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Who Benefits from the Supplemental Nutrition Assistance Program? An Analysis of Food Insecurity and Spending

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Abstract

Empirical methods for estimating the treatment effects of the Supplemental Nutrition Assistance Program (SNAP) routinely focus on the average treatment effect of the program. This statistic is satisfactory and useful for many policy makers, although researchers understand that it is unlikely that program effects are constant across the treatment population. Obviously, differences in treatment across observed household, individual or geographic characteristics could lead to heterogeneous outcomes. And there are good reasons to think that effects of treatment will vary across *unobserved* factors in household: food preferences, subjective poverty thresholds, discount rates, and financial acumen all could affect the distribution of outcomes not captured in the mean treatment effect. We estimate finite mixture models in order to address heterogeneity in response to receipt of SNAP and find that the data suggests two latent classes of recipients: one for whom SNAP has little or no effect, and one for whom SNAP has large and significant effects. This is true for both of the outcomes that we examine: food spending and food insecurity.

Keywords: Health, nutrition, heterogeneous treatment effects, finite mixture models.

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1 Introduction

Empirical methods for estimating the treatment effects of the Supplemental Nutrition Assistance Program (SNAP) routinely focus on the average treatment effect of the program. This statistic is satisfactory and useful for many policy makers, although researchers understand that it is unlikely that program effects are constant across the treatment population. Obviously, differences in treatment across observed household, individual or geographic characteristics could lead to heterogeneous outcomes. And there are good reasons to think that effects of treatment will vary across *unobserved* factors in household: food preferences, subjective poverty thresholds, discount rates, and financial acumen all could affect the distribution of outcomes not captured in the mean treatment effect.

This issue is not confined to studies of SNAP or food assistance, though it is particularly salient in this case. An important stylized fact to emerge from recent research concerned with the effects of the SNAP on food insecurity is that, on average, participation results in a **small** decrease in the likelihood of food insecurity (Yen et al., 2008; Ratcliffe et al., 2011; DePolt et al., 2009; Mabli et al., 2013). However, it seems likely that there would be many households for which SNAP has a very large effect–namely, those for whom disruption of eating patterns is a real possiblity–and those for which the effect is smaller. With respect to food spending, several decades of mixed results in this literature suggest–differences in methods, data, and focus notwithstanding–that we could be missing distributional effects that appear as statistical zeros.

In this study, we identify subgroups of the population for whom improvements in outcomes are largest and identify subgroups for whom SNAP may have little or no effect. We pay particular attention to two outcomes: food spending and food security. We chose these outcomes precisely because they are important for judging the program's effectiveness. Reduction in food insecurity is a primary goal of the program articulated in its enabling legislation; food spending is important not only because it is the assumed mechanism by which SNAP affects food security, but also because questions about SNAP's effectiveness in increasing *food*–as opposed to total–household spending have always been somewhat contentious. Moreover, food spending is particularly salient for households near the lower end of the food security spectrum–that is, for those whom household resources might prompt

disruptions in food intake.

For this study, 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). Finite mixture models (FMM) have received increasing attention in the statistics literature mainly because of the number of areas in which such distributions are encountered (See Lindsay, 1995; Peel and McLachlan, 2000). Econometric applications of finite mixture models include the seminal work of Heckman and Singer (1984) to labor economics, Wedel (1993) to marketing data, El-Gamal and Grether (1995) to data from experiments in decision-making under uncertainty, and Deb and Trivedi (1997) to the economics of health care. More recent applications include Ayyagari et al. (2013) and Deb et al. (2011) in studies of BMI and alcohol consumption, Bruhin et al. (2010) to experimental data and Caudill et al. (2009) and Günther and Launov (2012) to issues in economic development. Despite this growing use of FMM, they have not been brought to bear in food assistance program research.

We find that finite mixtures of two components are preferred for food security and three components for food spending, though two are preferred in estimating the marginal propensity to consume food out of SNAP. We find that, for these outcomes, SNAP improves outcomes significantly. It increases the probability of high food security by between 12 and 17 percentage points about half of the sample. It increases food spending by \$33 + a month for half of the sample, and almost \$100 a month for about a quarter of the sample, with no effect for about one quarter of the sample. These results suggest not only the importance of this program for low-income households, but also the importance of accounting for heterogeneity in outcomes in looking at treatment effects of food assistance programs.

