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Rasch Analyses of Very Low Food Security among Households and Children in the Three City Study*

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Abstract

The longitudinal Three City Study of low-income families with children measures food hardships using fewer questions and some different questions from the standard U.S. instrument for measuring food security, the Household Food Security Survey Module (HFSSM) in the Current Population Survey (CPS). We utilize a Rasch measurement model to identify thresholds of very low food security among households and very low food security among children in the Three City Study that are comparable to thresholds from the HFSSM. We also use the Three City Study to empirically investigate the determinants of food insecurity and of these specific food insecurity outcomes, estimating a multivariate behavioral Rasch model that is adapted to address longitudinal data. The estimation results indicate that participation in the Supplemental Nutrition Assistance Program and the Temporary Assistance for Needy Families program reduce food insecurity, while poverty and disability among caregivers increase it. Besides its longitudinal structure, the Three City Study measures many more characteristics about households than the CPS. Our estimates reveal that financial assistance through social networks and a household's own financial assets reduce food insecurity, while its outstanding loans increase insecurity.

Keywords

Rasch model; food insecurity; Three City Study

1. Introduction

Millions of American children suffer from food hardships. Coleman-Jensen et al. (2013) estimated that in 2012, 15.9 million U.S. children, approximately two out of every nine, lived in households that experienced food insecurity, meaning that their members “did not have access at all times to enough food for an active, health life.” They further estimated that

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8.3 million lived in households with food insecurity among children, meaning that the children themselves “lack(ed) consistent access to adequate food,” and that 1.0 million lived in households with very low food security among children, meaning that “children's regular meal patterns were disrupted and food intake was reduced to less than the amount that their caregivers considered adequate.” While food hardships are more prevalent than before the Great Recession, their incidence before the economic downturn was only modestly lower.

The causes of food insecurity among households with children are complex and involve many potential determinants (see Barrett 2002, Nord and Parker 2010, and Ribar 2013 for reviews). The principal source of information regarding food insecurity in the U.S., the annual Food Security Supplement of the Current Population Survey (CPS-FSS) includes measures of some of the relevant determinants, such as household demographic characteristics, food assistance use, and geography, but lacks measures of others, such as household wealth and credit constraints, participation in other assistance programs, and household members' health status. To better understand the determinants of food hardships among children, researchers have turned to richer data sources. However, as we explain below, these sources have other limitations.

In this paper, we investigate food insecurity using the Three City Study (TCS), a longitudinal study of 2,458 families with children living in low-income neighborhoods in Boston, Chicago, and San Antonio. In addition to a wider set of measures for a focused sample of disadvantaged families, the TCS also features a better and longer longitudinal design than the CPS-FSS. At the same time, an analysis of food hardships in the TCS, like analyses in several other surveys such as the Fragile Families and Child Well Being Study, the Women's Employment Study and the Early Child Longitudinal Surveys, raises some thorny challenges.

The first is that the sample for the TCS and several other surveys is much smaller than the sample for the CPS-FSS. The smaller sample leads to possible issues with statistical power. These issues are compounded when we consider some important food outcomes, such as food hardships among children, which have a low prevalence rate. The second is that the TCS only contains a subset of the hardship questions that are standardly used to classify households' food security status. Moreover, some of the food hardship questions from the TCS differ from questions in the CPS-FSS. To obtain estimates that are comparable to those from the CPS-FSS, we have to find a way to classify households using common food security thresholds.

We address these challenges and examine food security in the TCS through the application of Rasch models (Rasch 1960; Andrich 1988). The Rasch model is an item-response-theory model that is used to relate responses from multiple binary (yes/no) questions about an underlying condition to that condition. The USDA used a Rasch measurement model to develop its food security scale (Bickel et al. 2000) and to develop comparable measures from subsets of the food security questions and from alternative sets of questions. We utilize the Rasch model in a similar way to identify thresholds of very low food security among households (VLFS) and very low food security among children (VLFSAC) in the TCS that are comparable to thresholds from CPS-FSS. Thus, one of the contributions of this paper is

the development of indicators of VLFS and VLFSAC for the TCS, extending the capabilities of that survey.

We also empirically investigate the determinants of food insecurity using a multivariate behavioral version of the Rasch model. Behavioral Rasch models have been estimated by Rabbitt (2014) and Wilde and Norde (2005), using data from the CPS-FSS. We estimate our model using longitudinal data from the TCS, modifying the model to account for both serial correlation in the unobserved determinants of food security and possible correlations between those unobserved determinants and other observed explanatory variables. The behavioral Rasch model offers several advantages over more commonly used empirical approaches, such as standard binary-choice models and continuous regressions of food security Rasch scores. Unlike the binary-choice models, the behavioral Rasch model uses information from all of the component food security questions rather than an indicator based on a summary of those questions. Unlike regressions of Rasch scores which typically drop observations with all “yes” or all “no” answers to the food security questions (the majority of respondents in most surveys), the behavioral Rasch model can incorporate all of the observations from the TCS. Most importantly for our purposes, results from the behavioral Rasch model can be used also to estimate marginal effects of our explanatory variables on VLFSAC. It is not possible to obtain such estimates for the TCS using standard binary choice methods because of sample separation problems that stem from the low incidence of VLFSAC and from modest sample size of the TCS.

The remainder of the paper is organized as follows. In the next section we describe the food hardship measures from the TCS and use a Rasch measurement model to develop indicators for VLFS and VLFSAC. The following section discusses the longitudinal behavioral Rasch model. We next describe the explanatory variables and analysis sample that we construct from the TCS. Multivariate estimation results from the longitudinal Rasch behavioral model and from standard longitudinal binary-choice models are reported in the next section. Conclusions are offered in the final section.

2. Identifying levels of food security in the Three-City Study

In this section we describe the food hardship measures in the Three City Study and how we use these to identify VLFS and VLFSAC. The TCS is a longitudinal survey of 2,458 children and their caregivers who were initially living in low-income neighborhoods in Boston, Chicago, and San Antonio. At the time of the first interview, all the families had incomes below 200 percent of the poverty line and at least one child who was either 0-4 or 10-14 years old. In each family, interviews were conducted with a focal child and a caregiver (usually the focal child's mother) in three waves: 1999, 2000-1, and 2005. The interviews with the caregivers asked about household economic circumstances, household well-being, public assistance use, and demographic composition. Although we do not consider the data here, caregivers were also asked about schooling, behavioral, developmental, and health outcomes for the focal children. They were also asked about parenting practices, family routines, neighborhood conditions, and their own physical and mental health. Retention was high with 88 percent of the original caregivers participating in the second wave, and 80 percent participating in the third wave.

Of particular interest to our analysis, caregivers were asked in each wave about eight food hardships: four that either they or other adults in their households might have experienced and four that the focal child might have experienced. The specific hardships are described in Appendix Table A1. The four questions regarding adult hardships come directly from the U.S. Department of Agriculture's (USDA's) 18-item Household Food Security Survey Module (HFSSM), while the four questions regarding focal child hardships are nearly identical to HFSSM questions but ask about a focal child instead of asking about children generally.

The USDA uses the HFSSM to identify households that suffer from different levels of food insecurity. Households with children are classified as experiencing low food security if they affirm three or more of the 18 total hardship items and classified as experiencing very low food security, meaning that "food intake of one or more members was reduced and eating patterns disrupted because of insufficient money and other resources for food," if they affirm eight or more hardship items (Coleman-Jensen et al. 2013). Households with children are classified as experiencing low food security among children if they affirm two or more of the eight child-specific items and classified as experiencing very low food security among children if they affirm five or more child-specific items (Nord 2009). The overlap in questions between the HFSSM and the TCS suggests that it may be possible to identify conventional and comparable levels of food insecurity in the TCS, and we take up this issue in the first part of our study, adopting the formal methodology that the USDA used to develop a six-item food security scale from a subset of HFFSM items (Bickel et al. 2000). [1]

The formal approach rests on the assumption that responses to the HFSSM and TCS hardship items conform to a Rasch measurement model (Rasch 1960; Andrich 1988), a unidimensional item-response-theory model. For this model, let household i's underlying, unobserved (latent) food insecurity "score" at time period t be $\theta_{i,t}$ Also, suppose that there are J yes/no questions that might be asked of the household and that capture different levels of severity of food insecurity. The Rasch framework models the probability that the household answers "yes" to the jth question as

$$p_{j,i,t}=\frac{\exp(\theta_{i,t}-\delta_j)}{1+\exp(\theta_{i,t}-\delta_j)}, j=1, J \quad (1)$$

where $\exp(\cdot)$ is the exponential function and δ_j is a "calibration," or threshold, parameter. Higher values of the calibration parameter correspond to questions about more severe hardships. The model further assumes that the responses to each question are independent, conditional on $\theta_{i,t}$, and that each item is equally informative about $\theta_{i,t}$.

