

Statistical Considerations for the USDA Food Insecurity Index

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Abstract

This paper reviews the statistical properties of the model used to obtain estimates of the prevalence and severity of poverty-linked food insecurity and hunger in the United States. The U.S. Department of Agriculture has annually sponsored data collection efforts to obtain information on food insecurity and hunger since 1995. The assessment of household food insecurity is based on a one-parameter logistic item response model, also referred to as a Rasch model, and applied to a series of 18 questions reported in the Current Population Survey Food Security Module. The paper was used as the basis for discussions concerning future directions of research on the food insecurity measure.

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Key words: food insecurity, food security module, hunger, Rasch model, statistical methods.

STATISTICAL CONSIDERATIONS FOR THE USDA FOOD INSECURITY INDEX

1. Introduction

The U.S. Department of Agriculture (USDA) has sponsored annual data collection efforts to obtain information on food insecurity and hunger in the U.S. population since 1995. These efforts include modules in the Supplements to the Current Population Survey (CPS) of the U.S. Census Bureau in April 1995, September 1996, April 1997, and August 1998. The data provide the basis for obtaining estimates of the prevalence and severity of poverty-linked food insecurity and hunger in the United States; helping identify those groups in the population with the greatest problems of food insecurity and hunger; evaluating the impact of economic public programs and other variables on food security; and monitoring changes over time (Bickel, Andrews, and Klein 1996). The survey data provide information for measuring household-level food security.

Based on earlier research, the USDA has used an item response model approach to analyze food insecurity data from a set of survey questions in order to estimate the attribute “food insecurity.” Hamilton et al. (1997b) discuss the approach selected to define and quantify food insecurity, which is based on a one-parameter logistic item response model, also referred to as a Rasch model. Hamilton et al. (1997a) report the findings from the 1995 survey using this method. Ohls et al. (1999) propose an approach for allowing comparisons over time as well as between subpopulations of interest.

In this report, we discuss the statistical properties of the Rasch model and point out a number of issues and open questions about the current approach for estimating the severity and prevalence of food insecurity and hunger, as implemented by the USDA. The focus of the report is on statistical considerations in the underlying model, but many of these considerations have important practical implications as well. This report is intended as a basis for discussions concerning future directions of research and plans of work. Here, we indi-

cate possible directions for further research that would address the questions raised about estimation of the severity and prevalence of food insecurity and hunger.

Section 2 briefly reviews the one-parameter logistic item response model, with an emphasis on statistical features and the model's application to the 1995 CPS data. In Section 3, we discuss the possible objectives for food insecurity data analysis. Section 4 addresses some specific aspects of the one-parameter logistic item response model that may have implications for its applicability to the food insecurity data. Section 5 outlines several possible areas of further study. In Section 6, we conclude by briefly discussing alternative approaches for studying food insecurity in the United States.

2. Rasch Model

We begin by reviewing the statistical model used for estimating household food insecurity. Because item response models were originally designed for aptitude testing applications, the terminology used here will refer to the survey questions as items and to the respondents as individuals, with the underlying variables to be measured called the item difficulty and the respondent ability. In the food insecurity studies, ability corresponds to the severity of the food insecurity experienced by the respondent household, and difficulty is the severity of food insecurity that is implied by an affirmative response to the survey question.

A critical assumption underlying all item response models is that ability is an unobservable (also called latent), one-dimensional and continuous trait, which all respondents possess to varying degrees. At least conceptually, the model implies the existence of a continuous "scale" on which the items 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 (and sometimes, items) fall on that scale.

For simplicity, we consider items that have two answer categories (yes/no or true/false). Suppose that a sample of individuals was administered such a dichotomous question. Each individual responds to the question according to his/her latent ability: the more ability the individual has, the larger the probability that he/she will give a positive response. Empirical studies have shown that the plot of the probability of a positive answer as a function of the ability variable frequently behaves like a cumulative distribution

function (Figure 1). Among all the cumulative distribution functions, the logistic distribution has received the most attention.

Using standard item response model notation, suppose that a sample of N individuals was administered a set of n dichotomous items, with each individual receiving the whole set of n items. The goal is to estimate each individual's ability as well as each item's difficulty based on individual responses. To formalize, let θ_j be the j th individual's ability parameter for $j = 1, \dots, N$ and let β_i be the i th item's difficulty parameter for $I = 1, \dots, n$. If μ_{ij} is an indicator random variable that gives the dichotomous answer of person j to item i , then its distribution is

$$P(\mu_{ij} | \theta_j, \beta_i) = \frac{\exp(\mu_{ij}(\theta_j - \beta_i))}{1 + \exp(\theta_j - \beta_i)}. \quad (1)$$

It is assumed that the indicator variables μ_{ij} are independent of each other, conditional on the parameters ($\theta_j, j = 1, \dots, N$ and $\beta_i, I = 1, \dots, n$).

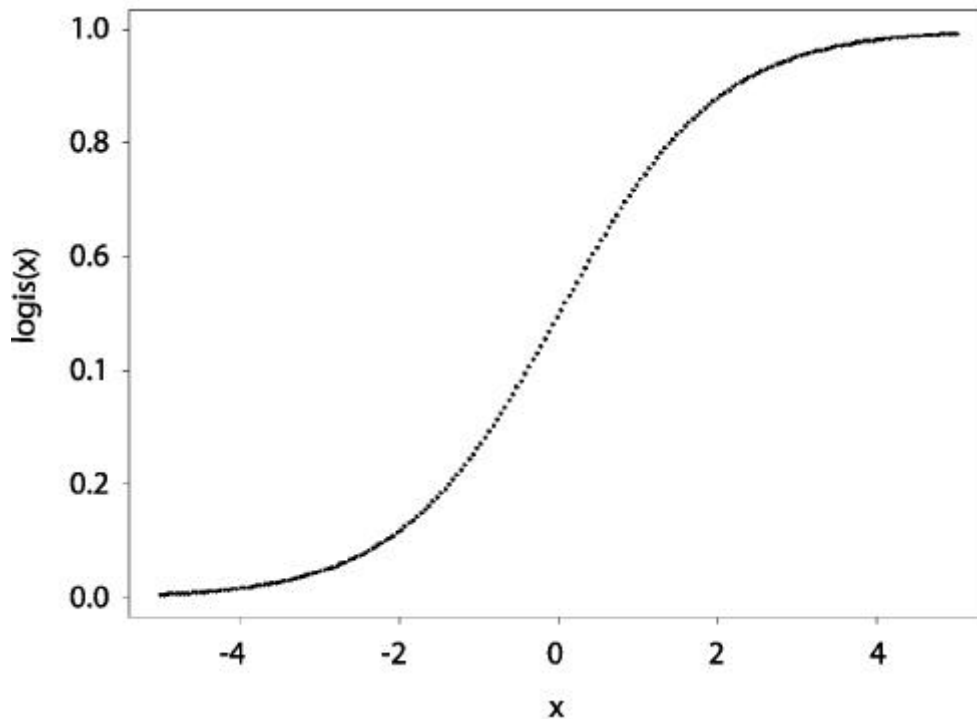


FIGURE 1. Logistic cumulative distribution function

The Rasch model provides a convenient framework in which to simultaneously estimate the individual ability and the item difficulty parameters, 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 nonresponse. Also, it is relatively easy to generalize to more complicated settings in which the items have different discriminating power, the individuals are thought to guess the answers to some or all of the questions, and so on. See Baker (1992) for more details on such generalizations.

The Rasch model as formulated in (1) is overparametrized; that is, there are more parameters to be estimated ($N + n$) than there are individuals providing data (N). Thus, the estimated values for the parameters are not unique. To obtain unique parameter values, it is necessary to normalize the parameters, for instance, by requiring that $\sum_{i=1}^n \theta_j = 0$ or that the parameters follow another similar restriction.

