (GSS, NMIMR and ORC Macro 2004). Analysis of the GDHS data shows that institutional births were attended by skilled health personnel (doctors, nurses and midwives), while home births were attended by unskilled attendants including traditional birth attendants and other relatives and friends (GSS, NMIMR, and ORC Macro 2004). The GDHS is a nationally representative survey aimed at collecting detailed information on demographic and health indicators. It adopts a multi-stage stratified sampling technique and administers face-to-face interviews at the household and individual levels. The 2003 GDHS collected data from 5,691 women aged 15–49 belonging to 6,251 households from the 110 districts of Ghana. The overall response rate for the 2003 GDHS was 93% (GSS, NMIMR and ORC Macro 2004). The 2003 GDHS was weighted to adjust for over-sampling in some regions.

The GDHS asked mothers of all children born in the five years preceding the survey about the assistance received for each delivery and the child's place of birth. The details regarding birthplace and other health-related information are available only for pregnancies that resulted in a birth in the five years preceding the survey. The outcome variable considered in the analysis is the proportion of institutional (hospitals, clinics, midwifery units) births. To retain the statistical power of the model, we considered 2,757 births including still-born (of these, 353 births occurred within the census window during April 1999–March 2000) during the five years preceding the GDHS (1999–2003). If a woman had more than two births in the period, we selected the most recent birth, for two reasons. First, the respondents (mothers) are likely to provide accurate responses for their recent birth experience. Second, our data investigations showed that there is high dependence or correlation in the choice of place of delivery. For example, if a woman had two children resulting from two pregnancies then she is likely to have given birth in the same place (home/institution). The modelling and estimation procedures are discussed in detail in the methodology section.

The auxiliary variables (covariates) derived from the 2000 GPHC included district-level data on the proportion of women of reproductive age, the total fertility rates (TFR) and the region of residence. The timing of the birth was added as a covariate to capture the period effect, particularly concerning births that occurred within the census window. The timing of births were categorised into three: births within census window and those prior to and after the census window. We used Principal Component Analysis (PCA) to derive a composite score for socio-economic development based on the following variables: literacy rate, employment rate, educational levels, level of urbanisation and employment in different sectors of the economy. A second PCA was carried out to determine access to health care services using the following variables; mean distance to the nearest traditional health facility, mean distance to the nearest hospital and mean distance to the nearest clinic. The reader is referred to Dunteman (1989) and Jolliffe (2002) for a more detailed discussion on PCA. The first principal component for socio-economic development explained 67% of the variability in the dataset, while adding the component for access to health care services explained 88%. It has to be noted that there are other indicators of access to care such as quality of care, access to drugs, hospital opening hours, user fees, confidence in the service providers and attitudes of health professionals (IMMPACT 2005; Opoku et al. 1997; D'Ambruoso, Abbey and Hussein 2005). However, the present analysis did not consider these indicators due to data limitations.

Using covariates from the 2000 Census to model births recorded in the survey may raise issues of comparability. However, using a combination of variables to derive composite indices minimises these effects. This is because not all the estimates for the selected variables will change significantly over a short period of time. Also, it is standard practice for all Demographic and Health Surveys to follow a five-year period for analysing birth history data (www.measuredhs.com).

The 2000 GPHC listing of Enumeration Areas (EAs), also referred to as Primary Sample Units (PSUs), was the sample frame adopted for the 2003 GDHS. PSUs were sampled from all the 110 districts of Ghana. The sampling design adopted stratifies the target population by districts. Since the 2000 GPHC was the sample frame adopted for the 2003 GDHS, the matching of survey information to the census covariates at the district level was straightforward.

## 3. Methodology

We now present the methodological framework used to derive the model-based estimates at district level and their standard errors. Let $N_d$ and $n_d$ be the population and sample sizes in district $d$ ($d = 1, \ldots, D$) respectively, where $D = 110$ is the number of districts (or small areas) in the population. More specifically, we specify $N_d$ as the total number of births in the $d$th district recorded in the GPHC and $n_d$ is the number of births recorded in the $d$th district based on GDHS data. Therefore, $N_d$ refers to births in the twelve months prior to the Census day (26 March 2000) and $n_d$ is the small sample of births recorded by the survey in the same period. Let $y_d$ denote the value of a response variable $y$ in the $d$th district, that is, the number of institutional births in the $d$th district. The subscript $d$ denotes the quantities belonging to district $d$. In addition, we used an extra subscript of $s$ and $r$ to denote the quantities related to the sample and nonsample parts of the population such that $y_{sd}$ and $y_{rd}$ are the sample and nonsample counts of institutional births in district $d$. Thus, the response variable $y_{sd}$ follows a binomial distribution with parameters $n_d$ and $\pi_d$, that is $y_{sd} \sim Bin(n_d, \pi_d)$, whilst $y_{rd} \sim Bin(N_d - n_d, \pi_d)$, where $\pi_d$ is the probability of an institutional birth in district $d$. Hereafter we refer to this probability as the probability of a "success." Further, $y_{sd}$ and $y_{rd}$ are assumed to be independent binomial variables with $\pi_d$ being common success probabilities. Let $\mathbf{x}_d$ be the $k$-vector of the covariates for district $d$. With these notations, the model linking the success probabilities with the covariates is the logistic linear mixed model of the form

$$logit(\pi_d) = \ln\left\{\frac{\pi_d}{1-\pi_d}\right\} = \eta_d = \mathbf{x}_d'\boldsymbol{\beta} + u_d, \quad d = 1, \ldots, 110 \tag{1}$$

