The Real Effect of SNAP Benefits for Food Insecurity

Abstract

This research investigates the effect of Supplemental Nutrition Assistance Program benefits (SNAP, formerly known as the Food Stamp program) for food insecurity. SNAP provides benefits to qualifying households for purchasing food. Some have suggested that SNAP benefits may be less effective in some areas because of geographic differences in food prices (Leibtag, 2007; Nord and Hopwood, 2007). We include food prices in our analysis to control for price differences. We find that holding food prices constant, an additional SNAP dollar per-capita reduces the probability of food insecurity by about 0.5 percent. However, we find that marginal effects vary with the level of benefit received and that marginal effects are largest at low benefit levels. Furthermore, we find that even though household incomes are higher when benefits are low, the probability of food insecurity is larger than when benefits are higher. Higher food prices decrease the purchasing power of SNAP benefits, reducing food security.

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1. Introduction

This research investigates the effects of Supplemental Nutrition Assistance Program (SNAP, formerly known as the Food Stamp program) benefits for food insecurity. SNAP provides benefits to qualifying households for purchasing food. Some have suggested that SNAP benefits may be less effective in some areas because of geographic differences in food prices (Leibtag, 2007; Nord and Hopwood, 2007). We include food prices in our analysis to control for price differences. We find that holding food prices constant, an additional SNAP dollar per capita reduces the probability of food insecurity by about 0.5 percent on average, but that marginal effects vary considerably with the level of SNAP benefits. The probability of food insecurity remains high when SNAP benefits are low and the marginal effect of a per capita SNAP dollar is largest when benefits are low.

Food insecure households are more likely to be SNAP participants. Previous research has investigated SNAP's ability to improve food security. Jensen (2002) notes that there is likely a positive correlation between a household's SNAP-participation decision and their food-insecurity status. Using full-information maximum likelihood, she jointly estimates limited-dependent variable equations and finds that expected SNAP benefits reduce the probability of food insecurity. Jensen probably estimated "expected SNAP benefits" because her data source, the CPS-FSS, did not capture actual SNAP benefits in the 2000 survey.[1] Gunderson and Oliveira (2001) estimate two equations for SNAP participation and food security using simultaneous probit, but are unable to identify a statistically significant link between the two. Wilde and Nord (2002) exploit the longitudinal nature of the CPS-FSS to control for unobserved household heterogeneity. But, again they are unable to identify a statistically significant causal relationship between SNAP and food insecurity.

Recent research uses instrumental variables to identify SNAP participation effects. Food insecurity status and food stamp participation are separate limited dependent-variable equations. Heterogeneity in participation rules across states exogenously shifts the participation equation allowing

[1] Jensen did not include food prices in her analysis.

the identification of the participation effect in the food insecurity equation (Yen, et al. 2008; Ratcliffe and McKernan, 2010). Another approach uses state-level errors in payments as instruments for benefits (Myzkerezi and Mills, 2010). These studies find a negative relationship between SNAP participation and food insecurity. They are also the most convincing research establishing the effectiveness of SNAP participation. They also highlight the effectiveness of instrumental variable estimation to disentangle the simultaneous determination of food insecurity and SNAP participation.[2]

This research follows a similar approach, but differs in two ways. First, a natural experiment creates the instrument we use in estimation. Recent legislation increased the maximum amount of SNAP benefits, and we use this exogenous increase to identify the causal effect of increased SNAP benefits for food insecurity. While recent research finds support for the notion that SNAP participation reduces food insecurity, all prior research has not always found a negative link. This research contributes to the body of knowledge concerning the efficacy of the program.

Second, this research differs in that we identify the marginal effect of an additional SNAP dollar on the probability that a household is food insecure controlling for geographic differences in the purchasing power of SNAP benefits. In contrast to previous studies that identify whether participation in SNAP affects the probability of food insecurity, we investigate whether SNAP effectiveness varies with the level of benefit received. The distinction is significant and policy relevant, because per capita SNAP benefits can vary from a few dollars per month up to two hundred dollars a month, depending on household size, income, and assets.

We use a non-linear instrumental variable (IV) probit estimator to estimate the probability of being food insecure as a function of per capita SNAP benefits. We subject our estimates to a variety of robustness checks using a variety of subsamples and estimation methods. Once we are convinced that IV probit gives consistent estimates, we use them to simulate the non-linear probabilities and marginal effects over different levels of SNAP benefits, for households likely to be SNAP eligible. We find that the

[2] Other studies that find that food stamps (or SNAP) reduce food insecurity include, DePolt et al. (2008), Nord and Golla (2009), and Borjas (2004).

probability of being food insecure is highest when SNAP benefits are low, even though household incomes are relatively high. Similarly, the marginal effect of each per capita SNAP dollar is largest when benefits are low.

Households must meet an income test and an asset test to be eligible for SNAP benefits. Once a household meets those tests SNAP benefits are determined according to a formula that takes into account net monthly household income. Households determine net monthly income as gross monthly income minus deductions. Net monthly income is multiplied by 0.3, and that amount is subtracted from the maximum monthly benefit for which the household qualifies. The reduction in benefits is based on the notion that households are expected to spend thirty percent of their own resources on food.

The implication of our findings is that households find it difficult to replace SNAP benefits with their own income given the current income deductions to benefits. The formula that reduces SNAP benefits by $0.30 for each dollar of net income appears too severe to alleviate food insecurity. This is emphasized by our marginal-effect estimates which show that increasing benefits to higher income, low benefit households, would have the largest effect on reducing the probability of food insecurity.

