Nutrition mapping in Morocco

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One major limitation to targeting policies and programs to reduce under nutrition is a lack of the information in a disaggregated level. This article uses the small-area estimation technique of Elbers, Lanjouw, and Lnajouw (2002, 2003) and Tomoki Fujii (2005) to estimate multiple equations while allowing for individual-specific random errors across equations (in addition to cluster and household-specific random errors). Estimates of the prevalence of stunting and underweight for children under age 5 in Morocco from Census data are disaggregated into 1666 communes by combining the National Anthropometry Survey. The results are robust, and the estimates are useful for policy analysis and formulation.

Introduction

Reducing under nutrition is central to promote economic development and human wel Understanding the distribution of under nutrition in a country and the underlying factors associated with prevalence are essential to develop effective, targeting policies and programs to reduce under nutrition.

Under nutrition is usually measured by anthropometric indicators height for age, weight for age and weight for height of children. Collecting data on under nutrition is time-taking, requiring special equipment and training to weight and measure household members and often involving detailed questionnaires to measure the factors associated with under nutrition. For this reason, nutrition information is not generally perceived by the general population (from census data for example). National estimates of nutritional status are based on representative sample surveys, at the national level that estimate the prevalence at the highly aggregated geographic units such as place of residence or in some cases the region. These aggregate estimates of under nutrition are ill-suited to guiding national policies and nutrition programs.

The disaggregation of poverty and under nutrition indicators becomes more important, especially when the national prevalence falls, to better locate areas where the problem of poverty or under nutrition is severe (Fujii 2005; Kam et al. 2005).

Disaggregated estimates of under nutrition allow policy makers to target nutrition-focused programs to the poorest populations and to design more effective policies to achieve the different groups among poorest or under nourished, making better use of scarce public resources to reducing poverty or improving the nutritional status of the population, including children.

Over the last years, much effort has been made to using small area to map the indicators of poverty, vulnerability and inequality at geographically disaggregated levels (Peter Lonjouw, al. 2003), but there have been fewer efforts to develop and map indicators of under nutrition at a local scale the more disaggregated. The first works of under nutrition mapping were developed by Tomoki Fujii in 2005 in Cambodia.

Methodology of Small Area Estimation

Small Area Estimation or mapping of indicators is a technique for developing geographically disaggregated estimates of the prevalence of a condition (poverty, under nutrition, etc.) by combining the survey data contains information on that condition with the census data that do not contain this condition but covers the whole population.

The methodology adopted to reconstruct the anthropometric indicators at census data is the same as that of the reconstitution of poverty indicators (HCP, 2004 and 2007).

It comes to regression analysis explaining the anthropometric indicators (height for age and weight for age) based on individual variables, households variables or geographical variables from the survey data and then applied to all the children in the census, producing a predicted value for each anthropometric indicator for each child.

The regression model to predict the anthropometric indicators in census data is :

$$Y = \beta_0 + \beta_1 W + \beta_2 X + \beta_3 Z + u$$

Where

Y is the outcome of interest (height for age, weight for age).

W is a vector of variables relating to the individual child (age, sex, etc.);

X is a vector of variables relating to the household and family, including for example characteristics of the household head (age, marital status, education, activity), composition of the household, indicators of the household's economic status and housing conditions;

Z is vector of characteristics of community (cluster), including for example marketing infrastructure, environmental indicators, availability of social services, and social and economic context.

u is the error term associated with the regression equaio.

The results of the regression estimated using survey data are then applied to the census, according to the following equation :

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 W + \hat{\beta}_2 X + \hat{\beta}_3 Z$$

Where W, X and Z are individual, household/family, and community (cluster) level variables drawn from the census, and the estimated β's are the parameters from the survey regression. The application of the parameters from the first regression produces a single estimate for the dependent variable (anthropometric indicator) without an error term associated with the regression. Since there is no measurement of the dependant variable in the census, there can be no estimate of a deviation between the predicted and actual outcome in this stage.