with $\pi_d = \exp(\eta_d)\{1 + \exp(\eta_d)\}^{-1}$. Here $\boldsymbol{\beta}$ is the $k$-vector of unknown fixed effects parameters and $u_d \overset{ind}{\sim} N(0, \phi)$ is the random effect that accounts for between district variability beyond that explained by the covariates included in the model. Model (1) relates the area level proportions to area level covariates. In reality, we assume that the proportions within a district will be stable over the five-year period. This type of model is often referred to as "area-level" model in SAE terminology (see Rao 2003). Such a model was originally used by Fay and Herriot (1979) for the prediction of mean per-capita income (PCI) in small geographical areas (less than 500 persons) within counties in the United States. We note that the Fay and Herriot method for SAE is based on the area level linear mixed model and their approach is applicable to a continuous variable. In contrast, model (1) is a special case of a generalised linear mixed model (GLMM) with logit link function (Breslow and Clayton 1993) and suitable for discrete, particularly binary variables. It is noteworthy that the Fay and Herriot model is not applicable in such cases. Alternative approaches to estimating the logistic model in the small area estimation case include empirical Bayes and hierarchical Bayes (Rao 2003). We have not considered these options in this article; instead we have applied a special case of GLMM with logit link function due to the binomial nature of the outcome variable. Saei and Chambers (2003) described this model in the context of SAE. By definition, the means of $y_{sd}$ and $y_{rd}$ given $u_d$ under Model (1) are:

$$E(y_{sd}|u_d) = n_d\left[\exp\left(\mathbf{x}_d'\boldsymbol{\beta} + u_d\right)\left\{1 + \exp\left(\mathbf{x}_d'\boldsymbol{\beta} + u_d\right)\right\}^{-1}\right] \tag{2}$$

$$E(y_{rd}|u_d) = (N_d - n_d)\left[\exp\left(\mathbf{x}_d'\boldsymbol{\beta} + u_d\right)\left\{1 + \exp\left(\mathbf{x}_d'\boldsymbol{\beta} + u_d\right)\right\}^{-1}\right] \tag{3}$$

The total number of institutional births in district $d$ is $T_d = y_{sd} + y_{rd}\,(d = 1, \ldots, 110)$. The first term $y_{sd}$, the sample count (i.e., the direct estimates from survey) for the census window, is known, whereas the second term, $y_{rd}$, the nonsample count, is unknown. Thus, an estimate $\hat{T}_d$ of the total number of institutional births in district $d$ is obtained by replacing $y_{rd}$ by its predicted value under Model (1). That is,

$$\hat{T}_d = y_{sd} + \hat{y}_{rd} = y_{sd} + (N_d - n_d)\left[\exp\left(\mathbf{x}_d'\hat{\boldsymbol{\beta}} + \hat{u}_d\right)\left\{1 + \exp\left(\mathbf{x}_d'\hat{\boldsymbol{\beta}} + \hat{u}_d\right)\right\}^{-1}\right] \tag{4}$$

To ensure consistency between $N_d$ and $n_d$, $\hat{T}_d$ was estimated using only births within the census window. The proportion $p_d$ of institutional births in a district $d$ is obtained as the births that occurred in a health institutions to the total number of births within that district. Thus, an estimate of $p_d$ is

$$\hat{p}_d = \frac{\hat{T}_d}{N_d} \tag{5}$$

For the estimation of unknown parameters in (4) or (5), we used an iterative procedure that combines the Penalized Quasi-Likelihood (PQL) estimation of $\boldsymbol{\beta}$ and $\mathbf{u} = (u_1, \ldots, u_D)$ with restricted maximum likelihood (REML) estimation of $\phi$ as described in Saei and Chambers (2003) and Manteiga et al. (2007). In particular, we adopted the Saei and Chambers (2003) algorithm for the parameter estimation.

We computed the mean squared error (MSE) estimates for (5) in order to assess the reliability of the estimates and to construct the confidence interval (CI) for these estimates. Following Saei and Chambers (2003) and Manteiga et al (2007), the mean squared error estimate of (5) under Model (1) is expressed as

$$mse(\hat{p}_d) = M_1(\hat{\phi}) + M_2(\hat{\phi}) + 2M_3(\hat{\phi}) \tag{6}$$

In Expression (6) the first two components $M_1$ and $M_2$ constitute the largest part of the overall MSE estimates. These are the MSE of the best linear unbiased predictor-type estimator when $\phi$ is assumed known (see Rao 2003). The third component, $M_3$, is the variability due to the estimate of $\phi$. For an analytical expression of these components of MSE, we denote by $\hat{\mathbf{V}}_{sd} = diag\{n_d\hat{p}_d(1-\hat{p}_d)\}$ and $\hat{\mathbf{V}}_{rd} = diag\{(N_d - n_d)\hat{p}_d(1-\hat{p}_d)\}$, the diagonal matrices defined by the variances of the sample and nonsample part, respectively. Let $\mathbf{A} = \{diag(N_d^{-1})\}\hat{\mathbf{V}}_{rd}$, $\mathbf{B} = \{diag(N_d^{-1})\}\hat{\mathbf{V}}_{rd}\boldsymbol{X}_r - \mathbf{A}\hat{\boldsymbol{T}}_s\hat{\mathbf{V}}_{sd}\boldsymbol{X}_s$ and $\hat{\boldsymbol{T}}_s = (\phi^{-1}\mathbf{I}_D + \hat{\mathbf{V}}_{sd})^{-1}$, where $\boldsymbol{X}_s$ and $\boldsymbol{X}_r$ are the sample and nonsample part of auxiliary information and $\mathbf{I}_D$ is an identity matrix of order $D$. Further we write $\mathbf{T}_{11} = \{\boldsymbol{X}_s'\hat{\mathbf{V}}_{sd}\boldsymbol{X}_s - \boldsymbol{X}_s'\hat{\mathbf{V}}_{sd}\hat{\mathbf{T}}_s\hat{\mathbf{V}}_{sd}\boldsymbol{X}_s\}^{-1}$ and $\hat{\mathbf{T}}_{22} = \hat{\mathbf{T}}_s + \hat{\mathbf{T}}_s\hat{\mathbf{V}}_{sd}\boldsymbol{X}_s T_{11}\boldsymbol{X}_s'\hat{\mathbf{V}}_{sd}'\hat{\mathbf{T}}_s$. With these notations, assuming Model (1) holds, the components of (6) are