Finally, by controlling for food prices, we estimate the purchasing power constant (i.e., real) effect of SNAP benefits. Although some have been concerned that the purchasing power of SNAP benefits is sensitive to geographic variation in food prices, previous studies have usually not controlled for food prices and may under- or over-estimate the effect of SNAP participation.[3]

2. SNAP and the American Recovery and Reinvestment Act (ARRA)

SNAP eligibility is determined by a household's income and resources, while the per-person benefit is determined by household income and deductions for certain expenses. Eligibility guidelines require gross monthly income to be equal or less than 130 percent of the poverty level, and net income after allowable expense deductions must be at or below the poverty line. Resource guidelines require households to have assets equal to $2,000 or less, while households with elderly or disabled members

[3] Gregory and Coleman-Jensen (2013) find that increases in food prices increase the probability of food insecurity, but do not examine the purchasing power of SNAP benefits directly.

may have assets equal to $3,250.[4] And, some persons are typically ineligible for food stamps regardless of income and resources, including undocumented immigrants, persons on strike, and some legal immigrants in the US for less than five years. In addition, childless unemployed adults are typically limited to three months of benefits.

Maximum household benefits increase at a decreasing rate with household-size. Households with zero net-income receive the maximum benefit, while benefits are reduced from the maximum by 30 cents for each dollar of net-income. Gross income is reduced by deductions for living expenses, including a standard deduction, and deductions for medical, dependent care, child support, and shelter expenses to arrive at net income.

The American Recovery and Reinvestment Act of 2009 (ARRA) affected federal food assistance in three primary areas. The ARRA expanded SNAP eligibility to jobless households with no children and increased maximum food benefits by 13.6 percent. The ARRA also provided additional funds to states for program administration. The ARRA allotted $500 million to the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) with $400 million devoted to an anticipated increase in demand for services. The ARRA provided $150 million for local agencies to support food banks, soup kitchens, and food pantries. The Act also provided funds to the National School Lunch Program (NSLP) and food distribution programs on Indian Reservations. But the funds, $100 million to the NSLP and $5 million to Indian Reservations, were designated for purchase of equipment and facility upgrades and are unlikely to have an impact of food security.

Beginning in April 2009, the ARRA temporarily increased the maximum SNAP benefit by 13.6 percent. Originally, the benefit increase was set to expire when the regular rate of benefit inflation overtook it, but legislation in 2010 instead terminated the increase in November 2013 (Dean and Rosenbaum, 2013). The Act also eliminated the three month limit on benefits for childless unemployed adults.

[4] These are 2012 limits, which are adjusted for inflation. Limits in 2008 and 2009 were lower.

The ARRA may affect food insecurity through two avenues. SNAP participation is likely to increase because of expanded eligibility standards. But, SNAP participation might also increase because of expanded food benefits. Prior to the Act some households may have chosen not to participate, even though they were eligible, because the benefit from participating did not exceed the perceived, perhaps psychic cost, of participating in SNAP. After the Act, the enhanced benefits likely changed the cost-benefit calculation for some households leading them to participate (Nord and Prell, 2011).

3. Conceptual Model

Households receive utility from food (F) and other goods (OG). Households may receive some of their food through SNAP benefits. Let S denote food items bought with SNAP benefits and let *f* denote food items bought with cash, and so F=f+S. Households may receive disutility from the stigma of using SNAP benefits denoted D(S). Conditioning on SNAP eligibility it seems reasonable to assume that households do not save, and the household problem is:

(1) $$Max\ U(F, OG) - D(S)\ s.t.\ I = p_{OG}OG + p_f(F - S)$$

The household's optimization problem results in their demand for SNAP foods, $S = S(p_f, p_g, I) \geq 0$, food, $f = f(p_f, p_{OG}, I)$, and other goods, $OG = OG(p_f, p_{OG}, I)$.

Each household has some minimal level of food required to meet their needs, F_{min}. If $F = S(p_f, p_{OG}, I) + f(p_f, p_{OG}, I) \geq F_{min}$ then the household is food secure. If $F = S(p_f, p_g, I) + f(p_f, p_{OG}, I) < F_{min}$ then the household is food insecure.

Given an appropriate functional form for household utility, e.g., as in a Linear Expenditure System, it is possible to rewrite demand functions as expenditures that are linear functions of prices and income. In this paper we are interested in the interaction of SNAP benefits and food insecurity and so focus on estimating SNAP demand, and assuming expenditures are linear in prices and income write it as

(2) $$p_f S_i = \alpha_o + \beta_{f1} p_{fi} + \beta_{OG} p_{OG,i} + \beta_I I_i + \boldsymbol{x_{1i}\beta_1} + \varepsilon_i,$$

where $p_f S$ is the per capita amount of SNAP benefits received by a household, $\boldsymbol{x_1}$ is a vector of demand shift variables, and the β_j are parameters to estimate. We are also interested in the effect of SNAP benefits for food security. Let $F_i^* = F_i - F_{min} = \alpha + \boldsymbol{x_{2i}\beta_2} + \beta_S p_f S_i + \beta_{f2} p_{fi} + e_i$, but F_i^* is unobserved. Instead, we observe food insecurity, FI, as $FI_i=0$ if $F_i^*>0$ and $F_i \geq F_{min}$. Alternatively, $FI_i=1$ if $F_i^*<0$ and $F_i<F_{min}$. The equation for food insecurity as

$$FI_i = \alpha + \boldsymbol{x_{2i}\beta_2} + \beta_S p_f S_i + \beta_{f2} p_{fi} + e_i, \qquad (3)$$

$\boldsymbol{x_{2i}}$ is a vector of exogenous variables affecting food security, and the β_j are parameters to estimate.

Equations (2) and (3) form the basis for estimation. In principle, equation (3) could be estimated in isolation, but previous studies have established that food insecure households are more likely to be SNAP recipients and so SNAP benefits are likely to be endogenous in that $E[e|p_f S] \neq 0$.

We investigate two methods to consistently estimate the parameters in equation 3. First, we assume (ε_i, e_i) has a mean-zero bivariate normal distribution and estimate equation 3 with a probit model taking account of the endogeneity of SNAP benefits. The log likelihood for observation i,

$$(4)\ lnL_i = FI_i ln\Phi(m_i) + (1 - FI_i)\ln[1 - \Phi(m_i)] + ln\phi\left(\frac{p_f S_i - (\alpha_o + \beta_{f1} p_{fi} + \beta_{OG} p_{OG,i} + \beta_I I_i + \boldsymbol{x_{1i}\beta_1})}{\sigma}\right) - ln\sigma$$

where $m_i = \frac{\alpha + \boldsymbol{x_{2i}\beta_2} + \beta_S p_f S_i + \beta_{f2} p_{fi} + \rho(p_f S_i - (\alpha_o + \beta_{f1} p_{fi} + \beta_{OG} p_{OG,i} + \beta_I I_i + \boldsymbol{x_{1i}\beta_1})}{(1-\rho^2)^{1/2}}$, ρ is the correlation between ε_i and e_i, Φ and ϕ are the standard normal distribution and density.

