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September 2002

CARD Working Paper 02-WP 310

Center for Agricultural and Rural Development Working Paper Series

Ames, Iowa 50011

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This research was supported in part by the U.S. Department of Agriculture, Economic Research Service, under cooperative agreement number 43-3AEM-8-80079. The authors benefited from useful comments and suggestions from Mark Nord.

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Abstract

Over the last decade, new information has been developed and collected to measure the extent of food insecurity and hunger in the United States. Common measurement of the phenomenon of hunger and food insecurity has become possible through efforts of the U.S. Department of Agriculture (USDA) to develop a set of survey questions that can be used to obtain estimates of the prevalence and severity of food insecurity. This paper takes a closer look at the measurement of food insecurity and the effect of household variables on measured food insecurity. The effects of demographic and survey-specific variables on the food insecurity/hunger scale are evaluated using a generalized linear model with mixed effects. Data come from the 1995, 1997, and 1999 Food Security Module of the Current Population Survey. The results generally validate the model currently used by the U.S. Department of Agriculture. In addition, our approach makes it possible to consider the effect of demographics and several survey design variables on food security among measurably food-insecure households. The analysis of the expanded model with the 1995 data finds results similar to those reported based on the Rasch model used by the USDA. Even though the sample size was reduced and a number of screening and questionnaire changes were introduced in 1997 and 1999, the results for those years appear mostly unchanged and confirm the robustness of the scale in measuring food insecurity. There is some evidence that interpretation of questions may vary among different demographic groups.

Keywords: food insecurity, household hunger, Rasch model.

AN EVALUATION OF THE USDA FOOD SECURITY MEASURE WITH GENERALIZED LINEAR MIXED MODELS

Introduction

During the last decade, new information has been developed and collected to measure the extent of food insecurity and hunger in the United States. The U.S. Department of Agriculture (USDA) has sponsored data collection to obtain information on food insecurity and hunger in the U.S. population since 1995, including support for annual food security supplements to the Current Population Survey (CPS) conducted by the U.S. Census Bureau. Common measurement of the phenomenon of hunger and food insecurity has become possible through efforts of the USDA and others to develop a set of survey questions that can be used to obtain estimates of the prevalence and severity of food insecurity (see USDA-HHS 1994; Frongillo et al. 1997; Bickel et al. 2000). The data provide the basis for estimates of prevalence and severity of poverty-linked food insecurity and hunger in the United States and are used to help identify those groups in the population at greatest risk.

Based on earlier research, the USDA has analyzed data taken from a set of survey questions about food insecurity using an item-response-model approach, in order to estimate food insecurity experienced at the household level. Hamilton et al. (1997a) discuss the approach selected to define and quantify food insecurity, based on a one-parameter logistic item response model, also referred to as a Rasch model. Hamilton et al. (1997b) report the findings from the 1995 survey using this method, and the USDA has reported findings for subsequent years (e.g., Bickel et al. 1999; Andrews et al. 2000; Nord et al. 2002). The resulting measure, or index, of degree of food insecurity or hunger has shown itself to be remarkably robust across different time periods and across some subpopulation groups (Nord and Jemison 1999; Nord and Bickel 2001; Ohls et al. 2001). However, further research is needed to understand the robustness of the method across different subgroups and in the context of alternative survey modes and experiences of hunger (Frongillo 1999; Derrickson et al. 2001).

This paper has two main purposes: to evaluate the robustness of the approach currently used for the measurement of food insecurity, and to measure the effect of household-level variables on measured food insecurity. Both purposes will be addressed by fitting the food security data with a class of models that generalizes the Rasch model and comparing the estimates obtained from the different models on several years of CPS data.

Earlier research has shown that the Rasch model is a useful way to assign "food security" measures, or scores, to households participating in the CPS survey modules. The model assumes, however, that the food insecurity questions are interpreted in the same manner by all households interviewed. If this assumption is violated, then the estimated question scores and the food security estimates derived from them are potentially biased. While it is possible to check this assumption by performing Rasch model fits for subsets of the population and comparing the results, this approach is cumbersome and the results are problematic to interpret statistically.

