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Hunger and Food Insecurity in Nairobi's Slums: An Assessment Using IRT Models

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ABSTRACT *Although linked to poverty as conditions reflecting inadequate access to resources to obtain food, issues such as hunger and food insecurity have seldom been recognized as important in urban settings. Overall, little is known about the prevalence and magnitude of hunger and food insecurity in most cities. Yet, in sub-Saharan Africa where the majority of urban dwellers live on less than one dollar a day, it is obvious that a large proportion of the urban population must be satisfied with just one meal a day. This paper suggests using the one- and two-parameter item response theory models to infer a reliable and valid measure of hunger and food insecurity relevant to low-income urban settings, drawing evidence from the Nairobi Urban Health and Demographic Surveillance System. The reliability and accuracy of the items are tested using both the Mokken scale analysis and the Cronbach test. The validity of the inferred household food insecurity measure is assessed by examining how it is associated with households' economic status. Results show that food insecurity is pervasive amongst slum dwellers in Nairobi. Only one household in five is food-secure, and nearly half of all households are categorized as "food-insecure with both adult and child hunger." Moreover, in line with what is known about household allocation of resources, evidence indicates that parents often forego food in order to prioritize their children.*

KEYWORDS *Food insecurity, Hunger, Sub-Saharan Africa, Slum, Nairobi*

INTRODUCTION

The issue of hunger and food insecurity in urban settings has become particularly salient since 2008 as "riots of hunger" took place in several capitals across the world following the wake of the global rise in the price of staple foods such as wheat, rice, and cooking oil. In less than a year, the price of wheat rose 130%, soya by 87%, and rice by 74%.[1] Although linked to poverty as conditions reflecting inadequate access to resources to obtain food, issues such as hunger and food insecurity have seldom been recognized as important in urban settings. Overall, little is known about the prevalence and magnitude of hunger and food insecurity in most cities. Yet, in sub-Saharan Africa where the majority of urban dwellers live on less

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than one dollar a day,[2] it is obvious that a large proportion of the urban population must be satisfied with just one meal a day.

In spite of this, little research has been carried out to appraise the scope of hunger and food insecurity in urban settings in sub-Saharan Africa.[3–5] In contrast, the physiological signs of extreme food deprivation (malnutrition) have been the subject of extensive research, with a particular focus on children, childbearing women, and persons suffering from chronic illnesses. However, despite a strong connection, the two issues are conceptually different. While food insecurity and hunger may lead to malnutrition over time, they may occur without the overt signs of suboptimal nutritional status.

Going without food unintentionally and regularly is not without adverse health effects over time. It may cause serious damage to the physical and mental health of those affected. Conversely, widespread hunger and food insecurity may also pose social problems. Fighting to address food insecurity may lead to socially undesirable actions such as theft or other criminal actions. Searching for enough food could also take away the attention of affected households from other priorities such as children's schooling or vaccination. Then, failure to deal with hunger and food insecurity problems in a country could render efforts to promote growth and better quality of life ineffective.

Assessing and monitoring the extent of food insecurity and hunger should therefore be taken as key parts of national strategies for improving livelihood in African countries. In food-rich countries such as the USA, Canada, UK, and New Zealand, this has been a routine exercise since the 1990s. In the USA, the Census Bureau has developed a US Food Security Scale, which is fielded each year through the Current Population Survey. In this country, food security, food insecurity, and hunger indicators are now essential components of a wider portfolio of indexes used for monitoring human development and household livelihood.

The purpose of this paper is to assess the scope of food insecurity and hunger among households in a poor urban informal setting, drawing evidence from the Nairobi Urban Health and Demographic Surveillance System (NUHDSS). The paper seeks to provide prevalence estimates of food insecurity and hunger in this setting (how many people are affected?), identify those who are affected, and determine the causes (why are people affected?).

But, beforehand, what is meant by the concepts "food insecurity" and "hunger"?

The World Food Summit defined food security as "when all people at all times have physical and economic access to sufficient, safe, and nutritious food for a healthy and active life."[6] Household food security is, therefore, a combination of availability of safe food and assured possibility for households to meet their dietary needs and food preferences in socially acceptable ways. Thus, households become food-insecure when there is uncertainty about food availability and access, insufficiency in the amount and kind of food necessary for meeting their dietary requirements, or the need to use socially unacceptable ways to acquire food.

An important consideration is that food insecurity is a dynamic experience rather than a static one. The experience varies through graded levels of severity ranging from uncertainty and anxiety about food to the extreme case of hunger. Hunger represents the more severe form of food insecurity.

Conceptually, food insecurity is defined as a composite phenomenon with various facets. Kendall et al.[7] suggest four defining features of food insecurity: the quantitative and qualitative aspects of the food available to the households, and the psychological and social components experienced by the household. However, this suggestion is not widely shared. Whereas the qualitative and quantitative aspects appear as the core components of food insecurity, the social and psychological dimensions have not yet been consistently characterized in food insecurity research to date. Hamelin et al.[8] suggest taking the social and psychological aspects as consequences of the phenomenon rather than core components of food insecurity. The focus of this paper is on the quantitative dimension of food insecurity. This is to emphasize that in poor urban settings, financial resource constraints constitute the primary barrier to food access. In such settings, food insecurity is mainly caused by low or unstable revenues, which lead to limited, inadequate, or insecure means of food acquisition. The strength of this approach is that the quantitative dimension is the most unambiguous aspect of food insecurity and the one that can be measured most precisely.[9]

Measuring and assigning a degree of food insecurity to households and/or individuals has proved to be a non-trivial task for researchers. The challenge consists of selecting a valid and reliable set of manifest indicators of food insecurity and transforming them into a unidimensional scale of severity. Various techniques exist for inferring a food insecurity measurement scale from a list of food deprivation indicators. A basic approach is the sum score technique which consists simply of a weighing or not-weighing summing up of the indicators. Factor analysis techniques are also widely used to check whether a set of indicators fit a unidimensional measurement scale. Factor analyses are performed by examining the pattern of correlations (or covariance) between the observed measures. Measures that are highly correlated (either positively or negatively) are likely influenced by the same factors, while those that are relatively uncorrelated are likely influenced by different factors. This paper uses an alternative approach, the item response theory (IRT) model, which allows generating a consistent measurement index jointly with estimating its determinants. The indicators used for generating the index are selected on the basis of their reliability and their ability to describe a single predominant trait.