Using the predicted value of anthropometric indicators for each child from this estimation method, computes an average of these indicators (weight or size) in each geographic unit. The analysis becomes somewhat more complicated if we also seek to estimate the distribution of these indicators in the geographic unit, for the purpose of computing the percent of children falling below under nutrition or stunting or for the purpose of computing standard errors (SE) of estimates.

In this case, we require SAE techniques (Small Area Estimation) that account for cluster-level effects. This estimation method was developed by Elbers, Lanjouw and Lanjouw (2002, 2003) in the disaggregated estimation indicators of poverty and inequality (povrety mapping). Using this estimation technique and methodology developed by the authors, Tomoki Fujii (2005) was able to estimate anthropometric indicators at a more disaggregated level in the case of Cambodia with some differences with this methodology.

First, the unit of analysis differs, Consumption data are usually produced at the household level, whereas anthropometric measures are produced at the individual level. (children under 5 years). The distribution terms in the Consumption data are decomposed into cluster and household specific effects, whereas the distribution terms in anthropometric measures are decomposed into three terms (cluster, household and individual specific effects). Second, the estimation of indicators of poverty and inequality consider only one equation, whereas the current approach simultaneously estimates multiple equations.

Finally, the general shape of the model is :

$$y_{chi}^{(k)} = E\left[y_{chi}^{(k)} \middle| x_{chi}^{(k)}\right] + u_{chi}^{(k)} = \left[x_{chi}^{(k)}\right]\beta^{(k)} + u_{chi}^{(k)}$$
$$= \left[x_{chi}^{(k)}\right]\beta^{(k)} + \eta_{c}^{(k)} + \varepsilon_{ch}^{(k)} + \delta_{chi}^{(k)}$$

Where :

$y_{chi}^{(k)}$ is the kth $(1 \leq k \leq K)$ anthropometric indicator of indicator.

$x_{chi}^{(k)}$ is a vector of observable characteristics that are used a predictor $y_{chi}^{(k)}$. In empirical application K=2, k=1 and k=2 as the standardized height and weight, respectively.

The cluster, household, and individual are denoted by the subscripts c, h and i respectively.

Data

The basic building blocks for this study comprise a surveys dataset and a census dataset. The surveys dataset used are NDS 2009-10 (National Demographic Survey) and Anthropometry National Survey 2011 (ANS). This Survey covered a sample of 10,426 households from a sample of more than 100,000 used as a basis to the National Demographic Survey 2009-2010. In addition to these two surveys, we also have the 2004 census data.

These sources should contain common variables and having the same definition to estimate a reasonable prediction model based on data from anthropometric survey (2011) and apply it to the NDS dataset 2009-10 and those of the Census 2004.

Two considerations are essential in the selection of datasets.

- Year of implementation: It is recommended that both under nutrition map object operations should not be far apart in time to ensure that the causes of under nutrition have not changed much in the time between censuses and surveys. In general, studies using SAE techniques use data from the survey and census between 0-4 years apart (Fujii 2004; Simler 2006; Benson 2006; Hentschel et al 2000).

- Comparable Variables: The second consideration for better implementation of SAE techniques is having a sufficient number of variables comparable between the two data sources (Survey and Census) for better prediction of the state nutrition of children. This consideration may even solve the problem of separation in time between the two operations.

Generally the information on children on household members or household characteristics are often present in the survey and in the census. However some variables suggested in the literature of the nutritional status of children are observed only in the survey data (age in months, the body mass index (BMI) of the child’s mother, etc.). This led us to be used in the prediction equation that common variables that are taken as proxies in variables suggested in the literature (age in years, sex of the child, the characteristics of head of the household).

The cluster characteristics are obtained from census data. We attributed these characteristics in survey data.

For reasons of representative survey data (NAS-2011), the 16 regions have been grouped into three main groups, based on their geographical proximity.

