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Malnourished but Not Destitute

The Spatial Interplay between Nutrition and Poverty in Madagascar

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Abstract

Hidden hunger, or micronutrient deficiencies, is a serious public health issue affecting approximately 2 billion people worldwide. Identifying areas with high prevalence of hidden hunger is crucial for targeted interventions and effective resource allocation. However, conventional methods such as nutritional assessments and dietary surveys are expensive and time-consuming, rendering them unsustainable for developing countries. This study proposes an alternative approach to estimating the prevalence of hidden hunger at the commune level in Madagascar by combining data from the household budget survey and the Demographic and Health Survey. The study employs small area estimation techniques to borrow strength from the recent census and produce precise and accurate estimates at the lowest administrative level. The findings reveal that 17.9 percent of stunted children reside in non-poor households, highlighting the ineffectiveness of using poverty levels as a targeting tool for identifying stunted children. The findings also show that 21.3 percent of non-stunted children live in impoverished households, reinforcing Sen's argument that malnutrition is not solely a product of destitution. These findings emphasize the need for tailored food security interventions designed for specific geographical areas with clustered needs rather than employing uniform nutrition policies. The study concludes by outlining policies that are appropriate for addressing various categories of hidden hunger.

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Malnourished but Not Destitute: The Spatial Interplay between Nutrition and Poverty in Madagascar

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1. Introduction

The issue of food insecurity among households in developing countries, where individuals or families struggle to access or afford nutritious food to meet their basic dietary needs, has garnered additional attention since the launch of the Sustainable Development Goals. This has led donors and philanthropic organizations to increase their effort to combat food insecurity, especially in poor countries where malnutrition is assumed to be high. Surprisingly, this problem persists even among households that are not considered monetarily poor. This phenomenon, known as hidden hunger, affects approximately 2 billion people worldwide, according to a study conducted by the World Food Programme (WFP, 2020). Hidden hunger is characterized by an inconsistency between adequate calorie intake and intake of essential vitamins and minerals, leading to various health problems, primarily manifested as stunted growth.

Identifying sub-regions or localities afflicted by hidden hunger, or micronutrient deficiencies, is crucial for targeted interventions and effective allocation of resources. Public health experts employ methods such as randomly collecting blood samples from representative population groups, analyzing them in laboratories to determine micronutrient levels, and comparing them against established reference values – nutritional assessment. This approach, combined with geographical mapping, helps identify areas in need, enabling experts to focus their interventions and resources accordingly. Additionally, dietary surveys and administrative data from ad hoc clinical examinations when patients happen to visit local health centers provide further insights into the nutritional status of the population.

Conducting expensive surveys, such as nutritional assessments and dietary surveys, to identify areas with a high prevalence of hidden hunger is not financially sustainable. Health experts instead resort to using poverty maps or standardized health surveys like the Demographic and Health Survey (DHS) or the Multiple Indicator Cluster Survey (MICS) to pinpoint malnourished individuals. However, relying solely on poverty maps assumes that malnourished individuals exclusively live in impoverished households. This may not always be accurate, since typical poverty measures do not measure differences in welfare levels among members of the same household. On the other hand, DHS or MICS surveys may miss households with average poor caloric intake as these surveys do not collect detailed food consumption data. To overcome this challenge and enhance precision in targeting, we recommend an alternative approach that combines small area estimates of monetary poverty and stunting.

This study aims to estimate the prevalence of hidden hunger in Madagascar by employing small area estimation techniques. Our approach involves identifying areas where poverty rates are low but stunting, a common indicator of malnutrition, is high; and vice versa. Poverty estimates are derived from the 2021/2022 household survey, which provides detailed food consumption at the household level. Stunting estimates, on the other hand, are derived from the 2021 Demographic and Health Survey (DHS), a nationally representative survey capturing anthropometric data and nutritional indicators. We develop a small area estimation (SAE) statistical model that "borrowed strength" from the 2018 census to allow the two nationally representative sources of survey data to produce precise and accurate estimates at the commune level and investigate the relationship between monetary poverty and nutrition. This approach enables us to estimate the prevalence of hidden hunger at the commune level within Madagascar and create a taxonomy of different types of hidden hunger, providing valuable insights for nutrition policy prioritization.

While the stunting rate in Madagascar stands at 40%, our research has unveiled new policy relevant insights after appending the two surveys at the commune level. For instance, 17.9% of stunted children reside in non-poor households, suggesting that using household poverty levels as a targeting tool for identifying stunted children is ineffective. Similarly, 21.3% of non-stunted children live in impoverished households, underscoring that malnutrition is not solely a product of destitution, reinforcing Sen's (1981) argument that famine or malnutrition is not the results of lack of food or poverty, but a result of entitlement failure.

The remainder of this paper is structured as follows: In the next section, we delve into the nutritional landscape of Madagascar, presenting key statistics on macronutrient and micronutrient consumption, as well as the distribution of caloric intake across the country. Section 3 provides a literature review to contextualize the paper's contributions. Section 4 outlines the data and methodology employed to implement the small area estimation approach for deriving nutrition and poverty indicators at the commune level. Our findings are presented in Section 5, and we conclude the paper in Section 6, offering policy recommendations.

2. Nutrition in Madagascar

Caloric intake

Table 1 provides information on the distribution of calorie intake in rural and urban areas of Madagascar for the year 2021-22, as well as the overall figures for the country. The data is categorized based on per capita real consumption (PCER) deciles, which divide the population into 10 equal groups based on their calorie intake and poverty status. In rural areas, the lowest PCER decile (1st) has an average calorie intake of 707 kcal per person per day, while the highest decile (10th) has a significantly higher intake of 3,827 kcal. This suggests a substantial disparity in calorie consumption between the most impoverished and least impoverished individuals in rural settings. The trend shows a gradual increase in calorie intake across the deciles, with each decile having a higher average intake than the previous one.

Table 1: Distribution of calorie intake (kcal/person/day) by per capita consumption deciles and urban/rural location, 2021-22

PCER deciles	Rural	Urban	Madagascar
1	707	669	696
2	1,120	1,051	1,098
3	1,380	1,211	1,330
4	1,596	1,415	1,535
5	1,793	1,540	1,700
6	1,983	1,709	1,868
7	2,203	1,776	2,010
8	2,487	2,046	2,253
9	2,859	2,309	2,543
10	3,827	3,451	3,572
Madagascar	2,112	2,227	2,167

Source: Staff calculations based on Enquête Permanente Aupres des Menages 2021-2022.