2 Related Research

There are large literatures devoted to the estimation of the treatment effects of SNAP participation. Food insecurity and food spending are among the more important outcomes for measuring success of SNAP, the former because it is the stated goal of the program's enabling legislation, and the latter because it presumed to be the mechanism by which

reductions in the former might happen. Both of these questions have literatures that extend back decades: for a comprehensive review of the literature before 2004, see Fox et al. (2004). A general overview of a theoretical framework for estimating treatment effects, as well as the recent history of empirical literatures can be found in Meyerhoefer and Yang (2011).

A recent history of the literature concerned with SNAP and food expenditures is outlined in Beatty and Tuttle (2015), although many of its insights might be brought to bear on food security as well. In brief, the authors suggest that questions about how SNAP effects spending have to contend with changes to the program itself and to econometric practice since the program's rollout. Perhaps the most important of changes to the program has been its modernization since Welfare Reform. Since that time, states have been given considerable leeway to relax eligibility rules set out by the federal government, which has precipitated enormous changes to the SNAP-recipient population. (See, on these questions, studies by (Ganong and Liebman, 2013; Ziliak, 2016).) Additionally, the administration of the program by electronic benefit card since the late 1990's has mostly eliminated the secondary market in food stamps. Meanwhile, econometric practice has undergone a "credibility revolution," which frequently looks to establish treatment effects that do not rely on the functional form of specifications or simple comparisons of treated and untreated households to establish effects. The variation in identification strategies is particularly evident in the spending literature, which has estimated marginal propensity to consume out of SNAP benefits using a range of comparison strategies (Fox et al., 2004; Wilde et al., 2009; Fraker, 1990), by cash-out experiments (Moffitt, 1989; Levedahl, 1995), and by looking at the phased roll-out of the SNAP program in the late 1960's (Hoynes and Schanzenbach, 2009). Beatty and Tuttle (2015) employ a difference-in-difference method and coarsened matching to get at the effect of changes in food stamp benefits due to the American Recovery and Reconstruction Act (ARRA) on food spending.

As mentioned above, the recent history of studies in SNAP on food insecurity appears to have overcome some of the problems of selection that plagued researchers for decades. Most recent studies have found that SNAP reduces food insecurity. Studies using control functions, in which functions of the unobservables are included in the model rather than differenced away, have been particularly prominent in this listerature. Examples of this

approach can be found in Yen et al. (2008), who found that SNAP significantly reduced severity of food insecurity; Mykerezi and Mills (2010), who showed that SNAP participation lowers household food insecurity by 18 percent; and Ratcliffe et al. (2011), who found that SNAP reduced the probability of food insecurity by 30 percent and the probability of very low food insecurity by 20 percent. Other methods that have found that SNAP reduces food insecurity include non-parametric bounding techniques (Kreider et al., 2012) and structural models (DePolt et al., 2009). Gregory et al. (2015) review and replicate studies using most of these methods. Mabli et al. (2013) used new data collection to examine the effect of SNAP on participants and found that it reduced the prevalence of food insecurity.

In all of the studies mentioned above, interest centers in some parameter or function of parameters that expresses a mean treatment effect. That is most often the average treatment effect but sometimes the average effect of treatment on the treated. While these are indispensable quantities of interest for both researchers and policy makers, it is important to understand the *distribution* of effects. In particular, we would like to know whether there are parts of the population of interest who benefit more, and others less, from SNAP. Finite mixture models, which we describe in more detail below, are one way to do that.

3 Data

The data for this application come from 2006-2013 December CPS Food Security Supplement (CPS-FSS). For each of these years of the CPS-FSS, our main specifications include households with annual incomes at or below 185 percent of the federal poverty line (FPL). We chose this income level for two reasons: first, it is the income cut-off that the CPS uses to determine the households asked about participation in SNAP. Second, although the gross income cut-off for SNAP eligibility is 130 percent of the FPL, the relaxation of categorical eligibility rules in many states has meant that a non-trivial fraction of household who enroll in SNAP have incomes above this threshold. We additionally restrict our analysis sample to households that responded to the FSS, that provided sufficient information to determine their food security status, and that provided information for other FSS measures that we use as explanatory variables.