The Rasch model has several useful properties. The first is that if households' responses to the hardship questions follow this model and if households answer all J questions, their food security status can be ranked and compared using simple counts of "yes" answers. More

[1]The USDA has also developed a five-item scale for the Survey of Income and Program Participation using questions that differ slightly from HFSSM items.

formally, the count of affirmed answers is a sufficient statistic for $\theta_{i,t}$. This property is the basis of the USDA's use of counts of affirmed hardships to assign a household's food security status. A second property is that the model can be used to identify values of $\theta_{i,t}$ (Rasch scores) even if only a subset of the J items are asked. This property allows the USDA to establish comparable thresholds for food security between households with children that answer all 18 HFSSM items and households without children that only answer the 10 household and adult-oriented HFSSM items. It is also the basis for setting the threshold for the six-item scale. A third property is that the Rasch model can be used to form estimates of $\theta_{i,t}$ from responses to overlapping sets of items that are not proper subsets. This final property is the basis for our formal comparisons of responses to the HFSSM and TCS food items.[2]

To make these comparisons, we estimate Rasch models and compute Rasch scores for responses to food hardship questions that were asked as part of the April 1999 Current Population Survey Food Security Supplement (CPS-FSS). The April 1999 CPS-FSS is a natural candidate for this analysis because it overlaps with the TCS coverage period. More useful still, the survey asked the standard 18 HFSSM items of seven eighths of its sampled households with children but asked a modified version of the HFSSM that included eight standard HFSSM items, four experimental items about individual focal adults, and six experimental items about individual focal children of the remaining eighth of its sampled households with children. These experimental questions included all four of the TCS focal-child food hardship items.

For our analyses, we pool the data from the two April 1999 CPS-FSS subsamples and estimate Rasch calibration parameters, δ_j's, for the union of the 18 standard HFSSM items from the first sample and the eight standard HFSSM items and the four experimental focal-child items that correspond to TCS items from the second subsample (22 unique items). We then use the resulting calibration parameters to estimate Rasch scores for the potential response patterns to the 18 standard items and for the potential response patterns to the eight TCS items. Finally, we assign cut-offs for thresholds of food security to the TCS response patterns based on their Rasch scores. Details of the procedure are described in Appendix A.

The formal Rasch analyses revealed that the TCS food security items could not identify households that were food secure separately from households with low food security but that the items could identify households with very low food security separately from other households. In particular, we classify TCS households that affirmed zero or one of the eight TCS food hardship items as being either food secure or having low food security and classify households that affirmed two or more of the eight TCS items as having very low food security. [3]

[2]Besides its strong assumptions, the Rasch model also has some other drawbacks. An important one for our purposes is that θ_i cannot be estimated if all of the items are affirmed or if none of them are affirmed.

[3]The inability of the TCS to discriminate between food security and low food security stems from the severity of the TCS items. The least severe TCS food security item asked about adults cutting the size of or skipping meals, which corresponds to the sixth least severe HFSSM item.

We followed a similar procedure to examine food security among children. For these analyses, we focused on the eight standard child-specific items from the HFSSM and the four focal-child-specific items that corresponded to the TCS. The analyses indicated that TCS households could be classified as having VLFSAC if they affirmed three or four child-specific TCS items.[4]

With these identification criteria in hand, we next examine the incidence of VLFS and VLFSAC in the TCS. Table 1 shows the response patterns for the TCS food hardship items for all of the caregivers across all three waves of the TCS for respondents who answered all eight TCS food hardship questions; this results in 6,308 total caregiver/year observations. In particular, Table 1 lists the number of observations with different numbers of affirmed adult hardships (organized by row) and affirmed child hardships (organized by column). Shading is used to indicate either VLFS or VLFSAC status. Unshaded cells are counts of observations that are neither VLFS nor VLFSAC; lightly shaded cells are counts of observations that are VLFS but not VLFSAC; and darkly shaded cells are counts that are both VLFS and VLFSAC.

5,347 observations (85 percent) are from caregivers who reported no food hardships at all, and an additional 346 observations (five percent) are from caregivers who reported only one food hardship. The remaining 615 (10 percent) are from caregivers who reported multiple food hardships and whose households are thus classified as having VLFS. Under our classification scheme, VLFSAC is a subset of VLFS. The figures from Table 1 indicate that only 79 observations (just over one percent) are from caregivers whose households had VLFSAC. VLFS and VLFSAC are severe conditions, so the low incidence—especially of VLFSAC—is not surprising, even in a relatively disadvantaged sample like the TCS. For example, Nord (2009), using national data from 2006-7, estimated that only 1.7 percent of households with children and with incomes below 185 percent of the poverty line experienced VLFSAC.

Other patterns are evident in Table 1. Among the households with any reports of hardships, adult hardships are reported more frequently than focal-child hardships. 934 observations are from caregivers who reported one or more adult hardships, while 297 observations are from caregivers who reported one or more child hardships. 270 observations (nearly all of the observations with child hardships) are from caregivers who also reported adult hardships. These reporting patterns are consistent with child hardships representing more severe conditions than adult hardships. The formal Rasch analyses, informal analyses, estimated incidence of VLFS and VLFSAC, and general patterns of responses give us confidence that the TCS hardship items can reliably identify VLFS and VLFSAC. We now turn our attention to investigating how different household characteristics are associated with VLFS and VLFSAC.

[4]In addition to these formal procedures we also conducted informal analyses of the April 1999 CPS-FSS data. The estimated calibration parameters for the standard and experimental child-oriented items from the CPS-FSS are very close, indicating that the general-children and focal-child-specific items discriminate food security status similarly. Given these results, we selected four standard items from the HFSSM that exactly corresponded to the TCS items and the four standard items from the HFFSM for children that corresponded to the TCS focal-child-specific items. We then compared the identification of VLFS and VLFSAC for different thresholds among these items to the identification of VLFS and VLFSAC among the full set of relevant standard HFSSM items. These analyses confirmed that the thresholds from the formal analyses did the best job of replicating the standard HFSSM results.

3. Longitudinal behavioral Rasch model

For our principal empirical analyses, we extend the Rasch measurement model to incorporate a multivariate behavioral component. Specifically, we assume that household i's latent food insecurity in time period t, $\theta_{i,t}$, depends linearly on a set of observed variables, $X_{i,t}$, and an unobserved variable $e_{i,t}$, such that

$$\theta_{i,t}=\beta X_{i,t}+e_{i,t}. \quad (2)$$

We make an additional distributional assumption that $e_{i,t} \sim N(0, \sigma_e^2)$ and combine the behavioral specification (2) with the measurement specification (1) to form a behavioral Rasch model.[5] To our knowledge, Rabbitt (2014) and Wilde and Nord (2005) are the only other researchers to have examined food insecurity using this framework.

The behavioral Rasch model offers several distinct advantages relative to the standard binary models of the incidence of food insecurity (Borjas 2004, Mabli et al. 2013, Nord and Prell 2011, Ratcliffe et al. 2011, Schmidt et al. 2012) and continuous models of food insecurity Rasch scores (Gibson-Davis and Foster 2006, Mykerezi and Mills 2010, Van Hook and Balistreri 2006). Unlike the binary-choice models, which use a single summary measure of food insecurity such as a household's VLFS status, behavioral Rasch models use all of the available information from the component food security items, making them more efficient than the binary models. This is especially important for investigating outcomes like VLFS and VLFSAC, which have a low-incidence and therefore few effective degrees of freedom. Behavioral Rasch models can also be used in situations in which the standard binary measures lead to sample separation problems (see, e.g., Zorn 2005). Indeed, sample separation does occur for VLFSAC in the TCS.