Similarly, in urban areas, the lowest PCER decile (1st) has an average calorie intake of 669 kcal, slightly lower than in rural areas. The highest decile (10th) in urban areas has a significantly higher intake of 3,451 kcal, which is considerably lower than the highest decile in rural areas. This indicates a disparity in calorie consumption between the least and most impoverished individuals in urban settings, albeit less pronounced than in rural areas. Looking at the overall figures for Madagascar, the average calorie intake is 2,112 kcal in rural areas and 2,227 kcal in urban areas. But also, more than 70 percent of the population do not meet the required caloric intake of 2,133 as recommended by local health authorities, highlighting the high prevalence of food insecurity and the inequality in access to food.

Malnutrition – Stunting

Malnutrition, specifically stunting, poses a significant barrier to alleviating extreme poverty in Madagascar, as the overall stunting rate among children 0-5 years old is approximately 40 percent (INSTAT and ICF, 2022). Madagascar grapples with high rates of micronutrient deficiencies, stemming from inadequate intake of essential vitamins and minerals crucial for growth, development, and immune function, such as iodine, Vitamin A, and iron. These deficiencies are predominantly linked to inadequate diets in terms of both quality and diversity, alongside insufficient quantity, contributing to stunted growth and adverse health outcomes. Moreover, a concerning 8 percent of children aged 0-5 experience wasting, heightening their vulnerability to illness and mortality. On a global scale, malnutrition is responsible for 45 percent of child deaths, with anemia alone contributing to about 20 percent of maternal fatalities (UNICEF, WHO, World Bank, 2020). Stunted growth also correlates with cognitive delays and reduced educational achievement, limiting long-term earning potential and workforce productivity. The annual economic burden of malnutrition in Madagascar is estimated to range from 7 to 12 percent of the Gross Domestic Product (GDP)[1].

The "first 1,000 days," spanning from conception to the age of two, represent a critical period for ensuring adequate nutrition due to the rapid pace of physical and cognitive development. Stunting during this timeframe indicates potentially irreversible effects on children's health and well-being. Notably, in Madagascar, a significant portion of children, around 40 percent, already experience stunted growth by the age of just 12 months, much earlier than in other countries, with growth impairment beginning as early as in utero due to high rates of early pregnancies and maternal malnutrition. Micronutrient deficiencies are also widespread, with 50 percent of children aged 6-59 months and 35 percent of women of reproductive age experiencing anemia, and 52 percent of children suffering from Vitamin A deficiency.

Global evidence emphasizes the potential of implementing a set of 10 high-impact nutrition interventions, centered on the critical "first 1,000 days," to significantly reduce stunting (Martorell, 2017). Ensuring access and utilization of these interventions through well-coordinated community-based and primary care services integrated into a robust maternal and child health program is a pivotal starting point. Additionally, effective prevention and management of infectious diseases play a crucial role in reducing the contribution of illness to malnutrition and stunting. Strengthening the foundational health and nutrition service delivery platform can also generate synergies with other sectors, expediting progress in reducing stunting. As a result, adopting a more targeted approach to

[1] UNICEF, 2017. Madagascar Nutrition Investment Case. UNICEF: Antananarivo.

prioritize nutritional issues is crucial for initiating efforts to address the problem, especially when resources are limited.

3. Literature Review

Prior studies have utilized SAE techniques to map food insecurity and nutritional trends at the sub-national level. Within this context, we identify two noteworthy trends in employing SAE to better understand nutritional outcomes in developing countries. One prevalent approach combines census data with household expenditure information, utilizing caloric intake thresholds as indicators of malnutrition. For instance, Hossain et al. (2020) applied the SAE methodology to estimate food insecurity at the district level in Bangladesh. They integrated data from the Household Income and Expenditure Survey 2010 with the Bangladesh Population and Housing Census 2011. Their approach gauged food insecurity prevalence based on a per capita calorie intake threshold of 2,122 kcal per day, derived from the survey.

Guha and Chandra (2021) also combined household expenditure data with census data to obtain estimate of food insecurity indicators at the district level for the rural area of the state of Uttar Pradesh in India. Their empirical evidence indicate that the estimates generated by SAE approach are reliable and representative. Spatial maps showing district level inequality in distribution of food insecurity in Uttar Pradesh is also produced. The disaggregate level estimates and spatial maps of food insecurity are found to be directly relevant to help the monitor the sustainable development goal indicator 2.1.2 - severity of food insecurity.

Another notable approach combines census data with standardized health surveys like the Demographic and Health Surveys (DHS) to estimate stunting rates at the subregional level. For instance, Sohnesen et al. (2017) employed this method in Ethiopia to estimate undernutrition within different woreda (sub-regions). Their findings revealed substantial variations in the prevalence of undernourished children within each woreda, highlighting location-specific challenges. Notably, they found limited correlation between the percentages of underweight and stunted children across woredas.

Other studies employed SAE to estimate dynamic changes in nutritional outcomes. In fact, to estimate the trends in age-specific chronic childhood undernutrition in all of Bangladesh's 64 districts spanning from 1997 to 2018, Das et al. (2023) employed advanced small area time-series models. These models integrated direct estimates derived from seven Demographic and Health Surveys, combining cross-sectional, temporal, and spatial data to make predictions for all districts during both survey and non-survey years. At the national level, their findings revealed a significant reduction in stunting prevalence, decreasing from approximately three in five children to one in three. However, the study also exposed substantial disparities in chronic undernutrition across the districts, with certain areas experiencing less pronounced declines. Moreover, these disparities became more apparent when examining stunting prevalence at the district-by-age level, where only districts in more socio-economically advantaged regions consistently reported declines in stunting across all age groups.

In our present study, we present small area estimates both of monetary poverty and stunting, allowing us to uncover a distinct dimension of undernutrition known as "hidden hunger". Our research unveils the prevalence of hidden hunger and employs a novel bivariate mapping approach to rank and categorize hidden hunger across various communes. This approach is valuable for facilitating location-specific policy interventions and increasing their impact since health and nutrition budget allocations are sent to the commune level basic health centers.