In contrast, the generalized linear mixed model (GLMM) used here makes it possible to incorporate household variables as well as interactions between these variables and the question scores. By having these types of variables explicitly in the model, we can answer questions like the following:

- Are certain demographic groups more likely to be food insecure?
- Are survey mode effects present in the survey?
- Are certain questions understood differently by certain demographic groups?

Hence, not only will it be possible to test some of the assumptions underlying the Rasch model on the CPS data, but we will also be able to estimate the effect of household variables on food insecurity.

The outline of the paper is as follows. First, we address methods of measurement. We review the Rasch and the generalized linear mixed models and show how the latter can be viewed as a direct generalization of the former. We fit the model to data from the Current Population Survey Food Security Module. Then, we use the results to validate the food security scale and to examine the effect of demographic and survey design variables on the scale.

Subjects and Methods

Methodology

The Rasch model currently used by the USDA for estimating household food security scores is a type of item response theory (IRT) model developed for the purpose of measuring the ability of individuals based on their answers to a set of questions (Baker 1992). The model implies the existence of a continuous "scale" on which the items (questions) can be placed based on their difficulty levels and on which individuals can be placed based on their ability levels. The main objective of item response models is to estimate where individuals will fall on that scale. In the USDA Food Security scale, households are asked a set of questions related to their experiences of food insecurity in order to measure the phenomenon as perceived by that household. Hence, the questions' "difficulty" is the level of food insecurity they capture, and the scale on which households are measured is the severity of the household's food insecurity.

As in the case of the USDA Food Security scale, we consider items to have only two-answer categories ("yes/no" or "true/false"). Suppose a set of such dichotomous questions was administered to a sample of households (or, more precisely, household representatives or respondents). Each household responds to each question according to its latent food security: the more severe the food insecurity of the household, the larger the probability of giving a positive response to any given question. At the same time, each question has an implied food insecurity level, with "harder" questions more likely to be answered negatively than "easier" questions, regardless of the household's food insecurity level.

Specifically, suppose that a sample of n households was administered a set of m dichotomous items, with each household receiving the whole set of m items. Based on their responses, the goal is to estimate each household's severity (or, in IRT terminology, its ability) as well as each item's implied food security (or its inherent difficulty). To formalize, let q_i be the ith individual's ability parameter for $i = 1, \ldots, n$ and let a_j be the jth item's difficulty parameter for $j = 1, \ldots, m$. If I_{ij} is an indicator random variable that gives the dichotomous answer of person i to item j, then its distribution is

$$\Pr(I_{ij} = 1 \,|\, q_i, a_j) = \frac{\exp(q_i - a_j)}{1 + \exp(q_i - a_j)} \,. \tag{1}$$

The indicator variables I_{ij} are assumed to be independent of each other, conditional on the parameters $(q_i, i = 1,...,n$ and $a_j, j = 1\ldots, m)$. An easy way to interpret model (1) is to note that when $q_i = a_j$, individual *i* has a 50 percent chance of answering question *j* affirmatively. When $q_i > a_j$, the individual is more than 50 percent likely to answer affirmatively, and conversely, when $q_i < a_j$, the individual is less than 50 percent likely to answer affirmatively.

The Rasch model provides a convenient framework in which to simultaneously estimate the individual abilities q_i and the item difficulty parameters a_j, based on a set of questions administered to a group of individuals. The model makes it possible to estimate these parameters even in the presence of item non-response, or if different but partially overlapping sets of questions are presented to respondents. In the USDA Food Security scale, for instance, households with children are asked 18 dichotomous questions, while households without children are asked only 10 questions (see Hamilton et al. 1997b). Also, it is relatively easy to generalize to more complicated settings in which the items have different discriminating power, the individuals are assumed to randomly guess the answers to some or all of the questions, and so on. See Baker (1992) for more details on such generalizations.