Analytically, the behavioral Rasch model is very similar to regressions involving the Rasch score. The main difference is that the behavioral Rasch model estimates all of the relevant parameters—the calibration parameters from equation (1) and the behavioral parameters from equation (2)—jointly, while Rasch score regression approach effectively estimates the parameters in two steps and usually from different samples. If they were applied to the same sample, the one-step behavioral Rasch model would be more efficient than the two-step Rasch score regression. Another advantage of the behavioral Rasch model is that it can incorporate observations in which either none or all of the hardship items are affirmed—situations in which it is not possible to estimate Rasch scores. Regression analyses of Rasch scores often either drop these problematic observations or assign an arbitrary score to them. Recall that just over five-sixths of the observations in the TCS are from caregivers who fail to affirm any hardships; the behavioral Rasch model allows us to consider these observations.[6]

[5]The model for the TCS can be specified as an eight-equation random-effects logit with different intercepts for each type of hardship. The specification for the jth hardship is $p_{j,i,t} = \exp(\beta X_{i,t} - \delta_j + e_{i,t}) / [1 + \exp(\beta X_{i,t} - \delta_j + e_{i,t})]$.

[6]Another 16 observations are from caregivers who affirm all eight TCS hardship items.

The main disadvantage of the behavioral Rasch model is that it imposes strong restrictions. First, it assumes that food security can be represented by a single underlying index, rather than multiple indices. One motivation for analyzing VLFSAC separately from VLFS is a concern that these conditions may stem from different processes. Second, the Rasch model assumes that responses to each of the food hardship items are equally informative about the underlying food security index. Less-restrictive models, such as the Multiple-Indicator Multiple Cause (MIMIC) model (see, e.g., DePolt et al. 2009; Ribar et al. 2006) allow for differences in the variances of the reporting errors of each hardship item.[7]

We extend the behavioral Rasch model to account for the longitudinal aspect of the data. In particular, we are concerned that the unobserved characteristics, $e_{i,t}$, that contribute to households' food insecurity in equation (2) may be correlated over time and correlated with the observed explanatory variables, $X_{i,t}$. To address the first concern, we respecify the unobserved term in our model with a random-effects component structure such that $e_{i,t} = \eta_i + \varepsilon_{i,t}$ where η_i is a time-invariant, household-specific error term (the random effect) and $\varepsilon_{i,t}$ is time-varying, household-specific error term. We further assume that both error terms are normally distributed, independent of each other, and independent of the observed explanatory variables.

To address concerns regarding possible associations between unobserved and observed characteristics, we follow Chamberlain (1982) and specify a correlated random-effects (CRE) model. In particular, we respecify the unobserved term in our model as

$$e_{i,t}=\gamma_1 X_{i,1}+\gamma_2 X_{i,2}+\gamma_3 X_{i,3}+\eta_i^*+\varepsilon_{i,t}^* \quad (3)$$

where η_i^* is a time-invariant normally-distributed error and $\varepsilon_{i,t}^*$ is a time-varying, normally-distributed error. DePolt et al. (2009) incorporate the same modification in their MIMIC analysis and refer to it as a "quasi-fixed-effects" estimator. We obtain maximum likelihood estimates of the model parameters using the aML software package (http://www.applied-ml.com).

The principal parameters of interest in our model are the coefficients in β, which represent the marginal effects of changes in the $X_{i,t}$ variables on the continuous food insecurity index, $\theta_{i,t}$. While these are important and informative by themselves, we are also keenly interested in the marginal effects of the elements of $X_{i,t}$ on VLFS and VLFSAC. A helpful feature of our model is that the estimation results can be used to calculate these marginal effects—that is, marginal effects for the probability that two or more of the eight food hardships are affirmed for VLFS and for the probability that three or more of the four child-specific hardships are affirmed for VLFSAC.

In addition to the longitudinal Rasch behavioral model, we also estimate standard longitudinal binary choice models of VLFS, including random effects logit models,

[7] In our empirical analyses, we estimate less restrictive specifications in a series of robustness checks but find that they do not substantively change our findings.

conditional fixed effects models, and CRE models. These models are estimated for purposes of comparison with previous research and as robustness checks.

4. Analysis data

Our multivariate analyses utilize a host of explanatory variables that are available in the Three City Study. Our analyses include several time-varying measures of household food assistance. We include a binary measure of whether the caregiver reported receiving a positive amount of SNAP benefits at the time of the interview. We also include binary measures of whether children in the household received free or reduced-price meals from the National School Lunch Program (NSLP), free or reduced-price meals from the School Breakfast Program, or benefits from the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC). To measure cash assistance, we also incorporate a binary indicator of whether the caregiver reported receiving positive cash benefits from the Temporary Assistance for Needy Families (TANF) program.

We also consider several time-varying measures of the household's income and wealth. We have two contemporaneous income measures: a binary indicator of whether the household's total cash income in the month of the interview was below the monthly equivalent of the federal poverty line and a continuous measure of the natural logarithm of the household's total monthly cash income. To account for net wealth and access to credit, we have binary measures of whether the family owned the home they were living in, owned a car, had any financial assets, and had any outstanding loans. Because earnings might be distinct from other sources of income and because market work might reduce the time available for home production, we also include separate binary indicators of whether the caregiver reported working full time or part time for pay at the time of the interview (the omitted category is not working).

In addition to their own resources, families are often able to obtain help from relatives and friends. Edin et al. (2013) found that these arrangements constituted a valuable private safety net that helped SNAP families avoid food insecurity. From the TCS questions on social networks, we include separate binary indicators for whether the caregiver reported having friends or relatives who would listen to her problems, provide child care or babysitting, help with errands and favors, and lend money.

The TCS also recorded standard information about the household's size and composition and about health status. Our analyses include controls for the focal child's age, the total numbers of adults and children in the household, the caregiver's marital status, the caregiver's disability status, and whether the caregiver reported being in poor health.

For some of our analyses (e.g., the random-effects models), we also include several fixed, time-invariant controls. These include binary measures of the focal child's gender, the focal child's race and ethnicity, the caregiver's nativity, and whether the caregiver completed high school or college. We also have dummy variables for the city of residence.

The TCS used a stratified sampling design for its initial interviews; the study also experienced modest levels of attrition across waves. To account for these issues, our

subsequent empirical analyses incorporate longitudinal sampling weights that are provided with the study.

We select an analysis sample that consists of caregivers who were coresiding with focal children and who participated in all three waves of the TCS. We drop observations from the third wave for caregivers whose focal children were older than 18 years because the child-specific food hardship questions would not have been applicable. We also drop observations for caregivers who failed to answer one or more of the food hardship questions or who failed to provide information for any of the other explanatory variables. Finally, we limit the analysis sample to caregivers with usable observations in all three waves; that is, we create a balanced panel. The resulting analysis data set has 3,309 observations for 1,103 caregivers.