These groups are : **Group 1:** Oued Ed-Dahab Lagouira, Laayoune-Sakia El Hamra-Boujedour, Guelmim-Es-Smara, Sous-Massa-Daraa and Marrakech-Tensift-Al Haouz, **Group 2:** Gharb-Chrarda-Beni Hssen, Chaouia-Ouardigha, Grand Casablanca, Rabat-Salé-Zemmour-Zaer and Doukkala-Abda, **Group 3:** Oriental, Tadla-Azilal, Meknes-Tafilalet, Fes-Boulemane, Taza-Al Hoceima-Taounate and Tangier-Tetouan.

The nutritional status of children differs widely according to place of residence, that we used two models for each group of regions, one for urban and one for rural, a total we used of six models.

Results :

The estimation results show that the models are well specified the in so far as the explanatory power was carried to more than 40% of rural areas 1, 2, 3, 4 and 7, and around 40% in other groupings of regions. Furthermore, the Fisher statistic attests the global significance of the different models used in the estimation.

The parameters obtained from the use of OLS were corrected through the use of SAE techniques (small areas estimation) to consider the effects on clusters. The charge of the coefficients simulated on the data of the END 2009 and the census 2004 (RGPH) led to the estimation of the prevalence of stunting and underweight children under 5 years at a disaggregated level up to the cluster. Because of the missing data at the census, the estimations were obtained for 1666 clusters on a set of 16681 clusters in the Kingdom of Morocco.

Regional prevalence of underweight

Région	Enquête_2011 Echantillon		Enquête_2009 Nutrition mapping		RGPH_2004 Nutrition mapping	
	fgt0	se_fgt0	fgt0	se_fgt0	fgt0	se_fgt0
Régions du Sud	0.235	0.047	0.209	0.052	0.136	0.034
Sous-Massa-Draa	0.211	0.038	0.268	0.046	0.170	0.039
Gharb-Chrarda-Bni Hssen	0.237	0.022	0.268	0.037	0.374	0.053
Chaouia – Ourdigha	0.147	0.025	0.189	0.035	0.267	0.043
Marrakech – Tensift – Al Haouz	0.222	0.031	0.245	0.043	0.245	0.062
Oriental	0.170	0.024	0.166	0.035	0.164	0.034
Grand Casablanca	0.139	0.027	0.102	0.019	0.151	0.024
Rabat – Salé – Zemmour – Zaer	0.114	0.016	0.143	0.028	0.190	0.030
Doukala – Abda	0.197	0.020	0.202	0.027	0.248	0.033
Tadla – Azilal	0.192	0.024	0.208	0.027	0.285	0.050
Meknès – Tafilalet	0.164	0.030	0.166	0.029	0.164	0.031
Fès – Boulemane	0.176	0.026	0.210	0.035	0.256	0.038
Taza – Al Hoceima – Taounate	0.302	0.030	0.303	0.036	0.329	0.041
Tanger – Tetouan	0.110	0.024	0.154	0.028	0.214	0.047
Total	**0.185**	**0.010**	**0.201**	**0.034**	**0.225**	**0.041**

1- Provincial prevalence of underweight

The estimated data of underweight (weight for age) give, nationally, an average prevalence of about 6.0%, this rate hides disparities at provincial level. Thus, in terms of multiple of the average, 21 provinces have a prevalence of underweight rate less than 75% of the national average and 11 provinces have a prevalence rate that exceeds 50%. The province whose children suffer most from underweight is Boulemane's province, followed by the province of Settat and Figuig with rates , respectively, 18.9% 16.1% and 13.6% .

The provinces less affected by the prevalence of underweight and whose rates do not exceed 2.5% are El Hajeb, Rabat, M'diq Fnidq, Oujda Angad and Tan Tan.