Overparametrization has significant consequences when Rasch model estimates for different data sets are compared. Such comparisons can be made only under the assumption that the true difficulty levels of common items (i.e., those items that occur in all data sets) are the same across the data sets. This assumption is difficult to check in practice. Even when the assumption holds, special care has to be taken so that the normalization of the item scores previously discussed is performed in a compatible way across respondent groups.

When no item nonresponse is present (i.e., the data for each respondent are complete), statistical theory implies that $\mu_j = \sum_{i=1}^n \mu_{ij}$, the sum of the positive responses for respondent j , is a sufficient statistic for the individual's ability parameter θ_j in Rasch models. In other words, the statistic μ_j contains complete information on the ability parameter θ_j . A characteristic of the Rasch model, compared with other item response models, is that, for a given set of questions and respondents with no missing data, it cannot distinguish among individuals having different patterns of item response but the same raw score. Thus, all item response patterns having the same number of correct responses yield the same estimated ability.

In addition, the sufficiency of μ_j implies that the number of distinct estimated ability parameters is, at most, $n + 1$ (maintaining that there is no missing data). Having a fixed

number of possible values for the ability estimates has a significant impact on the usefulness of these estimates for certain purposes, particularly if only a few questions are used to assess the severity of food insecurity (see Section 4).

One of the most common methods for estimating Rasch model parameters is the Unconditional Maximum Likelihood (UCON) method. This is the method implemented in BIGSTEPS (Linacre and Wright 1998). The likelihood function for model (1) is

$$l = \prod_{j=1}^N \prod_{i=1}^n P(\mu_{ij} | \theta_j; \beta_i) = \frac{\exp\left(\sum_{j=1}^N \sum_{i=1}^n (\theta_j - \beta_i)\right)}{\prod_{j=1}^N \prod_{i=1}^n (1 + \exp(\theta_j - \beta_i))}, \quad (2)$$

which is maximized simultaneously over the ability parameters θ_j and difficulty parameters β_i subject to an identifiability constraint such as $\sum_{i=1}^n \theta_j = 0$. Because of the complexity of the Rasch likelihood function, however, the problem still requires nonlinear optimization methods. Newton-Raphson optimization is commonly used.

It should be noted that expression (2) of the likelihood function depends critically on the assumption of conditional independence over the responses across individuals and items, since that assumption makes it possible to write l as a product of N times n separate probabilities. In practice, this conditional independence means that the questions cannot be directly related to each other and that the answers of one individual cannot depend on those of another individual. Hence, for any application of Rasch modeling to a set of data, it is important to evaluate carefully whether the assumption of conditional independence indeed holds.

Because of the conditional independence, Rasch models make it possible to jointly estimate the ability and difficulty parameters, even when not all individuals surveyed responded to every item. To see this, suppose that the j th individual responds to n_j items, for $j = 1, \dots, N$. In that case, the second product sign in the likelihood in (2) is over n_j terms instead of over n . The maximum likelihood estimator is still found by jointly maximizing over the parameters, subject to the identifiability constraints.

Most often, the individuals to be tested are thought of as a sample from a larger population, while the items used to test them are considered fixed. The number of ability

parameters θ_j is directly related to the sample size, and these parameters are referred to as incidental parameters. The item parameters β_i are called structural parameters. Neyman and Scott (1948) pointed out that when the incidental and structural parameters are estimated simultaneously, the estimators of the structural parameters may not be consistent. Ghosh (1995) proved that in these circumstances, the item parameter estimators are indeed inconsistent. Inconsistent estimators in this context means that even as the number of individuals increases, the estimators for the item difficulties remain biased. The lack of consistent estimators in this setting has been one of the main motivators for alternative methods for fitting Rasch models. At least two estimation methods have been proposed: (i) conditional maximum likelihood, which maximizes the likelihood function conditional on the sufficient statistics for the incidental parameters; and (ii) marginal maximum likelihood, in which the ability parameters are considered random, and random effects or Bayesian models are postulated.

One of the attractive aspects of Rasch models is that they can handle many different types of data. The partial credit model () is a generalization of the dichotomous Rasch model discussed above. It allows for multiple answer categories for each question. Specifically, the item i contains m_i “steps” of increasing (or decreasing) severity. Thus, a person can be assigned a score corresponding to

- (i) no credit (no steps completed),
- (ii) partial credit (few steps completed), or
- (iii) total credit (maximum steps completed).

The probability of person j scoring x (or completing x steps) on item i is

$$P_{ijx} = \frac{\exp \sum_{k=0}^x (\theta_j - \delta_{ik})}{\sum_{v=0}^{m_i} \exp \sum_{k=0}^v (\theta_j - \delta_{ik})},$$

where δ_{ik} is the relative difficulty of completing step k in item i , with the convention $\delta_{i0} = 0$ and $\sum_{k=0}^0 (\theta_j - \delta_{ik}) = 0$. Here $\delta_{ik} = d_i + \tau_{ik}$, where d_i is the scale parameter of item I , and τ_{ik} is the location of the step k in item i . The linear constraint $\sum_k \tau_{ik} = 0$ is imposed

for each i . Then the scale parameter d_i is the average of the relative difficulty parameters δ_{ik} for each item i . BIGSTEPS fits models with one rating scale (for example, when all questions are dichotomous), and in this case all questions belong to the same group. BIGSTEPS also fits models with several groups of questions. The questions that belong to the same group share the same rating scale. The Partial Credit Model corresponds to the case when each question has its own group, that is, the number of groups is actually the number of questions (Linacre and Wright 1998, p. 48; see also Wright and Masters 1982 for more details on rating scale models).

Abt Associates used Rasch modeling of the 1995 CPS Food Security Supplement data to create a food insecurity scale for U.S. households, as reported in Hamilton (1997b). In their approach, the households are “individuals” and the severity of food insecurity is the “ability.” The questionnaire included 58 questions with polychotomous responses. Abt Associates selected a subset of 18 questions based on nonlinear factor analysis and other statistical tests, as well as expert review and advice (Hamilton et al. 1997a), and also reduced the full set of responses to two response options in order to apply the dichotomous Rasch model methodology.

The data include two kinds of households, those with children and those without children. Households with children received 18 questions, whereas households without children received only 10, representing a subset of the 18 questions. This strategy inevitably yields missing data on the 8 questions not asked of the households without children. Other item nonresponse is likely to occur as well. As mentioned previously, the Rasch model provides a natural way to deal with item nonresponse. However, that approach is only valid under the assumption that the difficulty of the common item is constant across the respondents and that at least some of the questions overlap between groups of respondents who answered different questions. Under this assumption, the difficulty levels of the remaining questions are estimated based on the estimated difficulty of the common questions. This feature makes it possible to place households with and without children on the same scale. In practice, this approach requires that questions—such as “In the last 12 months, did you or other adults in your household ever cut the size of your meals or skip meals because there wasn’t enough money for food?”(Q24 in the 1995 CPS food

security questionnaire)—have the same implied food insecurity severity for households with and without children.

3. Uses of Rasch Scores for the Analysis of Food Insecurity Data

A primary use for the food insecurity data and the Rasch scores computed from the data is to estimate the prevalence of food insecurity in the country, for the population of U.S. households as a whole as well as for households with certain types of characteristics, for example, those with children or elderly inhabitants. Historically, this has involved estimating the percentages of the population or the subgroups that belong to several broad food insecurity categories. Such categories can be based directly on the answers to specific questions, or they can be based on a subdivision of the Rasch severity scale into ranges that define the food insecurity categories. The former approach was used by Kendall, Olson, and Frongillo (1995), while the latter was used in Hamilton et al. (1997b) to classify households into four food insecurity classes.