Means and standard deviations for the measures in the analysis data set are listed in Appendix B. Consistent with the focus of the TCS on disadvantaged families, the households in the analysis sample are disproportionately poor, with almost two-thirds having monthly incomes below the federal poverty line. Nearly half of the observations are from households that received benefits from the SNAP, and approximately three quarters are from households that received school meals. The selected observations in the analysis sample have smaller prevalence rates of VLFS and VLFSAC than the TCS generally. The unweighted incidence of VLFS in the analysis sample is 8.7 percent (the weighted rate is 7.5 percent), while the unweighted incidence of VLFS from the general sample in Table 1 was 9.7 percent. The combination of a low prevalence rate and a smaller sample leads to an especially low number of observations (27) from households that suffer from VLFSAC. The lower incidence of VLFS and VLFSAC in the analysis sample is mainly a result of the younger age of the focal children.[8]

5. Estimation results

We begin our multivariate empirical analysis by estimating standard longitudinal logistic binary-choice models of VLFS, using data from our balanced panel of caregivers and focal children. In particular we estimate a random-effects logit model, a conditional fixed effects logit model, and a CRE (quasi-fixed-effects) logit model, incorporating the measures described in the preceding section as explanatory variables. Coefficient estimates and other results from these models are reported in Table 2.[9]

Estimates from the random-effects logit model in the first column indicate that participation in the SNAP is significantly negatively associated with VLFS; the estimated marginal effect is sizeable (-2.8 percent, which is just over a third the incidence of VLFS of 7.5 percent in the weighted analysis sample). The negative association between SNAP and VLFS differs from most prior estimates from OLS and longitudinal models (see Gregory et al. 2013 for a review of previous findings) but is similar to the result reported by DePolt et al. (2009) for

[8]As mentioned, the analysis sample excludes observations for focal children who were older than 18 years in the third wave, all of whom were in the older cohort of study children (10-14 years when first interviewed). When the balanced-panel restriction is subsequently imposed, these children (the oldest children of the older cohort) are excluded altogether. As food hardships are less frequently reported for younger children, the selection on children's ages leads to a lower incidence of hardships.

[9]The low incidence and small numbers of households reporting VLFSAC precludes parallel analyses of that outcome.

adult hardships in the Three City Study. The negative findings for the TCS may reflect its sampling of a more homogeneous disadvantaged population than the CPS and other surveys.

Consistent with expectations, participation in the SBP and participation in TANF are also estimated to be negatively associated with VLFS, though the coefficient on SBP participation is statistically insignificant. The model, however, also produces the counter-intuitive result that participation in NSLP is positively associated with VLFS. Coleman-Jensen et al. (2013) found a similar relationship in descriptive analyses of the CPS-FSS.

Among the other coefficient estimates from the random-effects model, several are for variables that are available in the CPS and other surveys. As with previous descriptive and multivariate studies using the CPS, we find that poverty status, the number of adults, and the caregiver's disability status are significantly positively associated with VLFS and that home ownership and full-time work are negatively associated with VLFS.

However, the TCS also has other measures that are not recorded in the CPS. Especially important are the measures for a household's financial position and the strength of its social networks. Estimates from the random-effects model indicate that outstanding loans are significantly positively associated with VLFS and that vehicle ownership and the availability of child care and financial assistance through social networks are significantly negatively associated with VLFS.

Most of the significant associations from the random-effects specification maintain their signs and significance when we estimate a conditional fixed-effects logit. Among the food assistance variables, SNAP participation continues to have a significant negative association with VLFS, while NSLP participation has a significant positive association. SBP participation, which had a negative and insignificant coefficient in the random-effects model, is estimated to have a significantly negative association with VLFS in the fixed-effects specification. Among the other explanatory variables, the estimated coefficients on outstanding loans, full-time work, availability of child care through social networks, and the focal child's age lose their statistical significance.

Estimates from the longitudinal CRE logit model are listed in the third column of Table 3. These estimates are all qualitatively similar to the estimates from the conditional fixed-effects model. The only differences between the specifications are that the coefficients on WIC participation, TANF participation, and outstanding loans, which were marginally insignificant in the conditional fixed effects model, are marginally significant in the CRE model. The similarity of the results gives us confidence that the CRE specification is acting like a quasi-fixed effects model.

We now turn to estimates from our longitudinal behavioral Rasch model, which are reported in Table 3. Estimated coefficients and standard errors from the random-effects version of the model are listed in the first column of Table 3, and estimated results from the CRE version are listed in the second column. As we discussed, the coefficient estimates represent the conditional associations of the explanatory variables on the latent food insecurity index, which has an arbitrary scale and a nonlinear relationship with VLFS and VLFSAC. To examine these outcomes, we use the results from the longitudinal Rasch behavioral models

to predict the incidence of VLFS and VLFSAC and calculate marginal effects of the explanatory variables on them. The estimated marginal effects of the explanatory variables on VLFS appear in the table in brackets, and the estimated marginal effects for VLFSAC appear in italicized brackets.[10]

As with the standard binary-choice models, participation in the SNAP is estimated to have a substantial negative association with food insecurity. In the random-effects Rasch model, SNAP participation is estimated to reduce the probability of VLFS by 3.8 percent, which is similar to the result from the random-effects logit. However, unlike the standard approach, we are also able to estimate the marginal effect of SNAP participation on VLFSAC; the estimates indicate that SNAP receipt reduces the probability of this outcome by 0.7 percent, which is the same size as the mean of VLFSAC in the weighted analysis sample. The estimated associations in the CRE model are even stronger with marginal effects of -4.7 percent for VLFS (again similar to the random-effects logit) and -1.0 percent for VLFSAC. The large negative associations are consistent with the findings of DePolt et al. (2009).

The estimated coefficients on the other public assistance variables are statistically insignificant and generally have coefficients that are close to zero in the random effects specification. The coefficient estimates for participation in the SBP, NSLP, and WIC are also statistically insignificant in the CRE specification. Thus, the counter-intuitive positive findings from the standard models for NSLP and WIC participation largely disappear. In constrast, participation in the TANF program has a significantly negative coefficient and is estimated to reduce the probability of VLFS by 1.9 percent and the probability of VLFSAC by 0.4 percent.

Among the other explanatory variables, poverty status, outstanding loans, the number of adults, and caregiver disability are all estimated to have significant positive associations with food insecurity in the random-effects model, while car ownership, financial assets, the availability of child care and financial help from friends and relatives, and the caregiver's marital status are estimated to have significant negative associations.

The signs and significance for most of these coefficients are the same in the CRE model. The exceptions are the coefficients on car ownership and child care availability, which lose their significance. In addition, the number of minors is estimated to be significantly negatively associated with food insecurity in the CRE model. The statistically significant coefficients in the CRE model generally conform with expectations and with previous research.

Alternative specifications

The behavioral Rasch model makes several strong assumptions about the responses to the food hardship items. One assumption is that the items discriminate equally. To relax this assumption, we estimated an alternative version of the CRE specification that included separate discrimination parameters for six of the eight items.[11] Likelihood ratio comparisons

[10]For these estimates, we calculate differences in VLFS and VLFSAC outcomes for each household in the sample and calculate weighted averages of these marginal effects.

of the alternative and the restricted (behavioral Rasch) versions of the model strongly rejected the null hypothesis of equal discrimination (p-value = 0.002). However, there were no substantive changes to the results from Table 3.

The Rasch model also assumes that responses to all of the food hardship items are independent. This assumption is clearly violated for two of the child-specific items. In particular, one of the items asks whether the focal child ever skipped meals, and if this item is affirmed, a follow-on item asks how often the child skipped meals. To account for the dependency among these two items, we respecified our model so that it replaced the two logits for the separate items with a single ordered logit in which the outcomes were not skipping meals, skipping meals infrequently, and skipping meals frequently. Results from this model (not shown but available upon request) were also similar to the results from Table 3.

Perhaps the most consequential assumption of the Rasch model is that the responses to the separate food hardship items are all related to a single underlying scale. To address the possibility that the different items represented distinct components of food insecurity, we estimated separate longitudinal CRE models for the six items with sufficient numbers of affirmed responses to support these specifications.[12] Results from these models are reported in Table 4.

The estimated coefficients for most of our significant results from Table 3 have consistent signs across the different specifications for individual hardships. For example, all of the estimated coefficients for SNAP participation, TANF participation, the number of minors, and marriage are negative, and all of the estimated coefficients for the number of adults and disability status are positive. All but one of the coefficients for poverty status are positive, and the one negative coefficient is small and insignificant. A few other coefficients, however, have some inconsistent signs across the specifications. For example, financial assets are significantly negatively associated with adults cutting the size of meals or skipping meals but unexpectedly positively associated with the focal child skipping meals. Outstanding loans are positively associated with adults cutting the size of meals or skipping meals but negatively (albeit insignificantly) associated the caregiver losing weight and with the focal child skipping meals. In general, most of our significant results from Table 3 appear to be applicable to multiple individual hardships.