$$M_1(\hat{\phi}) = \mathbf{A}\hat{\mathbf{T}}_s\mathbf{A}'$$

$$M_2(\hat{\phi}) = \mathbf{B}\mathbf{T}_{11}\mathbf{B}', \text{ and}$$

$$M_3(\hat{\phi}) = trace\left(\hat{\nabla}_i\hat{\boldsymbol{\Sigma}}\hat{\nabla}_j'v(\hat{\phi})\right) \text{ with } \hat{\boldsymbol{\Sigma}} = \hat{\mathbf{V}}_{sd} + \hat{\phi}\mathbf{I}_D\hat{\mathbf{V}}_{sd}\hat{\mathbf{V}}_{sd}'$$

Here $v(\hat{\phi})$ is the asymptotic covariance matrix of the estimates of variance components $\hat{\phi}$, which can be evaluated as the inverse of the appropriate Fisher information matrix for $\hat{\phi}$. This also depends upon whether we are using maximum likelihood or restricted maximum likelihood (REML) estimates for $\hat{\phi}$. For REML estimates for $\hat{\phi}$, used in this article, $v(\hat{\phi}) = 2\left(\hat{\phi}^{-2}(D-2t_1) + \hat{\phi}^{-4}t_{11}\right)^{-1}$ with $t_1 = \hat{\phi}^{-1}\,trace\,(\hat{\mathbf{T}}_{22})$ and $t_{11} = trace\,(\hat{\mathbf{T}}_{22}\hat{\mathbf{T}}_{22})$. Let us write $\Delta = \mathbf{A}\hat{\boldsymbol{T}}_s$ and $\hat{\nabla}_i = \partial(\Delta_i)/\partial\phi\big|_{\phi=\hat{\phi}} = \partial(\boldsymbol{A}_i\hat{\boldsymbol{T}}_s)/\partial\phi\big|_{\phi=\hat{\phi}}$, where $\boldsymbol{A}_i$ is the $i$th row of the matrix $\boldsymbol{A}$. The analysis was conducted using R version 2.7.

## 4. Diagnostic Procedures

Usually two types of diagnostics are carried out while implementing SAE procedures: the model diagnostics and the diagnostics for the small area estimates. These are described below.

### *4.1. Model Diagnostics*

The model diagnostics are used to verify that the model assumptions are satisfied. Recall that in the logit link (see Section 3), the district level random effects were assumed to have a normal distribution with mean zero and variance $\phi$. If the model assumptions are satisfied then the area (district) level residuals are expected to be randomly distributed and not significantly different from the regression line $y = 0$, where under Model (1) the district level residuals are given by $r_d = \hat{\eta}_d - \mathbf{x}_d'\hat{\boldsymbol{\beta}}$ $(d = 1, \ldots, 110)$. Figure 1(a) shows the distribution of the district level residuals. The figure shows that the randomly distributed district level residuals and the line of fit do not significantly differ from the line

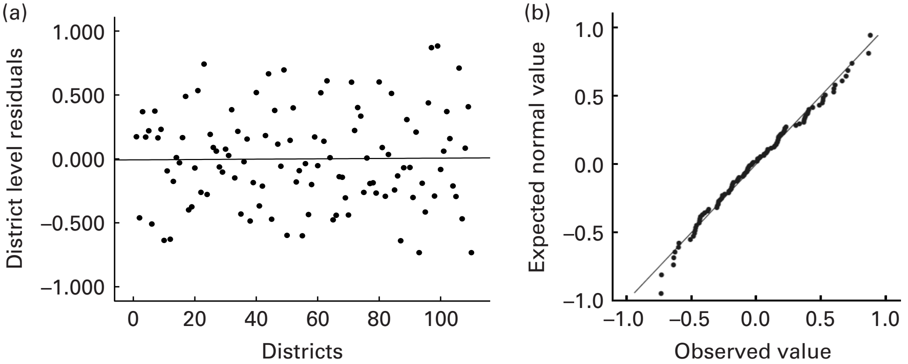


*Fig. 1. (a) Model diagnostic plot showing the distribution of the district level residuals. (b) q-q plot of the district level residuals*

$y = 0$ as expected. The q-q plot shown in Figure 1(b) also confirms the normality assumption.

### 4.2. *Diagnostics for Small Area Estimates*

The aim of this diagnostics procedure is to validate the reliability of the model-based small area estimates given by (5). We used the bias diagnostics together with the coefficient of variation and computed the 95% CIs of the model-based estimates (using the MSE derived using Equation 6) to validate the robustness of our model-based estimates relative to the direct estimates. The bias diagnostics are used to investigate if the model-based estimates are less extreme than the direct survey estimates. The direct estimates are calculated with survey weights. The direct estimates from the GDHS were