Like Cappellari and Jenkins,[10] the paper draws on the literature on item response theory from psychometrics and educational testing. Indeed, IRT methods were initially developed for ability/achievement tests. However, they are increasingly being applied to social and economic measures containing items that are scored in a dichotomous or polytomous fashion. And since experience-based food insecurity indicators are measured in a similar way, deriving a food deprivation scale from a set of food insecurity indicators is thus like constructing an academic ability scale from a set of test scores.

The paper is organized as follows: The next section describes the methodological framework for measuring hunger and food insecurity. "Context and Related Literature" sets out the context and some related literature, while "Data" presents the data. "Results" discusses the results and the last section concludes.

METHODOLOGICAL FRAMEWORK

Food insecurity is a latent trait; as such, it is inferred based on responses of persons to a set of items representing different observable indicators of deprivation. The strategy consists of summarizing the information from the different items into a single synthetic index. Among the various methods that are suggested for inferring a single indicator from a set of observed indicators of deprivation, the IRT approach emerges as one of the most suitable and innovative.* IRT models allow character-

*Cappellari and Jenkins[10] examine some methodological issues concerning the different approaches of construction of a deprivation scale from multiple deprivation indicators. They consider the theoretical foundations of the practice of constructing a deprivation scale as a raw or weighted sum score relatively weak.

istics of items (item parameters) and characteristics of individuals (latent measures) to be related to the probability of providing a particular response. They also allow representation of items and individuals on the same scale, which can be seen as an optimal scale design.

The IRT overcomes some of the problems and assumptions associated with traditional methodologies (e.g., classical test theory). In particular, the IRT does not require assumptions about sampling or normal distributions, which makes it ideal for performance assessment with different item structures. It also does not necessitate that measurement error be considered the same for all persons taking a test or answering a set of questions. IRT models describe a parametric relationship between item responses and the latent summarizing variable through a link function. Depending on the number of parameters used to model the responses to each item, the IRT models are one-parameter IRT, two-parameter IRT, or three- or four-parameter IRT. All models posit the assumption that a single underlying latent trait is the primary causal determinant of the observed responses to each test's item. However, they differ with respect to the way in which the latent trait is presumed to cause the item response.

In addition, two types of IRT models exist following the link function: the normal IRT model based on the cumulative normal probability distribution function, and the logistic model based on the logistic function. This paper uses the one- and two-parameter IRT models with a probit link to explore the issue of hunger and food insecurity in Nairobi's slums.*

IRT models assume *unidimensionality*, which means that all the items in the test measure the same latent trait, with the result that individuals can be ordered on a linear scale. In unidimensional IRT models, the observed responses to a test item are assumed to be determined by the combined action of the latent trait and the characteristics of the item (difficulty, discrimination, etc.). Related to unidimensionality is the assumption of *local independence* which postulates that the responses in a test are statistically independently conditional on the latent trait. Thus, local independence is evidence for unidimensionality if the IRT model contains person parameters on only one dimension. Additionally, IRT models assume that the probability of presenting a disadvantage is a non-decreasing function of the latent trait. This assumption refers to the *monotonicity*. Another important assumption is the *measurement invariance* propriety which postulates that items have equivalent proprieties across groups. A violation of this assumption suggests that systematic differences exist in how survey respondents understand the items or in how difficult items are to answer. In that case, inferences about group differences may not be correct. In the IRT literature, the violation of the *invariance* propriety is known as "item bias" or "differential item functioning."

Construction of a Synthetic Index

Let y_{ij}^{*} be measuring the latent deprivation of individual $j(=1,\ldots,m)$ for the item i $(=1,\ldots,n)$; the general form of the one-parameter IRT model is as follows:

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*Carlson et al.[30] use the simplest model of the IRT (Rasch model) to develop a benchmark measure of the severity and prevalence of food insecurity and hunger in the USA. Conversely, an alternative method similar to the Foster–Greer–Thorbecke poverty measurement approach has been developed by Gundersen (2008) to explore the extent, depth, and severity of food insecurity among the American Indians in the USA.

$$y_{ij}^* = \beta_i + \theta_j^* + \varepsilon_{ij} \quad (1)$$

$$y_{ij} = \begin{cases} 1 \; if \; y_{ij}^* > 0 \\ 0 \, \text{otherwise} \end{cases} \quad (2)$$

where θ_j^* is the latent score of deprivation for individual j, β_i is the difficulty of question or item i, and ε_{ij} is an error term. The parameter β_i represents the item i difficulty parameter (or the parameter of severity of item i). The parameter θ_j^* is the individual score of deprivation. According to the one-parameter IRT model, the probability of being deprived decreases with the difficulty parameter of the item, given θ_j^*, and increases with the individual deprivation score, given the difficulty parameter β_i. In addition, the probability of being deprived equals ½ when the individual deprivation score equals the item difficulty parameter.[11]

In what follows, we treat θ_j^* as random individual effects to use the standard maximum likelihood to estimate both the parameter β_i and the deprivation score θ_j^*. We also consider the error term ε_{ij} as normally distributed with zero-mean and fixed variance.

Note that the one-parameter IRT model is known as the Rasch model if θ_j^* are treated as parameters instead of random variables and the error term has a logistic distribution. The Rasch model has a particular property that distinguishes it from other IRT models. In the Rasch model, the score computed as the unweighted sum of the responses to the items constitutes a sufficient statistic of the latent trait. In other words, the simple aggregation of the indicators respecting the Rasch model assumptions gives the deprivation score. Conditional maximum likelihood can be used to estimate the item parameters. However, Cappellari and Jenkins[10] identify a potential problem related to the number of items, which is usually small. Conditional maximum likelihood methods can be used to estimate each item parameter when m tends to infinity and given n fixed, but the parameter θ_j^* cannot be estimated. Standard maximum likelihood estimates of θ_j^* are inconsistent as m tends to infinity, given n fixed.

To overcome this problem, the standard way forward consists of treating θ_j^* as individual random effects. In this case, the parameter β_i can be estimated using the standard maximum likelihood methods. In addition, the predicted values of θ_j^* are estimated using "empirical Bayes" (EB) methods, which make use of both the assumed latent variable distribution (the "prior") using the information about individuals' observed responses and the item response parameters. Thus, the predicted deprivation score for each individual is the expected value of the posterior distribution. The substantial advantage of the EB prediction of latent deprivation is that it provides more secure methodological foundation to the measurement of deprivation scales.