This is the so-called Instrumental Variable-Probit estimator (IV-probit) and can be estimated using maximum likelihood (ML). ML estimation requires an untestable distributional assumption, and the method does not address censored, at zero, SNAP benefits. To check robustness, we estimate equations 2 and 3 as a system using generalized method of moments (GMM), and account for non-negative SNAP benefits by estimating equation 2 as an exponential regression as suggested by Silva and Tenreyro (2006). Both ML and GMM give consistent estimates and we expect similar marginal effects, but ML is asymptotically more efficient.

Both methods require there to be at least one exogenous variable in $\boldsymbol{x_1}$ that is not included in $\boldsymbol{x_2}$ to identify β_S in equation (3). In other words, there must be a variable that affects food insecurity only through its effect on SNAP benefits. The ARRA exogenously increased SNAP benefits starting in April 2009. We define a binary variable that takes a value of 1 (ARRA) after the Acts implementation and include it as a regressor in equation 3. We restrict our attention to households whose food security could only be affected by the ARRA induced increase in SNAP benefits and identify β_S for those households.

The effect of food prices can directly impact food security, through β_{f2}, but also indirectly through their effect on SNAP benefits, β_S. So, $\frac{\partial FI}{\partial p_f} = \beta_S{*}\beta_{f1} + \beta_{f2}$. We suspect higher food prices to cause higher food insecurity and for the direct effect $\beta_{f2}$to be positive. We expect SNAP benefits to decrease food insecurity and for β_S to be negative. We also expect $\beta_{f1}$to be negative.

4. Data

The Current Population Survey – Food Security Supplement (CPS-FSS) supplies data for household characteristics including household food-security. Data for food prices comes from two separate sources. A first food-price source is compiled by members of the Council for Community and Economic Research (CCER) that are used to create the CCER Cost of Living Index. The second food price source comes from the Quarterly-Food-at-Home Database compiled by the Economic Research Service of USDA.

4.1 **Current Population Survey – Food Security Supplement (CPS-FSS)**

We use observations from the CPS-FSS from 2008 and 2009. The benefit of using this survey is that it includes household information, including whether the household received SNAP benefits and whether the household is food secure. Importantly the survey also includes geographic indicators that can be used to match household data with price data.

In general, households in the CPS are interviewed each month for four consecutive months, then ignored for eight months, then interviewed for the same four months the following year. The FSS of the CPS is conducted in December of each year. Each household is identified by a unique number so there is a subset of CPS households that are interviewed in December 2008 that are again interviewed in December 2009. We use the unique household indicator to identify households interviewed in December 2008 and 2009; we include only these households in the analysis. The ARRA took effect in April of 2009, so its effect for SNAP benefits will be fully implemented by December of that year.

The survey asks a number of detailed questions that are combined into a single overall measure of household food security called the household's food security scale. The scale is a continuous variable that measures the severity of a household's food insecurity and hunger. The scale provides a more thorough way of capturing the complex factors inherent when measuring food security. It is useful to summarize the continuous scale into discrete measure of food security for research purposes. In the CPS-FSS households are categorized as food secure, moderately food secure, low food secure, and very-low food secure. We define food secure households as those that are categorized as food secure or moderately food secure in the CPS-FSS. We define food insecure households as those that are categorized a low food secure or very low food secure.

In this article, we use the survey's "Detailed Food Security Status, 30-Day Recall" to define a household's food security status. The 30-day recall is based on a subset of questions to the questions that are asked to develop the 12-month recall scale. The 30-day recall question are used to determine whether the household experienced food insecurity during the last 30-days, while the 12-month recall are to determine food insecurity during the last 12-months. We use the 30-day recall because SNAP benefits are recorded per month in the survey.

4.2 CCER Food Prices

The Council for Community and Economic Research, CCER (formerly known as the American Chamber of Commerce Research Association, ACCRA), produces a "Cost of Living Index to provide a useful and reasonably accurate measure to compare cost of living differences among urban areas." The approach used in the Cost of Living Index is to divide consumer expenditures into categories, and then select individual items that represent those categories. The items used in the Cost of Living Index thus are surrogates for entire categories of consumer spending.

The Cost of Living Index consists of six major categories: grocery items, housing, utilities, transportation, health care, and miscellaneous goods and services. Prices for each of the surrogates are collected by volunteers that the organization deems reliable. Prices recorded are meant to represent prices paid by a "mid-management" household.

The CCER price data are collected from approximately 300 metropolitan areas in the US. Each urban area is identified by its Core Based Statistical Area code (CBSA). Some households in the CPS-FSS also include a CBSA identifier. Restricting the sample to households that were present in 2008 and 2009, and that were below 185 percent of the poverty level in either 2008 or 2009, we are able to match 1,964 CPS-FSS households, in 135 metropolitan areas, with CCER price data. The total number of observations is 3,928 observations (1964*2).

4.3 Quarterly Food at Home Database

The Quarterly Food-at-Home Database (QFAHPD) is constructed by the Economic Research Service (ERS) of USDA using Nielsen Homescan data. The Homescan data are from a household panel's purchases of grocery items from a variety of store types. Purchases are of both UPC coded items and random weight products. Households register to become panel members and those chosen receive a hand-held scanner to record their purchases. Households receive a set amount of points for recording their purchases that can be redeemed for merchandise.

Using these data, ERS estimates household-level quarterly prices for 54 food groups that correspond with the 2005 Dietary Guidelines for Americans. Prices are in dollars per 100 grams of food as purchased by consumers, and take into account premiums for processing and convenience.

