Economics Letters 173 (2018) 55–60

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Heterogeneous impacts of the Supplemental Nutrition Assistance Program on food insecurity[☆]

Partha Deb[a,*], Christian A. Gregory[b]

[a] Hunter College, Department of Economics, 695 Park Avenue, West 1524, New York, NY 10065, United States
[b] Economic Research Service, USDA, 355 E St. SW, Washington, DC 20003, United States

HIGHLIGHTS

- SNAP increases food security by 24 percentage points among low security individuals.
- SNAP decreases high insecurity by 23 percentage points among low security individuals.
- Low security individuals are more likely to report unmet food needs.

ARTICLE INFO

Article history:
Received 8 May 2018
Received in revised form 11 September 2018
Accepted 17 September 2018
Available online 24 September 2018

Keywords:
SNAP
Food stamps
Food insecurity
Finite mixture models

ABSTRACT

We study the effects of SNAP participation on food insecurity allowing for *a priori* unspecified heterogeneous treatment effects. Using finite mixture models, we identify a low food security class comprising almost 60% of the samples for whom SNAP participation increases the probability of no food insecurity by 14–37 percentage points across specifications and decreases the probability of very high insecurity by 14–35 percentage points. We find that SNAP participation has a small and statistically insignificant effect on food insecurity for the remaining 40% of the population. By examining posterior probabilities of class membership, we discover that individuals in the latter class are less likely to report unmet food needs and live in larger households where more consumption smoothing may be possible.

1. Introduction

A number of studies estimate causal effects of SNAP benefits on food insecurity using a variety of identification schemes (Jensen, 2002; Mykerezi and Mills, 2010; Meyerhoefer and Yang, Autumn 2011; Yen et al., 2008; Ratcliffe et al., 2011, e.g.,). Gundersen et al. (2017) raise questions about the validity of the existing methods and suggest abandoning the quest for point estimates in favor of bounds on those estimates. Regardless of approach, however, empirical methods for estimating the treatment effects of the Supplemental Nutrition Assistance Program (SNAP) have focused on the average treatment effect of the program. But, when program effects are not constant across the treatment population, knowledge of differences in treatment effects can be used to target policies and programs better. When differences in treatment effects are based on clearly observed characteristics such as gender, these can be taken into consideration easily. In other situations, there are good reasons to think that effects of treatment will vary across *unobserved*, or at least not so easily observed, factors in household characteristics such as food preferences, subjective poverty thresholds, subjective discount rates, and financial acumen. These cannot be easily explored using standard models.

In this study, we allow for the possibility of heterogeneous effects of SNAP participation on food insecurity in a general, a priori unspecified way. We identify subgroups of the population for whom improvements in outcomes are large and subgroups for whom SNAP may have little or no effect. Specifically, we estimate finite mixture models to explore the possibility of treatment effect heterogeneity, to estimate heterogeneous effects and to characterize the sources of such unobserved heterogeneity (McLachlan and Peel, 2004; Deb and Trivedi, 1997; Caudill et al., 2009; Günther and Launov, 2012).

2. Data

The primary individual-level data for this application come from 2006–2012 December CPS Food Security Supplement (CPS-FSS). For each of these years of the CPS-FSS, our main specifications

☆ The findings and conclusions in this publication are not been formally disseminated by the US Department of Agriculture and should not be construed to represent any Agency determination or policy. This research was supported in part by the extramural research program of the US Department of Agriculture, Economic Research Service, cooperative agreement number 58-5000-3-059. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

* Corresponding author.
E-mail addresses: partha.deb@hunter.cuny.edu (P. Deb), cgregory@ers.usda.gov (C.A. Gregory).

https://doi.org/10.1016/j.econlet.2018.09.011
0165-1765/

include households with annual incomes at or below 185 percent of the Federal poverty line. We choose this income threshold for two reasons. First, it is the income cut-off that the CPS uses to determine which households are asked about participation in SNAP. Second, although the gross income cut-off for SNAP eligibility is 130 percent of the Federal poverty line, the relaxation of categorical eligibility rules in many states means that a non-trivial fraction of households who enroll in SNAP have incomes above this threshold.