On another point, one noteworthy difficulty with the Rasch model as well as the one-parameter IRT in general is that it is very restrictive. They impose a set of stringent conditions that the items must fulfill. One of these strong assumptions concerns the equi-correlation between any pair of items. The two-parameter IRT model allows relaxing this condition, introducing second item parameter δ_i, called the *discrimination parameter*. The factor δ_i represents the extent to which item i discriminates between individuals of different deprivation scores. It indicates how well an item discriminates along the scale of deprivation continuum. The higher the discrimination parameter, the more desirable the item. The general form of the two-parameter IRT model is as follows:

$$y_{ij}^{*} = \beta_i + \theta_j^{*}\delta_i + \varepsilon_{ij} \tag{3}$$

$$y_{ij} = \begin{cases} 1 \; if \; y_{ij}^{*} > 0 \\ 0 \, \text{otherwise} \end{cases}. \tag{4}$$

One limit of the two-parameter IRT model is that the property of sufficiency of the score on the latent trait does not hold anymore. A change in the latent score of deprivation does not equally affect the items of deprivation.

One advantage of IRT models is that they also allow estimating the determinants of the latent trait jointly with the estimates of the IRT parameters.[10–12] For this purpose, one introduces into the model a structural equation that models the determinants of the latent deprivation. This transformation allows estimating the determinants of the latent deprivation. The structural equation is as follows:

$$\theta_j^{*} = Z_j\gamma' + \xi_j \tag{5}$$

where Z_j represents the vector of observed covariates, γ is the vector of the regression parameters, and ξ_j corresponds to a disturbance term assumed normally distributed with mean zero and fixed variance. Thus, the one-parameter IRT model becomes:

$$y_{ij}^{*} = \beta_i + Z_j\gamma' + \xi_j + \varepsilon_{ij} \tag{6}$$

While the two-parameter model is:

$$y_{ij}^{*} = \beta_i + Z_j\delta_i\gamma' + \xi_j + \varepsilon_{ij}. \tag{7}$$

This makes the problem similar to a multiple-indicator multiple cause (MIMIC) model. In what follows, we use this framework to derive a hunger and food insecurity index and investigate the impact of households' socioeconomic characteristics on their latent deprivation scales.

Item Testing and Selection

To check whether the items selected in our analysis match with the assumptions underlying IRT models, we conduct a Mokken scale analysis (MSA). MSA is a scaling technique for ordinal data and mainly used for scaling test and questionnaire data. MSA is based on the monotone homogeneity model, which is a nonparametric IRT model. MSA is related to nonparametric IRT models. However, it can also be used for parametric IRT models as the assumptions underlying the monotone homogeneity model are the same as those for parametric IRT models. These are unidimensionality, local independence, and monotonicity.[13,14]

MSA is based on three scalability coefficients: the scalability coefficient H_{ih} for pairs of items (i, h), the scalability coefficient H_i for an item with respect to other items in the test, and the scalability coefficient H for the total set of items in the test (for further details, see Van der Ark[13]). Under the monotone homogeneity model, higher positive H values reflect higher discrimination power of the items and, as a result, more confidence in the ordering of the respondents. Items with high H_{ih} discriminate well in the group in which they are used. In practice, H and H_i values are between 0 and 1. Mokken[15] recommended using $H = 0.3$ as a lower bound. That is, $0.3 \le H \le 0.4$ denotes a weak scale, $0.4 \le H \le 0.5$ denotes a medium scale, and $H \ge 0.5$ denotes a strong scale.

MSA uses an automated item selection procedure to partition the set of items into an unknown numbers of subsets of items, which constitute Mokken scales (denoted S_1, S_2,...). The mechanism works as follows: It starts by selecting the pair of items for which (1) H_{ih} is significantly larger than 0 and (2) H_{ih} is the largest among the coefficients for all possible item pairs. Then, a third item k is selected that (3) correlates positively with the items already selected, (4) has a H_i coefficient that is larger than 0, and (5) has a H_i coefficient that is larger than a user-specified value C. The program keeps selecting items as long as they are available and satisfy conditions 3, 4, and 5. Note that the process may leave some items unselected.

Conversely, following Cappellari and Jenkins,[10] we also use the Cronbach alpha statistic to check the internal consistency of our items. Indeed, the theory underlying Cronbach alpha refers to a classical measurement model with continuous indicators. Nevertheless, it can serve in our analysis as it is a useful tool allowing assessing the correlation between the items making up our synthetic index. If all items are perfectly correlated, the alpha statistic equals 1, reflecting a high internal consistency within the deprivation scale. We perform these tests using the MSP and Alpha modules of the statistical package STATA.

In addition, we analyzed the suitability of our items using the item characteristic curve (ICC) derived from the estimation of our two IRT models. The ICC is a useful graphical tool which describes the relationship between the latent deprivation score and the response to each item of deprivation scale. It is a two-dimensional scatter plot of deprivation scores by item response probability, depicting the item response that would be expected from an individual located at any given point on the underlying scale. Therefore, for each item of scale, we have one ICC. The distribution of deprivation scores do not need to follow a particular form (e.g., a normal distribution). In our case, the ICC is a plot of the household latent scale of food deprivation over the probability of being food-deprived.

CONTEXT AND RELATED LITERATURE

While rural poverty remains critical because most poor people live in rural areas, urban poverty is becoming a growing development concern. Rapid urbanization, growing unemployment, and poor planning and governance have resulted in mushrooming of slum settlements in major cities in Kenya and other African countries. The Kenyan Central Bureau of Statistics indicates that the proportion of people in Nairobi living below the poverty line has increased from 26.5% in 1992 to 50.2% in 1997.[16] The situation is even worse in Nairobi's informal settlements. Data routinely collected by the African Population and Health Research Center (APHRC) in two Nairobi slums (Viwandani and Korogocho) show that poverty rates in these two informal settlements were as high as 73% in 2003, although these have since fallen to 62% in 2006.[17] Gulyani and Talukdar[18] find the same poverty rate, 73% in 2004, based on a random sample of 1,755 households across Nairobi's informal settlements.