We use prices in the QFAHPD to construct an index of the cost of the thrifty-food-plan for a family of four, a male adult, a female adult, a child age 6 to 8 and a child age 9 to 11. We calculated the cost of the family thrift-food-plan for each household in the CPS-FSS that is located in a MSA that coincides with the market groups in the QFAHD. We find the average-annual cost of the family thrifty-food-plan, and then divide each household's food-plan cost by the annual average. A household with the average thrifty-food-plan cost would have an index value of 1.

QFAHD price estimates are available for 26 metropolitan areas called market groups. We matched QFAHD observations with CPS-FSS households by assigning each household's CBSA to the appropriate market group. If a household's CBSA could not be matched with a market group, it was eliminated from the data set. We are able to match 3,803 households below 185 percent of the poverty level with these price data.

4.4 Summary Statistics

Variable definitions are given in Table 1, and Tables 2 and 3 include summary statistics for two samples of the data. The first, in table 2, are for households in the CPS-FSS in 2008 and 2009 that we were able to match with the CCER grocery price index. The second, in table 3, are for households in the CPS-FSS in 2008 and 2009 that we were able to match with a thrifty food plan index using prices from the QFAHD.

It is interesting to consider temporal changes in key variables. In both samples, food insecurity declined between 2008 and 2009. Using the CCER data, 17.16 percent of these households were food insecure in 2008 compared to 15.78 percent in 2009. The QFAHD data show that 16.1 percent of these households were food insecure in 2008, but 15.44 percent of these same households were food insecure in 2009.

The decline in food insecurity is puzzling in that economic conditions worsened between 2008 and 2009 for the households. In these data, average household income declined from $27,593 to $24,973 in CCER data, and from $27,671to 25,309 in the QFAHD data. Similarly, the proportion of households with an unemployed head increased in both samples from 6.6 to 8.5 percent in the CCER data, and from 6.96 to 8.6 percent in the QFAHD data. However, the improvement in food security might be partially explained by the increase in SNAP benefits. Per capita SNAP benefits increased from $12.25 to $16.70 in the CCER sample and from $12 to $16.24 in the QFAHD sample. Conditioning on SNAP participation, SNAP benefits per capita increased from $81.58 to $91.11 in the CCER data, and from $81.26 to $93.41 in the QFAHD data.

These changes in mean values foreshadow the econometric results to come. Although economic conditions worsened for households in the data, food security was not adversely affected. Increases in household SNAP benefits seem to more than compensate for household's worsening financial situation.

5. Empirical Results

Results from estimating IV-probit models are in tables 4 through 7. Results in table 4 are for the first-stage SNAP per-capita equation (2) using four subsamples of households when the CCER grocery index is available. Results in table 5 are for the first-stage SNAP per-capita equation (2) using four subsamples of households when the TFP cost index is available. Results in tables 6 and 7 are for the probit model of food insecurity, equation (3), where samples are defined the same as in tables 4 and 5.[5]

5.1 Maximum Likelihood IV-Probit Results

The first sample in all tables includes households that are below 185 percent of the poverty level in either 2008 or 2009. The second sub-sample includes households that were below 130 percent of the poverty level in either 2008 or 2009. The third sub-sample includes households that were below 130 percent of the poverty level in 2008 or 2009, and that never participated in WIC, and that did not visit a food pantry in the 30 days prior to the survey, either in 2008 or 2009. The final sub-sample includes only households that were not below 130 percent of the poverty level in 2008, but were below 130 percent of the poverty level in 2009; these households also were never WIC participants nor did they visit a food pantry.

It appears ARRA is a relevant instrument in that there is a strong partial correlation between ARRA and per-capita SNAP benefits in the first-stage regressions in table 4. Results indicate the ARRA increased per-capita SNAP benefits about $3.56 in the first sample of households below 185 poverty in 2008 or 2009, and approximately $4.70 for households that were below 130% of the poverty level in 2008 or 2009, on average, conditioned on the other explanatory variables. Average benefits increased the most for households that fell below the 130 percent poverty line between 2008 and 2009. The marginal effects of ARRA are similar in table 5 when the larger sample with QFAHD prices is used.

The second condition for a valid instrument is that ARRA is uncorrelated with the error term in equation 3. Presumably, there are unobservable factors that affect food security, but that are not controlled in estimation, but that are captured in the error term of equation 3. As long as these unobservable factors

[5] Standard errors in all models are corrected for arbitrary correlation within household with cluster robust standard errors.

are uncorrelated with the included observables and the ARRA instrument, then coefficients are consistent. But, ARRA is essentially a time dummy and if unobservable factors changed between 2008 and 2009, then ARRA would be correlated with equation 3's error term; ARRA would be endogenous, and the estimated coefficients would be inconsistent. This is not a testable hypothesis given the model is just identified.

However, general economic conditions worsened between 2008 and 2009. Real GDP declined about 0.10% between quarter 4 2008 and quarter 4 2009, which should have increased the likelihood that a household would be food insecure. Indeed, food insecurity increased from 14.6 percent of the population in 2008 to 14.7 percent in 2009 (Nord et. al, 2009, and Nord, Andrews and Carlson, 2009). And as mentioned, incomes and unemployment deteriorated for households in our sample. So, the unobservable factors are likely to have adversely affected food security, thus working in the opposite direction of increasing SNAP benefits. If our results are biased, they should be biased toward a finding of no effect of increased SNAP benefits. That is, our estimates are likely conservative estimates of the effect of increased SNAP benefits.

Nevertheless, we check for evidence of inconsistent estimates caused by endogenous ARRA by restricting the sample to households that saw their financial conditions worsen in 2009. In the final column of tables 4 and 5, we show results from estimating the model including only households that were not below 130 percent of the poverty level in 2008, but were below that level in 2009. Restricting the sample this way dramatically reduces the number of observations and perhaps not surprisingly few coefficients are statistically significant; although in many instances the sign and magnitude agree with estimates from the other samples. But, ARRA appears to be a relevant instrument because it is statistically significant (Sample 4 column of tables 4 and 5).