6. Discussion and conclusion

In this paper, we used a Rasch measurement model to develop simple indicators based on counts of affirmed food hardship questions to classify households in the Three City Study with very low food security and very low food security among children. The TCS contains four questions regarding food hardships among adults that are identical to the HFSSM and

[11] We respecified the model as $p_{j,i,t} = \exp(\lambda_j \theta_{i,t} - \delta_j) / [1 + \exp(\lambda_j \theta_{i,t} - \delta_j)]$ where λ_j is the discrimination parameter. In the specification, λ_1 and λ_3 were normalized to 1 specifications that attempted to relax the restrictions on either of the remaining discrimination parameters failed to converge. For brevity, we discuss the results but do not report detailed estimates (these are available upon request).

[12] There were insufficient "yes" responses to the questions regarding the focal child frequently skipping meals and the focal child going hungry—the two most severe conditions asked by the TCS—to support CRE specifications.

four questions regarding food hardships among specific children that are similar to questions in the HFSSM. We were able to formally evaluate our thresholds—affirming two or more of the eight TCS questions for VLFS and affirming three or four of the four child-specific questions for VLFSAC—using data from the April 1999 CPS-FSS, which asked these exact same questions on an experimental basis.

The development of indicators of VLFS and VLFSAC increases the usefulness of the TCS for studying the causes and consequences of food insecurity. In addition to the standard control measures found in the CPS and other surveys, we examine measures for households' financial characteristics and social networks. Beyond these measures, the TCS also contains information on neighborhood conditions, parenting practices and attitudes, psychological distress, time use, and other characteristics that would be worthwhile to investigate in future research. The analyses in this paper also show that responses to the focal-child-specific food hardship questions are comparable to responses to HFSSM questions for children generally. Thus, the questions can be used to examine how the rich developmental, behavioral, and educational data that are available for focal children in the TCS are not only related to those children's hardships but also to conventional and comparable measures of VLFS and VLFSAC.

We further used observations from the TCS for multivariate analyses of food insecurity, estimating longitudinal Rasch behavioral models. With our definitions of VLFS and VLFSAC thresholds, we were able to estimate marginal effects of explanatory variables on these outcomes. The estimated marginal effects for VLFSAC from the Rasch model are especially important because it is not possible to estimate standard binary models of this outcome for the TCS with appreciable numbers of controls.

The estimates from the multivariate analyses consistently indicate that participation in the SNAP is strongly negatively associated with food insecurity and with the incidence of VLFS and VLFSAC. The estimated relationships are robust to different types of models, appearing in standard binary-choice models, the longitudinal Rasch behavioral models, and extensions of the Rasch models. They are also robust the inclusion of controls for time-invariant omitted variables in CRE specifications. The estimates from the multivariate models also generally indicate that TANF participation reduces food insecurity.

The multivariate results also buttress conventional findings that poverty and disability contribute to food insecurity, and provide new findings that financial assets and social support reduce food insecurity. Analyses of a few of these variables have been possible in the CPS-FSS, but analyses of several others, including debt, assets, and social support, are only possible through surveys like the TCS, which have extended sets of measures.

While our empirical analyses have necessarily focused on the Three City Study, we believe that application of the Rasch behavioral model will prove useful in other cross-section and longitudinal surveys, such as the Fragile Families and Child Well-Being Study and the Early Children Longitudinal Surveys, that measure children's food hardships but that have modest numbers of observations. In particular, the method can be applied to examine low-frequency outcomes, like VLFSAC, that appear at the far range of the food insecurity scale.

Appendix A. Identifying Very Low Food Security in the Three City Study

To identify Very Low Food Security (VLFS) and Very Low Food Security among Children (VLFSAC) in the Three City Study (TCS), we analyzed items from the TCS and the Food Security Supplement to the April 1999 Current Population Survey (CPS-FSS).

The TCS asks about eight food hardships. Four questions in the TCS that ask about adult hardships are identical to items in the CPS-FSS. Four other questions in the TCS that ask about hardships experienced by the focal child are based on CPS-FSS items that ask about children in the household generally.

The April 1999 CPS-FSS, however, featured a special split-ballot questionnaire in which 7/8ths of the households were asked the standard CPS-FSS items but 1/8th was asked experimental questions that included adult- and child-specific items. The table below lists the standard CPS-FSS items in the first column. An “A” following the item indicates that an experimental item was also asked in April 1999. The TCS items are listed in the second column, and the wording of the questions appears in the final column.

Table A1
Food hardship items from the April 1999 CPS-FSS and the TCS

CPS-FSS	TCS	Description
Household items		
HESS2		Worried food would run out
HESS3		Food bought didn't last
HESS4		Couldn't afford to eat balanced meals
Adult items		
HESH2,A	ST8	Adult(s) cut size of meals or skipped meals
HESH3		Respondent ate less than felt he/she should
HESHF2,A		Adult(s) cut size or skipped meals in 3 or more months
HESH4	ST10	Respondent hungry but didn't eat
HESH5	ST11	Respondent lost weight
HESSH1,A	ST9	Adult(s) did not eat for whole day
HESSHF1,A		Adult(s) did not eat for whole day in 3 or more months
Child items		
HESS5		Relied on few kinds of low-cost food to feed child(ren)
HESS6		Couldn't feed child(ren) balanced meals
HESH1,A		Child(ren) were not eating enough
HESSH2,A	ST12	Cut size of child(ren)'s meals
HESSH3,A	ST15	Child(ren) were hungry
HESSH4,A	ST13	Child(ren) skipped meals
HESSHF4,A	ST14	Child(ren) skipped meals in 3 or more months
HESSH5,A		Child(ren) did not eat for whole day

As the table indicates, the TCS directly overlaps with four of the standard CPS-FSS items and six of the experimental CPS-FSS items. Additionally, the standard and experimental CPS-FSS directly overlap on eight items.

Our formal analyses are based on estimates from Rasch measurement models, which are described in the text. An important feature of the Rasch model is that it also allows us to compare food security among households who are asked different subsets of a common set of questions. Indeed, this feature is used by the USDA to set comparable thresholds of food insecurity among households with children who are asked 18 questions in the CPS-FSS and households without children who are only asked 10 questions. Specifically, the USDA uses a Rasch measurement model to estimate (a) the 18 calibration parameters for the possible 18 items, (b) the 19 food security scores (θs) for the different types of households with children, and (c) the 11 food security scores for the different types of households without children. Bickel et al. (2000) describe how the resulting food security scores are compared to determine a household's food security status. From this procedure, households with children are identified as having low food security if they answer three or more questions affirmatively and as having very low food security if they answer eight or more questions affirmatively. Households without children are identified as having low food security if they affirm two or more items and having very low food security if they answer affirm six or more items.[13]

We apply a similar procedure to the union of the 22 items in the April 1999 CPS-FSS that either are a part of the standard food security scale (the 18 standard items) or are in the overlap between the TCS and the CPS-FSS experimental split ballot (the four experimental items).

To estimate the Rasch parameters, we utilize a two-step “conditional” approach (Andrich 1988).[14] In the first step, we estimate the calibration parameters for all 22 items using a conditional household fixed-effects logit procedure applied to all of the non-missing item responses from the analytical sample and incorporating the sampling weights that are provided with the survey. Estimates of the calibration parameters have an arbitrary location; to maximize the comparability with Bickel et al. (2000), we followed their procedure and normalized the parameters so that the mean of the 18 standard parameters was 7. Estimates of the normalized parameters appear below.

Table A2

Item Calibration Values from 1999 CPS-FSS – VLFS Analysis

CPS-FSS question	Universe	Description	Calibration
Household items			
HESS2 (=1,2)	All	Worried food would run out	2.246

[13]The formal labels for different food security statuses have changed since 2000; however, the thresholds have not.
[14]Bickel et al. (2000) followed a different joint estimation approach.