4. Application of the Small Area Estimation Approach

Data description

The 2018 census marked the third census undertaken in Madagascar, following the most recent one in 1993. The census enumeration process spanned from May 18 to June 25, 2018, encompassing the entirety of the country. During the 2018 census, Madagascar's population was estimated to be approximately 25,674,196 individuals residing in a total of 6,079,876 households. While most households live in rural areas (80.7%), the gender composition is slighted tilted toward women as they represent 50.7% of the population.

In parallel, the Enquête Permanente Aupres des Menages 2021-2022 (EPM21-22) represented a living standards measurement survey (LSMS) conducted between 2021 and 2022, encompassing all nine provinces and 22 regions. With the exception of one district (Mitsanjo), the survey covered all districts. The EPM is representative at both the national and regional levels. This means that we can use the data to draw inferences at the sub-regional level. A key objective of the EPM21-22 survey was to generate monetary poverty estimates, defined based on per capita consumption, using a national poverty line set at approximately 1.57 million ariary per year per person. Based on those estimates, 75.2 percent of the national population was poor (79.9 percent for rural and 55.5 percent for urban areas). This is a slight (non-statistically significant) increase from the 72.9 percent estimated for 2012. Rural poverty decreased from 80.6 percent in 2012 to 79.9 percent in 2022 (a statistically insignificant change), while average consumption among the rural poor increased by 1-percent per year.[2] At the same time, poverty significantly increased in urban areas, from 42.2 percent in 2012 to 55.5 percent in 2022.

The Demographic and Health Survey, carried out in 2021, spanned all nine provinces and 22 regions. Similarly to the EPM survey, we can use the DHS data to draw inferences at the sub-regional level. It entailed the surveying of a total of 20,510 households, comprising 5,146 in urban areas and 15,364 in rural areas. All women aged 15-49 living in the selected households or present the night before the survey were eligible for interviews. Additionally, a subsample of every other household included the weighing and measuring of all children under 5 years to assess their nutritional status (including wasting, underweight, and stunting). In this subsample, all children aged 6-59 months were eligible for anemia and malaria (RDT) tests. Furthermore, anthropometric measurements and anemia testing were also conducted for all women aged 15-49 in this subsample. Finally, in the other subsample of every other household, all men aged 15-59 were eligible for interviews, and gender-based violence questions were administered to one woman per household, randomly selected.

The 2021 DHS shows a modest improvement of stunting rate at 40% compared to 41.6% in 2018. In rural areas stunting declined from 42.6% to 40.5%, and in urban areas it also dropped from 37.7% to 35.5%. This suggests a positive trend in reducing child malnutrition, though there is still a considerable disparity between rural and urban regions, highlighting the need for continued efforts in addressing this issue, particularly in rural areas.

[2] Approximately 80 percent of Madagascar's population dwells in rural areas.

Identifying common variables between the surveys and the census

The Small Area Estimation (SAE) process entails constructing a statistical model for predicting the outcomes, which in this case are per capita consumption when estimating monetary poverty and height for age Z scores when estimating stunting. Ultimately, this model, which is trained using survey data to forecast monetary poverty, is utilized for poverty prediction within the census dataset. However, this is only feasible if there is a shared set of explanatory variables for the relevant outcome in both the survey (EPM21-22), DHS, and the 2018 census. Therefore, the initial step in the SAE process involves recognizing common variables suitable for prediction. In this context, "common" denotes variables measuring the same indicators and thus should exhibit similar distributions across these two data sources.

Identifying common variables involved three primary stages. Firstly, we sought variables that gauge the same phenomena. This was achieved through a careful review of the questionnaires from EPM21-22, DHS 2021, and the census to verify if the wording of the questions matched. Secondly, we compared the response categories for categorical variables to determine their alignment. In cases where differences were observed, we assessed if these categories could be merged for comparability. The third step involved comparing the means of the common variables. Drawing from previous SAE estimations, we categorized the prediction variables into three main groups:

- Demographic characteristics of the household head, including age, gender, marital status, and education level.
- Dwelling characteristics, encompassing materials used for the roof, walls, floor, etc.
- Household assets, which includes whether the household possesses common assets like bicycles, cars, radios, etc.

For instance, in the context of education, the first candidate variable is whether the household head attended school, a question posed similarly in both the census and EPM21-22. Thus, no significant transformation was necessary. The second candidate variable regarding education pertained to the highest level of education attained. However, there was a distinction in the response categories, with EPM21-22 offering more detailed options compared to the census. Consequently, the survey variables were adjusted to consolidate categories to match those in the census. Following this transformation process, the distribution of categories (the proportion in each category) was compared, and the variable was deemed acceptable due to its similar distribution in both the survey and census. This general process was replicated to identify the remaining variables, which were subsequently applied to the DHS dataset.

Statistical methodology

The statistical procedure used is the empirical best predictor model developed by Molina and Rao (2010) based on the work of Battese, Harter, and Fuller (1988). Since this method requires that the error terms be distributed normally, household per capita consumption is log transformed to better approximate normality. Sampling weights are applied in the consumption prediction model following Guadarrama et al (2018), as described in Skarke and Kreutzmann (2020). As is standard, household size was used as population weights when aggregating poverty headcount estimates across households in the census data.

The model used to generate the estimates can be described as follows:

$$Y_{rdh} = X_{rdh}\beta_1 + D_r\beta_2 + \nu_{ra} + \epsilon_{ragh} \tag{1}$$

Where:

Y_{rdh} represents the outcome of interest - log per capita consumption of household h or height for age Z score, within district d and region r. This value of consumption has been spatially deflated using estimated local prices.

X_{rah} represents the vector of household-level geospatial variables selected for the model.

D_r represents a set of regional dummy variables.

ν_{ra} is a conditional random effect, conditioned on the sample data. It is specified at the target area level a, and assumed to be normally distributed.

ϵ_{ragh} is a classical household-specific error term, assumed to be normally distributed.

The povmap package in R is used to perform the estimation (Edochie et al, 2023). Povmap is an extension of the EMDI package (Kreutzmann et al., 2019) that is publicly available on the Comprehensive R Archive Network (CRAN). To calculate point estimates, the package first estimates a weighted linear mixed model to calculate estimates of the coefficient vectors $\beta_1$and β_2 and the variance of $\nu_a$and ϵ_{ragh}. Survey weights are incorporated into model estimation following Guadarrama et al (2018), as described in Skarke and Kreutzmann (2021). Next, survey weights are normalized such that the sum in each district is equal to the unweighted number of observations, following "method 2" in Pfefferman et al (1998). The estimated model parameters include the conditional distribution of the area effect ν_a, conditional on sample per capita consumption Y_{agh}.