Even though the Rasch model (1) leads to an exponential family model, it cannot be fitted directly by maximum likelihood methods because of overparameterization. Hence, the estimated values are not unique. To solve this problem and get unique estimates, constraints are added, for instance, $\sum_{j=1}^{m} a_j = 0$. Several methods are then available to fit this kind of Rasch model, including unconditional maximum likelihood as used in Hamilton et al. (1997a).

No such simple adjustments are available, however, for incorporating household-level covariates such as the number of children or the gender of the household head into the model. Therefore, the Rasch model (1) will be replaced by a generalized linear mixed model (GLMM). This model reduces the number of parameters by assuming that the household parameters $q_i, i=1,\ldots,n$ follow a parametric distribution. Specifically, we assume that the severity parameter for the *i*th household can be written as

$$q_i = b_0 + b_1 x_{1i} + \ldots + b_p x_{pi} + g_i \ ,$$

where the $x_{1i},\ldots,x_{pi}$ are covariates of interest for household *i*, the $b_0,\ldots,b_p$ are unknown parameters determining the effect of the covariates on households in the population, and g_i is a household-specific deviation from this population trend. The $g_i, i=1\ldots,n$ follow a parametrically specific distribution. As is common practice in GLMM fitting, we will assume here that they are identically and independently normally distributed with mean 0 and unknown variance t^2.

The model we therefore are considering in this paper is

$$\operatorname{logit} \Pr\left(I_{ij}=1 \,|\, g_i, a_j\right) = b_0 + b_1 x_{1i} + \ldots + b_p x_{pi} - a_j + g_i \,, \qquad (2)$$

with $g_i \sim \mathrm{N}\left(0, t^2\right)$. The parameters $b_0,\ldots,b_p, a_j (j=1,\ldots,m)$ and t^2 are to be estimated from the data. This model will be fitted using restricted pseudo likelihood (REPL) maximization, which is implemented in the GLIMMIX routines available for the Statistical Analysis System (SAS) (Wolfinger and O'Connell 1993). The GLIMMIX program contains an additional parameter for deviation between the observed dispersion of the observations and that predicted by the exponential family model. We will not discuss that parameter here.

Several sets of covariates are of interest. Demographic variables make it possible to study household characteristics potentially affecting food security. Variables related to the interviewing process itself can be included in the model to determine if "mode effects" are changing the outcome of the survey estimates. In addition, interactions between these variables and the item difficulties will be studied, since these can point to differences in interpretation of the questions across population groups, a violation of the Rasch model assumptions.

Data

The data for analysis come from the CPS Food Security Module for the years 1995, 1997, and 1999. Table 1 shows the 18 food security questions of the 1995 CPS that were used in developing the Food Security scale. These questions correspond to the food insecurity items with parameters a_j mentioned previously and are coded as dichotomous variables. For a complete description of the questions and the coding of the answers, see Hamilton et al. 1997b. The questions NHES40–NHES50 and NHES56–NHES58 were asked only of households with children, while the remaining questions were asked of all households. Question NHES58 was treated as the comparison level and left out of the regression model.

In addition to these food security questions, the following household-specific demographic and survey mode variables, corresponding to $x_{1i},\ldots,x_{pi}$ in

TABLE 1. 1995 Current Population Survey Food Security Items

Item Code	Summary of Questions
NHES24	Adult cut size or skipped meals
NHES25	Adult cut size or skipped meals, 3+ months
NHES28	Adult not eat whole day
NHES29	Adult not eat whole day, 3+ months
NHES32	Adult eat less than felt they should
NHES35	Adult hungry but didn’t eat
NHES38	Adult lost weight
NHES40	Cut size of child’s meals
NHES43	Child skipped meal
NHES44	Child skipped meal, 3+ months
NHES47	Child hungry
NHES50	Child not eat for whole day
NHES53	Worried food would run out
NHES54	Food bought did not last
NHES55	Adult not eat balanced meals
NHES56	Couldn’t feed child balanced meals
NHES57	Child not eating enough
NHES58	Adult fed child few low-cost foods