CPS-FSS question	Universe	Description	Calibration
HESS3 (=1,2)	All	Food bought didn't last	3.035
HESS4 (=1,2)	All	Couldn't afford to eat balanced meals	3.881
Adult items			
HESH2 (= 1)	standard *	Adult(s) cut size of meals or skipped meals	5.559
HESH3 (= 1)	All	Respondent ate less than felt he/she should	5.728
HESHF2 (= 1,2)	standard	Adult(s) cut size or skipped meals in 3+ months	6.464
HESH4 (= 1)	all *	Respondent hungry but didn't eat	7.475
HESH5 (= 1)	all *	Respondent lost weight	8.482
HESSH1 (= 1)	standard *	Adult(s) did not eat for whole day	8.843
HESSHF1 (= 1,2)	standard	Adult(s) did not eat for whole day in 3+ months	9.565
Child items			
HESS5 (= 1)	All	Relied on few kinds of low-cost food	3.498
HESS6 (= 1)	All	Couldn't feed child(ren) balanced meals	5.050
HESH1 (= 1,2)	standard	Child(ren) were not eating enough	6.269
HESSH2 (= 1)	standard	Cut size of child(ren)'s meals	8.959
HESSH3 (= 1)	standard	Child(ren) were hungry	9.223
HESSH4 (= 1)	standard	Child(ren) skipped meals	9.901
HESSHF4 (= 1,2)	standard	Child(ren) skipped meals in 3+ months	10.207
HESSH5 (= 1)	standard	Child(ren) did not eat for whole day	11.615
Exper. child items			
HESSH2A (= 1)	exper. *	Cut size of focal child's meals	9.049
HESSH3A (= 1)	exper. *	Focal child was hungry	8.506
HESSH4A (= 1)	exper. *	Focal child skipped meals	9.278
HESSHF4A (= 1,2)	exper. *	Focal child skipped meals in 3+ months	9.418

* Item also appears in the TCS.

The values of the 18 standard calibration parameters differ modestly from those reported by Bickel et al. The differences mostly reflect the use of a conditional rather than a joint estimation procedure. The use of a different sample (1999 instead of 1998) and the inclusion of the experimental items do not alter the calibration estimates much. The severity ordering of the calibration parameters is identical to Bickel et al. The calibration parameters for the four experimental items are generally close to their standard item counterparts. The principle difference is that the severity of the experimental “child hunger” item (HESSH3A) is lower than that of the experimental “cut size” item (HESSH2A).

The calibration values also confirm that the TCS items are all relatively severe. The least severe TCS item asks about adults cutting the size or skipping meals; this corresponds to the sixth least severe item in the standard CPS-FSS. The remaining TCS items have above-average severity (they are or correspond to the second, third, and fifth through ninth most severe CPS-FSS items).

The second estimation step is to recover Rasch score values for (a) households with children that answered the 18 standard CPS-FSS items, (b) households without children that answered all 10 of the standard CPS-FSS items, and (c) hypothetical households with

children if they had been asked the eight TCS items. For a number of affirmative responses, r, and available items, J, the scores solve $r=\sum_{j=1}^{J}\exp(\theta_r-\delta_j)/[1+\exp(\theta_r-\delta_j)]$. The estimated scores for these response patterns are shown below.

Table A3
Rasch Scores for the standard CPS-FSS and TCS items – VLFS Analysis

CPS-FSS HH with children		CPS-FSS HH without children		TCS household with child		Household food security status category
"Yes" responses	Rasch score	"Yes" responses	Rasch score	"Yes" responses	Rasch score	
0	.	0	.			
1	1.814	1	2.151			Food secure
2	2.848	2	3.401			
3	3.618			0	.	
4	4.290	3	4.441	1	5.826	
5	4.906	4	5.373			Low food security
6	5.483	5	6.227			
7	6.037					
8	6.582					
9	7.124					
10	7.658			2	7.014	
11	8.176	6	7.060	3	7.810	
12	8.676	7	7.908	4	8.457	
13	9.170	8	8.806	5	9.066	Very low food security
14	9.680	9	9.920	6	9.730	
15	10.241	10	.	7	10.639	
16	10.922			8	.	
17	11.911					
18	.					

The orderings of the Rasch scores for the CPS-FSS items for households with and without children match the orderings reported by Bickel et al. (2000). Following their methodology, the Rasch score threshold for imputing low food security would be approximately 3.5 (the mid-point between the score for two affirmative responses for adult-only households and the score for three affirmative responses for households with children), and the threshold for imputing VLFS would be approximately 6.3 (the mid-point between the Rasch scores for households with children affirming seven and eight items). Applying these thresholds to the TCS, its items can identify households with VLFS (households that affirm two or more items), but its items cannot distinguish between food secure households and households with low food security.

VLFSAC

To analyze and identify food security among children in the TCS, we apply a similar procedure to the union of the 12 items in the April 1999 CPS-FSS that either are a part of the standard children's food security scale (the 8 standard items) or are in the overlap between the child-specific TCS and the CPS-FSS experimental split ballot (the four experimental items).

We re-estimated our conditional Rasch measurement models to first obtain calibration values that are specific to the children's items. We then recovered Rasch score values for the standard CPS-FSS child items and score values for the four experimental items that are also available in the Three-City questionnaire. We report the Rasch scores below.

Table A4
Rasch Scores for the standard CPS-FSS and TCS items – VLFSAC

CPS-FSS HH with child		TCS household with child		Child food security status category
"Yes" responses	Rasch score	"Yes" responses	Rasch score	
0	.			Food secure
1	2.082	0	.	
2	4.209	1	6.056	
3	6.182	2	7.196	Low food security among children
4	7.697			
5	8.759			
6	9.762	3	8.330	Very low food security among children
7	11.014	4	.	
8	.			

Nord (2009) defines households in the CPS-FSS that report one or fewer child hardships as showing no evidence of food insecurity among children, households that report two to four child hardships as having low food security among children, and households that report five or more child hardships as having VLFSAC. The Rasch score threshold between the first two categories is approximately 3.1, while the threshold between the next two categories is approximately 8.2. Using the four items from the TCS, we can identify households with VLFSAC as those that indicate three or four child-related hardships. We cannot distinguish between households that are food secure and that exhibit low food insecurity among children.

Appendix B. Means and standard deviations of the analysis sample

	Full sample		Very low food security		VLFS among children	
	Mean	(std. dev.)	Mean	(std. dev.)	Mean	(std. dev)
Very low food security	0.075	(0.263)	-		-	

	Full sample		Very low food security		VLFS among children	
	Mean	(std. dev.)	Mean	(std. dev.)	Mean	(std. dev)
VLFS among children	0.007	(0.085)	0.097	(0.296)	-	
SNAP	0.472	(0.499)	0.438	(0.497)	0.450	(0.508)
SBP	0.730	(0.444)	0.779	(0.416)	0.670	(0.480)
NSLP	0.752	(0.432)	0.820	(0.385)	0.722	(0.458)
WIC	0.345	(0.475)	0.310	(0.463)	0.042	(0.205)
TANF	0.242	(0.429)	0.236	(0.426)	0.312	(0.473)
Poverty	0.630	(0.483)	0.772	(0.420)	0.812	(0.399)
ln (household income)	0.176	(0.877)	0.086	(1.019)	-0.368	(1.674)
Own home	0.195	(0.396)	0.147	(0.355)	0.064	(0.250)
Own car	0.542	(0.498)	0.442	(0.498)	0.390	(0.498)
Any financial assets	0.393	(0.488)	0.344	(0.476)	0.475	(0.510)
Any outstanding loans	0.516	(0.500)	0.563	(0.497)	0.590	(0.502)
Work full-time	0.327	(0.469)	0.198	(0.399)	0.144	(0.358)
Work part-time	0.175	(0.380)	0.247	(0.432)	0.267	(0.452)
SN: Listen	0.546	(0.498)	0.433	(0.497)	0.441	(0.507)
SN: Child care	0.492	(0.500)	0.335	(0.473)	0.282	(0.460)
SN: Favor	0.451	(0.498)	0.294	(0.457)	0.238	(0.435)
SN: Money	0.365	(0.481)	0.177	(0.382)	0.238	(0.435)
FC age	7.643	(5.131)	9.341	(5.466)	14.142	(4.441)
Number of adults	1.898	(0.913)	2.100	(1.090)	1.956	(1.058)
Number of minors	2.901	(1.529)	2.856	(1.592)	3.076	(1.993)
CG married	0.330	(0.470)	0.312	(0.464)	0.307	(0.471)
CG disabled	0.183	(0.387)	0.369	(0.484)	0.465	(0.510)
CG poor health	0.251	(0.434)	0.382	(0.487)	0.715	(0.461)
FC female	0.515	(0.500)	0.578	(0.495)	0.659	(0.484)
FC black	0.425	(0.494)	0.465	(0.500)	0.780	(0.423)
FC Hispanic	0.534	(0.499)	0.465	(0.500)	0.220	(0.423)
CG foreign born	0.202	(0.401)	0.166	(0.373)	0.059	(0.241)
CG HS grad	0.401	(0.490)	0.369	(0.483)	0.393	(0.499)
CG college grad	0.187	(0.390)	0.187	(0.391)	0.379	(0.496)
Boston	0.317	(0.465)	0.340	(0.475)	0.432	(0.506)
Chicago	0.335	(0.472)	0.277	(0.448)	0.510	(0.511)
Wave	2.000	(0.817)	1.980	(0.807)	2.330	(0.858)
Observations	3,309		289		27	