If classification is the main purpose of the study, the Rasch model approach is not strictly necessary, since no underlying continuous population distribution for food insecurity is assumed. Whether specific questions or Rasch scale subdivisions are used to define the food insecurity categories, knowledge of subject matter is required to ensure that the categories are meaningful and correspond to actual differences in the underlying phenomenon. An advantage of using Rasch models for classification is that the food insecurity severity can be estimated for households with incomplete sets of answers, whether this is due to (random) item nonresponse or to forced skip patterns in the questionnaire. A disadvantage of using Rasch models is that the classification methodology is difficult to explain to the general public and may generate rankings that are inconsistent with summaries from question responses.

Another use of food insecurity data and Rasch scores is to provide the research community with a comprehensive data set on U.S. households that contains a measure of the food insecurity status for each household. For example, it may be of interest to analyze patterns of household-level food insecurity in the population in relation to specific factors using a regression or to characterize households that belong to a food insecurity category. For this application, some estimate of a food insecurity measure for individual

households is required, and food insecurity scores computed by Rasch model estimation have been included in public release data files for this purpose. One challenge in using Rasch scores, rather than some other discrete scale, is that the exact meaning of the food insecurity Rasch score is difficult to interpret.

Another objective of interest is to make inferences about individuals within households. However, a household-level score may not be well suited for this purpose because strong assumptions are required to use the data at the individual level. For example, one way to credit individual-level food insecurity scores is to assume that the household score applies equally to all household members, which in practice may be a poor assumption. Hence, careful consideration should be given to the use of household sample scores for estimating the population distribution of food insecurity across individuals.

Rasch model estimates of food insecurity provide a summary of the data captured by the survey questions. Whether this type of summary is appropriate for all of these intended uses remains an important question for future study. As part of this investigation, we will explore alternative methods for measuring food insecurity that are appropriate for the stated objectives.

4. Some Statistical Questions about the Current Model

There are a number of unresolved questions in the application of the Rasch model to the food insecurity data of the CPS. We focus here on the statistical aspects of the Rasch model approach. In particular, the following aspects warrant further attention.

1. Is a single one-dimensional index an appropriate measure for food insecurity, across household types, demographic groups, and regions in the United States?
2. Is a latent variable structure such as the Rasch model appropriate for measuring food insecurity and hunger?
3. What are the effects of the violation of the conditional independence assumption for at least some of the items on the CPS questionnaire?
4. What is the information loss caused by the reduction of all items on the CPS questionnaire to dichotomous variables?
5. How do we produce reliable population distribution estimators based on a scale with a small number of possible scores?

6. What are the implications of the fact that the unconditional maximum likelihood approach produces inconsistent estimators for the item parameters?

We will address each of these questions below.

4.1 Rasch Estimator as One-Dimensional Measure of Food Insecurity

As discussed in Section 2, the Rasch model assumes that the “ability” of individuals is a one-dimensional quantity that is present to varying degrees in the population, and that all items are being aimed to measure the level of that quantity.

Clearly, food insecurity is a multi-dimensional concept as it is experienced by different people in widely different sets of circumstances. The assumption of a one-dimensional underlying measure can still be warranted if all questions assess a unique dimension of food insecurity. Ohls et al. (1999) show that the food insecurity scale developed by Abt Associates indeed is robust across various ethnic groups. While Hamilton et al. (1997a) report that the Rasch model-derived scale is appropriate for households with and without children, recent work by Nord and Bickel (1999) shows that this scale underestimates food insecurity for households with children. Nord and Bickel (1999) postulate that this effect arises because food insecurity questions address more than one dimension of hunger, with child hunger representing a second dimension.

It is of interest to study the effect of questions measuring different dimensions in the latent trait on Rasch estimators, not only in the context of the food insecurity study but also more broadly. If Rasch model estimators are sensitive to this type of departure of its assumptions, a careful analysis of the dimensionality of the food insecurity scale should be performed.

4.2 Rasch Estimator as a Latent Measure of Food Insecurity

Traditional application of the Rasch model assumes that the trait to be measured is unobservable but can be assessed by a set of questions whose likelihood of answering “correctly” (or affirmatively) is related directly to the strength (or severity) of that trait. Intelligence is a typical example of a latent trait that is assessed by such a set of questions. Most people would agree that the response to a question such as How intelligent are you? is a poor representation of the respondent’s ability, compared to an estimate based on a set of indirect questions of varying difficulty.

In the present context, the Rasch model is used to evaluate food insecurity and hunger among U.S. households, and it is no longer clear whether a set of indirect questions is the best way to capture the “trait” of interest. Indeed, it becomes harder to discount the answer to direct questions such as Q35 in the CPS Food Security Supplement:

Q35: In the last 12 months, were you ever hungry but didn't eat because you couldn't afford enough food?

<1> *Yes*

<2> *No*

If a respondent answers this question affirmatively, it is likely that this person was indeed hungry sometime during the last 12 months. The Rasch model, however, gives such questions no more weight than other questions that ask about hunger or food insecurity in a more indirect way. For the 1995 CPS food insecurity data, 29 percent of respondents who were classified as “food insecure with hunger” answered no to Q35, and, conversely, 42 percent of respondents who answered Q35 affirmatively were not classified as “food insecure with hunger.” Both percentages raise questions about the nature of the Rasch severity scale as a measure of hunger among U.S. households.

Both this finding and the one-dimensionality assumptions raise serious methodological questions about the appropriateness of a unique Rasch scale for measuring food insecurity based on the CPS questions and should be explored further.

4.3 Conditional Independence Assumption

The specification of the Rasch model likelihood function and its estimation procedure depend critically on the assumption of independence between questions and individuals, given the difficulty and ability parameters. In the CPS food security questionnaire, there are three pairs of questions that obviously violate that conditional independence assumption because of fixed linkages between the responses generated by skip patterns. These questions are the pairs Q24-Q25, Q28-Q29 and Q43-Q44 (see the Appendix for a list of the questions).

For example, the first pair of questions is as follows:

Q24: In the last 12 months, did you ever cut the size of your meals or skip meals because there wasn't enough money for food?

- <1> Yes*
- <2> No (SKIP to Q28)*

Q25: How often did this happen?

- <1> Almost every month*
- <2> Some months, but not every month*
- <3> Only 1 or 2 months*

The patterns of questions and skips are analogous for the other two pairs of questions. Both questions in each pair are not only logically related, by asking about the same behavioral response, they are linked by the fact that the second question is only asked of those people who answered affirmatively to the first question. The resulting pattern of item nonresponse for the second question in these pairs is linked directly to the answers to the first question, so that it is inappropriate to treat those as if the nonresponse is non-informative. Previous researchers have addressed this issue by imputing a value of “only 1 or 2 months” (the lowest value) for the second question in the pair, if the answer was no in the first question. However, the resulting set of responses continues to violate the conditional independence assumption.

Since these questions are so closely related, a different solution is to combine each pair of questions into a single question. An example is as follows.

Q24-25: In the last 12 months, how often did you cut the size of your meals or skip meals because there wasn't enough money for food?

- <1> Almost every month*
- <2> Some months, but not every month*
- <3> Only 1 or 2 months*
- <4> Never*

This new question is no longer dichotomous, but, in principle, it could be made so by collapsing the answer categories into two mutually exclusive groups. A second alternative is to utilize a Rasch model that accommodates polychotomous answers, as explained in Section 2. Combining the three pairs of “linked” questions into new questions with more answer categories removes the violation on the conditional independence assumption while maintaining the full information contained in the survey responses. The effect of this change

taining the full information contained in the survey responses. The effect of this change on the results of the 1995 CPS food insecurity study will be discussed in Section 4.4.

Finally, we excluded the follow-up questions Q25, Q29, and Q44 from the scale. Figure 2 indicates that the estimates change, although the scale does not change. The exclusion of the “parent” questions Q24, Q28, and Q43 from the scale has the same effect (Figure 3).