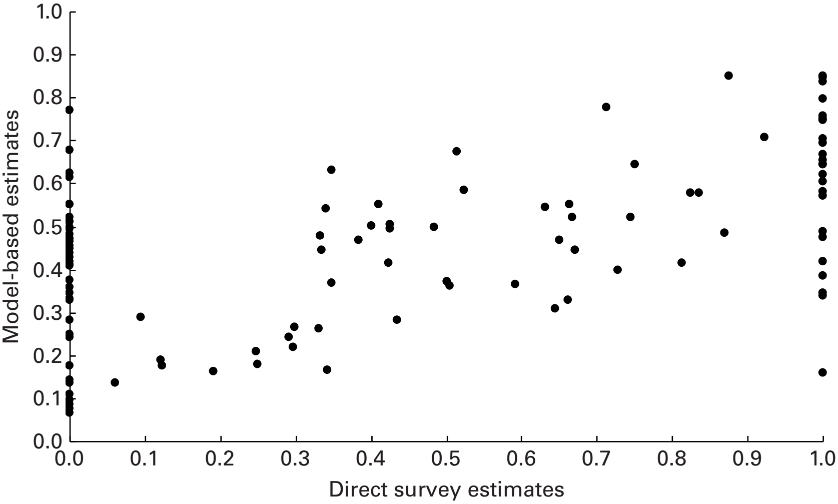


*Fig. 2. Bias Diagnostics*

estimated for only births within the census window. Figure 2 shows the bias scatter plot of the model-based estimates against that of the direct survey estimates. The figure shows that the model-based estimates are less extreme than the direct survey estimates, demonstrating the typical SAE outcome of shrinking more extreme values towards the mean. It has to be noted that districts with extreme direct survey estimates are mainly those with small sample sizes.

We computed the coefficient of variation (CV) to assess the improved precision of the model-based estimates compared to the direct survey estimates. The CVs show the sampling variability as a percentage of the estimate. Estimates with large CVs are considered unreliable. There are no internationally accepted tables available that allow us to judge what is "too large." Nonetheless the estimated CVs show that the model-based estimates have a higher degree of reliability than the (nonzero) direct survey estimates – the estimated CVs for the model-based estimates range between 1% and 33%, with 102 out of the 110 districts having CVs lower than 25%. The estimated CVs for direct survey estimates range between 29% and 392%. Approximate CIs for the direct estimates were calculated assuming that a simple random sample generated the weighted proportions. This ignores the effects of differential weighting and clustering within districts that would further inflate the true standard errors of the direct estimates. Figure 3 shows the 95% CIs for the model-based and approximate intervals for the direct survey estimates. The standard errors of the direct survey estimates are too large and therefore the estimates are unreliable.

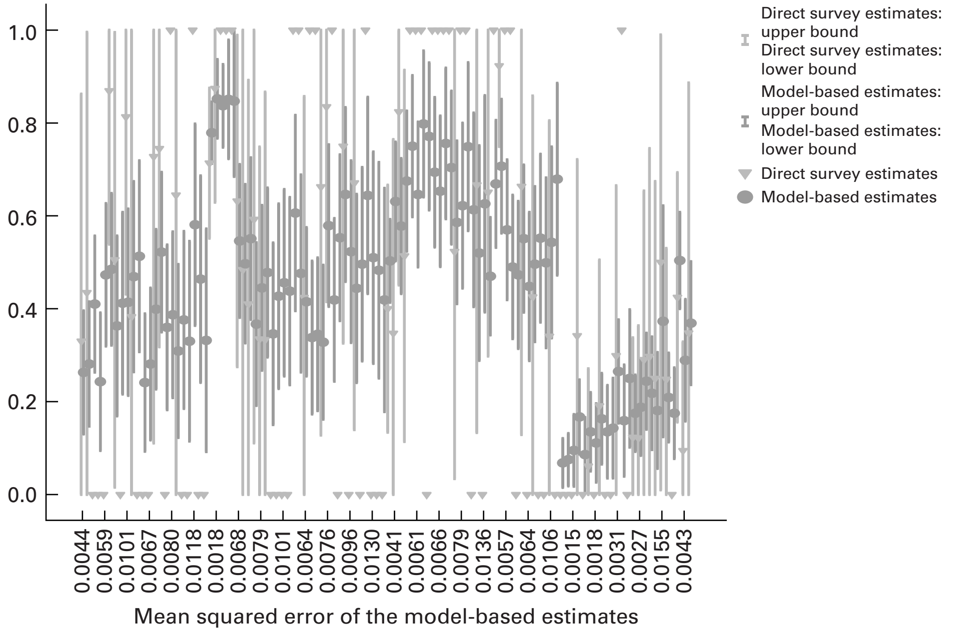


*Fig. 3. 95% Confidence intervals for model-based and direct estimates. Notes: The mean squared errors of the model-based estimates are ordered by regions in ascending order*

## 5. District-level Estimates

The diagnostic measures show that the estimates generated from the model-based approach are reliable and representative of the areas to which they belong. We mapped the model-based and direct survey estimates of the percentage of institutional births by district (Figures 4(a) and (b)). A comparison of the two maps shows that the model-based estimates are more stable and useful for resource allocation and policy decision-making. The bold lines in the figures show the regional boundaries and the thin lines are the district boundaries. The model-based and direct estimates from the births in the census year and their 95% CIs for individual districts are shown in Appendix I. For ease of understanding, we interpret the results in terms of percentages and not proportions. We hereafter interpret the results from the model-based approach. The estimates confirm a high degree of inequalities with regard to the distribution of institutional births. The estimates show that institutional births range from 7% in the Yendi district of the Northern region to 85% in the Ga district of the Greater Accra region. Institutional births are relatively low in the districts of the three Northern regions (Northern, Upper East and Upper West). For example, the East Mamprusi district was estimated to have the highest percentage (27%) of institutional births in the Northern region. This clearly suggests poor availability of institutional delivery care across the districts of the Northern region; the share of institutional births in most districts of the three Northern regions is way below the average for those in least developed countries (WHO 2007). The results for the three Northern regions also mimic the spatial variation in poverty levels – more than 40% of the population live in poverty in this region (Vanderpauye-Orgle 2002;