Note: Authors' estimates using data from the Three-City Study. Estimates incorporate sampling weights.

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Table 1

Counts of Adult and Focal Child Food Hardships in the Three-City Study and Incidence of Food Security

Count of adult hardships	Count of focal child hardships					Total
	0	1	2	3	4	
0	5,347	22	2	3	0	5,374
1	324	56	14	4	2	400
2	147	32	8	6	7	200
3	106	26	17	11	11	171
4	87	24	17	19	16	163
Total	6,011	160	58	43	36	6,308

Food secure or low food security (5,693 households)

Very low food security (615 households)

Very low food security among children (79 households)

Notes: Authors' calculations from co-resident caregivers in three waves of the Three-City Study who answered all eight food hardship questions.

Table 2
Longitudinal Logit Models of Very Low Food Security

VARIABLES	RE logit[a]	FE logit	CRE logit
SNAP	-0.9330***	-1.3222***	-1.2576***
	(0.2452)	(0.3402)	(0.3051)
	[-0.0277]		[-0.0430]
SBP	-0.3663	-1.2358**	-0.8461*
	(0.3788)	(0.5453)	(0.4568)
	[-0.0117]		[-0.0328]
NSLP	0.7987**	1.9252***	1.2844***
	(0.4022)	(0.5973)	(0.4695)
	[0.0198]		[0.0345]
WIC	0.2699	0.5077	0.4984*
	(0.2269)	(0.3307)	(0.2861)
	[0.0082]		[0.0175]
TANF	-0.5030*	-0.5713	-0.9480***
	(0.2661)	(0.3612)	(0.3226)
	[-0.0134]		[-0.0272]
Poverty	1.2160***	1.1097***	1.1373***
	(0.2647)	(0.3794)	(0.3105)
	[0.0301]		[0.0320]
ln (household income)	0.0714	0.1127	0.1592
	(0.1215)	(0.1692)	(0.1482)
	[0.0021]		[0.0052]
Own home	-0.9832***	-2.2345***	-1.3267***
	(0.3428)	(0.7231)	(0.4943)
	[-0.0226]		[-0.0339]
Own car	-0.8312***	-1.0883***	-0.9023***
	(0.2578)	(0.3949)	(0.3380)
	[-0.0244]		[-0.0297]
Any financial assets	-0.2959	-0.1876	-0.3588
	(0.2265)	(0.3170)	(0.2934)
	[-0.0083]		[-0.0113]
Any outstanding loans	0.7088***	0.5395	0.5032*
	(0.2265)	(0.3593)	(0.2882)
	[0.0209]		[0.0165]
Work full-time	-0.4698*	-0.2470	-0.5105
	(0.2652)	(0.3469)	(0.3293)
	[-0.0124]		[-0.0153]
Work part-time	0.4175	0.1725	-0.0741

VARIABLES	RE logit[a]	FE logit	CRE logit
	(0.2546)	(0.3943)	(0.3246)
	[0.0134]		[-0.0024]
SN: Listen	-0.0805	-0.2966	-0.2678
	(0.2290)	(0.3795)	(0.3021)
	[-0.0023]		[-0.0087]
SN: Child care	-0.4784**	-0.1092	0.0275
	(0.2395)	(0.3512)	(0.2947)
	[-0.0134]		[0.0009]
SN: Favor	-0.1336	0.5228	0.2201
	(0.2540)	(0.3681)	(0.3128)
	[-0.0038]		[0.0074]
SN: Money	-1.1258***	-1.5102***	-1.1644***
	(0.2752)	(0.4155)	(0.3360)
	[-0.0266]		[-0.0317]
Number of adults	0.4422***	0.3661**	0.3435**
	(0.1069)	(0.1658)	(0.1437)
	[0.0129]		[0.0112]
Number of minors	-0.1085	-0.1450	-0.1480
	(0.0764)	(0.1432)	(0.1349)
	[-0.0032]		[-0.0048]
CG married	-0.2658	0.2678	-0.3039
	(0.2643)	(0.4783)	(0.3943)
	[-0.0075]		[-0.0096]
CG disabled	0.9327***	0.6409*	0.6554*
	(0.2483)	(0.3701)	(0.3339)
	[0.0324]		[0.0237]
CG poor health	0.0802	0.2275	-0.1149
	(0.2223)	(0.3011)	(0.2769)
	[0.0024]		[-0.0037]
ln likelihood	-705.68	-132.69	-653.87
Observations	3,309	555	3,309
Households	1,103	185	1,103

Note: Authors' estimates using data from the Three-City Study. Estimates incorporate sampling weights. All models include controls for wave of interview. Standard errors of coefficients in parentheses; estimated marginal effects in brackets.

[a]Model also includes controls for focal child's age, gender, race, and ethnicity; caregiver's nativity; and city of residence.

*Significant at 0.10 level.

**Significant at 0.05 level.

***Significant at 0.01 level.

Table 3
Longitudinal Behavioral Rasch Model Results

VARIABLES	Random-effects specification	Correlated random-effects specification
SNAP	-1.3947***	-1.6798***
	(0.3081)	(0.3635)
	[-0.0384]	[-0.0468]
	[-0.0074]	*[-0.0097]*
SBP	-0.0155	-0.1704
	(0.5349)	(0.5176)
	[-0.0004]	[-0.0048]
	[-0.0001]	*[-0.0010]*
NSLP	0.3076	0.3911
	(0.4525)	(0.5224)
	[0.0082]	[0.0104]
	[0.0015]	*[0.0020]*
WIC	-0.1819	0.0561
	(0.3368)	(0.3283)
	[-0.0049]	[0.0016]
	[-0.0009]	*[0.0003]*
TANF	0.0582	-0.7203*
	(0.3393)	(0.3721)
	[0.0016]	[-0.0188]
	[0.0003]	*[-0.0036]*
Poverty	0.9938**	1.1548***
	(0.4993)	(0.3669)
	[0.0258]	[0.0301]
	[0.0046]	*[0.0056]*
ln (household income)	-0.1531	0.0485
	(0.2984)	(0.1657)
	[-0.0042]	[0.0013]
	[-0.0008]	*[0.0003]*
Own home	-0.8698	-0.5446
	(0.6172)	(0.5531)
	[-0.0218]	[-0.0142]
	[-0.0038]	*[-0.0027]*
Own car	-0.8769***	-0.2700
	(0.2958)	(0.3779)
	[-0.0242]	[-0.0074]
	[-0.0045]	*[-0.0015]*
Any financial assets	-0.7870**	-0.9051**
	(0.3517)	(0.3672)