The price-index coefficients are negative, and statistically significant in many cases.[6] A negative coefficient suggests household demand for foods bought with SNAP benefits is elastic. Households in

[6] The average price index is 1.00. As an example, the coefficient in the first column of table 4 indicates that a doubling of prices is associated with a $21.873 decrease in SNAP benefits per household member.

areas with high food prices purchase fewer SNAP foods, and the proportionate decrease in quantity purchased is larger than the proportionate increase in prices, and so total SNAP spending declines.

This is an interesting finding, but it is difficult to fully understand given the current evidence. It might be that the stigma from using SNAP benefits is higher in high-price areas. If high food prices reflect a higher cost of living in general (as in a high income area), households might be hesitant to participate in SNAP fearing judgment from their neighbors. On the other hand, it seems likely that food prices affect a household's food spending in general, and SNAP benefits are a portion of overall food expenditures. If so, then to fully understand the effect of food prices, it is necessary to simultaneously examine their effect on SNAP benefits, and other out-of-pocket spending on food. Such an examination is not possible with the current data set.

The results in tables 6 and 7 are the marginal effects of an IV-probit estimate of equation 3. In all 4 columns of both tables the marginal effect of SNAP per capita is statistically significant and negative. In the first results column in table 6 the marginal effect of an additional per capita SNAP dollar suggests a reduction in the probability of being food insecure of 0.5 percent. SNAP participants received an average monthly benefit of $78.83 in 2008 and yet 36.39% were food insecure. In 2009, the average benefit increased to $86.89, but the proportion of food secure declined to 31.75%. The 0.5 percent marginal effect predicts the eight-dollar increase in average SNAP benefit decreased the proportion of food insecure households by about 4.03 percent.

The following two columns in table 6 suggest a similar effect. The second column of results finds a negative effect of about .5 percent. The sample here includes households that were below 130 percent of the poverty level in 2008 or 2009. The third results column also suggests a negative 0.5 percent effect when the sample is restricted to households below 130 percent of the poverty level and that did not receive WIC and that did not visit a food pantry. Because the ARRA may have improved access to WIC and food pantries for some low-income households, the effect of SNAP benefits may be overstated in the first two results columns. But the estimates are nearly identical in the second and third results columns, so it seems unlikely that ARRA captures the effect of increased WIC participation and food pantry usage.

The final robustness check is in the last column of table 6. The sample is restricted to households that were above 130 percent of the poverty line in 2008, but below it in 2009. Households were also eliminated if they participated in WIC, or used a food pantry. The goal is to eliminate the possibility that unobservable factors that affect food insecurity changed between 2008 and 2009 in a way that would overstate the effect of SNAP benefits. Even when the sample is restricted to households whose food security is most likely to worsen between 2008 and 2009, SNAP benefits are estimated to have a mitigating effect. The marginal effect in the last column is negative 0.7 percent, larger in absolute value that any of the previously mentioned estimates, suggesting the earlier estimates are conservative.

Although it is likely that differing food prices affect the purchasing power of SNAP benefits, it is difficult to find data sources for geographically discriminated food prices. Even when available, it is questionable how well the prices in the data sets represent the food prices customers actually pay. Our solution is to check whether our results are sensitive to choice of food-price data. In table 7 we show results from estimating the model when food prices are taken from the QFAHD.

The strategy to determine samples is the same in table 7 as in table 6. We are able to match more households with price data, but the price data show less geographic variation. Nonetheless, table 7 results are similar to those in table 6. The marginal effect of per-capita SNAP benefits is a negative 0.4 percent for the largest sample, which is smaller than the corresponding estimate in table 6, but within its 95 percent confidence interval. Effects in the next two columns are smaller in absolute value, but statistically significant. The SNAP benefit marginal effect in the final column is a negative 0.7 percent, identical to the corresponding column in table 6.

Other estimates in tables 4 and 5 are consistent with theory and other SNAP studies. Interesting results include that even controlling for income, a household with an unemployed head received more SNAP benefits. Benefits increase with household size, and increase at a decreasing rate with age.

5.1 GMM Estimation

Econometricians are currently debating the merits of various limited-dependent variable models. Angrist and Pishke (2009) voice the argument that linear regression models do well at estimating marginal effects of independent variables and since most studies are primarily interested in marginal effects, linear models are sufficient. In this argument, non-linear models are unnecessarily complex, and their consistency is dependent on choosing the correct nonlinear model, which is not testable since the correct model is unknown. On the other hand, some researchers contend that nonlinear models should not be so easily dismissed. As an example, the linear probability model is biased and likely inconsistent unless the predicted values from the true linear model are within the unit interval (Horrace and Oaxaca, 2006).

Our approach uses a nonlinear IV-probit estimator. But, this approach may be criticized for the reasons mentioned and the IV-probit model is appropriate only for continuous endogenous regressors. SNAP per capita is continuous but with an overwhelming majority of zero observations. Some readers may be concerned that it is censored at zero (although it is accurately described as a corner solution). Given these concerns we check the robustness of our IV-probit results by estimating equations 2 and 3 with system generalized method of moments (GMM). Equation 3, the binary food insecurity equation, is estimated as a linear relationship (i.e., a linear probability model). But because SNAP per-capita is bounded at zero we estimate equation 2 as an exponential regression, i.e.,

$$p_f S_i = e^{(\alpha_o + \beta_{f1} p_{fi} + \beta_{OG} p_{OG,i} + \beta_I I_i + \boldsymbol{x_{1i}} \boldsymbol{\beta_1} + \varepsilon_i)}, \quad (4)$$

so that predicted SNAP benefits are also bounded at zero.

We contend that maximum likelihood, while not without concerns, is an efficient estimator. In contrast, linear probability models (LPM) with endogenous regressors are consistent, but not as efficient. Our strategy is to present results from system GMM as a robustness check to our maximum likelihood estimates. Both maximum likelihood and system GMM are consistent with appropriate instruments, and assuming the correct distribution when using ML. Therefore, we expect marginal effects to be similar no matter the estimation method. However, maximum likelihood should provide more efficient standard errors.