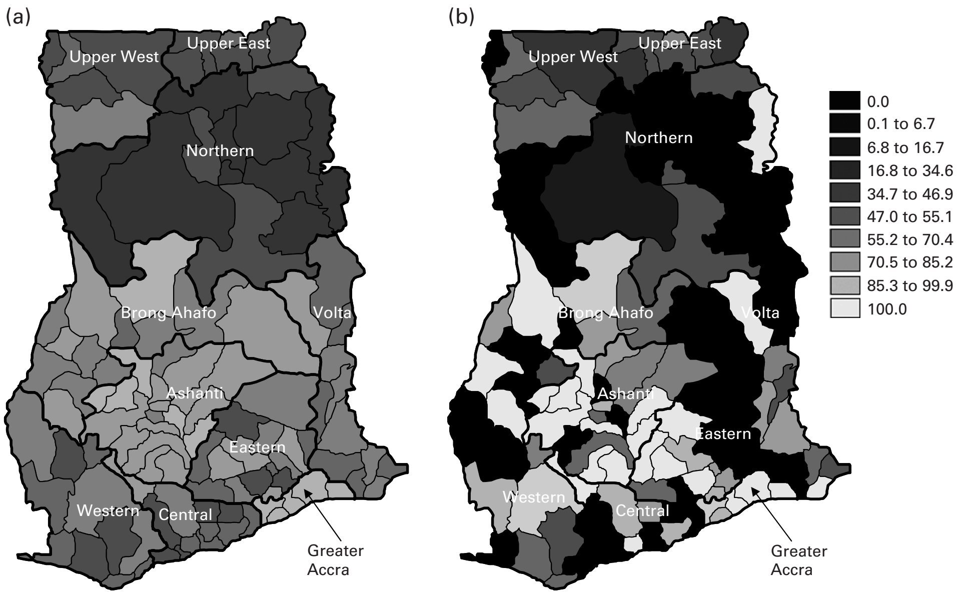


*Fig. 4. (a) Model-based estimates showing percentage of institutional births. (b) Direct estimates showing percentage of institutional births*

World Bank 2003), and these people are also the most disadvantaged in terms of access to health care services (Ghana Statistical Service, Ministry of Health and ORC Macro 2004).

Institutional care uptake is also poor in the coastal districts of the Central and Western regions. In most of the coastal districts, the percentages of institutional births vary between 17% and 47%. The districts in the Greater Accra and Ashanti regions, the two most developed regions in Ghana, unsurprisingly have the highest percentage of institutional deliveries. In the Greater Accra region, the distribution of institutional births ranges from 78% in the Accra Metropolis to 85% in the Ga district. The relatively low uptake of institutional delivery care in the Accra Metropolis compared to the rest of the Greater Accra region may be due to the growth of slum communities in the area as a result of migration from rural areas (Ghana Statistical Service 2002). Similar patterns are observed in the Kumasi Metropolis.

## 6. Discussion

This article demonstrates the application of small area estimation techniques to derive district level statistics of institutional births in Ghana using survey and census data. Although the SAE method for estimating proportions is well-developed (Saei and Chambers 2003; Manteiga et al. 2007), there is limited application in social sciences research. This article illustrates that the SAE method for estimating proportions is feasible with the type of outcome we have estimated.

An evaluation of the diagnostic measures confirms reasonably good precision of the model-based district estimates. The application of small area analysis is the first of its kind in the country, which lacks infrastructure and resources to collect representative data at the district level. The data from the census are usually limited as they tend to focus mainly on the basic socio-demographic and economic data. The GDHS, on the other hand, contributes to providing estimates at the regional and the national level. However, it is known that regional and national estimates usually mask variations (heterogeneity) at the district level and render little information for local-level planning and allocation of resources.

In the case of Ghana which has high levels of infant and maternal mortality, the availability of district-level data on health indicators is vital to monitoring health and facilitating a decentralised approach to health policy and planning. The district-level estimates derived from the analysis also confirm a high degree of inequalities with regard to the uptake of institutional delivery care. The district-level variations seen in the distribution of institutional care at birth highlight the urgent need for appropriate policy interventions to monitor the supply and utilisation of skilled care at childbirth in Ghana. The targets set by the UN General Assembly to achieve 80% skilled attendance at birth seem a distant goal in most districts of Ghana (AbouZahr and Wardlaw 2001; WHO 2006). This study has shown that with the availability of good auxiliary information and relevant survey data, policy-relevant local-level statistics could be derived to complement censuses which are limited in the amount of information they collect and are becoming less regular in sub-Saharan Africa.