Nairobi's slums are characterized by high levels of unemployment and under-employment, unstable livelihoods, and lack of basic amenities and social services. APHRC data demonstrate that very few slum residents are in stable and salaried employment. The majority earn their living through casual employment and informal businesses. A study based on data collected in 2003 and 2004 shows that for males aged 15 and above, only 9% of recent migrants and 13% of long-term residents were in salaried employment, while between 53% and 57% were either in casual employment or informal business, and between 2% and 25% were economically inactive.[19] The economic situation for females living in slum settlements is much more precarious, with only 2% being in salaried employment and 67% of the recent female migrants and 56% of the long-term residents being economically inactive.[19]

A review of studies on the causes of malnutrition and food insecurity in urban areas highlights that in an urban environment, there is a greater dependence on cash income for both food and non-food products, and there are weaker informal safety nets than in rural areas. Moreover, the higher labor force participation of women in activities outside the home often has negative consequences for child care, which, combined with greater exposure to environmental contamination, may result in poor child nutritional status.[3]

A quantitative analysis carried out by IFPRI in 12 sub-Saharan countries found that in all the countries under study, more than 30% of the urban population were energy-deficient, with this figure rising to over 70% in countries like Malawi, Ethiopia, and Zambia.[4] Another indicator of food insecurity recently considered is the household dietary diversity, defined as the number of foods or food groups consumed over a period of time. A study by Hoddinott and Yohannes[20] found that household dietary diversity not only increases the nutritional food base of the household but is also associated with higher spending on food, implying that food-secure households have tended not only to have more food availability but also more diverse nutritional composition. Conversely, food-insecure households enjoy less diversity.

In urban settings where the majority of households buy their own food, lack of income is the main challenge to food security.[21] A study in Accra, Ghana, found that households purchase 90% of their food.[5] Urban dwellers, unlike their rural counterparts, cannot rely on their own production of food, and food expenditure can make up a large percentage of total household expenditure (42% in Korogocho and 35% in Viwandani). Lack of access to regular employment and thus a regular source of income may be expected to be associated with a heightened risk of food insecurity.

In most developing countries, the informal sector plays a major role in the economy.[21] It is estimated that 40% of the urban work force in Kenya, and 90% of the work force in Sierra Leone, finds employment in the informal sector.[22] The work capacity of the poor in urban areas can be jeopardized by their own health status, with those experiencing poorer health having a lower working capacity and lower paying jobs.[23] The health and nutritional status of the urban population has a direct impact on the ability to generate income and thus protect the household members from food insecurity.[21] Thus, a negative cycle may be set in motion by poor nutrition, leading to poor health and low income-earning capacity, then food insecurity.

DATA

Over the last two decades, there have been significant methodological shifts in measuring household food insecurity. Two major shifts are a move from a focus on objective to subjective measures, and a growing emphasis on direct and fundamental measures instead of reliance on proxy measures. These changes have been mainly driven by four major studies in the USA. These are the food sufficiency status question (later the third National Health and Nutrition

Examination Survey); the Community Childhood Hunger Identification Project; Radimer/Cornell measure of hunger and food insecurity; and the Food Security Core Module, or the US Household Food Security Survey Module (HFSSM). The latter is widely accepted as the best instrument available for measuring food insecurity. It contains a set of 18 questions related to the household's inability to purchase food, which are used to derive a food security index. Using the index, households are classified according to whether they are food-secure, food-insecure without hunger, or food-insecure with hunger.[24] Households are ranked according to their degree of food insecurity, with households ranked in the bottom of the scale if they report that they have run out of food and both adult and child members of the household have not eaten all day.

It is worth noting that all four instruments have been developed and used in the US context. However, there are several studies that successfully adapted and applied the HFSSM approach in diverse countries.[25–27] It is also worth mentioning the Food and Nutrition Technical Assistance project funded by the US Agency for International Development, aimed at designing a household food insecurity measurement instrument to be used cross-culturally.[28]

The survey used in this paper was not specifically designed for measuring household food insecurity. It is not a local adaptation of the HFSSM. However, it comprises a module on food consumption with a list of items which overlap with the 18 items proposed for food insecurity measurement in the US HFSSM. This study takes advantage of the availability of this information to investigate the extent of food insecurity in the setting covered by this survey. The paper picks only the food insecurity dimensions that are acknowledged as common across cultures and countries. This strategy is based on the recommendations of Coates et al.[29] Coates et al. explored commonalities of food insecurity experience in 15 countries using 22 separate scales and found that four domains (uncertainty/worry, insufficient quantity, inadequate quality, and social acceptability) form the basis of the universal food insecurity experience at a household level.

The paper uses household data collected from the Viwandani and Korogocho slums in the NUHDSS. This is a longitudinal study following up with individuals and other primary subjects once every 4 months to collect key demographic data. The data contain a series of questions about food production and consumption, in addition to more conventional indicators of household living standards such as expenditure, income, assets, dwelling characteristics, livestock, etc. The data on household amenities, food situation, assets, and income are collected once a year for all households residing within the surveillance areas. Within the 4-month visitation cycle, these data are collected for new households that are immigrating into the study areas, while the dwelling unit characteristics and amenities data are collected for households that expel movements (move from one dwelling unit to another within the study area).

The questionnaire module "food production and consumption" is a checklist containing 16 ordinal or dichotomous items. Each item consists of a statement that describes households' food situation in terms of access, variety, etc. We focus on food access using four dichotomous indicators variables. These indicator variables summarize responses to questions put to households asking whether:

1. They had enough food during the last 30 days;
2. They had money to get more if the food they bought finished during the last 30 days;

3. Children in the household failed to eat for a whole day or slept hungry because there was not enough food during the past 30 days;
4. Adults in the household failed to eat for a whole day because there was not enough food during the past 30 days.