The outcome variables in our analyses are an count variable that indicates the number

of conditions affirmed among the adult questions in the CPS food security module (FSM), and a continuous variable that indicates the amount that the household spent on food in the previous week. For food insecurity, we consider a count of the affirmatives in the adult FSM rather than an ordinal variable indicating the level of food insecurity so that households with and without children will comparable in the analysis. The food spending is constructed from a series of questions in the FSM that ask about expenditures at grocery and non-grocery stores on food and non-food expenditures in the previous week. Our principal explanatory variables are indicators for the receipt of any SNAP benefits in the previous year and the amount of SNAP benefits received the last time they were received. For models that examine spending we count as SNAP participants any households whose respondents affirm that they participated in SNAP in November or December of the year in question.

We include a number of variables that adjust for additional demographic, labor market, and economic well-being of the household: these variables include the household heads gender, age, race, ethnicity, nativity, marital status, education, and employment status ; the number elderly members in the household; the number of disabled members of the household; the number of children in the household; residence in urban area; household income; homeownership, and state and year fixed effects. We include these variables because of their theoretical or empirically established relation to food security or spending (Barrett, 2002).

4 Methods

We estimate a gamma regression for spending on food. Using a gamma regression allows us to naturally the positive, highly skewed distribution of spending into account. We estimate an ordered probit model for the item response raw scale of food insecurity.

We use a control function method to take the endogeneity of enrollment in SNAP into account in the negative binomial and ordered probit models into account. Because these models are nonlinear, standard instrumental variables regression does not apply. In the control function approach, we estimate the probability of enrollment in SNAP using outreach spending per capita as an excluded instrument. We then calculate residuals from this logit

regression and include both the indicator for SNAP and the residual in the regressions.

Finally, we use finite mixture models (of gamma regressions and ordered probits) to elicit the existence and nature of possible heterogeneity in the effects of SNAP on food spending and food insecurity.

4.1 Finite mixture model

Most empirical models for estimating treatment effects assume that the effect is constant across the population. Yet there are many reasons for expecting that treatment effects are not constant. In most large experiments or quasi-experimental designs, there are many opportunities for the actual treatment to be heterogeneous across individual characteristics, household characteristics, sites or geographies, for the intensity of treatment to vary, and for compliance to and effects of treatment to vary by individual or group characteristics. Heterogeneity in each of these dimensions lead to heterogeneity of treatment effects. In this analysis, we expect heterogeneous treatment effects because, for example, calorie labeling and posting requirements vary across jurisdictions, because only a fraction of the population may observe calorie labels; and because individuals may substitute calories across restaurant and non-restaurant meals.

Heterogeneity of treatment effects is typically explored via the use of interaction terms in regression analyses or by stratifying the sample by indicators of the source of heterogeneity. For example, stratified analyses by race or gender are commonplace. However, there are data and statistical limits to the amount of stratification that can be done given a sample, and such analyses increase the risk of false findings. Furthermore, often heterogeneity exists along the distribution of the outcome itself, by complex configurations of observed characteristics, or on unobserved characteristics. Quantile regressions are an appealing technique to explore heterogeneity along the outcome distribution but does not provide insight into the other dimensions of heterogeneity. Finite mixture models can be formulated to do just that – identify heterogeneous treatment effects, if they exist, and characterize that heterogeneity along dimensions of the outcome distribution, observed characteristics and unobserved characteristics.

The density function for a C-component finite mixture (Deb and Trivedi, 1997; Deb, et

al., 2011; Ayyagari, et al., 2013), is

$$f(y|\mathbf{x};\theta_1,\theta_2,...,\theta_C;\pi_1,\pi_2,...,\pi_C) = \sum_{j=1}^{C} \pi_j f_j(y|\mathbf{x};\theta_j) \tag{1}$$

where $0 < \pi_j < 1$, and $\sum_{j=1}^{C} \pi_j = 1$ and f_j denotes an appropriate density given the characteristics of the error terms. As we will describe below, normally (Gaussian) distributed components appear to be appropriate in the context of the outcome of interest. We estimate the parameters of this model using maximum likelihood. Inference is based on standard errors adjusted for clustering at the county level.