The procedure takes 100 draws of ν_a and ϵ_{agh} and adds them to $X_{ag}\hat{\beta}_1 + X_a\hat{\beta}_2$ to generate simulated values of the outcome for the full set of households. For each of the 100 simulations, the implied poverty rate is calculated across all households contained within each district, using the household size variable in the census as aggregation weights when averaging across households. The poverty line used is 1,570,739, which translates to about 96 cents per day at current market exchange rates. This was selected such that the overall poverty rate in the survey data is consistent with the reported 75.2% national rate. For stunting, the relevant threshold is height-for-age Z score of -2. The implied poverty or stunting rates for each district are then averaged across the 100 simulations. Because the random area effect is conditioned on the sample data, the estimates place a larger weight on the model predictions from the model when they are precise relative to the direct survey estimates, and conversely a larger weight on the survey estimates when they are more precise relative to the model predictions.

The estimates obtained from the simulation were then benchmarked to match the survey estimates at the regional level published in World Bank (2023), to arrive at poverty estimates for each district. The benchmarking procedure used the "benchmark complement" option in the povmap package. This option multiplied the estimated proportion of non-poor by a constant in each region, chosen to ensure that the proportion of non-poor in the small area estimates matched the proportion of non-poor from the survey at the regional level. The final benchmarked head count estimates were then obtained by subtracting the estimated share of non-poor from 100 percent. Benchmarking the proportion of people that are not poor instead of the proportion of poor avoids generating poverty estimates that exceed 100 percent.

Estimates of mean squared error were calculated using the parametric bootstrap procedure implemented by the povmap package (Gonzalez-Manteiga et al, 2007). The Povmap package implements the bootstrap procedure in a way that takes the benchmarking procedure into account. As is standard when estimating uncertainty using this method, the estimates are assumed to be unbiased, which implies that the standard error is the square root of the estimated mean squared error (Tzavidis et al, 2018). This allows for the estimation of standard errors, and CVs for each target area.

Comparisons of the model-based and direct estimates at the regional level suggest modest amounts of model and sampling error. Comparing the estimated precision of the small area estimates with the direct estimates show a large efficiency gain from incorporating auxiliary data from the census. Unfortunately, due to the age of the census, and the fact the COVID – 19 pandemic happened between the census and the budget survey, the estimates will only slightly reflect the changes caused by the COVID – 19 pandemic and are better measures of long-term structural poverty.

5. Study Findings

Small area poverty maps

The variables selected to predict per capita consumption as well as the resulting coefficients from the linear mixed model are provided in table A1 of the annex. Table 2 presents a set of model diagnostics relating to the fit of the model and the consistency of the normality assumptions with the sample data. Overall, the model explains 57 percent of the variation in log per capita consumption when not considering the conditional random effect, and 61 percent when the conditional random effect is included. The model was estimated in a subsample of 16,052 households, because data from 819 households, or about 5 percent of households, were dropped due to missing data in the set of predictors. Similarly, approximately 16,500 census households, or about 3 percent of households, were dropped from the census due to missing predictors.

Regarding the distribution of the residuals, the conditional random effect has a skewness of -0.30 while the error term has a skewness of 0.38. This is slightly different from the benchmark values of 0 characterizing the normal distribution. The estimated kurtosis, which is 4.2 for the random effect and 4.1 for the idiosyncratic error term, differs moderately from the benchmark value of 3 that characterizes a perfectly normal distribution.

Table 2: SAE diagnostics for monetary poverty

Characteristic	Value
Marginal R^2	0.568
Conditional R^2	0.613
Random effect	

Skewness	-0.302
Kurtosis	4.222
Idiosyncratic error term	
Skewness	0.378
Kurtosis	4.114
Number of sample observations	16,052
Number of census observations	5,892,548

Source: Authors' estimations

Figure 1: Map showing proportion of poor people (poverty rate) at commune level

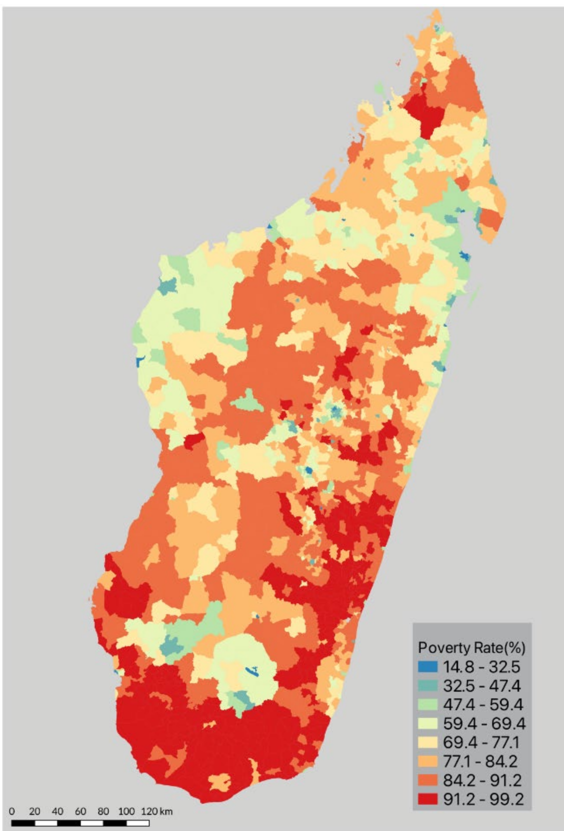
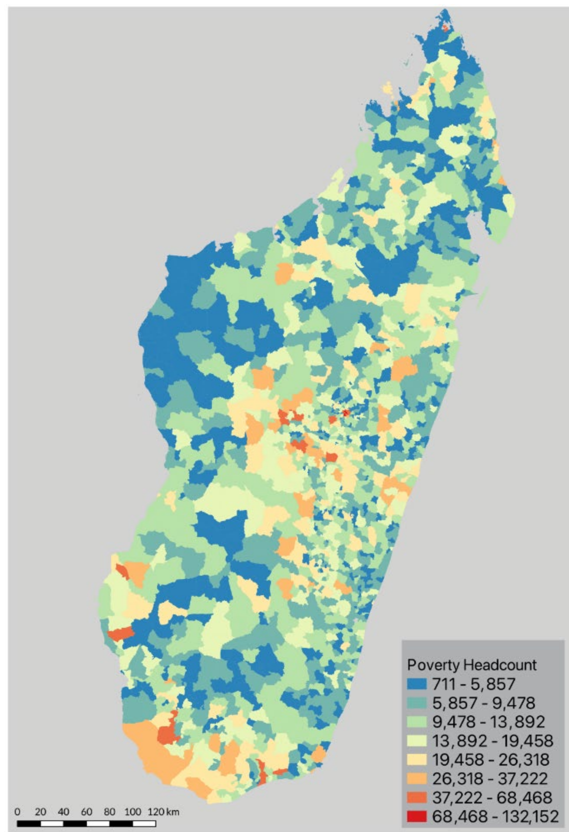