Tables 8 shows the equation 4 coefficients when equations 2 and 4 are estimated with system GMM using the CCER data. Coefficients in the exponential regression can be interpreted as semi-elasticities since $\ln(p_f S_i) = \alpha_o + \beta_{f1} p_{fi} + \beta_{OG} p_{OG,i} + \beta_I I_i + \boldsymbol{x_{1i}} \boldsymbol{\beta_1} + \varepsilon_i$ and for example, $\frac{\partial \ln(p_f S_i)}{\partial I} = \beta_I$.

The ARRA dummy is a relevant instrument and suggests that, ceteris paribus, SNAP per capita increased 19.2 to 26.7 percent in Table 8. Table 9 includes the corresponding results using the QFAHD data. The ARRA dummy coefficients are similar to those in table 8, with the exception of the results for the fourth sub-sample.

Tables 10 and 11 show the counterpart system GMM estimates to the IV-probit estimates in tables 6 and 7. The system GMM estimates are very similar to the IV-probit estimates. The system GMM results are usually less efficient than the IV-probit results, but that is expected since IV-probit maximum likelihood is the more efficient estimator.

Overall, the system GMM estimates support our conclusions based on the IV-probit estimates. Increases in per capita SNAP benefits decrease food insecurity. We prefer the ML estimates in tables 6 and 7 because they are consistent and efficient, given correct specification of the data generating distribution. Estimates in tables 10 and 11 are also consistent, but not as efficient. Our concern is that assuming an inappropriate distribution may lead to biased and/or inconsistent ML estimates. Comparing corresponding estimates quells these concerns. For example, in table 6 the marginal effect of a $1 increase in SNAP per capita is -0.5 percent, with a 95 percent confidence interval ranging from -0.3 to -0.9 percent. We conclude, with a 5 percent chance of a type 1 error, the true marginal effect is in that range. The corresponding marginal effect in table 10 from the GMM estimate is -0.5 percent, which is within the 95 percent confidence interval for the IV-probit estimate. This relationship holds true for each of the IV-probit estimates and their corresponding system GMM estimate. The GMM estimate is within the 95 percent confidence interval for the corresponding IV-probit estimate.

5.4 The Nonlinear Marginal Impact of Each SNAP Dollar

So far we have been concerned with consistently estimating the marginal effect of a per capita SNAP dollar. We used a variety of samples and subsamples and a variety of estimation methods. All methods report similar marginal effects, although the IV-pprobit estimates are usually more efficient in that their standard errors are smaller. Thus, as we proceed, we use the IV-probit estimates to simulate the effect of different levels of SNAP benefits on propensity of households' food insecurity.

A benefit of the IV-probit estimator over IV linear regression, or the GMM estimator we use, is that IV-probit is a non-linear estimator. A non-linear estimator is capable of indicating whether marginal effects are linear across all levels of SNAP benefits. We next consider whether SNAP benefits are equally effective at reducing food insecurity as the level of SNAP benefit varies.

Prior research suggests that SNAP participation reduces the probability of food insecurity by about 15 percent. For example, Ratcliffe and McKernan find a reduction in food insecurity from SNAP participation of 16.2 percent, and Mykerezi and Mills report a negative 14.1 to 16.8 percent reduction. If we (somewhat arbitrarily) assume SNAP results in a 15 percent reduction in the probability of food insecurity, then we can calculate the implied marginal effect of a SNAP per capita dollar for these studies. The average SNAP household received $86.63 in our data, so the average marginal effect of a SNAP dollar is -15/86.63 = -0.173 percent.[7] This estimate is much lower than our estimated marginal effects, which range from -0.3 to -0.7 percent. It appears some of the discrepancy is because Ratcliffe and McKernan and Mykerezi and Mills did not include food prices in their analysis. We estimated all the models without food prices included and find that marginal effects are smaller in absolute value. But, allowing for non-linear marginal effects also explains some of the discrepancy. Marginal effects are

[7] It is well known that SNAP participation is underreported in census data. This underreporting is also apparent in the SNAP benefits data. FNS reports average SNAP benefits per person of $125.31 in 2009. Using that figure, the average marginal effect of a SNAP dollar is -0.12 percent.

largest when per capita SNAP benefits are low. Because the majority of households receive high levels of per capita benefits, the mean is skewed high and the implied marginal effect is low.

Figure 1 shows the predicted probabilities (and 95 percent confidence intervals) of being food insecure at various levels of per capita SNAP benefits using the IV-probit estimates. We estimated the probability of food insecurity for each household in the sample given each household's characteristics. That is, we do not evaluate probabilities at variable averages, but instead evaluate each household's probability given that household's characteristics. We then average probabilities for households that have different levels of SNAP benefits. So each probability in figure 1 is the average probability for households with each level of SNAP benefit. We use the same method to estimate standard errors and use them to construct ninety-five percent confidence intervals.

We calculated probabilities, then took averages because we want to know the estimated probability of food insecurity, conditioned on each household's actual characteristics. We did not want to impose an income level on a household then calculate the probability of food insecurity. Instead, we wanted to know, given a household's income, SNAP benefit, and other characteristics, what is the probability that household is food insecure. We also report average household income in figure 1, where income levels are noted on the right-hand axis.

All the probability profiles suggest a similar relationship between the probability of food insecurity, household income, and SNAP benefits. As per capita benefits increase, the probability of food insecurity decreases. However, the profiles show that there is a significant probability of food insecurity for households that receive less than about $100 dollars in benefits per person per month. This is true even though household incomes are higher for those households.[8]

Figure 2 shows estimated marginal effects of SNAP benefits (and 95 percent confidence intervals) for the probability of food insecurity. Each figure suggests the same general finding as in figures 1; the marginal impact of a SNAP dollar is largest when households receive low levels of benefits.

[8] Incomes are very volatile in figure 1 because we report total household income, whereas SNAP benefits on the horizontal axis are per capita. Per capita SNAP benefits are reduced based on net household income.

The marginal effect is larger, even though households that receive lower benefits also have higher incomes.