Our measure of food insecurity is an ordinal variable calculated as the sum of affirmative responses to the following adult food insecurity-related questions in the food security module of the CPS-FSS:

1. Worried food would run out
2. Food bought would not last
3. Could not afford to eat balanced meals
4. Adult(s) cut size or skipped meals
5. Respondent ate less than should have
6. Adult(s) cut/skipped in 3+ months
7. Respondent hungry but did not eat
8. Respondent lost weight
9. Adult(s) not eat for whole day
10. Adults(s) not eat for day 3+ months.

Our measure implies that more affirmative responses are associated with greater insecurity but only in a qualitative way. Fig. 1 shows the distributions of the values of food insecurity by SNAP status.

Our principal explanatory variable is an indicator for the receipt of any SNAP benefits in the previous year. Exogenous covariates include the household head's gender, age, race, ethnicity, nativity, marital status, education, and employment status; indicators for household size, and whether the household has an elder member, a child and a disabled member; residence in urban area; household income and home ownership. We also include measures of the socioeconomic status of residents of the state: income per capita, poverty rate, unemployment rate and the percent of households receiving supplemental security income. The regression models also include year fixed effects. In our analysis of the determinants of heterogeneity (class membership), we also include measures of subjective food needs.

We consider a number of alternate samples in our analysis: stratified by income (income-to-poverty ratio $\leq$ 1.85 – our main sample – and $\leq$ 1.30), date (post Great-Recession), family structure, and whether additional covariates are available for the sample. These samples were chosen to demonstrate the robustness of our regression results.

3. Methods

We estimate a finite mixture model of ordered probit regressions to elicit the existence and nature of possible heterogeneity in the effects of SNAP on food insecurity. We use a control function approach to adjust for the endogeneity of SNAP receipt.

3.1. Control function approach

In the control function approach (Newey et al., 1999; Blundell and Powell, 2004; Wooldridge, 2015), we first estimate a logit regression of a binary indicator for SNAP participation on an excluded instrument and all our control variables. We estimate residuals from that regression and include those as an additional covariate in the finite mixture models. The excluded instrumental variable measures the proportion of months in the year the state had simplified reporting requirements. Our identification strategy relies on the notion that, after controlling for a number of socioeconomic characteristics at the state level (income per capita, poverty rate, unemployment rate and the percent of households receiving supplemental security income), a state's reporting requirements do not directly affect an individual's food insecurity. In fact, there is no evidence that states might change their rules within a year based on food insecurity rates nor, more broadly, based on the socioeconomic status of residents of the state.

3.2. Finite mixture model

Let $f_c(y_i|\mathbf{x}_i;\theta_c)$ denote the probability of observing a particular value of an ordered multinomial outcome for class (subpopulation) c where $c = 1, 2, \ldots, C$. Let $\mathbf{x}_i$ denote the vector of observed characteristics and θ_c denote the parameters of the distribution $f_c(.)$. Let π_c denote the probabilities of membership in each class such that $0 < \pi_c < 1$, and $\sum_{c=1}^{C}\pi_c = 1$. Then, the distribution function for a C-component finite mixture (Deb and Trivedi, 1997; McLachlan and Peel, 2004), is

$$f(y_i|\mathbf{x}_i;\theta_1,\theta_2,\ldots,\theta_C;\pi_1,\pi_2,\ldots,\pi_C) = \sum_{c=1}^{C}\pi_c f_c(y_i|\mathbf{x}_i;\theta_c). \quad (1)$$