Figure 2: Map showing number of poor people at commune level



Source: World Bank, 2023

The two maps in Figure 1 and Figure 2 provide the spatial distribution of proportion of the population who are poor and number of the people who are poor, respectively, at the commune level. At the commune level, pockets of poverty appear to be in the south and southeast portion of the country, as well as a commune near the northern tip. The number of poor people is also concentrated in communes in the southern tip as well as those in the high plateau of the middle of the country. However, we also note that communes in the west and in the north have lower numbers of poor people. This also includes some communes in the south.

Table 3 shows the 10 poorest communes. Only the commune ID is provided with the associated district in which the commune is located[3]. The second and third columns show the 10 poorest communes in terms of prevalence, while the fourth and fifth columns show the 10 communes with the largest numbers of poor people. The table shows that the poorest by prevalence commune is in Betioky-Atsimo district while by number of poor people, the poorest commune is in Antananarivo district where poverty rate is one of the lowest.

Table 3: Communes with highest estimated poverty rates

Rank	Highest rate			Highest number		
	Commune Id	**District**	**Poverty rate**	**Commune Id**	**District**	**Estimated Number of poor**
Poorest	51827	Betioky-Atsimo	99.2	11104	Antananarivo	132,330
2	23510	Ikongo	99.1	11105	Antananarivo	116,006
3	23513	Ikongo	99.0	11101	Antananarivo	101,600
4	51829	Betioky-Atsimo	99.0	11102	Antananarivo	67,882
5	51823	Betioky-Atsimo	98.9	11106	Antananarivo	57,074
6	51824	Betioky-Atsimo	98.9	41102	Mahajanga-1	55,586
7	51825	Betioky-Atsimo	98.9	51305	Morombe	53,842
8	51818	Betioky-Atsimo	98.8	52101	Ambovombe-Androy	51,662
9	51821	Betioky-Atsimo	98.8	13107	Miarinarivo	50,751
10	51830	Betioky-Atsimo	98.8	61101	Antsiranana-1	47,019

Source: Authors' estimations

Small area stunting maps

In Demographic and Health Surveys (DHS), stunting is measured through the collection of anthropometric data from children under the age of five. Specifically, children's height is measured and compared to standardized growth references, typically provided by the World Health Organization (WHO) Child Growth Standards. Stunting is assessed by calculating the height-for-age z-score (HAZ) for each child, which quantifies how many standard deviations their height deviates from the median height of a healthy reference population. Children with a HAZ score of less than -2 are classified as stunted, indicating that their height falls significantly below the expected average for their age. The 2021 DHS in Madagascar uses this data to monitor and assess the prevalence and severity of stunting in different countries, providing valuable insights for public health interventions and policy planning.

[3] We deliberately kept the names of the communes anonymous.

The regions of Bongolava and Sofia have the highest percentages of children weighing less than 2.5 kg, with 19% and 17%, respectively. On the other hand, the regions of Ihorombe and Anosy have the lowest percentages of low-birth-weight children, at around 8%. In other words, stunting seems prevalent in the least poor regions of Madagascar and less prevalent in the poorest regions. These findings emphasize the importance of regional context in addressing child undernutrition, highlighting the need for tailored approaches that consider socioeconomic factors, health care access, and nutritional practices to improve child health outcomes across Madagascar.

But these heterogeneities also exist within regions at the commune level. We therefore applied the SAE approach in the DHS data to produce stunting estimates at the commune level and produce the map presented under figure 3. The maps highlight higher stunting rates among communes located in high plateau of the regions in the center, also known for its better agro-ecological advantage for agricultural production. We also note the higher stunting rates among communes in the regions in the east and southeast of the country.

Linguistic, historical, and DNA research suggests that the central highlands of Madagascar were settled by people with an Austronesian background 1,200 years ago (most likely South Borneo); the coastal areas were settled later by people mainly from East Africa (Hurles et al 2005). Can this partly explain the stunting patterns? Our limited data does not allow us to verify this hypothesis.

The variables selected to predict stunting as well as the resulting coefficients from the linear mixed model is provided in table A2 of the annex. Table 4 presents a set of model diagnostics relating to the fit of the model and the consistency of the normality assumptions with the sample data. Overall, the model explains 7.5 percent of the variation in heigh for age Z score when not considering the conditional random effect, and 11.3 percent when the conditional random effect is included. The model was estimated in a subsample of 6,379 children again of approximately 3.2 million children in the census.

Regarding the distribution of the residuals, the conditional random effect has a skewness of 0.144 while the error term has a skewness of 0.004. The estimated kurtosis, which is 2.4 for the random effect and 3.05 for the idiosyncratic error term, differs moderately from the benchmark value of 3 that characterizes a perfectly normal distribution.

Table 1: SAE diagnostics for stunting

Characteristic	**Value**
Marginal R^2	0.075
Conditional R^2	0.113
Random effect	
Skewness	0.144
Kurtosis	2.442
Idiosyncratic error term	
Skewness	-0.004
Kurtosis	3.050
Number of sample observations	6,379

Number of census observations	3,234,861

Source: Authors' estimations

When examining the number of stunted people, it leads us to a distinct conclusion as depicted in figure 4. It is evident that there is a notable prevalence of stunted individuals in all communes, and this observation implies that there is no clear inclination toward any particular area.