The possible response categories to these questions were *often true*, *sometime true*, *never*, and *don't know*. Table 1 presents the percentage of households that responded to each question over the period 2006–2008. During this period, on average, only 28% of households living in Viwandani declare being food-secure, compared to 7% in Korogocho. Looking at the evolution year by year, we even notice a worsening of the situation. Food insecurity has increased over time in both sites. In 2006, 36% of residents in Korogocho did not have enough food to eat (either always or sometimes); by 2008, this had increased to 55%. Similarly, in Viwandani, the percentage of households in this position rose from 24% of households in 2006 to 41% in 2008. It is noteworthy that the two sites do not experience the same level of food insecurity. Residents of Viwandani appear more food-secure than those of Korogocho. This may be related to the differences in the characteristics of the two slums. Korogocho has a more settled population, since many of the residents have been there for many years. In contrast, in Viwandani (situated in the proximity of the industrial area), the population is mainly made up of young males and is also better educated compared to that in Korogocho. Both slums also have different employment profiles, with Viwandani having more people engaged in formal income-generating activities compared to Korogocho.[19]

The rising trend of food insecurity in both sites is consistent with the frequency and order of households' affirmative answers to the other items of the module. In Korogocho, 90% of households in 2008 reported that it was sometimes or often true that "the food that you bought finished and there was not money to get more," compared to 75% in 2006. Again, the figures were lower in Viwandani, but still reflect the upward trend over time (57% in 2006, rising to 65% in 2008). In 2008, 45% of residents of Korogocho said that it was sometimes or often true that their children would go to sleep hungry because there was not enough food to feed them.

Conversely, almost all households reported that they would change their food consumption patterns were they to receive additional funds of 2,000 Kenya shillings each month, with the majority stating that they would buy more nutritious food.

In what follows, since we are using IRT models for dichotomous variables, we focus on the response category *never* and re-categorize the responses into two options: *true* or *false*. For the first two questions, each variable is assigned 1 if households respond negatively and 0 otherwise. For questions 3 and 4, each variable is scored 1 if the answer is positive and 0 otherwise. These four variables are representatives of those used in literature. They are a subset of those used in the Radimer/Cornell hunger and food insecurity measures and the US HFSSM.[7,30–34]

Table 1 gives a descriptive summary of how much each variable is endorsed (score 1) in our sample. Our initial overall sample comprises 13,058 households. As one of our indicator variables focuses on child hunger, the analysis here is limited to households with children (6,971). To prepare the data for analysis, any household with missing information were removed, leaving 6,795 households with children with completed information. About 21% of households in this sample scored 0 for any of the four indicators. Fifteen percent have been given score 1 for one indicator, the same proportion for two indicators, and 45% for three indicators. Only 4% of

TABLE 1 Items on household insecurity, with percentage of affirmative responses to each statement in Viwandani and Korogocho in 2006–2008

	Korogocho				Viwandani			
	2006	2007	2008	Avg.	2006	2007	2008	Avg.
"Which of these statements best describe the food eaten by your household during the last 30 days?"								
Your HH had enough of the kinds of food it wanted to eat	13.7	4.3	1.6	6.9	37.4	27.9	19.9	27.7
Your HH had always the kinds of food it wanted, but not enough food	47.8	47.9	43.7	46.6	32.3	41.2	38.7	37.9
Sometimes your HH did not have enough food to eat	32.1	44.6	48.4	41.3	19.6	26.5	36.8	28.2
Your HH often did not have enough food to eat	4.4	3.0	6.2	4.5	3.6	4.0	4.4	4.0
"The food that you bought finished and didn't have money to get more"								
Often True	10.9	9.0	7.1	9.0	8.9	7.9	6.5	7.6
Sometime true	63.5	74.9	81.8	73.2	47.8	58.0	58.5	55.8
Never true	23.3	15.8	10.9	16.7	31.8	33.2	34.6	33.4
"During the past 30 days, children in your HH failed to eat for a whole day/slept hungry because there wasn't enough money for food"								
Often True	3.9	1.8	1.1	2.3	1.7	0.9	0.4	0.9
Sometime true	28.4	41.9	44.4	38.2	9.1	7.8	8.3	8.3
Never true	26.3	20.0	17.2	21.2	27.9	32.5	33.3	31.7
"During the past 30 days, you or other adult(s) in your HH failed to east for a whole day/slept hungry because there wasn't enough money for food"								
Often True	9.4	4.7	3.1	5.8	6.3	4.9	3.9	4.8
Sometime true	59.7	68.8	74.9	67.8	40.3	41.9	43.4	42.1
Never true	28.3	26.2	21.9	25.6	42.6	52.1	52.4	49.9
If your HH received additional Ksh. 2000 each month, would you change anything about what your HH eat?								
Yes	83.7	88.8	95.4	89.3	76.9	86.0	85.8	83.5
No	13.5	10.6	4.4	9.8	15.7	12.7	13.5	13.8
What is the main change that you would make to your household's food consumption?								
Buy more food items of what is being eaten	18.8	15.9	13.1	16.0	31.8	29.8	34.1	31.8
Buy more nutritious food items	55.0	60.5	60.0	58.5	42.3	40.6	42.0	41.6
Buy great variety of food	26.0	23.5	26.9	25.4	25.9	29.6	23.8	26.6

For each question, the statement scores sum up to 100. The gap corresponds to missing answer, don't know, or refusal.

the sample report having 1 for the all four indicators. We report details of household demographic and socioeconomic characteristics in the Appendix.

RESULTS

Item Selection and Internal Consistency

We test whether our items fulfill the IRT assumptions using the MSA. As mentioned previously, the MSA is an automated item selection procedure which allows identifying a set of items pertaining to a unique scale and respecting the IRT hypothesis. Table 2 shows the results of the Mokken scale procedure. It comprises a series of diagnostics that allow an investigation of the relationship between item scores and the latent trait score. The first column corresponds to the items' name or label and the second is "easiness" of the items. The easiness gives the proportion of households who have been assigned 1 for the item. What this tells us is how much of the latent trait (food deprivation here) does a household have to have before we would expect it to take the value 1 (i.e., yes) on the observed variable. The item "Food finished and no money" appears as the easiest. The item "Often do not have enough to eat" is the least positively reported. In the terminology of hierarchical scales, this item is referred as the "hardest" and thereby represents a greater amount of the latent trait being measured (food deprivation). The third column of the table reports the Loevinger H coefficient. The z statistic (corresponding to the test that the observed coefficient H is 0) is reported next.

The Loevinger H coefficient for the whole scale is 0.88, which suggests that the four items form a strong scale according to the IRT assumptions. Closer inspection of these items shows that the Loevinger coefficient for each item is >0.30. The items "Food finished and no money" and "Adult failed to eat a whole day" display very high values (of 0.94 and 0.91, respectively). This suggests that these two items discriminate well between households. From the two-parameter IRT estimation, we expect high values of the factor associated to these two items.