The ordered probit model is a natural starting point for modeling the ordinal measure of food insecurity which takes values $y_i = 0, 1, 2, \ldots, J$. We extend the ordered probit model to allow for differences in determinants across a priori unobserved subpopulations in the data using a finite mixture of ordered probit regressions. For individuals in class c, the ordered probit distribution function for outcomes $j = 0, 1, 2, \ldots, J$ can be written as

$$f_c(y_i|\mathbf{x}_i;\theta_c) = \begin{cases} \Phi(-\mathbf{x}_i'\beta_c), & \text{if } y_i = 0 \\ \Phi(\mu_{1,c} - \mathbf{x}_i'\beta_c) - \Phi(-\mathbf{x}_i'\beta_c), & \text{if } y_i = 1 \\ \Phi(\mu_{2,c} - \mathbf{x}_i'\beta_c) - \Phi(\mu_{1,c} - \mathbf{x}_i'\beta_c), & \text{if } y_i = 2 \\ \ldots, & \ldots \\ 1 - \Phi(\mu_{J-1,c} - \mathbf{x}_i'\beta_c), & \text{if } y_i = J \end{cases} \quad (2)$$

where β_c are "regression" coefficients and $0 < \mu_{1,c} < \mu_{2,c} < \cdots < \mu_{J-1,c}$ are "threshold" coefficients for observations in class c. Without additional restrictions on $\{\mu_{j,c}\}$ and β_c, which are generally specified to vary across each latent class, a finite mixture model of such ordered probit probabilities is not uniquely identified (Teicher, 1963; Grün and Leisch, 2008). So we parameterize the component distribution for an identified finite mixture of ordered probit regressions as follows:

$$f_c(y_i|\mathbf{x}_i;\theta_c) = \begin{cases} \Phi(-\mathbf{x}_i'\beta_c), & \text{if } y_i = 0 \\ \Phi(\tau_c\mu_1 - \mathbf{x}_i'\beta_c) - \Phi(-\mathbf{x}_i'\beta_c), & \text{if } y_i = 1 \\ \Phi(\tau_c\mu_2 - \mathbf{x}_i'\beta_c) - \Phi(\tau_c\mu_1 - \mathbf{x}_i'\beta_c), & \text{if } y_i = 2 \\ \ldots, & \ldots \\ 1 - \Phi(\tau_c\mu_{J-1} - \mathbf{x}_i'\beta_c), & \text{if } y_i = J \end{cases} \quad (3)$$

with $\tau_1 = 1$. This specification allows the β_c coefficients to vary freely across latent classes but restricts the threshold parameters to be *proportional* across latent classes while being equal across classes for the first threshold τ_1. Note that we have experimented with other sets of restrictions and have found this to be the most computationally stable and to generically deliver the most intuitive results in this study and in small simulation trials we used to validate the model.

We estimate the parameters of this model using maximum likelihood. Inference is based on standard errors adjusted for clustering at the state level. We use nonparametric, clustered bootstrap to obtain standard errors that account for errors due to generated regressors (the residuals in the control function approach).