(2), are included in the analysis. The age of the household reference person is treated as a continuous variable. It was included as a linear (AGE) and a quadratic term (AGESQ) in order to capture some non-linear effects. The variable PHONEINT is a dummy variable denoting whether the food security interview was conducted by phone (PHONEINT = 1) or in person (PHONEINT = 0). Some of the CPS interviews were conducted in Spanish if the respondent did not have sufficient knowledge of English. The variable SPKSPNSH is a dummy variable with a value of 1 if Spanish was the only language spoken by all members of the household age 15 and over, and with a value of 0 otherwise. The variable MALE codes the gender of the household reference person, with a value of 1 if male and with 0 otherwise. Ethnicity is also recoded into two groups, with MINORITY = 0 for non-Hispanic white and MINORITY=1 for all other groups. The variable CHILD is an indicator variable taking the value of 1 if there are any children present in the household, and taking 0 otherwise. Here, the term “children” refers to anybody who is under 18 years old. UNEMPLOY is an indicator variable for the employment status of the household reference person at the time of the interview. It takes a value of 1 if he or she is unemployed, and takes 0 otherwise. Metropolitan status of the location of the household is included in the model as the indicator variable METRO, equal to 1 if the household is in a Metropolitan Statistical Area.

Income is measured relative to the state and household-size-specific poverty levels determined by the U.S. Census Bureau and is used to classify the households into four categories. The indicator variables POVCATx, with $x = 1,2,3,4$, correspond to income levels below 100 percent (POVCAT1), 100 to 150 percent (POVCAT2), 150 to 185 percent (POVCAT3), and more than 185 percent of the poverty level (POVCAT4). The variable POVCAT1 was treated as the comparison level and left out of the regression.

Marital status of the household reference person is captured by the indicator SINGLE. In addition to “never married,” SINGLE = 1 also includes situations such as married but spouse absent, divorced, separated, and widowed. For education, LOWEDU = 0 is the code for household reference persons with high school diploma or above, and LOWEDU = 1 is the code for those without high school diploma.

These data are available for each of the Food Security Module surveys since 1995. We will discuss the model fits for the survey years 1995, 1997, and 1999 in the results section. The numbers of households with complete and valid data available for all the variables (with the exception of the child-specific food security questions for households without children and additional questionnaire skip patterns in 1997 and 1999), and who answered affirmatively to at least one of the food insecurity questions are 16,185 for 1995, 3,817 for 1997, and 5,475 for 1999. Because of the much larger sample size available for 1995, we will focus primarily on the data from that survey year. It should be noted that since the models are only fitted on household who displayed at least measurable levels of food insecurity as noted above, the interpretation of the household estimates is, strictly speaking, only valid for that subset of the overall population.

For 1997 and 1999, the sample sizes are smaller because more stringent screening criteria were used in those years. In addition to a set of initial screening questions, households who responded negatively to subsequent sets of questions were also screened out before completing the full set of Food Security items (Bickel et al. 2000). Specifically, respondents who answered negatively to a set of "easier" food security items were not asked the remaining "harder" items. As recommended by the USDA, we imputed the answer no (or zero) for these "harder" skipped questions for all the applicable households. In 1997, two of the eight rotation groups that completed the Food Security questionnaire were given some experimental questions as part of the survey. Hence, as recommended by the USDA, households in these rotation groups were removed from the analysis.

Results

1995 Food Security Results

The mixed logistic model (2) was fitted to the 1995 data with the item questions and demographic and survey mode variables that entered the model linearly, for a total of 31 degrees of freedom. Table 2 shows the parameter estimates with their corresponding *p*-values. Note that, relative to model (2), the signs for the item parameters are changed to be positive, so that all the model parameters are estimated and interpreted in the same manner: the higher the estimated parameter value, the higher the probability of observing a positive (yes) answer. The estimate of t^{2}, the variance of the random household effect g_i, is $\hat{t}^2 = 8.49$.