Table 5 illustrates that communes situated within the Antsirabe II district exhibit the highest rates of stunting. These communes are nestled in the high plateau region, renowned for its fertile land. Conversely, the largest concentration of stunted children can be found in communes within the districts of Antananarivo Renivohitra, Antsirabe II, and Toamasina II. While the first two districts are also situated within the central high plateau, Toamasina II represents a coastal district in the East, characterized by substantial levels of precipitation. In essence, areas with the highest agricultural production coincide with the highest rates of stunting and the greatest numbers of stunted children.

Figure 3: Map showing proportion of stunted people (stunting rate) at commune level

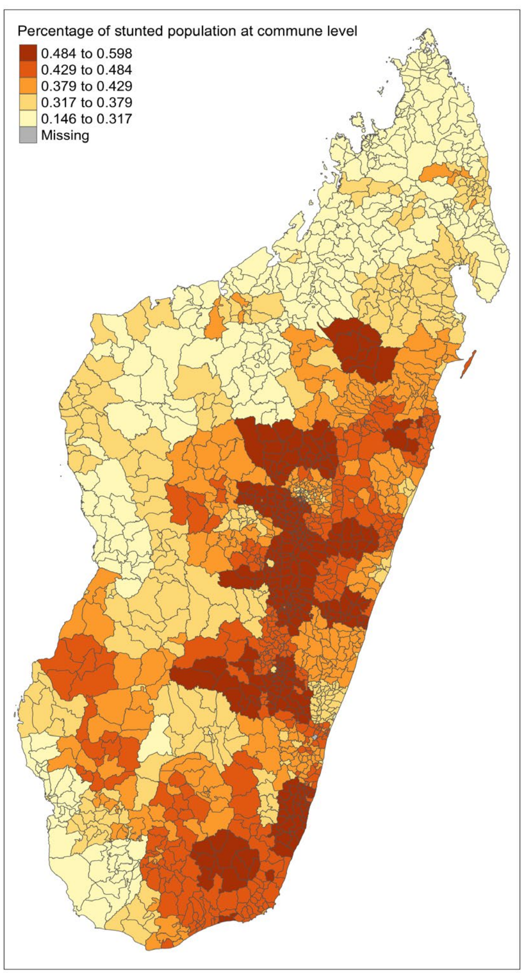
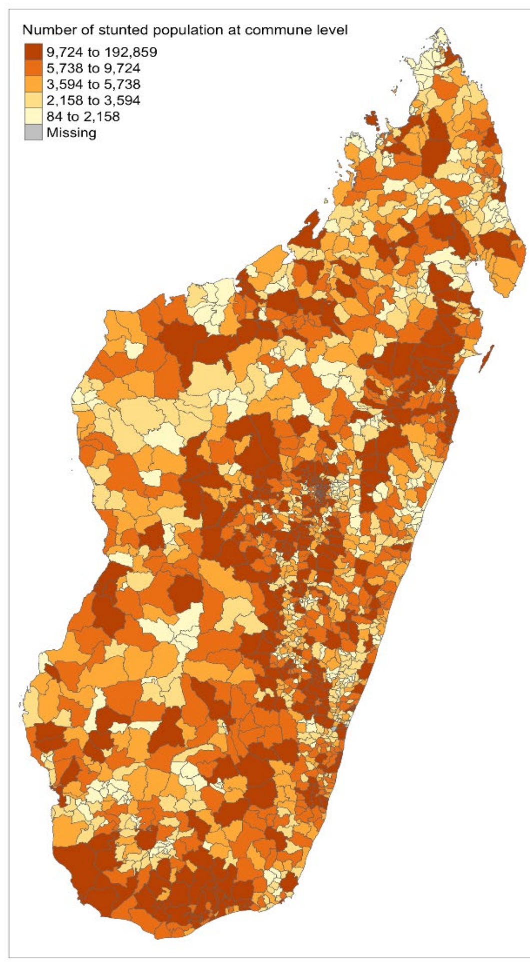


Figure 4: Map showing number of stunted people at commune level



Source: Authors' estimations

Tables 5: Communes with highest estimated stunting rates

Rank	Highest rate			Highest number		
	Commune ID	DISTRICT	Stunting rate	Commune ID	DISTRICT	Estimated number of stunted children
1	118370	Antsirabe II	59.80	101005	Antananarivo Renivohitra	192,859
2	118310	Antsirabe II	59.33	102039	Antananarivo Avaradrano	144,928
3	118170	Antsirabe II	59.29	118010	Antsirabe II	141,220
4	118332	Antsirabe II	59.14	101006	Antananarivo Renivohitra	107,916
5	118290	Antsirabe II	59.13	102079	Antananarivo Avaradrano	106,032
6	118350	Antsirabe II	59.09	310030	Toamasina II	98,555
7	110292	Ambatolampy	59.07	102319	Antananarivo Avaradrano	89,019
8	118250	Antsirabe II	58.95	310010	Toamasina II	65,808
9	118130	Antsirabe II	58.93	103172	Ambohidratrimo	54,678
10	118190	Antsirabe II	58.78	118331	Antsirabe II	54,101

Source: Authors' estimations

Interplay between poverty and stunting and categorization of hidden hunger

We have used an innovative method to create a bivariate map that integrate poverty and stunting data derived from the applications of SAE. This map ranks communes based on their combined levels of poverty and stunting, offering valuable insights into their socio-economic and nutritional status. Our visualization includes two maps: one that combines poverty rates and stunting rates (Figure 5), and another that combines the number of stunted children with the number of impoverished households (Figure 6). In this visual representation, communes shaded in a deep purple hue indicate regions where both poverty and stunting rates (or numbers) are high, as one would expect. Conversely, communes shaded in gray represent areas where both stunting, and poverty rates (and numbers) are low. The remaining seven color shades provide a spectrum of options for tailored policy interventions, addressing the unique nutritional and poverty challenges that different communes are facing.

The maps presented in Figure 5 serve as valuable tools for nutrition practitioners to refine their intervention strategies. For instance, in communes where stunting is prevalent, but poverty is not a significant issue, practitioners should incorporate elements that address behavioral changes in their interventions, helping households overcome non-financial barriers preventing them from adopting nutritious diets. In communes where both poverty and stunting rates are high, policy makers can employ traditional stunting prevention interventions. For the remaining communes where stunting rates are low, and poverty levels vary from high to low, policymakers can implement conventional poverty reduction measures or choose to simply provide reminders on good nutritional practices, respectively.