As a further step, in post estimation, we calculate the posterior probability that observation y_i belongs to component c (the prior probability is assumed to be a constant):

$$\Pr[y_i \in \text{class}c|\mathbf{x}_i, y_{i;}\theta] = \frac{\pi_c f_c(y_i|\mathbf{x}_i,\theta_c)}{\sum_{j=1}^{C} \pi_j f_j(y_i|\mathbf{x}_i,\theta_j)}, \qquad c = 1,2,..C \tag{2}$$

which we use to explore the determinants of class membership.

Specifically, we assign an observation i into class $j = \arg\max_c \Pr[y_i \in \text{class }_c|\mathbf{x}_i, y_{i;}\theta]$. Then we treat the classification as known and stratify the sample by latent class in subsequent descriptive analysis of the relationship between observed covariates and class membership.

4.2 Control function methods: Two-Stage Residual Inclusion: 2SRI

As mentioned above, identification of the effects of SNAP has long had to contend with the selection problem. That is, households that participate in SNAP are likely systematically different from those who do not in ways that are not observed by the researcher. The recent literature on both spending and food insecurity has been keen to address this problem. In order to identify SNAP participation in our models, we use a control function approach – two-stage residual inclusion (2SRI). This method is a non-parametric identification strategy developed and used in the context of health econometrics (Terza et al., 2008; Lindrooth and Weisbrod, 2007; Petrin and Train, 2010) that has recently been used to examine the effect of participation in the National School Lunch Program and child food insecurity (Ishdorj and Higgins, 2015). It consists of estimating a "control function" from the regression of a binary indicator for SNAP participation on instruments and all of our control variables and

then taking the residual of that regression and putting it in the finite mixture model. The intuition behind this method is that the residual controls for everything that is unexplained about participation by the observables and the instrument in the second stage (finite mixture) specification. Although this is a limited information maximum likelihood approach, because the form of the residuals can be varied, the power of identification does not come from the functional form specified for the residuals.

5 Results

5.1 Descriptive Measures

Table 1 shows descriptive statistics for our outcomes of choice – food security and food spending – for each of the samples that we use for our main analysis: these samples are stratified by income (income-to-poverty ratio≤ 1.85 – our main sample – and ≤ 1.30), date (post Great-Recession), family structure, and whether additional covariates are available for the sample. We present them here to show not only that the samples are very similar, but that the differences between SNAP and non-SNAP groups for each of the samples are also quite similar. For example, for all of the samples, the mean food security score (number of affirmatives) is about 3.2 for SNAP participants and 1.3 for non-SNAP participants. Similarly, for all of the samples except single female respondents, the differences in unconditional food spending are less than 10 percent between non-SNAP and SNAP households. It is somewhat larger for female respondents, but still less than 10 percent.

Table 2 shows descriptive statistics for our primary sample, which is comprised of households at or below 185 percent of poverty for all of the years in our sample. SNAP households are disadvantaged in several important ways, relative to low-income non-SNAP households. They generally have less income, as is well established in the literature on food security (Coleman-Jensen et al., 2015), perhaps as a result of having less education. On the other hand, the reduced income could reflect the fact that SNAP households have more disabled members and are more likely to have an adult not in the labor force because of a disability– which are both increase the likelihood of food insecurity (Coleman-Jensen and Nord, 2013). This is also reflected the lower level of full-time employment by the main wage earner in the SNAP household. SNAP households also have more children and elderly persons in

the household. It is also well established in the literature that elderly persons have lower SNAP take-up rates than younger households (Ziliak, 2016; Wu, 2009). Survey respondents in SNAP households are more likely to be unmarried, black, and Hispanic than their non-SNAP counterparts.

5.2 Preliminary Regressions

Table 3 shows the average marginal effects of the instrument–simplified reporting–in our first stage regressions on SNAP participation. These regressions control additionally for all of the observed characteristics summarized in table 2. Additionally, the additional covariate sample includes a dummy variable for whether the primary earner in the household works full time. We show the results of these regressions to address one of the fundamental assumptions of instrumental identification strategies – namely, that the instrument has to be non-trivially associated with the outcome of interest. For all of the samples and for both of the outcomes, our instrument is significant at $p < .01$– that is, they all have test statistic values in excess of 10, the rule of thumb value for "strong" instruments (Staiger and Stock, 1997).