TABLE 2. Parameter estimates for generalized linear mixed model without interactions for the 1995 data

Effect		Estimate	*p*-Value
INTERCEPT		-3.97	0.0001
AGE		0.1021	0.0001
AGESQ		-0.0015	0.0001
PHONEINT		-0.16	0.0046
SPKSPNSH		0.23	0.2243
MALE		-0.12	0.0542
MINORITY		0.48	0.0001
CHILD		0.08	0.2475
UNEMPLOY		0.63	0.0001
METRO		0.25	0.0001
POVCAT2		-0.77	0.0001
POVCAT3		-1.34	0.0001
POVCAT4		0.90	0.0001
SINGLE		0.61	0.0001
LOWEDU		0.41	0.0001
QUESTION	NHES24	-1.21	0.0001
QUESTION	NHES25	-2.11	0.0001
QUESTION	NHES28	-4.35	0.0001
QUESTION	NHES29	-4.97	0.0001
QUESTION	NHES32	-1.36	0.0001
QUESTION	NHES35	-3.01	0.0001
QUESTION	NHES38	-4.20	0.0001
QUESTION	NHES40	-4.33	0.0001
QUESTION	NHES43	-5.48	0.0001
QUESTION	NHES44	-6.00	0.0001
QUESTION	NHES47	-4.57	0.0001
QUESTION	NHES50	-7.33	0.0001
QUESTION	NHES53	1.50	0.0001
QUESTION	NHES54	0.58	0.0001
QUESTION	NHES55	0.30	0.0001
QUESTION	NHES56	-1.24	0.0001
QUESTION	NHES57	-2.61	0.0001
QUESTION	NHES58	0.00	

A major reason for performing the GLMM analysis is to study the effect of the household-level demographic and survey mode covariates on food security, both as a validation of the original scale and to estimate the effect of demographics on the likelihood of experiencing food insecurity among measurably food insecure households. For the validation portion, we note that all the food security items are highly significant. The ordering of the questions found here is identical to that calculated using the Rasch model and used as the basis for developing the USDA Food Security classification in Hamilton et al. (1997b). The correlation between that scale and the GLMM parameter estimates is -0.9994, further indicating the high level of agreement between both models. Hence, it appears that fitting the model with household covariates and a household random effect results in virtually identical item scores as those found with fixed household effects and no covariates.

The results for the survey mode variables are mixed. The variable SPKSPNSH is not statistically significant for any reasonable significance level. However, PHONEINT is significant, although less so than most other variables, and the size of the effect is small compared to that of the other significant variables. Overall, this indicates a weak mode effect for phone compared to in-person interviewing, with a slight decrease in the reported food security for phone interviewing.

Among the demographic variables, Table 2 shows that all parameters except CHILD, the presence of children, are significant for any reasonable significance level, and MALE is almost significant at the 95 percent level. Note that positive parameter estimates mean that these variables increase the likelihood of answering yes to any of the questions, implying an increase in food insecurity. The effects of most variables are as expected: minority households (MINORITY) and those with unemployed (UNEMPLOY), single (SINGLE), or lower-educated (LOWEDU) household reference persons all have positive estimated coefficients, indicating higher food insecurity. Households in metropolitan areas (METRO) also have slightly higher food insecurity than those living in non-metropolitan areas. The remaining two demographic variables, age and income relative to poverty level, require additional explanation.

The combined effect of the linear and quadratic age terms (AGE, AGESQ) imply that the reported food insecurity increases until age 35 and then steadily decreases as the household reference person becomes older. While somewhat counterintuitive, this is consistent with the analysis of Qi (1999), which found that households with heads over 60 years old reported less food insecurity than did younger households, and with USDA reports on household food security (Bickel et al. 1999; Andrews et al. 2000; Nord et al. 2002), which consistently found lower rates of food insecurity among the elderly.