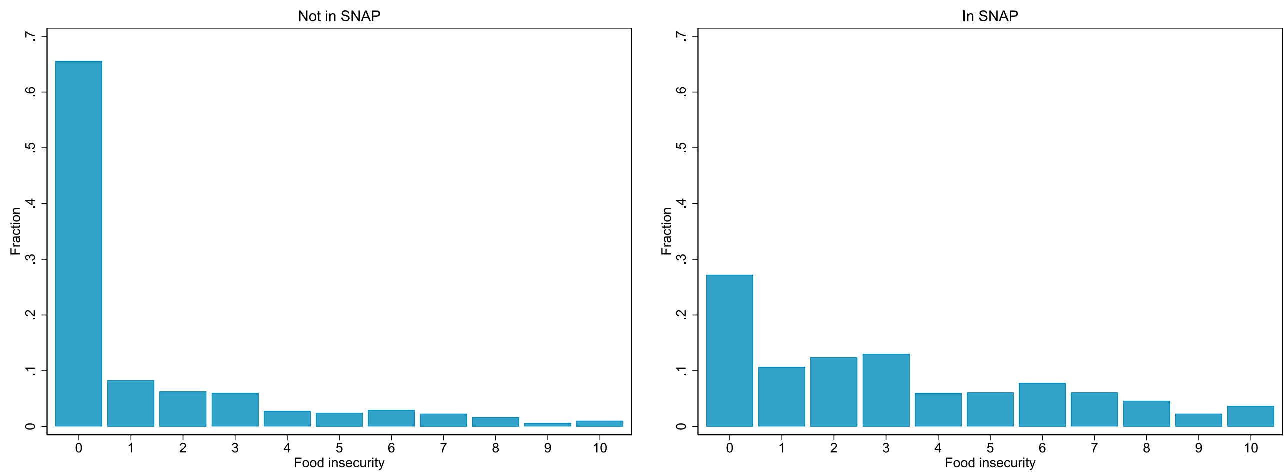

Fig. 1. Distributions of food insecurity by SNAP status.

3.3. Posterior classification of observations

In a post-estimation step, we calculate the posterior probability that observation y_i belongs to class c:

$$\Pr[i \in \text{class } c|\mathbf{x}_i, y_i; \boldsymbol{\theta}] = \frac{\pi_c f_c(y_i|\mathbf{x}_i, \boldsymbol{\theta}_c)}{\sum_{k=1}^{C} \pi_k f_k(y_i|\mathbf{x}_i, \boldsymbol{\theta}_k)}, \qquad c = 1, 2, ..C. \tag{4}$$

We estimate OLS regressions of the predicted latent class to explore the relationships between observed covariates and class membership.

4. Results

Results of first-stage logit regressions show that simple reporting requirements are a highly significant and substantial predictor of enrollment in SNAP. In each case, the marginal effect is in the order of a 10 percentage point increase. When these models are estimated using linear regression, we find that the first-stage F-statistics are typically 30–35 and, for one sample, as high as 75. Thus the instrument is relevant. To confirm the exogeneity of the instrument, we estimated a regression, using a state by year panel, of the state's simple reporting rule on the state's average food insecurity in the prior year and a number of state level characteristics (income per capita, poverty rate, unemployment rate and the percent of households receiving supplemental security income). The p-value on the coefficient of food insecurity is 0.73; the p-value for the joint test of coefficients on all other state characteristics is 0.74. There is no evidence that the instrument might be endogenous.

The results shown in Table 1 show the value of the control function empirical strategy. When food insecurity is modeled using ordered probit regressions and SNAP assumed to be exogenous, it is significantly associated with lower probabilities of no affirmations and higher probabilities of food insecurity. These results are completely reversed in sign when the endogeneity of SNAP is taken into account. Now SNAP receipt is significantly associated with higher probabilities of no affirmations and lower probabilities of food insecurity.

Statistical model selection criteria (AIC and BIC) show that two-class mixtures of ordered probit regressions fit the data adequately. We report marginal effects of SNAP on no affirmative responses ($y = 0$) and on "high" food insecurity ($y \geq 3$) in Table 2. Our estimates show that food security is substantially improved for individuals in class 1. Their likelihood of reporting no affirmative responses increases by 24 percentage points while their likelihood of reporting three or more affirmative responses decreases by 23 percentage points. There is no change in food insecurity for individuals in class 2: the estimated effects are small and statistically insignificant. For the main sample, we report bootstrap standard errors for the control function estimator in square brackets. They do not change any qualitative conclusions.

Table 1
Effects of SNAP on food insecurity.