Figure 5: Stunting and Poverty rates

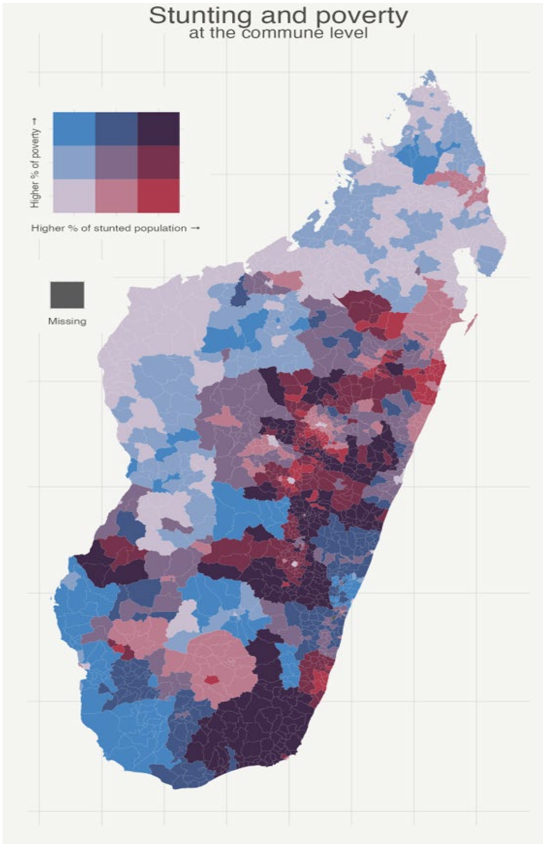
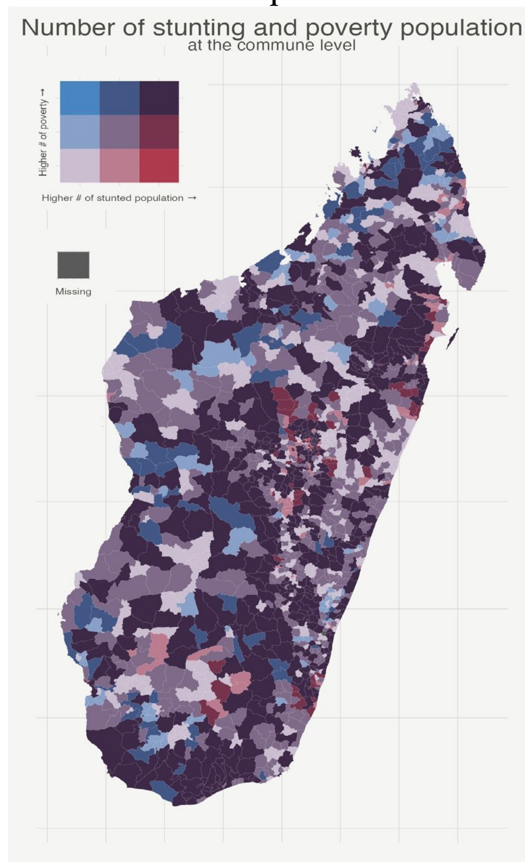


Figure 6: Number of stunted children and Number of poor households



Source: Authors' estimations

The findings underscore a crucial point made by Brown et al. (2017), suggesting that malnourished individuals are not predominantly located within economically disadvantaged households. We discovered that within communes characterized by low stunting rates, approximately 21.3% of the population actually experience higher levels of poverty, constituting roughly 7.25% of the entire population of Madagascar. Conversely, in communes with high stunting rates, about 17.9% of the population has a lower poverty rate, accounting for approximately 8.1% of the overall population. These observations carry important implications for the relationship between malnutrition and household poverty, challenging conventional assumptions that malnutrition is generally linked to destitution (Schiff et al, 1990; Adeyeye et al, 2017).

6. Conclusion and Policy Recommendations

We propose a tool for identifying and categorizing hidden hunger by leveraging routine nationally representative household data and applying an SAE approach. We applied the methodology in Madagascar and generated categories of hidden hunger that should help inform the design of locally adapted policies. While the stunting rate is 40%, we found that 17.9% of stunted children live in non-poor households, implying that using household poverty level as a targeting tool for reaching stunted children is not effective. Also, 21.3% of non-stunted children live in poor households, confirming that malnutrition is not necessarily due to destitution.

The results emphasize the need for delinking malnutrition from poverty and designing nutrition policies according to the specific nutritional challenges faced by communes. For instance, in communes where stunting is prevalent, but poverty is not a significant issue, practitioners should incorporate elements that address behavioral changes in their interventions to help households overcome non-financial barriers preventing them from adopting nutritious diets. This involved identifying non-monetary barriers and challenges and designing interventions that “nudge” individuals toward healthier choices through repetitive messaging integrated in community based nutritional programs (Galasso and Umapathi, 2009). In communes where both poverty and stunting rates are high, policy makers can employ traditional stunting reduction interventions as stunting there may be highly linked to poverty. Facilitating access to lipid-based nutrient supplement to parents of stunted children can increase their children’s micronutrient status (Steward et al, 2020). For the remaining communes where stunting rates are low, and poverty levels vary from low to high, policy makers should prioritize policies that equipe commune level health facilities and those that reduce poverty, respectively (Razakamanana et al. 2023).

Sen (1981) argued in his influential book "Poverty and Famines" that food scarcity *due to poverty* is not the only cause of famines and malnutrition. He emphasized the importance of examining entitlements and other social and economic factors that affect people's ability to access food. Sen's work has had a profound impact on how policymakers and researchers approach hunger and poverty, emphasizing the need to address not just food production, but also distribution, access, and social safety nets. Our findings add to this work by highlighting the importance of behaviors and norms, which can help to explain why malnutrition is so prevalent in many non-poor communes.

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Annex

In A1 the variables selected through the LASSO procedure to predict per capita consumption as well as the resulting coefficients from the linear mixed model used to simulate poverty in the census are provided. To interpret the coefficients, there are three aspects pertaining to them which are important as described below:

- **Statistical significance of the coefficient.** The coefficient is subjected to t-test to determine whether it is significantly different from zero or statically significant at 95 percent confidence level. In Table A1, all coefficients with one or more asterisks are statistically significant at 95 percent confidence level.
- **Direction (whether its negative or positive) of the coefficient.** A positive coefficient indicates that the variable leads to an increase in per capita consumption, while a negative coefficient leads to a reduction in the response variable.
- **Size of the coefficient.** This indicates magnitude of the effect or influence of the variable on the response (per capita income) whether positive or negative. For example, a large positive coefficient means the variable leads to larger increases in the per consumption while a large negative coefficient means the variable leads to large decrease in per capita income.