The parameter estimates for the three income categories (POVCAT*x*) in Table 2 imply that food insecurity decreases with increasing income, up to 185 percent of the poverty level, but then increases sharply to a level above even that of POVCAT1 (which is set to 0 by default). While at first surprising, this finding is in fact an artifact of the screening procedures used in the 1995 CPS survey. Households with income below 185 percent of the poverty level were automatically taken through the food security questionnaire in 1995, while those with income above that line were included only if they answered several food insecurity “screening” questions affirmatively. Hence, because of this difference in screening procedures, households in the POVCAT4 category were more likely to be food insecure than were those in the other income groups, and this effect is reflected in the parameter estimates in Table 2.

The model was refitted after omitting the variables SPKSPNSH, MALE, and CHILD. None of the remaining parameters changed significantly, and their results are omitted here. We will keep these variables in the model, because some of the further models’ extensions, as well as the models for other years, did find some of these variables to be significant.

Next, the model is fitted with interaction terms between the household variables (excluding AGESQ) and each of the questions (i.e., items), resulting in a model with 236 parameters for estimation. This model is of interest for studying the effect of household-specific variables on the probability of answering individual questions rather than on the underlying food security level as in the linear model. This extended model is found to fit the data better, as measured by both AIC and BIC (see, e.g., Nishii 1984), frequently used goodness-of-fit criteria in generalized regression and mixed models.

The inclusion of interaction terms produced some changes in the parameter estimates of the main effects. Table 3 shows that the main effects of both mode

TABLE 3. Parameter estimates for main effects in generalized linear mixed model with interactions for the 1995 data

Effect	Estimate	*p*-Value
INTERCEPT	-3.59	0.0001
AGE	0.1072	0.0001
AGESQ	-0.0015	0.0001
PHONEINT	0.04	0.6414
SPKSPNSH	0.37	0.1509
MALE	-0.36	0.0003
MINORITY	0.47	0.0001
CHILD	-0.34	0.0001
UNEMPLOY	0.63	0.0001
METRO	-0.02	0.8525
POVCAT2	-0.63	0.0001
POVCAT3	-1.00	0.0001
POVCAT4	0.86	0.0001
SINGLE	0.46	0.0001
LOWEDU	0.41	0.0001
QUESTION NHES24	-0.96	0.0001
QUESTION NHES25	-2.08	0.0001
QUESTION NHES28	-4.35	0.0001
QUESTION NHES29	-4.98	0.0001
QUESTION NHES32	-1.85	0.0001
QUESTION NHES35	-2.85	0.0001
QUESTION NHES38	-4.68	0.0001
QUESTION NHES40	-5.48	0.0001
QUESTION NHES43	-6.62	0.0001
QUESTION NHES44	-7.23	0.0001
QUESTION NHES47	-5.19	0.0001
QUESTION NHES50	-8.11	0.0001
QUESTION NHES53	1.30	0.0001
QUESTION NHES54	0.46	0.0126
QUESTION NHES55	-0.27	0.1014
QUESTION NHES56	-2.08	0.0001
QUESTION NHES57	-3.35	0.0001
QUESTION NHES58	0.00	

variables, PHONEINT and SPKSPNSH, are now insignificant. This indicates that their effect seen in Table 2 was due to interaction effects on individual questions instead of to an overall effect on the food insecurity level. Among the demographic variables, the main effect for METRO becomes insignificant, but CHILD and MALE become significant.

Including the interactions in the GLMM model had some effect on the parameter estimates for the main effects of the food security questions shown in Table 3. The correlation with the original Hamilton et al. (1997b) findings degraded only slightly, to -0.986, but the ordering of the food insecurity questions' main effects displays several differences compared to that in Table 2 and in the USDA Food Security scale. However, since the overall effect of a question is now composed of a main effect and several interactions, the interpretation of a single "ordered item scale" is no longer appropriate.

Many but not all of the individual interactions between the household variables and the questions are significant, and the relationships between them are complex. Because of the large number of interactions, the individual parameter estimates are not shown here. Table 4 displays the direction of the interactions that are statistically significant at the 95 percent level, as well as the number of interactions that are significant for each of the household variables and the food insecurity items. A large number of significant interactions for a household variable might indicate that households with that characteristic tend to respond to many individual food insecurity questions differently than other households. Equivalently, food insecurity questions with a large number of interactions indicate that these are interpreted differently by households with different characteristics.