## Appendix

*Appendix I: Model-based estimates of proportion of institutional births*

| Region/district | Model-based estimates | | | | Direct estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Standard error | 95% CI | | Estimate | Standard error | 95% CI | |
| | | | Lower bound | Upper bound | | | Lower bound | Upper bound |
| Western Region | | | | | | | | |
| JOMORO | 0.41 | 0.10 | 0.22 | 0.61 | 0.00 | 0.00 | 0.00 | 0.00 |
| NZIMA EAST | 0.28 | 0.07 | 0.15 | 0.42 | 0.43 | 0.29 | 0.00 | 1.00 |
| AHANTA WEST | 0.47 | 0.10 | 0.26 | 0.67 | 0.38 | 0.34 | 0.00 | 1.00 |
| SHAMA-AHANTA EAST | 0.41 | 0.07 | 0.26 | 0.56 | 0.00 | 0.00 | 0.00 | 0.00 |
| MPOHOR-WASSA EAST | 0.51 | 0.10 | 0.31 | 0.72 | 0.00 | 0.00 | 0.00 | 0.00 |
| WASSA WEST | 0.26 | 0.07 | 0.13 | 0.40 | 0.33 | 0.27 | 0.00 | 0.86 |
| WASSA AMENFI | 0.49 | 0.08 | 0.32 | 0.65 | 0.87 | 0.17 | 0.54 | 1.00 |
| AOWIN-SUAMAN | 0.41 | 0.10 | 0.21 | 0.61 | 0.81 | 0.19 | 0.43 | 1.00 |
| JUABESO-BIA | 0.47 | 0.08 | 0.32 | 0.63 | 0.00 | 0.00 | 0.00 | 0.00 |
| SEFWI WIASO | 0.24 | 0.07 | 0.09 | 0.39 | 0.00 | 0.00 | 0.00 | 0.00 |
| SEFWI BIBIANI | 0.36 | 0.10 | 0.17 | 0.56 | 0.51 | 0.25 | 0.02 | 1.00 |
| Central Region | | | | | | | | |
| KOMENDA-EDINA-EGYAFO-ABIREM | 0.24 | 0.07 | 0.09 | 0.39 | 0.00 | 0.00 | 0.00 | 0.00 |
| CAPE COAST | 0.33 | 0.12 | 0.09 | 0.57 | 0.00 | 0.00 | 0.00 | 0.00 |
| ABURA-ASEBU-KWAMANKESE | 0.39 | 0.09 | 0.21 | 0.57 | 1.00 | 0.00 | 1.00 | 1.00 |
| MFANTSIMAN | 0.36 | 0.09 | 0.18 | 0.54 | 0.00 | 0.00 | 0.00 | 0.00 |
| GOMOA | 0.40 | 0.09 | 0.23 | 0.57 | 0.73 | 0.31 | 0.11 | 1.00 |
| EFUTU-EWUTU-SENYA | 0.46 | 0.11 | 0.24 | 0.69 | 0.00 | 0.00 | 0.00 | 0.00 |
| AGONA | 0.28 | 0.08 | 0.12 | 0.44 | 0.00 | 0.00 | 0.00 | 0.00 |
| ASIKUMA-ODOBEN-BRAKWA | 0.31 | 0.09 | 0.12 | 0.50 | 0.64 | 0.34 | 0.00 | 1.00 |
| AJUMAKO-ENYAN-ESIAM | 0.38 | 0.10 | 0.19 | 0.57 | 0.00 | 0.00 | 0.00 | 0.00 |
| ASSIN | 0.52 | 0.09 | 0.35 | 0.69 | 0.74 | 0.22 | 0.32 | 1.00 |

*Appendix I: Continued*

| Region/district | Model-based estimates | | | | Direct estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Standard error | 95% CI | | Estimate | Standard error | 95% CI | |
| | | | Lower bound | Upper bound | | | Lower bound | Upper bound |
| LOWER DENKYIRA | 0.33 | 0.11 | 0.11 | 0.55 | 0.00 | 0.00 | 0.00 | 0.00 |
| UPPER DENKYIRA | 0.58 | 0.11 | 0.36 | 0.80 | 1.00 | 0.00 | 1.00 | 1.00 |
| Greater Accra Region | | | | | | | | |
| ACCRA METROPOLITAN | 0.78 | 0.03 | 0.71 | 0.85 | 0.71 | 0.08 | 0.55 | 0.88 |
| GA | 0.85 | 0.04 | 0.77 | 0.94 | 0.87 | 0.13 | 0.63 | 1.00 |
| TEMA | 0.84 | 0.04 | 0.75 | 0.93 | 1.00 | 0.00 | 1.00 | 1.00 |
| DANGME WEST | 0.85 | 0.06 | 0.72 | 0.98 | 1.00 | 0.00 | 1.00 | 1.00 |
| DANGME EAST | 0.85 | 0.08 | 0.68 | 1.00 | 1.00 | 0.00 | 1.00 | 1.00 |
| Volta region | | | | | | | | |
| SOUTH TONGU | 0.46 | 0.10 | 0.26 | 0.66 | 0.00 | 0.00 | 0.00 | 0.00 |
| KETA | 0.48 | 0.11 | 0.26 | 0.69 | 1.00 | 0.00 | 1.00 | 1.00 |
| KETU | 0.45 | 0.09 | 0.27 | 0.62 | 0.33 | 0.21 | 0.00 | 0.75 |
| AKATSI | 0.55 | 0.09 | 0.38 | 0.73 | 0.41 | 0.25 | 0.00 | 0.89 |
| NORTH TONGU | 0.43 | 0.10 | 0.23 | 0.63 | 0.00 | 0.00 | 0.00 | 0.00 |
| HO | 0.55 | 0.08 | 0.38 | 0.71 | 0.63 | 0.18 | 0.27 | 0.99 |
| KPANDU | 0.37 | 0.09 | 0.19 | 0.54 | 0.59 | 0.25 | 0.11 | 1.00 |
| HOHOE | 0.48 | 0.09 | 0.30 | 0.66 | 0.33 | 0.27 | 0.00 | 0.87 |
| JASIKAN | 0.50 | 0.09 | 0.33 | 0.67 | 0.48 | 0.35 | 0.00 | 1.00 |
| KADJEBI | 0.35 | 0.10 | 0.15 | 0.54 | 0.00 | 0.00 | 0.00 | 0.00 |
| NKWANTA | 0.44 | 0.10 | 0.24 | 0.64 | 0.00 | 0.00 | 0.00 | 0.00 |
| KRACHI | 0.61 | 0.11 | 0.40 | 0.82 | 1.00 | 0.00 | 1.00 | 1.00 |
| Eastern Region | | | | | | | | |
| BIRIM NORTH | 0.42 | 0.09 | 0.24 | 0.59 | 1.00 | 0.00 | 1.00 | 1.00 |
| BIRIM SOUTH | 0.42 | 0.08 | 0.26 | 0.58 | 0.42 | 0.22 | 0.00 | 0.86 |
| WEST AKIM | 0.52 | 0.10 | 0.33 | 0.72 | 0.00 | 0.00 | 0.00 | 0.00 |