Given the interpretation framework explained above, there are several predictors whose coefficients are statistically significant at the 95 percent confidence level. For example, all the assets except for landline are statistically significant and positive. This is what would be expected that ownership of assets indicates or is positively associated with higher per capita consumption. Furthermore, among all the assets that are positively associated with per capita income, car has the largest influence, which matches with what is expected in low-income regions that households who own a car often have higher income. On the other hand, large household size and large dependency ratio are often associated with poorer households. This is evident in Table A1 where both household size and dependency ratio have negative coefficients. Household head demographic characteristics such as age, sex and education attendance are also statistically significant. Households with older heads have higher per capita income, while those heads who attended school also have higher income as would be expected. When it comes to household head sex, female-headed households, controlling for other factors, have lower per capita consumption than the male headed households. In general, the signs (direction), size and statistical significance of coefficients do match with what would be expected.

Table A1 : Estimated model coefficients (poverty)

Category/ Variable		**Standard Error**
(Intercept)	14.595***	0.061
Region name		
Vakinankaratra	0.042	0.079
Itasy	-0.024	0.104
Bongolava	-0.042	0.120
Haute Matsiatra	-0.043	0.084
Amoroni'mania	-0.17	0.097
Vatovavy Fitovivany	-0.14	0.084

Ihorombe	-0.081	0.105
Atsimo Atsinanana	0.016	0.091
Atsinanana	0.029	0.082
Analanjirofo	0.091	0.084
Alaotra Mangoro	-0.14	0.087
Boeny	0.198**	0.089
Sofia	0.080	0.079
Betsiboka	-0.081	0.106
Melaky	0.298**	0.088
Atsimo Andrefana	-0.07	0.076
Androy	-0.29**	0.097
Anosy	-0.09	0.104
Menabe	0.067	0.087
Diana	0.010	0.087
Sava	-0.060	0.094
Age of household head	0.003***	0.00033
Household size	-0.11***	0.002
Dependency ratio	-0.097***	0.005
Urban/Rural classification		
Rural	0.015	0.010
Sex of household head		
Female	-0.072***	0.012
Marital Status		
Single	Omitted	
Married	-0.23***	0.015
Divorced/separated	-0.11***	0.016
Widowed	-0.17***	0.019
Ever attended school		
Yes	0.071***	0.011
Highest education level completed/attended		
None	Omitted	
Preschool	-0.014	0.059
Primary	Not selected	
General/technical secondary	0.093***	0.009
Superior	0.259***	0.017
Wall material		
Cinder block, stone	Omitted	
Baked brick	0.003	0.011
Stem/bark/Leaf	-0.058***	0.016
Sheet (Corrugated or galvanized)	-0.042**	0.019

Plank	-0.048**	0.016
Bozaka	-0.12***	0.03
Recovered material	-0.21	0.147
Other	-0.072	0.039
Material for the roof		
Tile	Omitted	
Sheet (corrugated or galvanized)	0.044**	0.018
Cement/fibro-cement	Not selected	
Bozaka	-0.062**	0.02
Stem/Bark/Leaf	-0.076***	0.022
Salvage material	Not selected	
Other	Not selected	
Material for the floor		
Bare ground/Earth/Sand	Omitted	
Stem/Bark/Leaf/Bamboo	0.098***	0.019
Mat	0.070***	0.013
Rudimentary plank	0.124***	0.015
Parquet/Waxed wood/polished wood	0.138***	0.020
Cement	0.109***	0.013
Vinyl, tile, carpet, rug	0.217***	0.022
Other	0.096**	0.043
Energy for cooking		
Charcoal		
Firewood	-0.16***	0.011
Oil	-0.069	0.179
Gas	0.354***	0.073
Electricity	0.036	0.052
Dung	Omitted	
Other	-0.16**	0.078
Energy for lighting		
Network electricity	Omitted	
Oil lamp	-0.091***	0.010
Candle/Paraffin/Wood/Board	-0.11***	0.020
Other	-0.14***	0.031
Household Assets		
TV	0.212***	0.011
Stove	0.144**	0.050
refrigerator_freezer	0.225***	0.019
washing_machine	0.150**	0.052
Sewing machine	0.082***	0.020
Computer	0.239***	0.021

internet_equip	0.264***	0.077
Car	0.418***	0.035
ac_fan	0.187***	0.025
Motorcycle	0.256***	0.019
Landline	-0.37	0.221

Notes: * = p<.05, ** = p<.01, *** = p<.001

In table A2 the variables selected through the LASSO procedure to predict stunting as well as the resulting coefficients from the linear mixed model used to simulate stunting in the census are provided. To interpret the coefficients, there are three aspects pertaining to them which are important as described below. The child's age, the presence of a person under the age of 15 in the household, the mother's marital status (being married), and the mother's highest level of education achieved are all negatively associated with the likelihood of having a stunted child in the household. On the other hand, having a female child and owning a radio, TV, and refrigerator are positively linked to having a stunted child in the household, underscoring the idea that income and wealth may not necessarily be correlated with stunting. Notably, the remaining factors included in the regression do not demonstrate statistical significance.

Table A2 : Estimated model coefficients (stunting)

Variable	**coefficient**	**Standard error**
(Intercept)	-0.017	0.067
Provinces		
prov_code_2	0.137	0.074
prov_code_3	0.114	0.080
prov_code_4	0.481***	0.079
prov_code_5	0.270***	0.078
prov_code_6	0.499***	0.099
Child age (months)	-0.0092***	0.001
Having a person below 15 in the household	-0.026***	0.007
Having a person above 64 in the household	0.074	0.039
Gender of child	0.166***	0.024
Marital status of parent	-0.015	0.041
Highest education level	-0.021	0.026
Wall material	0.028	0.038
Floor type	0.028	0.031
Radio ownership	0.070**	0.028
TV ownership	0.174***	0.044
Refrigerator ownership	0.173**	0.084
Computer Ownership	0.118	0.084
Car Ownership	0.103	0.119
Motorcycle Ownership	0.020	0.065

Notes: * = p<.05, ** = p<.01, *** = p<.001