SPKSPNSH has significant interactions with only two questions, both of which are related to child hunger, while PHONEINT interacted with nine questions. Such interactions between the survey mode and the food security measurements clearly are not desirable and warrant further study.

Demographic characteristics with the largest numbers of interactions are the metropolitan status (METRO) and the minority status (MINORITY). It certainly seems plausible that households living in metropolitan areas or those belonging to minority

TABLE 4. Direction and number of significant interactions (95 percent level) for the household variables and food security questions in the 1995 data

Variable	24	25	28	29	32	35	38	40	43	44	47	50	53	54	55	56	57	Number
AGE	-		-	-	-	-	-						-	-		+		9
PHONEINT	-	-	-	-		-		+					-	-			-	9
SPKSPNSH								+	+									2
MALE	+	+	+	+	+	+	+	+							+			9
MINORITY	-	-	-	-	-	-		+					+	+		+	+	11
CHILD			+	+	+	+							+	+				6
UNEMPLOY		+	+	+		+		+	-	-	+		+	+	+			11
METRO	+	+	+		+	+	+	+	+	+	+		+	+	+	+	+	15
POVCAT2		-		-				-	+					-				5
POVCAT3		-			-					+	-		-	-	-			7
POVCAT4	+				+							+	-					4
SINGLE	+		+	+	+	+	+	+	+	+								9
LOWEDU	-	-			-	-		-	-					+				7
Total	8	8	8	8	9	9	4	9	6	4	3	1	8	9	4	3	3	

groups might interpret some of the questions on the Food Security questionnaires differently. Therefore, further study on such interpretation differences among these population groups also is recommended.

Finally, it can be seen that a number of food security questions display much higher numbers of significant interactions than do others. For example, many of the measures associated with more severe food insecurity showed statistically significant interactions: “Adult cut size or skipped meals” (NHES24 and NHES25), “adult did not eat for a whole day” (NAES28 and NHES29), “adult eats less than should” (NHES32), and “adult hungry but didn’t eat” (NHES35). These results suggest differences in response or reporting of adults’ behaviors with respect to the food insecurity measure.

In order to assess the practical importance of these interactions, the food security question severity levels were recalculated for specific demographic subgroups. For instance, if we consider the minority respondents only, then the question severity as applied to that demographic group (ignoring the interactions with the other variables) is the sum of the main question effect and the interaction effect between minority and that question. In this manner, a new food insecurity scale can be obtained for that demographic group and compared with the no-interaction scale or the original Rasch scale (at least up to a linear transformation of the scale).

Such demographic group-specific scales were calculated for minority, unemployed, metropolitan, and single subgroups, as well as for all of the two-way intersections between those subgroups. In all of those cases, the correlation between the subgroup-specific scale and the original Rasch scale remained above 96 percent. This analysis was repeated using all the interaction effect estimates for each subgroup or using only the ones that were found to be statistically significant. The correlations remained equally high in both cases. Hence, it appears that while the interactions are indeed statistically significant (because of the large sample size), they are not large enough to indicate significant departures from the overall food security for subpopulations.

1997 and 1999 Food Security Results

The same analysis was performed on the 1997 and 1999 data. Table 5 provides the parameter estimates for the GLMM models without interactions fitted to the 1997 and the 1999 data. The variables SKSPNSH, MINORITY, and LOWEDU are not significant at

TABLE 5. Parameter estimates for generalized linear mixed model without interactions for the 1997 and 1999 data