ENTRY NUMBER	RAW SCORE	COUNT	MEASURE	ERROR	INFIT		OUTFIT		PTBIS CORR.	QUES
					MNSQ	ZSTD	MNSQ	ZSTD		
9	27	4331	5.31	.21	.99	0.0	6.17	1.8	.16	Q50C
7	133	4330	3.23	.10	.89	-1.5	.82	-.4	.34	Q43C
8	255	4331	2.25	.08	.86	-2.7	.91	-.3	.43	Q47C
2	510	7860	2.20	.06	1.09	2.6	1.55	2.3	.31	Q28
6	288	4330	2.05	.08	.97	-.5	1.25	.9	.42	Q40C
5	601	7835	1.92	.05	1.05	1.7	1.33	1.7	.36	Q38
4	1221	7854	.62	.04	.88	-5.1	.76	-2.8	.51	Q35
14	777	4322	.20	.05	.99	-.4	.78	-2.2	.55	Q57C
3	2630	7853	-1.22	.03	.91	-4.9	.89	-2.7	.54	Q32
13	1451	4323	-1.30	.04	1.01	.4	.85	-2.8	.56	Q56C
1	2789	7857	-1.38	.03	1.01	.7	1.16	3.7	.50	Q24
15	2293	4322	-2.75	.04	1.11	5.0	1.15	1.8	.44	Q58C
12	4600	7835	-3.08	.03	.99	-.6	1.23	3.5	.42	Q55
11	4946	7836	-3.38	.03	.88	-8.6	.97	-.4	.43	Q54
10	6285	7843	-4.65	.03	1.12	7.9	2.57	8.3	.18	Q53
MEAN	1920.	6204.	0.00	.06	.99	-.4	1.49	.8		
S.D.	1910.	1756.	2.73	.04	.08	3.9	1.33	2.9		

FIGURE 2. Scale with follow-up questions excluded

ENTRY NUMBER	RAW SCORE	COUNT	MEASURE	ERROR	INFIT		OUTFIT		PTBIS CORR.	QUES
					MNSQ	ZSTD	MNSQ	ZSTD		
9	29	4304	5.09	.20	1.06	.4	5.73	1.8	.16	Q50C
7	87	4302	3.69	.12	.88	-1.4	.39	-1.3	.31	Q44C
2	332	7816	2.75	.07	1.03	.7	1.26	.8	.28	Q29
8	257	4304	2.09	.08	.88	-2.4	.88	-.4	.43	Q47C
6	290	4303	1.90	.08	.97	-.6	1.27	.9	.43	Q40C
5	625	7791	1.75	.05	1.05	1.4	1.33	1.7	.37	Q38
4	1248	7814	.47	.04	.91	-3.8	.82	-2.1	.50	Q35
14	779	4295	.06	.05	.96	-1.2	.76	-2.5	.55	Q57C
1	1916	7804	-.50	.04	1.06	2.8	1.29	4.7	.48	Q25
3	2657	7812	-1.36	.03	.95	-3.1	.97	-.7	.53	Q32
13	1453	4296	-1.44	.04	.98	-.9	.82	-3.4	.56	Q56C
15	2295	4295	-2.90	.04	1.10	4.6	1.14	1.8	.44	Q58C
12	4627	7798	-3.23	.03	.98	-1.1	1.27	3.9	.42	Q55
11	4973	7799	-3.54	.03	.87	-9.1	.92	-1.1	.42	Q54
10	6312	7806	-4.83	.03	1.12	7.5	2.36	7.0	.17	Q53
MEAN	1859.	6169.	0.00	.06	.99	-.4	1.41	.7		
S.D.	1916.	1749.	2.80	.04	.08	3.7	1.23	2.8		

FIGURE 3. Scale with parent questions excluded

4.4 Dichotomous Answer Categories

In addition to the pairs of questions discussed in Section 4.3, there are several questions with more than two possible answers. Questions Q52–Q58 (see Appendix) are all of the following form:

Q53: “I worried whether my food would run out before I got money to buy more.” Was [this statement] often, sometimes or never true for you in the last 12 months?

- <1> Often true*
- <2> Sometimes true*
- <3> Never true*

In the original scale development of the food insecurity scale, the answers to this question were transformed to yes/no answers by collapsing some of these answers, thereby reducing the information used in the classification of households on the food insecurity scale.

The PCM (partial credit model) is of interest as a technique not only to include all the answer categories for questions Q52–Q58 but also to collapse the questions Q24–Q25, Q28–Q29 and Q43–Q44 without making them dichotomous. We fitted the PCM on the set of 1995 CPS food insecurity questions used in the original scale, but without collapsing the answer categories for any questions. Figure 4 gives the item parameter estimates and goodness-of-fit statistics computed by BIGSTEPS, following the procedure explained in Hamilton et al. (1997b). Figure 5 shows the same estimates and statistics for the PCM, also fitted with BIGSTEPS.

In these two figures, the columns have the following interpretation:

- (i) ENTRY NUMBER: the sequence number of the question.
- (ii) RAW SCORE: the number of “yes” answers to that question.
- (iii) COUNT: the total number of valid responses for that question.
- (iv) MEASURE: the estimate of the severity parameter.
- (v) ERROR: the standard error of the estimate.
- (vi–vii) INFIT/OUTFIT: BIGSTEPS goodness-of-fit statistics: MNSQ is the mean square statistic with expectation 1; ZSTD is the mean square statistic standardized to approximate a theoretical distribution with mean 0 and variance 1.

ENTRY NUMBER	RAW		MEASURE	ERROR	INFIT		OUTFIT		PTBIS	QUES
	SCORE	COUNT			MNSQ	ZSTD	MNSQ	ZSTD	CORR.	
12	29	4333	4.91	.21	1.08	.5	5.98	1.8	.18	Q50C
10	87	4331	3.48	.13	.83	-1.8	.28	-1.6	.34	Q44C
9	135	4332	2.86	.10	.88	-1.7	.78	-.5	.37	Q43C
4	332	7884	2.55	.07	.89	-2.5	.55	-1.9	.35	Q29
11	257	4333	1.88	.08	.93	-1.3	.96	-.1	.44	Q47C
3	537	7887	1.81	.05	.97	-1.0	1.16	.7	.39	Q28
8	290	4332	1.68	.08	1.01	.3	1.28	1.0	.44	Q40C
7	625	7859	1.54	.05	1.10	3.0	1.31	1.6	.39	Q38
6	1248	7881	.27	.04	.91	-4.0	.77	-2.7	.54	Q35
17	779	4324	-.14	.05	1.07	2.3	.86	-1.4	.53	Q57C
2	1916	7871	-.70	.04	.93	-3.4	.75	-4.7	.58	Q25
5	2657	7880	-1.55	.03	.94	-3.6	.94	-1.5	.57	Q32
16	1453	4325	-1.64	.04	1.08	3.3	.94	-1.0	.54	Q56C
1	2816	7884	-1.72	.03	.88	-7.2	.87	-3.2	.59	Q24
18	2295	4324	-3.09	.04	1.14	6.5	1.29	3.3	.43	Q58C
15	4627	7862	-3.42	.03	1.03	2.1	1.60	7.9	.41	Q55
14	4973	7863	-3.72	.03	.92	-5.9	1.06	.8	.42	Q54
13	6312	7870	-4.99	.03	1.16	9.9	3.03	9.4	.18	Q53
MEAN	1743.	6299.	0.00	.06	.99	-.3	1.36	.4		
S.D.	1833.	1761.	2.70	.04	.10	4.2	1.25	3.5		