VARIABLES	Random-effects specification	Correlated random-effects specification
	[-0.0209]	[-0.0242]
	[-0.0038]	*[-0.0047]*
Any outstanding loans	1.0031***	0.6121*
	(0.3309)	(0.3411)
	[0.0277]	[0.0169]
	[0.0052]	*[0.0033]*
Work full-time	-0.5055	-0.3791
	(0.4989)	(0.3725)
	[-0.0133]	[-0.0104]
	[-0.0024]	*[-0.0020]*
Work part-time	0.0868	-0.3533
	(0.4346)	(0.3861)
	[0.0025]	[-0.0098]
	[0.0005]	*[-0.0019]*
SN: Listen	0.2541	0.0658
	(0.3219)	(0.3427)
	[0.0070]	[0.0018]
	[0.0013]	*[0.0004]*
SN: Child care	-0.9975***	-0.4146
	(0.3054)	(0.3260)
	[-0.0269]	[-0.0113]
	[-0.0050]	*[-0.0022]*
SN: Favor	-0.2773	0.1243
	(0.2922)	(0.3412)
	[-0.0075]	[0.0035]
	[-0.0014]	*[0.0007]*
SN: Money	-0.9336***	-0.8833**
	(0.3343)	(0.3584)
	[-0.0241]	[-0.0229]
	[-0.0043]	*[-0.0043]*
Number of adults	0.4858***	0.2847*
	(0.1493)	(0.1701)
	[0.0134]	[0.0079]
	[0.0025]	*[0.0016]*
Number of minors	0.0112	-0.3005*
	(0.1707)	(0.1583)
	[0.0003]	[-0.0083]
	[0.0001]	*[-0.0016]*
CG married	-0.6437*	-0.8087*
	(0.3485)	(0.4417)
	[-0.0170]	[-0.0212]

VARIABLES	Random-effects specification	Correlated random-effects specification
	[-0.0031]	*[-0.0040]*
CG disabled	1.1112***	0.9036**
	(0.3403)	(0.4205)
	[0.0343]	[0.0271]
	[0.0067]	*[0.0055]*
CG poor health	0.0329	-0.2151
	(0.3029)	(0.3535)
	[0.0009]	[-0.0059]
	[0.0002]	*[-0.0012]*
ln likelihood	-2445.65	-2382.41
Observations	3,309	3,309
Households	1,103	1,103

Note: Authors' estimates using data from the Three-City Study. Estimates incorporate sampling weights. All models include controls for wave of interview. Standard errors of coefficients in parentheses; estimated marginal effects on VLFS in brackets; estimated marginal effects on VLFSAC in italicized brackets.

* Significant at 0.10 level.

** Significant at 0.05 level.

*** Significant at 0.01 level.

Table 4

Correlated Random-Effect Logit Model Results for Specific Food Hardships

VARIABLES	Adult(s) cut size or skip meals	Adult(s) did not eat for whole day	Caregiver hungry but did not eat	Caregiver lost weight	Cut size of focal child's meals	Focal child skipped meals
SNAP	-0.9382***	-0.5928	-1.4957***	-1.6890***	-0.8292	-1.8254*
	(0.2349)	(0.4010)	(0.3459)	(0.4799)	(0.5470)	(1.0736)
SBP	0.1822	-0.0088	-0.5625	-1.7377**	-0.1796	-2.0067*
	(0.3419)	(0.6159)	(0.5177)	(0.7548)	(0.7543)	(1.2045)
NSLP	-0.0649	0.1608	1.0668**	1.0494	-0.9249	2.1957*
	(0.3471)	(0.6351)	(0.5341)	(0.7584)	(0.7687)	(1.1396)
WIC	0.1579	-0.1107	0.0808	-0.4104	1.9846***	-0.2778
	(0.2184)	(0.3621)	(0.3047)	(0.4419)	(0.6254)	(1.1374)
TANF	-0.3693	-1.5688***	-1.1102***	-1.1209**	-0.6129	-3.0277**
	(0.2433)	(0.4108)	(0.3652)	(0.4763)	(0.5507)	(1.1865)
Poverty	0.4032*	1.1355***	0.8631**	0.7553	-0.1985	1.3911
	(0.2344)	(0.4205)	(0.3386)	(0.5426)	(0.5758)	(1.0637)
ln (HH income)	0.0776	0.2601	-0.0041	-0.3063	-1.1777***	-0.4367
	(0.1148)	(0.1882)	(0.1642)	(0.2358)	(0.3169)	(0.4571)
Own home	-0.0747	-1.0372*	-1.2821**	-0.5886	-2.7060**	-0.9166
	(0.3435)	(0.6051)	(0.5378)	(0.8089)	(1.1343)	(2.0312)
Own car	0.0178	-0.5434	-1.4070***	-0.8227*	0.6659	0.0496
	(0.2514)	(0.4040)	(0.3685)	(0.4952)	(0.6335)	(1.1696)
Any fin. assets	-1.0311***	-0.6408	-0.3229	0.3044	-0.0517	1.7129*
	(0.2439)	(0.3972)	(0.3265)	(0.5014)	(0.4966)	(1.0291)
Outstanding loans	0.4090*	0.4524	0.4599	-0.1104	0.0308	-0.3184
	(0.2168)	(0.3529)	(0.3039)	(0.4401)	(0.5495)	(0.9668)
Work full-time	-0.0331	-0.0187	-0.4757	-0.6019	0.5226	-0.2561
	(0.2561)	(0.4331)	(0.3565)	(0.5264)	(0.6205)	(1.1924)
Work part-time	-0.3955	-0.0304	-0.0472	0.7112	0.3277	-0.6546
	(0.2572)	(0.4501)	(0.3741)	(0.5237)	(0.5287)	(1.1591)

VARIABLES	Adult(s) cut size or skip meals	Adult(s) did not eat for whole day	Caregiver hungry but did not eat	Caregiver lost weight	Cut size of focal child's meals	Focal child skipped meals
SN: Listen	0.0600	-0.0793	-0.5721*	-0.5627	0.0288	0.1529
	(0.2271)	(0.3916)	(0.3337)	(0.4583)	(0.5181)	(0.9324)
SN: Child care	-0.4957**	0.1952	0.0635	-0.5658	0.0584	1.3090
	(0.2189)	(0.3731)	(0.3159)	(0.4735)	(0.5570)	(1.0014)
SN: Favor	0.3271	0.1054	0.3789	0.1435	-0.9669	-1.8214*
	(0.2368)	(0.3905)	(0.3497)	(0.5199)	(0.6455)	(0.9730)
SN: Money	-0.2378	-0.8924**	-1.2409***	-1.5245***	0.7932	0.2707
	(0.2335)	(0.4155)	(0.3613)	(0.5604)	(0.6682)	(1.2498)
Number of adults	0.0050	0.2088	0.2344	0.2302	0.3454	0.7276*
	(0.1145)	(0.1907)	(0.1620)	(0.2212)	(0.2803)	(0.4091)
Number of minors	-0.1578	-0.4854***	-0.3779**	-0.3401*	-0.0956	-0.1195
	(0.1057)	(0.1795)	(0.1504)	(0.2038)	(0.2633)	(0.4636)
CG married	-0.3761	-0.3943	-0.7443*	-0.2225	-0.3207	-1.9321
	(0.2952)	(0.5077)	(0.4344)	(0.6048)	(0.8356)	(1.4474)
CG disabled	0.7697***	0.2724	0.3653	1.1465**	1.7313***	0.5440
	(0.2748)	(0.4241)	(0.3943)	(0.5269)	(0.6095)	(0.9870)
CG poor health	-0.3188	-0.2869	-0.2467	0.3986	0.1995	1.4581
	(0.2250)	(0.3341)	(0.3001)	(0.4257)	(0.4780)	(1.0053)
Log likelihood	3,309	3,309	3,309	3,309	3,309	3,309

Note: Author's estimates using data for 3,309 observations (1,103 households) from the Three City Study. Estimates incorporate sampling weights. All models include controls for wave of interview and CRE observed controls. Standard errors of coefficients in parentheses.

*Significant at 0.10 level.

**Significant at 0.05 level.

***Significant at 0.01 level.