The results presented in the figures point to several factors reflecting the efficacy of SNAP. First, SNAP households have the greatest probability of being food insecure, when SNAP benefits are below \$100 per person per month. The maximum monthly per person benefit is \$200, so that figure seems sufficient to significantly alleviate the probability of food insecurity. On the other hand, when households receive less than \$100 per person, per month the likelihood of food insecurity is significant. This has two implications for policy. The recent ARRA increased benefits across the board, however the beneficial food security effects of that increase was most likely felt by households that received less than \$100 a month in benefits. Likewise, the recent (2013) decrease in SNAP benefits is likely to have its largest food security impact on those low-benefit households. On the other hand, the ARRA increase in benefits, and the subsequent 2013 decrease in benefits, is likely to have had a relatively small marginal impact on the food security of households that received benefits above about \$100 a month. Second, if future SNAP benefits changes are contemplated, they would be most effective for food security if they increased allowable benefits for those households that otherwise would receive less than \$100 per person per month.

5.3 The Effect of Food Prices for Food Insecurity

It's interesting to note that the food price-index coefficient is not statistically significant in any of the food insecurity equations estimated. But, food prices are negatively related to SNAP per capita in many of the benefit equations. Thus, these results suggest that higher food prices affect food insecurity through the purchasing power of SNAP benefits.

Table 12 shows the effects of food prices on food insecurity as $\frac{\partial FI}{\partial p_f} = \beta_S * \beta_{f1}$, where β_S is the appropriate marginal effect from estimating equation 3. Estimates in table 12 can be interpreted as elasticities; and, for example, the IV-pProbit estimate from the largest CCER sample suggests a 1 percent increase in food prices increases food insecurity 0.0813 percent. All of the estimates in table 12 are positive, but relatively few of them are statistically significant.[9]

We experimented by including a general cost of living index in the CCER models in addition to the grocery price index. The CCER calculates a composite index from all recorded prices that is meant to measure overall geographic purchasing power variation. When included, the composite index dominated the grocery price index in that the composite coefficient was negative and significant in the benefits equation, but the grocery index was not. The grocery index and composite index are highly correlated and we speculate there is insufficient information to uniquely identify separate coefficients. We chose to include the grocery index because it seems most appropriate when examining food purchases and food insecurity. But, the food price index coefficient is likely best interpreted as a general cost of living effect.

We are somewhat surprised that the price index is not significant in the food insecurity equation. If a higher cost of living decreases the purchasing power of SNAP benefits, then we expect it would also affect a household's ability to purchase other food. If so, then a higher cost of living should be associated with more food insecurity independent of its effect through SNAP benefits.

Because we do not observe a direct effect of cost of living on food insecurity, we speculate that households in high cost areas substitute away from other goods toward food. That is, food purchases may be more price insensitive than other goods. If so, a complete model of household purchases is necessary to better understand household allocation decisions. The current data do not allow for this type of examination and we leave it for future research.

Conclusion

We believe the results build a convincing case that additional SNAP spending decreases food insecurity and confirm earlier studies that found that SNAP participation reduces food insecurity. Our approach differs from previous studies in that we model food insecurity as a function of SNAP benefits received; earlier studies modeled food insecurity as a function of SNAP participation. We are interested in

[9] These results are consistent with findings in Gregory and Coleman-Jensen (2013).

identifying the marginal effects of SNAP benefits. By modeling food benefits directly rather than SNAP participation, our approach accounts for differences in the purchasing power of SNAP benefits because of differences in cost-of-living.

To control for differences in purchasing power we include spatially and temporally varying food-price indexes in our regressions. Interestingly, our findings suggest that households that live in areas with high food prices have a higher probability of being food insecure, but this price effect runs only through the purchasing power of SNAP benefits. That is to say, we don't find any negative consequences of high prices for insecurity, except because SNAP benefits purchase less food where prices are high. Part of the explanation is that our results suggest the demand for SNAP foods is elastic; when prices are high households don't utilize SNAP foods enough to offset the effect of the higher prices.

We hope our results will contribute to ongoing policy debates in several respects. First, our estimates suggest households must receive more than $100 in benefits per household member to reduce the probability of food insecurity to near zero. Second, the ARRA increases in SNAP benefits expired on November 1, 2013. Our results suggest that this change, and any future changes, are likely to have the largest food security impacts on persons receiving less than about $100 in monthly per person benefits. Finally, SNAP benefits are not indexed for differences in purchasing power in the continental United States. Our results suggest SNAP participating households in higher cost areas are more susceptible to food insecurity than identical households in the lower cost areas. This discrepancy could be alleviated if SNAP benefits were geographically indexed.

Our research has the following limitations which are common in the SNAP literature. We use households that are interviewed in the CPS-FSS in 2008 and 2009, which are not random. The generalizability of our estimates outside the given sample may be questioned. But, our estimates are robust in a variety of subsamples. Relatedly, it appears SNAP benefits are underreported in the CPS-FSS and our estimates may be criticized on these grounds. But, it is important to recall that we use an instrumental variable estimator, and that IV estimators are consistent even in the face of miss-measured variables. What is important is that the instrument exogenously shifts the SNAP benefits equation. Even though our sample is not random, and to the extent that SNAP benefits are underreported, our results represent the first step in investigating the causal marginal effects of SNAP benefits with the best available data. Future research with better data could further bring insights to this important policy issue.

Table 1. Variable Names

Variable Name	**Definition**
Food Insecure	A binary variable for whether the household was food insecure in the last 30 days.
Snap per Capita	Nominal food stamp dollars received in the most recent month, divided by the number of persons in the household .
House Income	A continuous measure of income. The mid-point of upper and lower values of the categorical income values in the CPS-FSS
Age	The age of the person answering the survey in the CPS-FSS
Age Squared	Age x age
Married	Binary variable for whether the household in a married couple (married=1).
Own Home	Whether the household owns their home (ownhome=1).
HS Graduate	Binary variable for whether the person answering the survey graduated high-school. Not a high school graduate is the base.
College Graduate	Binary variable for whether the person answering the survey graduated college. Not a college graduate is the base.
Minority	Binary variable for whether the person answering the survey identified themselves as non-caucasian.
Unemployed	Person answering survey unemployed.
No children	Binary variable equal to 1 if no children in the household.
HH Size	Number of persons in the household.
ARRA	Binary variable = 1 in 2009.
Grocery Index	Continuous grocery price index from CCER.
Thrifty Food Plan Index	Continuous composite thrifty food plan cost index constructed using QFAHD.