FIGURE 4. Item severity table from BIGSTEPS for dichotomous answer model

ENTRY NUMBER	RAW		MEASURE	ERROR	INFIT		OUTFIT		PTBIS	QUESTIG
	SCORE	COUNT			MNSQ	ZSTD	MNSQ	ZSTD	CORR.	
9	31	4338	3.72	.19	1.00	0.0	1.83	1.0	.20	Q50C 0
7	261	4337	1.57	.06	1.13	1.5	1.13	.3	.37	Q43Ca 0
8	259	4338	1.20	.07	.88	-2.6	.59	-2.4	.46	Q47C 0
2	1152	7954	1.03	.03	1.33	7.3	1.61	2.5	.41	Q28a 0
6	292	4334	1.03	.07	.94	-1.4	.81	-1.1	.45	Q40C 0
5	687	7921	.80	.05	.94	-2.1	.75	-2.4	.46	Q38 0
14	869	4329	.74	.04	.96	-1.3	.74	-3.4	.57	Q57C 0
4	1315	7948	-.22	.04	.84	-8.1	.62	-6.5	.57	Q35 0
13	1652	4327	-.27	.04	.99	-.3	.80	-5.0	.59	Q56C 0
1	5671	7951	-1.01	.02	1.19	8.7	1.34	6.5	.58	Q24a 0
15	2669	4329	-1.28	.03	1.12	5.3	1.12	4.7	.51	Q58C 0
11	5773	7930	-1.52	.02	.90	-7.3	.88	-8.2	.54	Q54 0
12	5623	7929	-1.57	.02	1.02	1.3	1.01	.9	.53	Q55 0
3	2724	7947	-1.74	.03	.87	-9.0	.81	-6.3	.56	Q32 0
10	7535	7937	-2.47	.02	1.13	8.7	1.14	8.0	.40	Q53 0
MEAN	2434.	6257.	0.00	.05	1.01	0.0	1.01	-.8		
S.D.	2405.	1799.	1.59	.04	.13	5.5	.35	4.7		

FIGURE 5. Item severity table from BIGSTEPS for partial credit model

According to Hamilton et al. (1997b), items with both infit and outfit mean square (MNSQ) statistics larger than 1.2 indicate a poor fit and “are targeted for removal from the scale.” Items with both infit and outfit MNSQ smaller than 0.8 are redundant with respect to the information they share with other items in the scale.

When comparing these two figures, we see that the scores for the questions and their relative ordering are affected. In particular, the relative difficulty of question Q32 is severely affected, and question Q35 and Q57 reverse relative positions. This is in addition to changes in the questions that have been combined. At the same time, the goodness of fit, as measured by the in-fit and out-fit statistics (Wright and Douglas 1977), is degraded for several of the items. This is surprising because the changes we implemented in the PCM model are aimed at improving the model fit, by bringing it closer to the data or by removing assumption violations. It would also be of interest to evaluate whether these findings on the PCM model continue to hold for subgroups of the U.S. population, such as the ethnic groups studied by Ohls et al. (1999). The effect of these changes on prevalence estimates is unclear, because any changes in the scale such as those in Figures 4 and 5 require that the food insecurity categories be redefined based on the changed scale. The findings reported here certainly suggest that further investigation is required on the effects of combining questions and allowing for the full ranges of possible answers to appear in the Rasch model.

4.5 Estimation of Population Distributions

The Rasch model and PCM produce maximum likelihood estimators of item difficulties and respondent abilities for a given data set. If the specified model is (approximately) correct for the data, then these estimators are valid representations of the underlying true values for individual item and respondent parameters. In the current application, interpretation problems arise from the fact that the estimated respondent abilities are for a random sample of households. The estimated parameters for the households in this sample are to be used in the estimation of the underlying ability distribution for all U.S. households, which is assumed to be continuous under the Rasch model. In this context, it is possible that the distribution of estimated abilities in the sample is a poor representation of that population distribution, because only a small number of values for the ability estimates are possible (because of the small number of questions; see Section 2).

This problem is especially severe for the CPS food insecurity studies, because only 18 dichotomous questions are used. Since the total number of correct answers is a sufficient statistic for the Rasch model, the number of possible values for the ability estimates is correspondingly small, as explained in Section 2. This statement is only strictly true if

all respondents answer all questions; but even after accounting for the presence of item nonresponse, the number of different values for the ability estimates is approximately 90, with only 30 of them having non-negligible numbers of occurrences, in the Abt Associates model. The PCM results in more possible values for the ability estimates, but that number is still extremely small compared to the number of respondents. For the estimation of the 1995 CPS food insecurity data, 110 different values for the ability parameters were found, with 40 of these occurring more than a few times. If the number of questions would be decreased further in the future, this problem would become more serious.

An important statistical question is how to develop an improved approach to estimate the distribution of food insecurity for U.S. households. Nord (1999) fitted a normal distribution function to the household severity estimates by assuming that these estimates represent the tail of a national “food security distribution,” of which only the most severe end was measured. An alternative approach is to estimate the distribution function of food (in)security for the sampled population only. This topic provides an interesting area for further research.

4.6 Inconsistency of Maximum Likelihood Estimates

In the unconditional maximum likelihood approach, the estimators of the parameters are not consistent, as was discussed in Section 2. Given the large sample sizes available in the CPS food insecurity studies, consistency is of more than theoretical interest. There is a way to correct for bias in the estimators yielded by UCON. Wright and Douglas (1977) have compared the estimates yielded by UCON and conditional maximum likelihood estimation methods, and concluded that the factor $(n - 1)/n$ would help in reducing the bias of item parameters (here, n is the number of items). The bias correction is implemented in UCON (see Baker 1992, Sec. 5.6.1) as follows: the final item and ability parameter estimates are obtained by repeating the iteration-anchoring schema until an overall convergence criterion is achieved; the final item parameters are corrected for bias (i.e., multiplied by $(n - 1)/n$), and the ability parameters are obtained by the Newton-Raphson procedure. However, the bias correction may not help if the number of items is small ($n < 10$) as van den Wollenberg, Wierda, and Jansen (1998) pointed out. Wright (1988) has recommended that the number of items should be at least 20 in order for the bias correction to be efficient.

In principle, there are several ways to remedy the inconsistency problem. As explained earlier, it is possible to apply a “consistency correction” to the maximum likelihood estimators and assume that it also is appropriate for small numbers of questions. This solution is not very satisfactory. A completely different approach is to replace the unconditional maximum likelihood approach with a conditional maximum likelihood or marginal likelihood approach. These latter two methods both provide consistent estimators for Rasch models parameters but under different sets of assumptions. This area needs further exploration and careful examination of the practical implications.

5. Selected Topics for Further Study of the Current Model

To date, we have limited our analysis to the 1995 CPS food insecurity data. We have not yet explored the effects of the 1996 and 1997 questionnaire experiments or the statistical aspects of using Rasch modeling for measuring changes in food insecurity over time.

In addition to the problems identified in Section 4, there are a number of important issues on the estimation of food insecurity in the United States that need to be addressed

1. There is a desire to produce a smaller set of questions for estimating food insecurity prevalence.
2. The impact of the changes introduced in the 1998 CPS questionnaire, especially the introduction of new “skip patterns,” needs to be carefully evaluated.
3. Possible uses for the responses to the thirty-day items could be assessed.
4. There is strong interest in looking at food insecurity for certain subpopulations, in particular, among households with older adults or young children.

5.1 Reducing the Number of Questions

There are two main reasons why it would be useful to have a smaller number of questions measuring household food insecurity:

1. If the main purpose of the questionnaire is to classify households in a few food insecurity categories, less information may be needed to classify households than the current set of questions used to estimate the (continuous) food insecurity scores (as explained in Section 4.5). The reductions of respondent burden and nonresponse may offset this loss of precision.

2. A small set of food insecurity questions easily could be added to other surveys measuring other dimensions of food insecurity and nutritional status.

One of the challenging issues related to a reduction in the number of questions is how to relate the new, shorter questions and measurements calculated from its items to the data already collected using the longer version. An additional problem is the fact that smaller sets of questions make estimation of food insecurity distributions for U.S. households more difficult.