Tables 4 and 5 show the results of the second stage regressions with and without the inclusion of the residuals from the first stage in the specification. In the case of table 4, we show the marginal effect of SNAP on the probability of having no affirmative responses and the probability of having 3 or more affirmative responses–that is, being food insecure. In table 5, we show the average marginal effects on spending. For each of the outcomes, the results without the residuals are called the "Exogenous" specifications, as it reflects the assumption that SNAP participation is exogenous to the relevant outcome, while the "Endogenous" specifications include the residuals because we relax that assumption.

In table 4 we note that there is a strong positive association of SNAP with food insecurity for the specifications without the residuals, as has been found in much of the literature. (See Gregory et al. (2015) for more on this.) According to these results, SNAP reduces the probability of no affirmative responses by about 20 percentage points and increases the probability of food insecurity by between 16 and 19 percentage points. However the 2SRI results tell another story: when the control function is applied to the second stage, we find

that the probability of zero affirmative response *increases* by 10 - 26 percentage points, and the probability of food insecurity *decreases* by 9 to 21 percentage points. These are ranges that have been reported in a recent replication study (Gregory et al., 2015) as well as Ratcliffe et al. (2011).

In table 5 we show that when we don't account for endogeneity, the effect of SNAP on food spending is small and positive, increasing expenditure in the previous week by about $2. When the residuals from the first stage are included in the outcome specification, we find that expenditure increases by about 10 times the amount predicted in the exogenous regressions–by about $20 for the previous week's spending.

5.3 Finite Mixture Model Results

Tables 6 and 7 show the results from our finite mixture models using 2SRI and the same first stage instruments and residuals as noted above. Where as the results in tables 4 and 5 assume that there is no treatment effect heterogeneity, the finite mixture models (FMMs) let the data speak directly to that question. For both food insecurity and spending, we used AIC to choose the model that best fit the data; for both, a model with two latent classes fit the data best. Both table 6 and 7 show that SNAP has little or no effect for some households in the sample, but has large and significant effects for another class of households. For example, for each of the samples that we construct, we find that the average marginal effect on the probability of reporting no affirmations is roughly zero for a little more than half of the sample, but that for the remainder of the sample, the effect on the probability of zero affirmations is large and significiant: between 20 and 31 percentage points. Likewise, the probability of food insecurity is statistically unchanged for the first group, but large and significant for the second, reducing the probability between 19 and 33 percentage points.

We see similar results for the food spending models in table 7, although the fraction of the sample that shows little or no response to SNAP is a bit smaller in this context. About 30 to 35 percent of the sample sees little significant increase in spending as a result of SNAP, but the remainder of the sample see large and significant increases in the previous week's spending – between $50 and $70, depending on the sample.

The densities for all of these results are shown in figure 6.

6 Discussion

While the literature on the causal effects of SNAP has to date focused on the average treatment effect and not really looked into treatment effect heterogeneity, we use finite mixture models to look at the effect of SNAP on both food spending and food insecurity across latent classes. We find that there is a sizeable subsample of SNAP participants for which SNAP has little to no effect on either of these outcomes, while the remainder enjoy even larger effects than was previously understood. While some households see their food security status unchanged by SNAP, a fraction of households see outsized gains in the probability of no affirmations (of between 20 and 31 percentage points) and reductions in the probability of food insecurity (of roughly the same magnitude). At the same time, a small fraction of households sees very little increase in spending due to SNAP, while a large fraction of the sample sees large and statistically significant increases in previous week's spending–between $50 an $70.

The spending estimates, in particular, may seem particularly large, given that the unconditional mean of spending was $100. However, the CPS-FSS is conducted in the week of December containing the 12th day, which means that, for many recipients in the sample, SNAP benefits will have been received relatively recently. Given what we know about SNAP cycling, these increases in spending seem altogether plausible.

We have estimated these models on a wide array of samples to demonstrate their robustness to sample choice and characteristics. In particular, we highlight the fact that, in using just the sample that would have been affected by the increase in SNAP benefits due to ARRA, we find results that are qualitatively similar to those for the whole sample. We also note that, choosing the income cut off for our sample below 185% of the FPL has no affect on the results.