Sample	AME (Exogenous)		AME (Endogenous)	
	$\Pr(y=0)$	$\Pr(y \geq 3)$	$\Pr(y=0)$	$\Pr(y \geq 3)$
Income-poverty ratio $\leq$ 1.85	-0.223^{***} (0.007)	0.183^{***} (0.006)	0.200^{***} (0.032) [0.046]	-0.164^{***} (0.026) [0.038]
Income-poverty ratio $\leq$ 1.3	-0.235^{***} (0.008)	0.204^{***} (0.007)	0.115^{***} (0.037)	-0.099^{***} (0.032)
2009 onwards	-0.234^{***} (0.007)	0.195^{***} (0.006)	0.194^{***} (0.045)	-0.162^{***} (0.038)
Primary families only	-0.217^{***} (0.008)	0.177^{***} (0.006)	0.297^{***} (0.047)	-0.243^{***} (0.039)
Female respondents only	-0.221^{***} (0.009)	0.184^{***} (0.007)	0.227^{***} (0.033)	-0.189^{***} (0.027)
+ primary earner works fulltime	-0.223^{***} (0.007)	0.183^{***} (0.006)	0.143^{***} (0.027)	-0.118^{***} (0.022)

Significance levels denoted by * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Cluster-robust standard errors from second-stage regressions in parentheses; non-parametric cluster-bootstrap standard errors in square brackets.
Income-poverty ratio $\leq$ 1.85 if not specified otherwise.
Models control for age, income and income squared; indicators for number of household members, for whether the household has an older member, a child and a disabled member, for gender, black race, hispanic ethnicity, high school diploma, bachelors degree, graduate degree, foreign born, owns a home and lives in a metro area; state-level income per capita, poverty rate, unemployment rate and the percent of households receiving supplemental security income; year indicators.

Fig. 2 shows the predicted distributions for each class. Individuals in the first latent class (about 60% of the sample) are more food insecure — their probability of reporting no affirmative responses is 0.54 as compared to the second latent class, for whom this probability is 0.63. Likewise, their probability of reporting 3 or more affirmative responses to the FSS is 0.36, as opposed to 0.12 for the second latent class.

Among the alternative specifications, the probabilities of being food secure are generally stable across samples except for the sample of poorer households where the rate is lower. The marginal effects in class 1 are always statistically significant although they vary a bit in magnitudes across samples. The marginal effects in class 2 are always small and statistically insignificant.

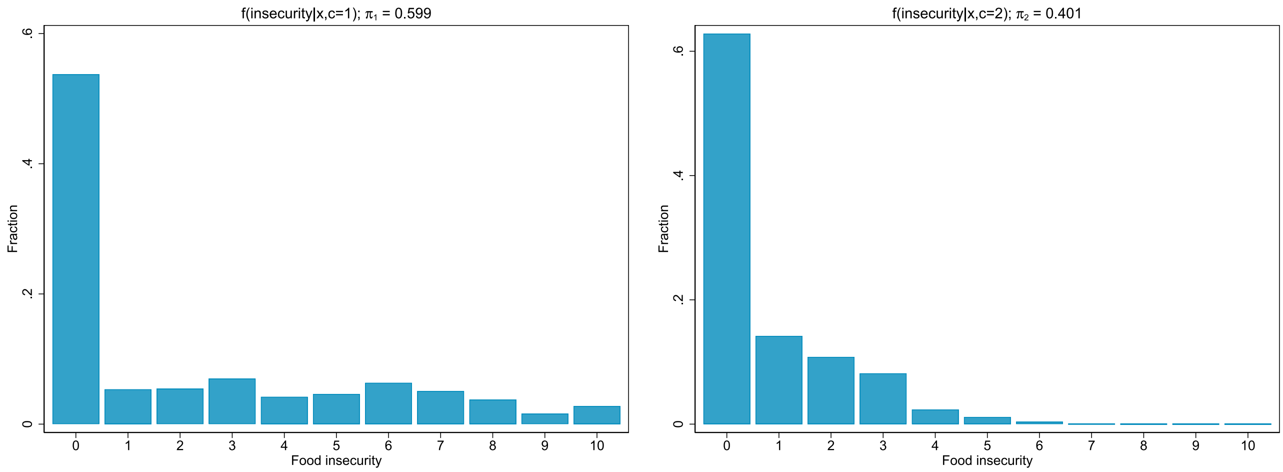

Fig. 2. Distributions of food insecurity by latent class.