2- Provincial prevalence of stunting

For the prevalence of retardation growth (height for age), the data estimated from the approach of nutrition mapping gives a national prevalence rate of 20,1%. The rate of prevalence of retardation growth differs also from province to province. Thus, one third of provinces (25) have a prevalence of retardation growth's rate less than 75% of the average rate and about 15% (11 provinces) have a prevalence rate that exceeds the average rate of 50%.

The provinces whose 5 years children suffer the most from retardation growth are Boulemane (43.9%), Azilal (40,5%), Sidi Slimane (38,4%) and Sidi Kacem (38,3%). In contrast, provinces with the lowest prevalence of retardation growth's rate are Tan – Tan, Oujda – Angad, Laayoune and Agadir Ida Ou Tanane with a rate which doesn't exceed 11,4%.

3- Child's under nutrition and different forms of poverty

The link between child under nutrition and living standards of households shows that higher the standard of living increases, fewer children are at risk of under nutrition. Indeed, the highest prevalances of underweight and retardation growth are recorded in the poorest towns whether by the monetary approach or as multidimensional approach.

The prevalence of underweight records low rates for children living in the clusters less affected by monetary and multidimensial poverty. Indeed, the rate of prevalence of underweight reaches only 5,3% in the 20% of clusters less affected by monetary poverty and by multidimensial poverty. This rate increases up to 20% of the following clusters and stabilizes from the 3rd poorest quintile.

Regarding the correlation between the prevalence of underweight and various forms of poverty, it is noted that while the correlation is positive, it is low especially with monetary poverty. Indeed, the correlation coefficient of the prevalence of underweight is only 0,044 with monetary poverty and exceeds 0.12 with multidimensional poverty.

The prevalence of stunting is also positively correlated with the different forms of poverty. Indeed, the poorest the clusters are (monetary or multidimensional perspective), the most of these children run the risk of stunting.

Observing the quintiles of rates of different forms of poverty, the prevalence of stunting is increasing from the least poor clusters to the poorest ones. Thus, the prevalence of stunting going from 17.1% in the least affected clusters by the monetary poverty (quintile 1) to 29.8% in the most affected clusters by monetary poverty (quintile 5). According to the approach of multidimensional poverty, these percentages are 17.1% and 32.9% respectively (ACM approach) and 17.3% and 34.1% (OPHI approach).

Compared to the prevalence of underweight, the prevalence of stunting is highly correlated with the different forms of poverty. Indeed, the correlation coefficient between the prevalence of stunting and monetary poverty rate reached 0.206, exceeding 0.42 in connection with the multidimensional poverty.

4- Child Under nutrition and Literacy

In terms of Human development plan, the prevalence of child under nutrition is negatively correlated with the degree of literacy of the population. In other words, the lowest the literacy rate is in clusters, higher the prevalence of underweight and stunting is. Indeed, the table below shows that the literacy rate of the 10 years old population and more decreases in as the prevalence rate of stunting and in a lesser extent the prevalence of the underweight increase.

This correlation is much clearer for stunting than underweight. Indeed, the literacy rate increased from 65.5% in 20% of clusters whose children have a low prevalence rate of stunting to 61.3% in the 20% clusters following and only 38, 4% in the clusters characterized by high rates of prevalence of stunting.

For underweight, if the literacy rate is the highest in the 20% of clusters with low prevalence of underweight, it varies little in the other classes of clusters (2nd to 5th quintile).

5- Child Under nutrition and equipment rate of rural clusters in water and electricity

The prevalence of underweight and stunting among children under 5 years old is clearly related to the lack of local physical infrastructure. In rural areas, the proportion of clusters connected to the drinking water network is higher in clusters where stunting prevalence rates and prevalence of underweight rates are the lowest. This rate decreases from 33.4% in the first quintile of clusters that record the lowest prevalence of stunting rate to 11.5% in the clusters belonging to the fourth and fifth quintiles. These percentages increase to 33.1% and 12.6% respectively for the classification of clusters according to the prevalence of underweight.

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