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Table 1: Summary statistics of outcomes

Sample		Food insecurity		Food spending		Total spending	
		Not SNAP	SNAP	Not SNAP	SNAP	Not SNAP	SNAP
Income-poverty ratio ≤ 1.85	$\overline{Y}$	1.30	3.19	89.78	93.80	105.50	108.14
	N	43,893	9,114	38,817	7,967	38,817	7,967
Income-poverty ratio ≤ 1.3	$\overline{Y}$	1.44	3.28	86.08	91.41	101.02	105.14
	N	28,145	8,048	24,497	7,009	24,497	7,009
2009 onwards	$\overline{Y}$	1.32	3.22	93.00	96.73	109.46	111.88
	N	27,124	6,573	22,731	5,574	22,731	5,574
Primary families only	$\overline{Y}$	1.21	3.04	110.07	119.03	130.13	138.30
	N	18,377	3,636	16,751	3,278	16,751	3,278
Female respondents only	$\overline{Y}$	1.28	3.21	84.01	93.52	99.37	107.85
	N	23,785	5,674	20,762	4,948	20,762	4,948
Additional covariate	$\overline{Y}$	1.30	3.19	89.78	93.80	105.50	108.14
	N	43,893	9,114	38,817	7,967	38,817	7,967

Table 2: Summary statistics of covariates

	Not in SNAP	In SNAP
Age (in 10 years)	5.639	5.457
Female	0.532	0.623
Black race	0.157	0.270
Hispanic ethnicity	0.144	0.158
Married	0.276	0.156
High school diploma	0.626	0.566
Bachelors degree	0.088	0.043
Graduate degree	0.030	0.012
Foreign born	0.151	0.116
Income ($10K)	1.626	1.286
Income squared	3.439	2.462
Own Home	0.533	0.316
Household size	1.911	2.097
Metro area	0.778	0.756
Number of Elderly People in Home	2.724	2.640
Number of Children in the Home	0.066	0.166
Number of Disabled People in Home	0.353	1.025
N	45,776	9,364

Summary statistics for census division and year indicators not shown.

Table 3: First stage logit regressions of SNAP

Sample	Average Marginal Effect	
	Food security	Food spending
Income-poverty ratio ≤ 1.85	0.185***	0.178***
	(0.027)	(0.027)
Income-poverty ratio ≤ 1.3	0.230***	0.221***
	(0.032)	(0.032)
2009 onwards	0.219***	0.212***
	(0.014)	(0.013)
Primary families only	0.138***	0.135***
	(0.023)	(0.024)
Female respondents only	0.202***	0.192***
	(0.032)	(0.031)
Additional covariate	0.186***	0.178***
	(0.027)	(0.027)

Significance levels denoted by * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Income-poverty ratio ≤ 1.85 if not specified otherwise.
Models control for age, income and income squared, number of household members, number of older members, number of children, number of disabled members, and indicators for gender, black race, hispanic ethnicity, high school diploma, bachelors degree, graduate degree, foreign born, owns a home, lives in a metro area, Census divisions and year.
Additional covariate includes an indicator for whether the primary earner in the household works full time.

Table 4: 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 ≤ 1.85	-0.211***	0.172***	0.129***	-0.106***
	(0.007)	(0.005)	(0.042)	(0.034)
Income-poverty ratio ≤ 1.3	-0.221***	0.188***	0.075	-0.064
	(0.008)	(0.007)	(0.052)	(0.044)
2009 onwards	-0.222***	0.184***	0.098*	-0.081*
	(0.008)	(0.007)	(0.059)	(0.049)
Primary families only	-0.195***	0.154***	0.260***	-0.206***
	(0.011)	(0.008)	(0.080)	(0.064)
Female respondents only	-0.219***	0.179***	0.101	-0.083
	(0.009)	(0.008)	(0.062)	(0.051)
Additional covariate	-0.213***	0.173***	0.106***	-0.087***
	(0.007)	(0.005)	(0.037)	(0.030)

Significance levels denoted by *$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Income-poverty ratio ≤ 1.85 if not specified otherwise.
Models control for age, income and income squared, number of household members, number of older members, number of children, number of disabled members, and indicators for gender, black race, hispanic ethnicity, high school diploma, bachelors degree, graduate degree, foreign born, owns a home, lives in a metro area, Census divisions and year.
Additional covariate includes an indicator for whether the primary earner in the household works full time.