Variable	1997 Estimates	1999 Estimates
INTERCEPT	**-1.06**	**-0.53**
AGE	**0.0582**	**0.0760**
AGESQ	**-0.0007**	**-0.0009**
PHONEINT	**-0.19**	**-0.13**
SPKSPNSH	0.19	0.18
MALE	**0.13**	-0.08
MINORITY	0.01	0.06
CHILD	**-0.24**	**-0.48**
UNEMPLOY	**0.30**	**0.24**
METRO	0.12	**0.12**
POVCAT2	**-0.19**	**-0.41**
POVCAT3	**-0.42**	**-0.38**
POVCAT4	**-0.58**	**-0.73**
SINGLE	**0.47**	**0.35**
LOWEDU	0.09	0.11
QUESTION NHES24	**-0.84**	**-2.00**
QUESTION NHES25	**-1.71**	**-2.77**
QUESTION NHES28	**-3.82**	**-5.02**
QUESTION NHES29	**-4.46**	**-5.68**
QUESTION NHES32	**-1.03**	**-2.15**
QUESTION NHES35	**-2.56**	**-3.74**
QUESTION NHES38	**-3.57**	**-4.65**
QUESTION NHES40	**-3.91**	**-5.11**
QUESTION NHES43	**-4.79**	**-6.09**
QUESTION NHES44	**-5.30**	**-6.41**
QUESTION NHES47	**-4.31**	**-5.37**
QUESTION NHES50	**-6.44**	**-7.44**
QUESTION NHES53	**1.88**	**1.48**
QUESTION NHES54	**0.72**	**0.49**
QUESTION NHES55	**0.30**	**-0.39**
QUESTION NHES56	**-1.22**	**-1.51**
QUESTION NHES57	**-2.16**	**-2.71**
QUESTION NHES58	0.00	0.00

Note: Numbers in bold are significant at the 95 percent confidence level.

the 95 percent level in both years, and MALE and METRO are not significant in one of the two years. There is a high degree of agreement between both sets of parameter estimates, with all significant coefficients for household characteristics having the same signs and similar sizes. There is also a high level of agreement with the 1995 analysis. The most noticeable difference is that the higher income category (POVCAT4) no longer represents the most food insecure households. Instead, households in POVCAT4 are now the least food insecure, which is more in line with expectations of the relationship between food insecurity and income. Another difference between these and the 1995 results is that the presence of children (CHILD) appears to reduce the observed food insecurity in 1997 and 1999.

As in 1995, the correlation between the question scores calculated in the GLMM and the official Rasch scores from the USDA are very good, at -0.9976 for 1997 and -0.9986 for 1999. Hence, the presence of household-specific covariates and the random-effect assumption for the household effects does not appear to change the question parameters.

We also fitted the models with interactions, and, unlike in 1995, the AIC and BIC criteria indicate that the model without interactions provides a better fit to the data relative to the number of parameters used. This agrees with the finding in the previous section that the interactions do not appear to be of major practical importance.

Discussion

The Rasch model has been used by the USDA as an approach for summarizing the answers of households to the CPS food security questions and for assigning households to food security categories. While this approach is very useful for calculating food security scores for individual households, it does not allow incorporation of household-level covariates into the model and direct estimation of the effect of such covariates on household food insecurity status. The GLMM approach used in this paper makes the estimation of these effects possible and shows that, not surprisingly, many of the demographic variables appear to have an effect on the food insecurity of households with measurable levels of food insecurity.

The predicted effects for the demographic variables were as expected: those household representatives who speak Spanish, who are from minority groups, who are unemployed, single, or who have lower education were more likely to be food insecure. Males were less likely to be food insecure. The income effects for 1995 reflect different screening criteria for different income groups. The effects of income estimated in 1997 and 1999 do not suffer from this screening effect and show consistent effects of income: those with the least income were most likely to be food insecure. Age has a non-linear effect on food insecurity, with older respondents, other factors held constant, being less likely to report food insecurity or hunger.

The analysis performed here also makes it possible to test some of the assumptions underlying the Rasch model. In particular, the Rasch model assumes that a unique measure of food security is appropriate for all households. The presence of numerous interactions between the individual questions and both survey mode and demographic variables indicates that further testing of this assumption might be of interest. In particular, it appears that minority respondents and those living in metropolitan areas respond to many of the questions somewhat differently than other households. While the overall magnitude of these differences did not appear to be sufficient to invalidate the food security scale currently used by the USDA, additional study of possible differential question interpretation by subpopulations is needed.

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