*Appendix I: Continued*

| Region/district | Model-based estimates | | | | Direct estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Standard error | 95% CI | | Estimate | Standard error | 95% CI | |
| | | | Lower bound | Upper bound | | | Lower bound | Upper bound |
| KWAEBIBIREM | 0.64 | 0.11 | 0.43 | 0.86 | 1.00 | 0.00 | 1.00 | 1.00 |
| SUHUM-KRABOA-COALTAR | 0.34 | 0.08 | 0.17 | 0.50 | 1.00 | 0.00 | 1.00 | 1.00 |
| EAST AKIM | 0.58 | 0.09 | 0.40 | 0.75 | 0.83 | 0.21 | 0.41 | 1.00 |
| FANTEAKWA | 0.51 | 0.11 | 0.28 | 0.74 | 0.00 | 0.00 | 0.00 | 0.00 |
| KOFORIDUA | 0.44 | 0.10 | 0.24 | 0.65 | 0.67 | 0.27 | 0.14 | 1.00 |
| AKWAPIM SOUTH | 0.65 | 0.09 | 0.46 | 0.83 | 0.75 | 0.22 | 0.33 | 1.00 |
| AKWAPIM NORTH | 0.33 | 0.08 | 0.16 | 0.49 | 0.66 | 0.27 | 0.13 | 1.00 |
| YILO KROBO | 0.50 | 0.10 | 0.29 | 0.70 | 0.00 | 0.00 | 0.00 | 0.00 |
| MANYA KROBO | 0.55 | 0.09 | 0.37 | 0.73 | 0.00 | 0.00 | 0.00 | 0.00 |
| ASUOGYAMAN | 0.42 | 0.12 | 0.18 | 0.66 | 0.00 | 0.00 | 0.00 | 0.00 |
| AFRAM PLAINS | 0.48 | 0.12 | 0.25 | 0.72 | 0.00 | 0.00 | 0.00 | 0.00 |
| KWAHU SOUTH | 0.35 | 0.08 | 0.18 | 0.51 | 1.00 | 0.00 | 1.00 | 1.00 |
| Ashanti Region | | | | | | | | |
| ATWIMA | 0.65 | 0.08 | 0.49 | 0.80 | 1.00 | 0.00 | 1.00 | 1.00 |
| AMANSIE WEST | 0.63 | 0.12 | 0.39 | 0.86 | 0.00 | 0.00 | 0.00 | 0.00 |
| AMANSIE EAST | 0.63 | 0.06 | 0.50 | 0.76 | 0.35 | 0.21 | 0.00 | 0.76 |
| ADANSI WEST | 0.65 | 0.08 | 0.49 | 0.82 | 1.00 | 0.00 | 1.00 | 1.00 |
| ADANSI EAST | 0.62 | 0.09 | 0.44 | 0.80 | 1.00 | 0.00 | 1.00 | 1.00 |
| ASHANTI AKIM SOUTH | 0.76 | 0.08 | 0.59 | 0.92 | 1.00 | 0.00 | 1.00 | 1.00 |
| ASHANTI AKIM NORTH | 0.69 | 0.08 | 0.53 | 0.86 | 1.00 | 0.00 | 1.00 | 1.00 |
| EJISU-JUABEN | 0.77 | 0.08 | 0.61 | 0.93 | 0.00 | 0.00 | 0.00 | 0.00 |
| BOSOMTWI KWANWOMA | 0.70 | 0.08 | 0.54 | 0.87 | 1.00 | 0.00 | 1.00 | 1.00 |
| KUMASI METROPOLITAN | 0.50 | 0.04 | 0.41 | 0.59 | 0.40 | 0.14 | 0.13 | 0.67 |
| KWABRE | 0.58 | 0.07 | 0.43 | 0.72 | 0.82 | 0.19 | 0.45 | 1.00 |
| AFIGYA SEKYERE | 0.61 | 0.10 | 0.40 | 0.82 | 0.00 | 0.00 | 0.00 | 0.00 |