Table 5: Effects of SNAP on Food and Total Spending

Sample	Food spending		Total spending	
	AME (Exog)	AME (Endo)	AME (Exog)	AME (Endo)
Income-poverty ratio ≤ 1.85	2.013***	17.781***	1.444***	17.805***
	(0.476)	(4.143)	(0.546)	(4.778)
Income-poverty ratio ≤ 1.3	1.982***	15.352***	1.387**	15.276**
	(0.582)	(5.232)	(0.636)	(6.230)
2009 onwards	2.493***	20.613***	2.036***	21.470***
	(0.585)	(4.588)	(0.678)	(5.023)
Primary families only	2.314***	21.911***	1.746***	22.527***
	(0.598)	(3.659)	(0.658)	(4.422)
Female respondents only	2.797***	16.372***	2.281***	16.051***
	(0.532)	(4.552)	(0.616)	(5.068)
Additional covariate	2.159***	17.230***	1.635***	17.521***
	(0.479)	(3.984)	(0.551)	(4.648)

Significance levels denoted by *$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Income-poverty ratio ≤ 1.85 if not specified otherwise.
Models control for age, income and income squared, number of household members, number of older members, number of children, number of disabled members, and indicators for gender, black race, hispanic ethnicity, high school diploma, bachelors degree, graduate degree, foreign born, owns a home, lives in a metro area, Census divisions and year.
Additional covariate includes an indicator for whether the primary earner in the household works full time.

Table 6: 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 ≤ 1.85	AME	0.026	0.265***	-0.017	-0.285***
		(0.069)	(0.068)	(0.045)	(0.074)
	π	0.672	0.328	0.672	0.328
		(0.031)	(0.031)	(0.031)	(0.031)
	Pr(y)	0.710	0.367	0.143	0.474
Income-poverty ratio ≤ 1.3	AME	-0.197	0.195***	0.105	-0.188***
		(0.131)	(0.063)	(0.069)	(0.061)
	π	0.418	0.582	0.418	0.582
		(0.041)	(0.041)	(0.041)	(0.041)
	Pr(y)	0.633	0.498	0.126	0.400
2009 onwards	AME	-0.133	0.213***	0.075	-0.205***
		(0.107)	(0.077)	(0.062)	(0.075)
	π	0.487	0.513	0.487	0.513
		(0.058)	(0.058)	(0.058)	(0.058)
	Pr(y)	0.694	0.492	0.124	0.392
Primary families only	AME	0.151	0.313***	-0.089	-0.303***
		(0.133)	(0.083)	(0.085)	(0.080)
	π	0.627	0.373	0.627	0.373
		(0.134)	(0.134)	(0.134)	(0.134)
	Pr(y)	0.659	0.488	0.139	0.407
Female respondents only	AME	-0.088	0.311***	0.054	-0.322***
		(0.078)	(0.098)	(0.048)	(0.108)
	π	0.674	0.326	0.674	0.326
		(0.087)	(0.087)	(0.087)	(0.087)
	Pr(y)	0.685	0.382	0.139	0.498
Additional covariate	AME	0.009	0.230***	-0.006	-0.244***
		(0.067)	(0.071)	(0.043)	(0.076)
	π	0.661	0.339	0.661	0.339
		(0.033)	(0.033)	(0.033)	(0.033)
	Pr(y)	0.711	0.376	0.142	0.465

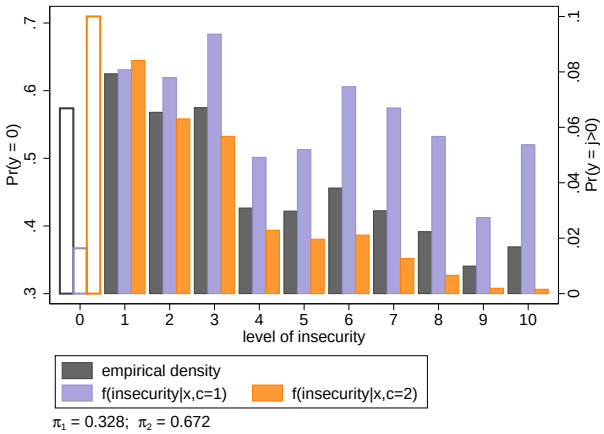
Significance levels denoted by *$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Income-poverty ratio ≤ 1.85 if not specified otherwise.
Models control for age, income and income squared, number of household members, number of older members, number of children, number of disabled members, and indicators for gender, black race, hispanic ethnicity, high school diploma, bachelors degree, graduate degree, foreign born, owns a home, lives in a metro area, Census divisions and year.
Additional covariate includes an indicator for whether the primary earner in the household works full time.