Conversely, we tested the reliability of the scale formed by the four items using the Cronbach alpha test. In general, the Cronbach alpha statistic increases when the intercorrelations between items increase. Our test gives an alpha statistic of 0.73, which indicates a strong scale and high internal consistency.

TABLE 2 Mokken scale statistics for food deprivation items

Items label	Easiness $P(X=1)$	Loevinger H coefficient	z stat
Often do not have enough food to eat	0.06	0.38	10.78***
Adult(s) failed to eat for a whole day	0.63	0.91	77.15***
Food finished and no money to get more	0.78	0.94	66.60***
Children failed to eat for a whole day/slept hungry	0.49	0.84	70.10***
Scale		0.88	8523***

*$p<0.05$; **$p<0.01$; ***$p<0.001$. The "z-stat" column represents the Z-statistics of the null hypothesis significance test for each H, with the null hypothesis being that the H value is zero and the alternative hypothesis being that the H value is positive.

IRT Model Estimates

Table 3 reports the estimates of the IRT models. Across the columns are statistics corresponding to one-parameter IRT specification as well as the two-parameter model and the two-parameter estimation with the variance of the latent deprivation scale set to 1. The two-parameter IRT specification is based on the relaxation of the equi-correlation assumption incorporated by the one-parameter model. It takes into account a discrimination parameter which allows consideration of the fact that some items have stronger (or weaker) relations to the latent scale being assessed than others. We tested the two models (one-parameter versus two-parameter) to check which model fits our data better. The likelihood ratio test rejects the one-parameter model in favor of the two-parameter one (LR $X^2(3)=2046.13$; Prob. $>X^2=0.000$), suggesting that the four items have different discrimination power.

Estimates from Table 3 indicate that the item "Children failed to eat for a whole day/slept hungry" is the most discriminating variable, followed by the item "Adult failed to eat a whole day." The least discriminating item is "Food finished and no money." The item "Often do not have enough to eat" displays a parameter close to 0, which suggests that this item is not a discriminating variable. These results mean that at a low level of food deprivation index (–1 for instance), one should expect the item "Children failed to eat for a whole day/slept hungry" have the lowest probability rate of affirmative response, the item "Adult failed to eat a whole day" a higher rate, and the item "Food finished and no money" the highest rate. In

TABLE 3 Estimates from the probit IRT models

	One-parameter		Two-parameter		Two-parameter (fixed variance)	
Indicators	Est.	SE	Est.	SE	Est.	SE
Difficulty parameter						
Often do not have enough food to eat	3.48	0.15	1.63	0.03	1.63	0.03
Food finished and no money to get more	−1.03	0.14	−1.56	0.24	−1.56	0.24
Children failed to eat for a whole day/slept hungry	0.72	0.14	1.07	0.37	1.07	0.37
Adult(s) failed to eat for a whole day	−0.05	0.14	−0.47	0.35	−0.47	0.35
Discrimination parameter						
Often do not have enough food to eat	1	–	1	Fixed	0.16	0.02
Food finished and no money to get more	1	–	13.78	2.20	2.26	0.12
Children failed to eat for a whole day/slept hungry	1	–	21.95	3.61	3.60	0.22
Adult(s) failed to eat for a whole day	1	–	21.11	3.77	3.46	0.32
Estimate of Variance	2.39	0.10	0.03	0.01	1.0	0.0
Log-likelihood	−14,126.8		−10,617.7			
Log-likelihood test ratio	LR $\chi^2(3)=2{,}046.13$					
One-parameter IRT nested in two-parameter IRT	Prob. $>\chi^2=0.0000$					

contrast, at a higher level of food deprivation, one could expect a reversed pattern or all items having the highest probability rate of affirmative responses.

This hierarchy between items at a low deprivation scale is in line with Radimer's characterization of food insecurity as a "managed process." This means that within households, individual members experience food insecurity differently at different times and to different degrees. Looking at food insecurity experience among low-income women with children in the USA, Radimer et al.[34] found that anxiety about enough food occurred first, followed by compromise in the quality and then quantity of women's food intakes, along with a more general deterioration in quality at the household level. Compromises in the quality and quantity of children's intakes did not occur until later. Radimer's observation is that children's eating patterns were rarely affected. In sum, quantity was preserved at the expense of quality, and children were protected from compromise.[9]

Results from Table 3 also confirm the items' ranking in terms of difficulty (parameter β_i) as suggested by the Mokken scale analysis. The item "Often do not have enough to eat" is clearly the most severe in both the one-parameter and the two-parameter IRT models, followed by the item "Children failed to eat for a whole day/slept hungry." This means that the probability that a household which "has not enough to eat" to be deprived of the other items is higher than 0.5. For a better understanding, be reminded that the notion of latent scale implies a certain relationship between the so-called scale and the items that tap it. The latent variable is regarded as the cause of the items' score. That is, the strength or the quantity of the latent variable is presumed to cause an item to take a certain value. In our case, this means that the probability of getting affirmative response for the item "Often do not have enough to eat" is associated with a high level of food deprivation. At low levels of food deprivation scale (for instance, $\theta<1$), this probability stays close to zero, while the probability of getting the other items endorsed is very high

The ICCs give a great illustration of the results above. The ICC displays the form of the functional relationship between the food latent deprivation scale and the observed items' responses. The vertical axis is the probability of getting the item right (affirmative response or endorsement). The horizontal axis depicts the food deprivation latent scale (θ). Figure 1 displays the ICC for the food deprivation scale. In the one-parameter IRT model, all items exhibit ICCs having the same shape because we assume in this model equal discrimination power for all items. This means that all the ICCs have the same slope and they do not intersect. In the two-parameter model, the ICCs do not exhibit the same shape as the items do not have identical discrimination power (factor δ_i).

It is customary to set the latent scale (θ) by considering the sample mean equal to 0 and the standard deviation equal to 1. Thus, in the graph, the center of the latent scale is 0 and the numbers go up and down from there. For instance, 1 corresponds to 1 standard deviation above the mean, and –1 to 1 standard deviation below the mean. This suggests that the probability of getting affirmative responses to the items increase as the food deprivation score increases.