5.2 Evaluating 1998 Changes

In 1998, the food security questionnaire underwent a major restructuring, including question reordering, the insertion of two internal screens, and revised initial screening criteria. It is crucial to assess the effect of these changes on the resulting model fits and to develop methods to make meaningful comparisons across study years.

Because of the presence of new screening patterns to shorten the food insecurity module for a significant portion of the respondents, the proportion of respondents with item nonresponse is going to increase dramatically. One of the proposed ways to handle this problem is to impute the values for the remaining questions based on the ones already answered by the respondent. For example, if a respondent answers questions in a manner that meets the skip criteria, then the answers to the remaining questions assume no indication of food insecurity behaviors. This raises some methodological concerns, because the resulting data set containing real and imputed responses will violate the assumption of conditional independence between the responses. In particular, when nonresponse is caused by a skip in the questionnaire, as for questions Q24–Q25 (see Section 4.3), this Rasch model is no longer strictly appropriate because nonresponse is not random.

The CPS food insecurity data sets contain very small numbers of “true” item nonresponse (i.e., caused by the respondents refusing to answer certain questions). For the surveys prior to 1998, the procedure has been to remove all households with more than 50 percent item nonresponse in fitting the Rasch model but to use the model predicted scores for all households with missing items to estimate their food insecurity status, regardless of the origin of the item nonresponse (Hamilton 1997b). This procedure is

appropriate when the “pattern” of item nonresponse does not contain any information about the missing items.

Other changes, such as question ordering, can have an effect on the perceived severity level of specific questions. Such shifts in perceived severity will be challenging to evaluate, because interyear comparability for Rasch scores depends critically on the assumption that the question severities remain constant.

5.3 Thirty-Day Questions

The CPS food security questionnaires include several questions related to the last 30 days of household food insecurity related behavior. These questions have not been studied to the extent that the 12-month ones have (see Hamilton et al. 1997a, b). Four years of data have now been gathered, and many of the questions lend themselves to direct comparison with the questions on the last 12 months of behavior.

One potential advantage of the 30-day questions is that they attempt to quantify the frequency of the hunger or food insecurity events by asking “how many days in the last 30 days” certain events occurred. These questions may be useful in generating summary statistics related to food insecurity levels. On the other hand, the responses to the 30-day questions may not be as useful as those of the 12-month modules. In that case, removal of these questions from the CPS food security questionnaire should be carefully evaluated.

It is possible that food insecurity and hunger are subject to significant seasonal patterns. If that is the case, responses to the current 30-day questions might not be a good indication of long-term food insecurity, because the seasonal effect cannot be measured using the CPS data. Before the 30-day data are further analyzed, it will be necessary to specify exactly what constitutes food insecurity and how its severity is measured over different time frames.

5.4 Estimation for Subpopulations

There is substantial interest, both from policymakers and from researchers, in a more detailed assessment of food insecurity and its causes and effects for specific subpopulations at risk, including minorities, children, and the elderly. In particular, because the current scale and classification as described in Hamilton (1997a) emphasizes children and their

reactions to food insecurity, there is reason to believe that the current scale is not necessarily the best way to study food insecurity in households with older adults.

Kendall, Olson, and Frongillo (1995) find in their study of 193 households in New York State that hunger and food insecurity are experienced differently at the household and individual levels, and that the individual level differs in adult and child aspects. Hence, a unique household-level scale might not provide a valid representation of food insecurity for households and individuals or for particular subpopulations.

We intend to explore these issues in more detail, specifically for the older population, for households with and without children, and for other defined subpopulations.

6. Alternative Approaches for Measuring Food Insecurity in the U.S. Population

In this section, we will briefly discuss alternative approaches for measuring food insecurity in the United States. There are two main dimensions to this approach: survey design, and construction of the food insecurity measure.

6.1 Survey Design for Food Insecurity Measurement

Because some aspects of food insecurity and hunger are primarily observed as individual experiences (Kendall, Olson, and Frongillo 1995), a survey designed specifically to study these phenomena would sample all individuals in the target population. In contrast, the CPS Food Security Supplement is a household-level survey, even though it includes a few questions that ask about the food insecurity of the individual respondent. This has at least two disadvantages. It is necessary to make strong assumptions about individual experiences, for example, that the food insecurity status of individuals within households is the same for all household members. It is unclear whether these assumptions are warranted for subpopulations such as children or elderly household members.

It should be recognized that individuals who are not included in the household frame, such as homeless and institutionalized people, are excluded from the survey. Given that these groups are especially at risk for food insecurity and hunger, this could lead to a significant bias in the prevalence estimates. Designing a survey to target these groups presents formidable practical and methodological challenges and is not the focus of our research.

One of the main purposes for the development of a food insecurity index and the annual CPS Food Security Supplement is to track the prevalence of food insecurity and hunger over time. Given this goal, the statistical efficiency of the survey could be increased by using a rotating panel design, so that the changes in the food insecurity status of the same individuals or households can be measured. A related issue concerns the exact measurement period to be used in the survey. If a 12-month recall is used, the food insecurity events will be reported with a potentially large amount of measurement error. If a 30-day recall period is used, the low prevalence of respondents who experience such events makes it difficult to achieve appropriate sample sizes for estimating prevalence and potentially introduces a seasonal component into the measurements.

If food insecurity does not correlate closely to either income or program participation (see Frongillo 1999), the screening of households based on such factors can lead to significant bias. However, since the prevalence of food insecurity and hunger appears to be low, some form of screening could still be cost effective. If the food security survey continues to be conducted as part of other nationwide surveys (e.g., the NHANES), a new set of carefully designed screening questions assessing the likelihood of food insecurity could be used. We could evaluate the effect of skip pattern differences in the 1998 survey compared to earlier ones, for example.

6.2 Elements of a Food Insecurity Measure

Food insecurity and hunger can be conceptualized as a progression of increasingly severe responses to an individual's economic and social situation, and the severity of the food insecurity can be accurately assessed through a carefully designed set of questions (e.g., Kendall, Olson, and Frongillo 1995). The questions in the CPS Food Security Supplement follow this methodological premise by evaluating several aspects of the household's responses to food insecurity. Abt Associates selected a subset of these questions and modeled the responses as a dichotomous Rasch model.

While the household scores are assumed to represent a quantitative measure of the severity of food insecurity, Rasch scores do not provide any information about the precise nature of the level of food insecurity. Specifically, they do not contain any information about the severity, duration, or frequency of the food insecurity or hunger events that presumably underlie the perception of hunger. Information contained in the CPS Food

Security Supplement questions that address these dimensions of food insecurity are largely ignored. Basing a food insecurity severity measure more directly on these quantitative aspects would significantly enhance the perceived validity of the measure.

Another problem with the Rasch model estimates stems from the fact that these estimates are to be used to track the prevalence of food insecurity over time. As explained in Section 2, the Rasch model is overparametrized, making it difficult to compare directly the estimates for different sets of people, unless assumptions are made about the perceived difficulty levels of the questions across these sets of people. A measure more directly related to quantifiable aspects of food insecurity also would make this longitudinal aspect easier to implement.

Based on work by Nord and Bickel (1999) and Kendall, Olson, and Frongillo (1995), it would appear that food insecurity is a multidimensional concept, experienced differently by different household types and population groups. While an overall measure of food insecurity, valid for the whole U.S. population, would be desirable, it is likely that such a measure would underestimate hunger and food insecurity for certain subgroups, especially for children and elderly adults.

7. Summary

The USDA currently estimates household food insecurity prevalence and severity using Rasch model methodology, and it is likely to continue to do so in the future. This report reviews some of the model assumptions underlying this approach and raises several issues with its current implementation. We outline some tasks that would help in understanding this methodology in the context of food insecurity.

At the same time, it appears that food insecurity is a complex issue that may not be fully captured by a one-dimensional item response model, especially as it will be used to track food insecurity over time, across different surveys, and for different subpopulations. Therefore, we have identified also some tasks that explore different approaches to asuring food insecurity.