Table 2
Effects of SNAP on food insecurity by latent class.

Sample		$\Pr(y=0)$		$\Pr(y\geq 3)$	
		Class 1	Class 2	Class 1	Class 2
Income-poverty ratio $\leq$ 1.85	AME	0.241***	0.036	−0.225***	−0.019
		(0.037)	(0.054)	(0.034)	(0.028)
		[0.047]	[0.095]	[0.043]	[0.050]
	π	0.599	0.401	0.599	0.401
		(0.023)	(0.023)	(0.023)	(0.023)
	Pr(y)	0.537	0.628	0.354	0.121
Income-poverty ratio $\leq$ 1.3	AME	0.144**	−0.019	−0.139**	0.010
		(0.056)	(0.071)	(0.054)	(0.039)
	π	0.611	0.389	0.611	0.389
		(0.023)	(0.023)	(0.023)	(0.023)
	Pr(y)	0.486	0.588	0.403	0.137
2009 onwards	AME	0.220***	0.086	−0.208***	−0.046
		(0.055)	(0.059)	(0.052)	(0.031)
	π	0.596	0.404	0.596	0.404
		(0.024)	(0.024)	(0.024)	(0.024)
	Pr(y)	0.519	0.635	0.370	0.127
Primary families only	AME	0.373***	0.055	−0.347***	−0.031
		(0.054)	(0.089)	(0.049)	(0.050)
	π	0.597	0.403	0.597	0.403
		(0.043)	(0.043)	(0.043)	(0.043)
	Pr(y)	0.539	0.563	0.348	0.142
Female respondents only	AME	0.282***	0.011	−0.263***	−0.006
		(0.037)	(0.069)	(0.034)	(0.037)
	π	0.640	0.360	0.640	0.360
		(0.025)	(0.025)	(0.025)	(0.025)
	Pr(y)	0.547	0.568	0.351	0.133
+ primary earner works fulltime	AME	0.180***	−0.013	−0.168***	0.007
		(0.040)	(0.051)	(0.037)	(0.027)
	π	0.599	0.401	0.599	0.401
		(0.023)	(0.023)	(0.023)	(0.023)
	Pr(y)	0.538	0.628	0.354	0.122

Significance levels denoted by * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Cluster-robust standard errors from second-stage regressions in parentheses; non-parametric cluster-bootstrap standard errors in square brackets.
Income-poverty ratio $\leq$ 1.85 if not specified otherwise.
Models control for age, income and income squared; indicators for number of household members, for whether the household has an older member, a child and a disabled member, for gender, black race, hispanic ethnicity, high school diploma, bachelors degree, graduate degree, foreign born, owns a home and lives in a metro area; state-level income per capita, poverty rate, unemployment rate and the percent of households receiving supplemental security income; year indicators.

The latent class probabilities are very stable across the samples. Because the bootstrap resampling approach is computationally time-consuming, we do not repeat the bootstrap analysis for the alternate samples.

4.1. Determinants of class membership

Using the estimates from the finite mixture models, we compute posterior probabilities of class membership for food insecurity. We estimate OLS regressions of the posterior probabilities of being in class 2 on two sets of characteristics. One set of characteristics comprises the regressors in the finite mixture model (except the SNAP indicator). The second set consists of two subjective variables indicating whether the individual needed to spend more to meet food needs and whether the individual could have spent less and met food needs.