Focusing on the two-parameter graph in Figure 1, we notice that the rightmost curve corresponds to the ICC of the most difficult item, "Often do not have enough to eat." In the graph, the probability of getting this item endorsed at 50% is associated with a food deprivation scale of almost 2.0. And a vertical line projected from that point to the curves of the other items shows that households with such a food deprivation score (2.0) are expected at 100% to declare being deprived in the

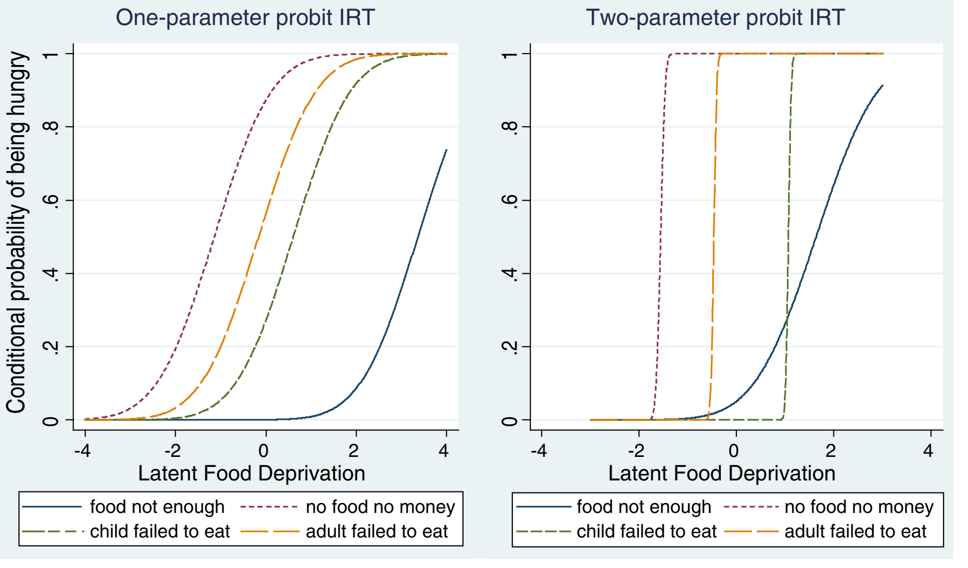

FIGURE 1. Item characteristics curves for the food deprivation scale.

three items. This confirms that the probability that a household which "has not enough to eat" is deprived of the other items is higher than 0.5.

In the same graph, the steepness of the ICCs in their middle sections reflects the discrimination power of the items. The flatter the curve, the less the items discriminate since the probabilities of correct response at low and high deprivation rates are nearly the same. The steeper the curve, the better the item can discriminate because the probability of a correct response at low deprivation scores is not the same as it is at high deprivation scores. The graph shows that the most discriminatory item is "Children failed to eat for a whole day/slept hungry." This item has a step function; the probability of getting it endorsed (affirmative response) is zero until the food deprivation index reaches 1.0, at which point the probability jumps to 100%. Above a food deprivation score of 1.0, the curve gets flat. The graph is in line with Radimer's statement, as until the food deprivation of score gets to 1.0, households preserve their children from getting hungry, while adults are yet failing to eat.

Validity Analysis

Latent scale validity is the degree to which the index measures what it proposes to measure. To test the validity of our latent food deprivation score, we use the criterion-related validation strategy, which consists of comparing the inferred measure to some variables that are admitted to be related to the phenomenon being measured (food insecurity). The intuition is that if our food insecurity scale is valid, then we should expect it to correlate in a predictable way with some variables commonly used to measure food insecurity (for instance household income, anthropometry indicators, etc.).

In our validity test, we focus on how the inferred food insecurity scale correlates with household income. For this purpose, we also explore the potential determinants of food deprivation by including a supplementary structural equation into the IRT model (Eqs. 6 and 7). Our explanatory variables include the characteristics of the

TABLE 4 Determinants of latent food deprivation

	One-parameter IRT		Two-parameter IRT	
Variables	Est.	(SE)	Est.	(SE)
Household income quintile (ref. first quintile)				
Second quintile	−0.19	(0.06)**	−0.02	(0.01)**
Third quintile	−0.41	(0.07)***	−0.05	(0.01)***
Fourth quintile	−0.56	(0.08)***	−0.06	(0.01)***
Fifth quintile	−0.58	(0.10)***	−0.07	(0.01)***
Household characteristics				
Location: Korogocho (ref. Viwandani)	1.58	(0.05)***	0.18	(0.03)***
Size	0.00	(0.01)	−0.00	(0.00)
Composition (ref. adult 25–49)				
Proportion of children under 5	0.17	(0.13)	0.01	(0.02)
Proportion of children 5–10	0.15	(0.16)	0.01	(0.02)
Proportion of adolescents 11–15	0.22	(0.18)	0.02	(0.02)
Proportion of adults 16–24	0.09	(0.11)	0.01	(0.01)
Proportion of adults 50 and +	0.22	(0.19)	0.03	(0.02)
Characteristics of the household head				
Education level (not educated)				
Primary school	−0.21	(0.09)*	−0.04	(0.01)**
Secondary school	−0.30	(0.10)**	−0.04	(0.01)**
High school	−1.23	(0.31)***	−0.12	(0.04)**
Education level unknown (missing)	0.05	(0.14)	−0.00	(0.02)
Immigrant (not enumerated)	0.17	(0.05)***	0.02	(0.01)*
No. of households	6,795		6,795	

*$p<0.05$; **$p<0.01$; ***$p<0.001$

head of household (gender, age, education level, and enumeration status[*]), the characteristics of the household (size and composition), and the household income ranking based on the monthly household adult equivalent expenditure. Table 4 reports the impact of different covariates on the latent food deprivation scale. Focusing on our criterion of interest, we notice that in both IRT models, food deprivation has a significant and negative association with household income level. Household food status scale worsens significantly as its income is low. Food deprivation is higher for households at the bottom of the income distribution. Results from Table 5 confirm the negative association between food insecurity and household income distribution. The proportion of households in each food deprivation group is inversely proportioned to households' income category. For instance, only 13% of households in the first quintile appear food-secure, compared to 30% in the fifth quintile. In sum, our food deprivation scale is perfectly consistent as expected with household income status. This provides evidence of the validity of our measure.