Appendix

1995 Food Insecurity Questions

(Also see <http://www.ers.usda.gov/Data/foodsecurity/CPS/> for the full questionnaires.)

April 1995

II. FOOD SUFFICIENCY

S11A These next questions are about the food eaten in your household.

Which of these statements best describes the food eaten in your household—
enough of the kinds of food we want to eat, enough but not always the kinds of
food we want to eat, sometimes not enough to eat, or often not enough to eat?

- <1> Enough of the kinds of food we want to eat (skip to S15)
- <2> Enough but not always the kinds of food we want to eat (skip to S15)
- <3> Sometimes not enough to eat (Skip to S13)
- <4> Often not enough to eat (Skip to S13)

Blind <D> or <R> skip to S15

S11 These next questions are about the food eaten in your household.

Which of the following statements best describes the amount of food eaten in
your household—enough food to eat, sometimes not enough to eat, or often not
enough to eat?

- <1> Enough food to eat
- <2> Sometimes not enough to eat (SKIP TO S13)
- <3> Often not enough to eat (SKIP TO S13)

Blind <D> or <R> skip to S15

S12 Do you have enough of the KINDS of food you want to eat, or do you have
enough but NOT ALWAYS the KINDS of food you want to eat?

- <1> enough of the kinds you want (SKIP TO S15)
- <2> enough but not always the kind you want (SKIP TO S15)

Blind <D> or <R> skip to S15

S13 Here are some reasons why people don't always have enough to eat. For each one, please tell me if that is a reason why YOU don't always have enough to eat.

READ LIST.

		YES	NO
S13A	Not enough money for food	<input type="checkbox"/>	<input type="checkbox"/>
S13B	Too hard to get to the store	<input type="checkbox"/>	<input type="checkbox"/>
S13C	No working stove	<input type="checkbox"/>	<input type="checkbox"/>
S13D	No working refrigerator	<input type="checkbox"/>	<input type="checkbox"/>
S13E	Not able to cook or eat because of health problems	<input type="checkbox"/>	<input type="checkbox"/>

Blind <D> or <R> for each category

III. COPING MECHANISMS AND FOOD SCARCITY

S15 People do different things when they are running out of money for food in order to make their food or their food money go further.

In the last 12 months, since May 1994, did you ever run short of money and try to make your food or your food money go further?

- <1> Yes
- <2> No

Blind <D> or <R>

S16 In the last 12 months, did you ever run out of the foods that you needed to make a meal and didn't have money to get more?

- <1> Yes
- <2> No

Blind <D> and <R>

CKALT If onpath entry in S11A go to CK17A else go to CK17.

CK17A If POOR equals 1 go to CK171 else
 if POOR equals 2 and (onpath entry of 3, 4, D or R in S11A) or (onpath entry of 1, D, or R in S16) or (onpath entry of 2 in S11A and onpath entry of 1, D or R in S15) then go to CK171 else
 if POOR equals 2 and (onpath entry of 1 in S11A) or (onpath entry of 2 in S11A and onpath entry of 2 in S15) then end the supplement interview else all others go to CK171.

CK17 If Poor equals 1 go to CK171 else

if Poor equals 2 and (onpath entry of 2, 3, D or R in S11) or (onpath entry of 1, D or R in S16) or (onpath entry of 1 in S11 and onpath entry of 2, D or R in S12 and onpath entry of 1, D or R in S15) then goto CK171 else
if Poor equals 2 and (onpath entry of 1 in S11 and onpath entry of 1 in S12) or (onpath entry of 1 in S11 and onpath entry of 2, D or R in S12 and onpath entry of 2 in S15) then end the supplement interview else all others go to CK171.

CK171 If onpath entry of 2, D or R in S16 skip to S18 else ask S17

S17 In the last 30 days, did you ever run out of the foods that you needed to make a meal and didn't have money to get more?

- <1> Yes
- <2> No

Blind <D> or <R>

S18 In the last 12 months, did (you/you or other adults in your household) ever get food or borrow money for food from friends or relatives?

- <1> Yes
- <2> No

Blind <D> or <R>

S19CK IF HHMEM=1 and anyone in the household is AGE=17 or less ask S19 else skip to S20

S19 In the last 12 months, did (you/you or other adults in your household) ever send or take (CHILD'S NAME/the children) to the homes of friends or relatives for a meal because you were running out of food?

- <1> Yes
- <2> No

Blind <D> or <R>

S20 In the last 12 months did (you/you or other adults in your household) ever serve only a FEW KINDS of low-cost foods—like rice, beans, macaroni products, bread or potatoes—for SEVERAL DAYS IN A ROW because you couldn't afford anything else?

- <1> Yes
- <2> No

Blind <D> or <R>

S21 In the last 12 months, did (you/you or other adults in your household) ever put off paying a bill so that you would have money to buy food?

<1> Yes

<2> No

Blind <D> or <R>

S22 In the last 12 months, did (you/you or other adults in your household) ever get emergency food from a church, a food pantry, or food bank?

<1> Yes

<2> No

Blind <D> or <R>

S23 In the last 12 months, did (you/you or other adults in your household) ever eat any meals at a soup kitchen?

<1> Yes

<2> No

Blind <D> or <R>

S24 In the last 12 months, since May 1994, did (you/you or other adults in your household) ever cut the size of your meals or skip meals because there wasn't enough money for food?

<1> Yes

<2> No (SKIP TO S28)

Blind <D> or <R> skip to S28

S25 How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

<1> Almost every month

<2> Some months but not every month

<3> Only 1 or 2 months

Blind <D> or <R>

S26 Now think about the last 30 days. Did (you/you or other adults in your household) ever cut the size of your meals or skip meals in the last 30 days because there wasn't enough money for food?

<1> Yes

<2> No (SKIP TO S28)

Blind <D> or <R> skip to S28

S27 In the last 30 days, how many days did this happen?

_____ days
<1-30>

Blind <D> or <R>

S28 In the last 12 months, since May 1994, did (you/you or other adults in your household) ever not eat for a whole day because there wasn't enough money for food?

<1> Yes
<2> No (SKIP TO S32)

Blind <D> or <R> skip to S32

S29 How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

<1> Almost every month
<2> Some months but not every month
<3> Only 1 or 2 months

Blind <D> or <R>

S30 Now think about the last 30 days. Did (you/you or other adults in your household) ever not eat for a whole day in the last 30 days because there wasn't enough money for food?

<1> Yes
<2> No (SKIP TO S32)

Blind <D> or <R> skip to S32

S31 In the last 30 days, how many times did this happen?

_____ times
<1-30>

Blind <D> or <R>

S32 In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money to buy food?

- <1> Yes
- <2> No (SKIP TO S35)

Blind <D> or <R> skip to S35

S33 Did this happen in the last 30 days?

- <1> Yes
- <2> No (SKIP TO S35)

Blind <D> or <R> skip to S35

S34 In the last 30 days, how many days did you eat less than you felt you should because there wasn't enough money to buy food?

___ number of days
<1-30>

Blind <D> or <R>

S35 In the last 12 months, since May 1994, were you ever hungry but didn't eat because you couldn't afford enough food?

- <1> Yes
- <2> No (SKIP TO S38)

Blind <D> or <R> skip to S38

S36 Did this happen in the last 30 days?

- <1> Yes
- <2> No (SKIP TO S38)

Blind <D> or <R> skip to S38

S37 In the last 30 days, how many days were you hungry but didn't eat because you couldn't afford enough food?

___ number of days
<1-30>

Blind <D> or <R>

S38 Sometimes people lose weight because they don't have enough to eat. In the last 12 months, did you lose weight because there wasn't enough food?

<1> Yes

<2> No (SKIP TO S40CK)

Blind <D> or <R> skip to S40CK

S39 Did this happen in the last 30 days?