The results presented in Table 3 show that household size is a significant determinant of class membership. The larger the household size, the more likely it is they belong to class 2, the less food insecure group and the group helped less at the margin by SNAP. Individuals who report unmet food needs are much less likely to be in class 2. On the other hand, individuals who report spending more on food than they need are more likely to be in class 2. Recall that the food security of individuals in class 2 is not modified by SNAP participation. Individuals of black race and Hispanic ethnicity are more likely to be in class 2. The effects of other characteristics such as age, gender, marital status, education, home ownership and residence in a metropolitan area are either not significant determinants of class membership or have small effects.

5. Conclusion

This paper shows that SNAP helps those who are most likely to be most food insecure, reducing their probability of high food insecurity by about 23 percentage points, almost half of the prevalence for this population. We also find SNAP has little measurable effect on food insecurity for almost 40% of the sample. This does not mean that SNAP has no impact on these households, however. First, although the effect is statistically insignificant, the point estimates (in the main sample) show that SNAP does reduce food insecurity by small amounts. The analysis may not have statistical power to detect small effects with sufficient precision, especially given that the standard errors of the estimates are adjusted for clustering at the state-level. Second, our finding may be, in part, a consequence of temporal features of the data. SNAP participation and indicators of food insecurity are measured over the year prior to the survey.

Table 3
Correlates of posterior probabilities of class membership.

	PIR $\leq$ 1.85	PIR $\leq$ 1.3	2009 on	Families	Female	+ works
Age (in 10 years)	−0.000	−0.001	0.001	−0.000	0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female	−0.000	−0.001	0.000	0.000		−0.000
	(0.002)	(0.003)	(0.003)	(0.003)		(0.002)
Black race	0.014***	0.015***	−0.016***	0.013***	−0.015***	0.014***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Hispanic ethnicity	0.012***	0.012***	−0.014***	0.012***	−0.013***	0.012***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
Married	−0.006**	−0.007**	0.009***	−0.003	0.004	−0.006**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
High school diploma	−0.004	−0.006	0.004	−0.003	0.006	−0.004
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Bachelors degree	−0.005	−0.004	0.006	−0.001	0.001	−0.005
	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)	(0.004)
Graduate degree	−0.012**	−0.013*	0.016***	−0.011**	0.012**	−0.012**
	(0.005)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)
Foreign born	−0.004	−0.001	0.003	−0.005	0.004	−0.004
	(0.003)	(0.005)	(0.004)	(0.005)	(0.005)	(0.003)
Income ($10K)	−0.004	−0.001	0.002	−0.004	0.005	−0.004
	(0.003)	(0.006)	(0.002)	(0.004)	(0.003)	(0.003)
Income squared	−0.000	−0.001	0.001	−0.000	0.000	−0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Own Home	−0.004**	−0.005**	0.004	−0.003	0.005*	−0.004**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Metro area	0.000	−0.001	0.001	0.000	−0.000	0.000
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Household size is 2	0.010***	0.011***	−0.012***		−0.012***	0.010***
	(0.002)	(0.003)	(0.003)		(0.003)	(0.002)
Household size is 3	0.017***	0.016***	−0.019***	0.005	−0.019***	0.017***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
Household size is 4	0.025***	0.022***	−0.027***	0.012**	−0.030***	0.025***
	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)	(0.004)
Household size is 5	0.027***	0.020***	−0.028***	0.014**	−0.027***	0.027***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.008)	(0.006)
Household size is 6 or more	0.038***	0.029***	−0.044***	0.020***	−0.039***	0.037***
	(0.006)	(0.009)	(0.007)	(0.006)	(0.009)	(0.006)
Any elderly person in home	0.007**	0.012***	−0.009**	0.009**	−0.011***	0.007**
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Any child in home	0.007	0.013**	−0.007	0.004	−0.004	0.007
	(0.005)	(0.005)	(0.004)	(0.007)	(0.005)	(0.005)
Any disabled person in home	0.010**	0.010**	−0.013**	0.003	−0.000	0.010**
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Food spend not enough for need	−0.126***	−0.132***	0.137***	−0.099***	0.094***	−0.125***
	(0.007)	(0.008)	(0.006)	(0.007)	(0.008)	(0.007)
Food spend more than enough for need	0.014***	0.017***	−0.014***	0.014***	−0.014***	0.014***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)

Significance levels denoted by * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Cluster-robust standard errors in parentheses.
Income-poverty ratio $\leq$ 1.85 if not specified otherwise.