*Appendix I: Continued*

| Region/district | Model-based estimates | | | | Direct estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Standard error | 95% CI | | Estimate | Standard error | 95% CI | |
| | | | Lower bound | Upper bound | | | Lower bound | Upper bound |
| SEKYERE EAST | 0.68 | 0.08 | 0.52 | 0.83 | 0.51 | 0.20 | 0.11 | 0.91 |
| SEKYERE WEST | 0.59 | 0.09 | 0.41 | 0.76 | 0.52 | 0.25 | 0.03 | 1.00 |
| EJURA SEKODUMASI | 0.52 | 0.12 | 0.29 | 0.75 | 0.67 | 0.27 | 0.13 | 1.00 |
| OFFINSO | 0.75 | 0.08 | 0.60 | 0.90 | 1.00 | 0.00 | 1.00 | 1.00 |
| AHAFO-ANO SOUTH | 0.80 | 0.08 | 0.64 | 0.96 | 1.00 | 0.00 | 1.00 | 1.00 |
| AHAFO-ANO NORTH | 0.75 | 0.09 | 0.57 | 0.93 | 1.00 | 0.00 | 1.00 | 1.00 |
| Brong-Ahafo Region | | | | | | | | |
| ASUNAFO | 0.67 | 0.07 | 0.53 | 0.81 | 1.00 | 0.00 | 1.00 | 1.00 |
| ASUTIFI | 0.50 | 0.09 | 0.32 | 0.68 | 0.00 | 0.00 | 0.00 | 0.00 |
| TANO | 0.54 | 0.10 | 0.34 | 0.75 | 0.34 | 0.24 | 0.00 | 0.81 |
| SUNYANI | 0.47 | 0.08 | 0.31 | 0.63 | 0.00 | 0.00 | 0.00 | 0.00 |
| DORMAA | 0.49 | 0.08 | 0.34 | 0.64 | 1.00 | 0.00 | 1.00 | 1.00 |
| JAMAN | 0.47 | 0.06 | 0.34 | 0.60 | 0.65 | 0.18 | 0.30 | 1.00 |
| BEREKUM | 0.68 | 0.10 | 0.47 | 0.89 | 0.00 | 0.00 | 0.00 | 0.00 |
| WENCHI | 0.57 | 0.08 | 0.42 | 0.72 | 1.00 | 0.00 | 1.00 | 1.00 |
| TECHIMAN | 0.45 | 0.08 | 0.29 | 0.61 | 0.00 | 0.00 | 0.00 | 0.00 |
| NKORANZA | 0.55 | 0.08 | 0.39 | 0.71 | 0.66 | 0.27 | 0.13 | 1.00 |
| KINTAMPO | 0.71 | 0.07 | 0.56 | 0.85 | 0.92 | 0.09 | 0.75 | 1.00 |
| ATEBUBU | 0.50 | 0.08 | 0.33 | 0.66 | 0.43 | 0.22 | 0.00 | 0.86 |
| SENE | 0.55 | 0.09 | 0.37 | 0.73 | 0.00 | 0.00 | 0.00 | 0.00 |
| Northern Region | | | | | | | | |
| BOLE | 0.08 | 0.03 | 0.02 | 0.13 | 0.00 | 0.00 | 0.00 | 0.00 |
| WEST GONJA | 0.14 | 0.04 | 0.05 | 0.22 | 0.06 | 0.11 | 0.00 | 0.27 |
| EAST GONJA | 0.17 | 0.04 | 0.09 | 0.25 | 0.34 | 0.19 | 0.00 | 0.72 |
| NANUMBA | 0.14 | 0.05 | 0.04 | 0.24 | 0.00 | 0.00 | 0.00 | 0.00 |

*Appendix I: Continued*

| Region/district | Model-based estimates | | | | Direct estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Standard error | 95% CI | | Estimate | Standard error | 95% CI | |
| | | | Lower bound | Upper bound | | | Lower bound | Upper bound |
| ZABZUGU-TATALI | 0.11 | 0.04 | 0.03 | 0.20 | 0.00 | 0.00 | 0.00 | 0.00 |
| SABOBA-CHEREPONI | 0.16 | 0.06 | 0.04 | 0.28 | 1.00 | 0.00 | 1.00 | 1.00 |
| YENDI | 0.07 | 0.03 | 0.02 | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 |
| GUSHIEGU-KARAGA | 0.14 | 0.05 | 0.04 | 0.25 | 0.00 | 0.00 | 0.00 | 0.00 |
| SAVELUGU-NANTON | 0.09 | 0.04 | 0.01 | 0.17 | 0.00 | 0.00 | 0.00 | 0.00 |
| TAMALE | 0.16 | 0.05 | 0.07 | 0.26 | 0.19 | 0.16 | 0.00 | 0.51 |
| TOLON-KUMBUNGU | 0.25 | 0.07 | 0.10 | 0.40 | 0.00 | 0.00 | 0.00 | 0.00 |
| WEST MAMPRUSI | 0.10 | 0.04 | 0.02 | 0.17 | 0.00 | 0.00 | 0.00 | 0.00 |
| EAST MAMPRUSI | 0.27 | 0.06 | 0.15 | 0.38 | 0.30 | 0.19 | 0.00 | 0.67 |
| Upper East Region | | | | | | | | |
| WA | 0.19 | 0.05 | 0.08 | 0.29 | 0.42 | 0.14 | 0.16 | 0.69 |
| NADAWLI | 0.22 | 0.06 | 0.10 | 0.34 | 0.25 | 0.14 | 0.00 | 0.53 |
| SISSALA | 0.37 | 0.12 | 0.12 | 0.62 | 0.09 | 0.12 | 0.00 | 0.33 |
| JIRAPA-LAMBUSSIE | 0.24 | 0.05 | 0.14 | 0.35 | 0.35 | 0.27 | 0.00 | 0.89 |
| LAWRA | 0.18 | 0.06 | 0.06 | 0.31 | 0.00 | 0.00 | 0.00 | 0.00 |
| Upper West Region | | | | | | | | |
| BUILSA | 0.18 | 0.04 | 0.09 | 0.26 | 0.12 | 0.12 | 0.00 | 0.36 |
| KASENA-NANKANA | 0.50 | 0.05 | 0.40 | 0.61 | 0.30 | 0.23 | 0.00 | 0.75 |
| BONGO | 0.21 | 0.05 | 0.11 | 0.30 | 0.50 | 0.25 | 0.01 | 0.99 |
| BOLGATANGA | 0.29 | 0.07 | 0.16 | 0.42 | 0.29 | 0.19 | 0.00 | 0.65 |
| BAWKU WEST | 0.37 | 0.07 | 0.24 | 0.50 | 0.25 | 0.22 | 0.00 | 0.67 |
| BAWKU EAST | 0.18 | 0.05 | 0.08 | 0.27 | 0.12 | 0.11 | 0.00 | 0.34 |

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Received June 2008
Revised July 2009