<1> Yes

<2> No

Blind <D> or <R>

S40CK If HHMEM=1 and AGE<=17 of anyone in the household ask S40 else skip to S53.

S40 The next questions are about (CHILD'NAME/children living in the household who are under 18 years old).

In the last 12 months, since May 1994, did you ever cut the size of (CHILD's NAME/any of the children)'s meals because there wasn't enough money for food?

<1> Yes

<2> No (SKIP TO S43)

Blind <D> or <R> skip to S43

S41 Did this ever happen in the last 30 days?

<1> Yes

<2> No (SKIP TO S43)

Blind <D> or <R> skip to S43

S42 In the last 30 days, how many days did you cut the size of (Child's name/the children)'s meals because there wasn't enough money for food?

_____ days

<1-30>

Blind <D> or <R>

S43 In the last 12 months, since May 1994, did (Child's name/any of the children) ever skip a meal because there wasn't enough money for food?

- <1> Yes
- <2> No (SKIP TO S47)

Blind <D> or <R> skip to S47

S44 How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

- <1> Almost every month
- <2> Some months but not every month
- <3> Only 1 or 2 months

Blind <D> or <R>

S45 Now think about the last 30 days. Did (Child's name/the children) ever skip a meal in the last 30 days because there wasn't enough money for food?

- <1> Yes
- <2> No (SKIP TO S47)

Blind <D> or <R> skip to S47

S46 In the last 30 days, how many days did this happen?

_____ days
<1-30>

Blind <D> or <R>

S47 In the last 12 months, (was CHILD'S NAME/were the children) ever hungry but you just couldn't afford more food?

- <1> Yes
- <2> No (SKIP TO S50)

Blind <D> or <R> skip to S50

S48 Did this ever happen in the last 30 days?

- <1> Yes
- <2> No (SKIP TO S50)

Blind <D> or <R> skip to S50

S49 In the last 30 days, how many days (was CHILD'S NAME/were the children) hungry but you just couldn't afford more food?
___ number of days

<1-30>

Blind <D> or <R>

S50 In the last 12 months, since May 1994, did (Child's name/any of the children) ever not eat for a whole day because there wasn't enough money for food?

<1> Yes

<2> No (SKIP TO S53)

Blind <D> or <R> skip to S53

S51 Did this ever happen in the last 30 days?

<1> Yes

<2> No (SKIP TO S53)

Blind <D> or <R> skip to S53

S52 In the last 30 days, how many days did (Child's name/the children) not eat for a whole day because there wasn't enough money for food?

_____ days

<1-30>

Blind <D> or <R>

S53 Now I'm going to read you several statements that people have made about their food situation. For these statements, please tell me whether the statement was often, sometimes, or never true for (you/you or the other members of your household) in the last 12 months.

The first statement is "(I/We) worried whether (my/our) food would run out before (I/we) got money to buy more." Was that often, sometimes or never true for you in the last 12 months?

<1> Often true

<2> Sometimes true

<3> Never true

Blind <D> or <R>

S54 "The food that (I/we) bought just didn't last, and (I/we) didn't have money to get more." Was that often, sometimes or never true for you in the last 12 months?

<1> Often true

<2> Sometimes true

<3> Never true

Blind <D> or <R>

S55 “(I/we) couldn’t afford to eat balanced meals.” Was that often, sometimes or never true for you in the last 12 months?

<1> Often true

<2> Sometimes true

<3> Never true

Blind <D> or <R>

S56CK If any HHMEM=1 and AGE<=17 in household ask S56 else end the supplement interview.

S56 “(I/we) couldn’t feed (CHILD’S name/the children) a balanced meal, because (I/we) couldn’t afford that.” Was that often, sometimes or never true for you in the last 12 months?

<1> Often true

<2> Sometimes true

<3> Never true

Blind <D> or <R>

S57 “(CHILD’s name was/The children were) not eating enough because (I/we) just couldn’t afford enough food.” Was that often, sometimes or never true for you in the last 12 months?

<1> Often true

<2> Sometimes true

<3> Never true

Blind <D> or <R>

S58 “(I/we) relied on only a few kinds of low-cost food to feed (CHILD’s name/the children) because (I was/we were) running out of money to buy food.” Was that often, sometimes or never true for you in the last 12 months?

<1> Often true

<2> Sometimes true

<3> Never true

Blind <D> or <R>

References

- Baker, F.B. 1992. *Item Response Theory*. New York: Marcel Dekker, Inc.
- Bickel, G., M. Andrews, and B. Klein. 1996. "Measuring Food Security in the United States: A Supplement to the CPS." In *Nutrition and Food Security in the Food Stamp Program*. Edited by D. Hall and M. Stavrianos. Washington, D.C.: U.S. Department of Agriculture, Food and Consumer Service, Office of Analysis and Evaluation. January.
- Frongillo, E. 1999 or 1996?. "Validation of Measures of Food Insecurity and Hunger." In *Nutrition and Food Security in the Food Stamp Program*. Edited by D. Hall and M. Stavrianos. Washington, D.C.: U.S. Department of Agriculture, Food and Consumer Service, Office of Analysis and Evaluation. January.
- Ghosh, M. 1995. "Inconsistent Maximum Likelihood for the Rasch Model." *Statistics & Probability Letters* 23: 165–70.
- Hamilton, W.L., J.T. Cook, W.W. Thompson, L.F. Buron, E.A. Frongillo, C.M. Olson and C.A. Wehler. 1997a. *Household Food Security in the United States in 1995: Summary Report of the Food Security Measurement Project*. Washington, D.C.: U.S. Department of Agriculture, Food and Consumer Service. September.
- . 1997b. *Household Food Security in the United States in 1995: Technical Report of the Food Security Measurement Project*. Washington, D.C.: U.S. Department of Agriculture, Food and Consumer Service. September.
- Kendall, A., C.M. Olson, and E.A. Frongillo. 1995. "Validation of the Radimer/Cornell Measures of Hunger and Food Insecurity." *Journal of Nutrition* 125: 2793–2801.
- Linacre, J.M., and B.D. Wright. 1998. "A User's Guide to BIGSTEPS and WINSTEPS." Rasch-Model Computer Program, Version 2.85. Chicago: MESA Press.
- Neyman, J., and E.L. Scott. 1948. "Consistent Estimates Based on Partially Consistent Observations." *Econometrica*, 16 (1), 1–32.
- Nord, M. 1999. "Upward Bias on Food Insecurity and Hunger Prevalence Estimates Due to Measurement Error." Working Paper #FS-8. U.S. Department of Agriculture, Economic Research Service, Washington, D.C. 12 January.
- Nord, M., and G. Bickel. 1999. "Estimating the Prevalence of Children's Hunger from the Current Population Survey Food Security Supplement." Manuscript. U.S. Department of Agriculture, Economic Research Service, Washington, D.C. 17 February.
- Ohls, J., A. Prakash, L. Radbill, and A. Schirm. 1999. "Methodological Findings and Early Conclusions based on the 1995, 1996, and 1997 Food Security Data." Working draft. Mathematica Policy Research, Inc. Princeton, NJ. 5 January.

- van den Wollenberg, A.L., F.W. Wierda, and P.G.W. Jansen. 1998. Consistency of Rasch Model Parameter Estimation: A Simulation Study." *Applied Psychological Measurement*, 12: 307–13.
- Wright, B.D. 1988. "The Efficacy of Unconditional Maximum Likelihood Bias Correction: Comment on Jansen, van Wollenberg, and Wierda." *Applied Psychological Measurement* 12: 315–23.
- Wright, B.D., and G.A. Douglas. 1977. "Best Procedures for Sample-Free Item Analysis." *Applied Psychological Measurement* 1: 281–95.
- Wright, B.D., and G.N. Masters. 1982. *Rating Scale Analysis*. Chicago: MESA Press.