It is entirely likely that SNAP benefits reduces food insecurity over short, but critical periods of time, yet that effect is diluted to the point of statistical insignificance over the one year horizon. Finally, the 40% class may consist of many inframarginal households at the extensive margins of the measure of food insecurity. Data on food spending and SNAP receipts suggest that about 25% of households may be inframarginal. For these households, SNAP participation may not change food security along the extensive margins implied by the measure of food insecurity. Yet, SNAP may decrease food insecurity along the intensive margins in substantive ways.

The results with respect to subjective food needs are very suggestive, but it is unclear precisely how to interpret them. The results might lead policy makers to be gratified that those who report "less than needed" on their availability of food are most helped by SNAP. In addition, the strong associations of the subjective food needs measures and latent class membership suggests that there may be cognitive framing issues (Kapteyn et al., 1988) in responses to the food security questions.

References

Blundell, R.W., Powell, J.L., 2004. Endogeneity in semiparametric Binary Response Models. Rev. Econom. Stud. 71, 655–679.

Caudill, S.B., Gropper, D.M., Hartarska, V., 2009. Which microfinance institutions are becoming more cost effective with time? evidence from a mixture model. J. Money Credit Bank. 41 (4), 651–672.

Deb, P., Trivedi, P.K., 1997. Demand for medical care by the elderly: a finite mixture approach. J. Appl. Econometrics 12 (3), 313–336.

Grün, B., Leisch, F., 2008. Identifiability of finite mixtures of multinomial logit models with varying and fixed effects. J. Classification 25 (2), 225–247.

Gundersen, C., Kreider, B., Pepper, J.V., 2017. Partial identification methods for evaluating food assistance programs: a case study of the causal impact of snap on food Insecurity. Am. J. Agricu. Econ. 99 (4), 875–893.

Günther, I., Launov, A., 2012. Informal employment in developing countries: Opportunity or last resort?. J. Dev. Econ. 97 (1), 88–98.

Jensen, H.H., 2002. Food insecurity and the food stamp program. Am. J. Agricu. Econ. 84 (5), 1215–1228.

Kapteyn, A., Kooreman, P., Willemse, R., 1988. Some methodological issues in the implementation of subjective poverty definitions. J. Hum. Resour. 23 (2), 222–242.

McLachlan, G., Peel, D., 2004. Finite Mixture Models. John Wiley & Sons.

Meyerhoefer, C.D., Yang, M., Autumn 2011. The relationship between food assistance and health: A review of the literature and empirical strategies for identifying program effects. Appl. Econ. Perspect. Policy 33 (3).

Mykerezi, E., Mills, B., 2010. The impact of food stamp program participation on household food insecurity. Am. J. Agricu. Econ. 92 (5), 1379–1391.
Newey, W.K., Powell, J.L., Vella, F., 1999. Nonparametric estimation of triangular simultaneous equations models. Econometrica 67 (3), 565–603.
Ratcliffe, C., McKernan, S., Zhang, S., 2011. How much does the supplemental nutrition assistance program reduce food insecurity?. Am. J. Agricu. Econ. 93 (4).
Teicher, H., 1963. Identifiability of finite Mixtures. Ann. Math. Stat. 34 (4), 1265–1269.
Wooldridge, J.M., 2015. Control function methods in applied econometrics. J. Hum. Resour. 50 (2), 420–445.
Yen, S.T., Andrews, M., Chen, Z., Eastwood, D.B., 2008. Food stamp program participation and food insecurity: an instrumental variables approach. Am. J. Agricu. Econ. 90 (1).