Table 7: Effects of SNAP on Food and Total Spending by Latent Class

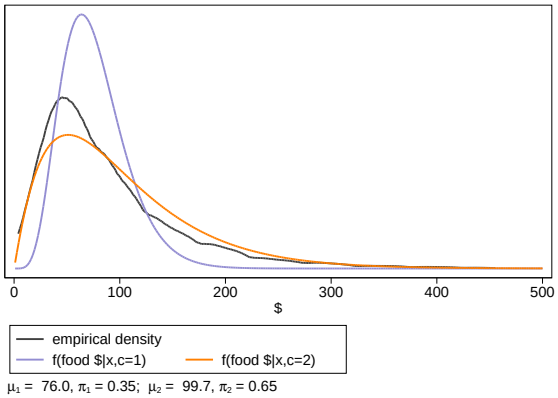
Sample		Food spending		Total spending	
		Class 1	Class 2	Class 1	Class 2
Income-poverty ratio ≤ 1.85	AME	6.551	57.836***	10.566	57.987***
		(10.562)	(11.180)	(12.332)	(13.748)
	π	0.346	0.654	0.348	0.652
		(0.025)	(0.025)	(0.020)	(0.020)
	E(y)	75.978	99.716	88.052	117.311
Income-poverty ratio ≤ 1.3	AME	-7.070	54.692***	1.939	51.019***
		(12.470)	(14.286)	(13.842)	(17.623)
	π	0.336	0.664	0.329	0.671
		(0.025)	(0.025)	(0.028)	(0.028)
	E(y)	72.299	96.484	83.014	113.010
2009 onwards	AME	7.819	65.456***	17.863	67.234***
		(15.434)	(12.550)	(16.285)	(15.230)
	π	0.320	0.680	0.326	0.674
		(0.025)	(0.025)	(0.022)	(0.022)
	E(y)	77.919	102.706	90.718	120.963
Primary families only	AME	20.064	69.902***	18.246	75.781***
		(26.874)	(13.792)	(28.567)	(16.936)
	π	0.293	0.707	0.307	0.693
		(0.042)	(0.042)	(0.028)	(0.028)
	E(y)	96.312	118.946	112.151	141.195
Female respondents only	AME	10.373	48.323***	9.746	49.693***
		(12.673)	(12.598)	(14.622)	(14.573)
	π	0.336	0.664	0.347	0.653
		(0.037)	(0.037)	(0.031)	(0.031)
	E(y)	72.780	94.258	84.398	111.857
Additional covariate	AME	1.751	58.461***	5.739	59.430***
		(9.448)	(11.262)	(11.423)	(13.939)
	π	0.352	0.648	0.354	0.646
		(0.025)	(0.025)	(0.020)	(0.020)
	E(y)	76.188	99.758	88.367	117.317

Significance levels denoted by *$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
Income-poverty ratio ≤ 1.85 if not specified otherwise.
Models control for age, income and income squared, number of household members, number of older members, number of children, number of disabled members, and indicators for gender, black race, hispanic ethnicity, high school diploma, bachelors degree, graduate degree, foreign born, owns a home, lives in a metro area, Census divisions and year.
Additional covariate includes an indicator for whether the primary earner in the household works full time.

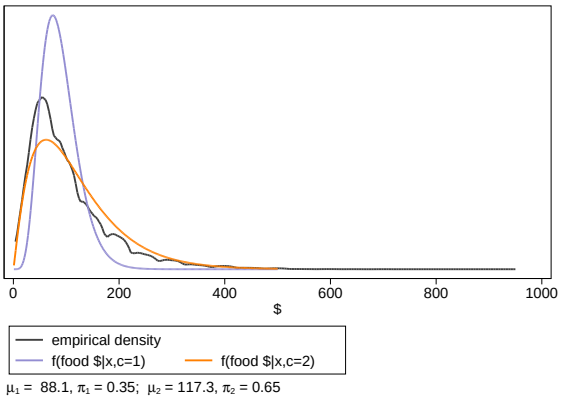
Figure 1: Distributions of Food Insecurity and Spending Conditional on Latent Class



(a) Food insecurity



(b) Food spending



(c) Total spending