[*] The enumeration status is a binary variable which refers to the residence status of the individual in the survey area when the NUHDSS was started. If someone was enumerated at that time, this person scores 1, otherwise 0. Those who have not been enumerated are also called immigrants (meaning immigrant in the DSS area).

TABLE 5 Food situation status: prevalence and households' characteristics

	Food situation status									
			Food insecure							
	Food secure		Without hunger		With adult hunger		With child hunger		With adult and child hunger	
	N	%	*N*	%	*N*	%	*N*	%	*N*	%
All households	1,456	21.6	1,025	15.2	937	13.9	53	0.8	3,259	48.4
Location										
Korogocho	415	11.3	330	9.0	238	6.5	44	1.2	2,636	72.0
Viwandani	1,041	33.9	695	22.7	699	22.8	9	0.3	623	20.3
Household head characteristics										
Female	450	20.5	303	13.8	279	12.7	16	0.7	1,148	52.3
Male	1,006	22.2	722	15.9	658	14.5	37	0.8	2,111	46.6
Not educated	56	10.9	59	11.5	28	5.5	2	0.4	367	71.7
Primary school	749	20.4	533	14.5	484	13.2	35	0.9	1,873	51.0
Secondary school	561	26.6	372	17.6	349	16.5	11	0.5	819	38.8
High school	18	42.9	9	21.4	8	19.0	00	0.0	7	16.7
Monthly adult equivalent expenditure quintiles										
First quintile	300	13.4	327	14.6	217	9.7	17	0.8	1,379	61.6
Second quintile	393	21.0	287	15.3	253	13.5	18	1.0	919	49.1
Third quintile	344	27.5	196	15.6	239	19.1	12	1.0	461	36.8
Fourth quintile	246	31.5	116	14.9	127	16.3	2	0.3	289	37.0
Fifth quintile	147	30.0	80	16.4	90	18.4	3	0.6	169	34.6
Household composition										
Children below 11	1,088	21.6	788	15.6	696	13.8	40	0.8	2,432	48.2
No children below 11	368	21.8	237	14.1	241	14.3	13	0.8	827	49.0
Children 11–15	417	19.3	296	13.7	185	8.6	26	1.2	1,236	57.2
No children 11–15	1,039	22.7	729	16.0	752	16.5	27	0.6	2,023	44.3
Less 11 and above 49	100	17.2	66	11.3	41	7.0	6	1.0	369	63.4
No less 11 or above 49	1,356	22.1	959	15.6	896	14.6	47	0.8	2,890	47.0

Prevalence Estimates and Households' Characteristics

With the empirical Bayes prediction of the latent food deprivation score, it is possible to study the incidence and severity of hunger and food insecurity once a cutoff point has been identified. There is no obvious way to fix such a cutoff point. However, some approaches can be explored. One can adopt a relative approach fixing a specific quintile of the index $\left(\theta_j^*\right)$, the second quintile, or the third, or whatever. Another way consists of using an absolute approach by setting a specific value taken as a threshold of food deprivation.

In what follows, we adopt a categorical approach[30] by specifying different ranges of food situation status. This allows comparing the incidence of food insecurity and hunger across different population groups. Based on our four items, we distinguish five food deprivation statuses: "food-secure," "food-insecure without hunger," "food-insecure with adult hunger," "food-insecure with child hunger," and "food-insecure with both adult and child hunger." Table 5 reports the five food deprivation statuses across population groups.

Overall, just one fifth of slum-dwelling households are food-secure, while nearly half (48.4%) are food-insecure with both adult and child hunger. There is significant variation between the two slum settings, with nearly three quarters of households in Korogocho experiencing food insecurity with both adult and child hunger, compared to just over 20% in Viwandani.

Results do not show a significant relationship between gender of the household head and the severity of food insecurity, although female-headed households are slightly more likely then male-headed households to experience food insecurity with both adult and child hunger (52.3% versus 46.6%). Education is, however, strongly related to food security, with those living in households where the head has no education being much more likely to experience hunger than those with high school education. Household composition also matters, with households containing both children under 11 and adults aged 50 and over being the most likely to be food-insecure.

CONCLUSION

This paper has explored the utility of using four dichotomous indicator variables to develop a food hunger index for use in a resource poor urban setting. Our analysis suggests that such an approach is possible. In line with what is known about household allocation of resources and the fact that parents will often forego food in order to prioritize their children, the analysis found that the most discriminatory item is "Children failed to eat for a whole day/slept hungry." This was found to be the case in both the Mokken scale analysis and the two-parameter IRT model.

Food insecurity among slum dwellers in Nairobi is widespread, with nearly half of all households being categorized as "food-insecure with both adult and child hunger" and only one in five are food-secure. Food insecurity is higher for households at the bottom of the income distribution. There is also a higher incidence of food deprivation when the household head is not educated or has joined the setting as a migrant. Furthermore, the research highlights that the NUHDSS survey instrument could validly be used to identify those households suffering food insecurity and hunger in Nairobi. The "food consumption" module of this instrument has the advantage of being short and easy to implement. And since this survey is routinely collected, it provides the opportunity to monitor household food situation over time in relation to all the dynamics and shocks happening in this area. Further research will focus on this issue.

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APPENDIX

TABLE 6 Household demographic and socioeconomic characteristics

Descriptive statistics		
Variables	Mean	SE
Household characteristics		
Size	4.27	2.54
Composition		
No. of children under 5	0.64	0.71
No. of children 5–10	0.74	0.89
No. of children 11–15	0.43	0.71
No. of adults 16–24	0.84	1.12
No. of adults 25–39	1.12	0.95
No. of adults 40–49	0.31	0.55
No. of adults 50 and +	0.17	0.44
Location (%)		
Korogocho	54.21	49.8
Viwandani	45.78	49.8
Head of household characteristics		
Age	35.42	13.61
Female (%)	32.70	46.91
Immigrant (%)	39.26	48.83
Not educated	07.62	26.54
Attended primary school	54.55	49.80
Attended secondary school	31.40	46.41
Attended high school	00.63	07.93
Missing information on school	05.78	23.34
Monthly adult equivalent expenditure (per quintile, Kenya—Shillings)		
First quintile	1,595.72	452.50
Second quintile	2,705.94	302.05
Third quintile	3,976.10	443.85
Fourth quintile	5,979.10	778.86
Fifth quintile	13,370.54	6,742.32

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