Table 2. Summary Statistics when CCER Grocery Index is Available

Variable	Obs	Mean	Std. Dev.
Food Insecure	3,928	0.165	0.371
Household Income	3,928	2.628	2.290
Age	3,928	51.370	18.223
Age Squared	3,928	2970.880	1942.918
Married	3,928	0.374	0.484
Own Home	3,928	0.587	0.492
HS Graduate	3,928	0.654	0.476
College Graduate	3,928	0.136	0.343
Non-white	3,928	0.221	0.415
Unemployed	3,928	0.075	0.264
No Children	3,928	0.383	0.486
Grocery Index	3,928	0.997	0.114
HH Size	3,928	2.608	1.668
Snap per Capita	3,928	14.477	39.066
ARRA	3,928	0.500	0.500

Table 3. Summary Statistics when QFAHD TFP Cost Index is Available

Variable	Obs	Mean	Std. Dev.
Food Insecure	7,606	0.158	0.364
Household Income	7,606	2.649	2.342
Age	7,606	52.105	18.125
Age Squared	7,606	3043.408	1950.624
Married	7,606	0.369	0.483
Own Home	7,606	0.564	0.496
HS Graduate	7,606	0.634	0.482
College Graduate	7,606	0.140	0.347
Non-white	7,606	0.209	0.407
Unemployed	7,606	0.078	0.268
No Children	7,606	0.393	0.488
TFP Index	7,606	0.991	0.062
HH Size	7,606	2.607	1.682
Snap per Capita	7,606	14.123	39.194
ARRA	7,606	0.500	0.500

Table 4. First-Stage Snap Per-Capita Dependent Variable, CCER Sample

	Sample 1	Sample 2	Sample 3	Sample 4
Household Income	-2.983***	-2.738***	-1.760***	-0.511*
	(0.39)	(0.48)	(0.37)	(0.28)
Age	0.488**	0.757**	0.840**	0.39
	(0.24)	(0.35)	(0.40)	(0.53)
Age Squared	-0.006***	-0.010***	-0.010***	-0.005
	(0.002)	(0.003)	(0.004)	(0.005)
Married	-13.054***	-13.466***	-9.765***	(2.62)
	(1.78)	(2.43)	(2.56)	(3.50)
Own Home	-9.409***	-10.275***	-10.358***	-7.326**
	(1.54)	(2.19)	(2.41)	(3.68)
HS Graduate	-0.59	1.07	1.70	1.09
	(1.71)	(2.32)	(2.48)	(3.39)
College Graduate	-6.660***	-8.705***	-6.430*	-4.90
	(2.12)	(3.33)	(3.32)	(3.69)
Non-white	10.180***	11.593***	8.011***	7.45
	(2.11)	(2.81)	(3.09)	(5.03)
Unemployed	10.965***	12.337***	11.033**	6.31
	(2.98)	(3.83)	(4.76)	(6.91)
No Children	-9.776***	-8.875***	-4.48	2.73
	(2.36)	(3.28)	(3.49)	(4.68)
Grocery Index	-21.873***	-24.887***	-19.602**	-20.40
	(5.56)	(9.52)	(9.48)	(12.98)
HH Size	1.249**	-0.08	-0.63	-0.65
	(0.49)	(0.68)	(0.73)	(1.13)
ARRA	3.562***	4.657***	4.765***	7.185***
	(0.89)	(1.36)	(1.47)	(2.57)
Constant	45.338***	49.703***	33.825**	27.71
	(9.52)	(14.07)	(15.18)	(19.68)
athrho	0.964***	0.971***	0.979**	1.262***
	(0.33)	(0.37)	(0.41)	(0.47)
lnsigma	3.589***	3.774***	3.730***	3.587***
	(0.04)	(0.04)	(0.05)	(0.12)
Log-likl	-2.12E+04	-1.38E+04	-1.06E+04	-3.58E+03
N	3,928	2,440	1,918	672

* p<0.10, ** p<0.05, *** p<0.01 Standard Errors in () robust to arbitrary heteroskedasticity and correlation within households.

Table 5. First-Stage Snap Per-Capita Dependent Variable, QFAHD Sample

	Sample 1	Sample 2	Sample 3	Sample 4
Household Income	-2.554***	-2.540***	-1.922***	-0.552***
	(0.262)	(0.379)	(0.273)	(0.205)
Age	0.498***	0.689***	1.013***	0.227
	(0.179)	(0.257)	(0.274)	(0.378)
Age Squared	-0.006***	-0.009***	-0.011***	(0.004)
	(0.002)	(0.002)	(0.002)	(0.003)
Married	-13.211***	-13.995***	-10.853***	-6.404**
	(1.265)	(1.715)	(1.853)	(2.838)
Own Home	-10.726***	-12.343***	-11.521***	-7.398***
	(1.126)	(1.562)	(1.659)	(2.398)
HS Graduate	-3.591***	-2.623	-1.187	-0.381
	(1.353)	(1.800)	(1.870)	(2.926)
College Graduate	-8.721***	-11.054***	-8.832***	-5.483*
	(1.616)	(2.423)	(2.362)	(3.057)
Non-white	6.781***	6.178***	4.122*	4.292
	(1.535)	(2.018)	(2.202)	(3.220)
Unemployed	8.467***	10.312***	8.151**	5.365
	(2.096)	(2.740)	(3.167)	(4.406)
No Children	-9.929***	-10.253***	-7.438***	-4.618
	(1.727)	(2.321)	(2.476)	(3.724)
Thrifty Food Plan Index	-22.215***	-36.993***	-17.325	-20.872
	(8.238)	(12.197)	(12.853)	(16.963)
HH Size	0.708*	-0.564)	-0.915)	-0.797
	(0.362)	(0.502)	(0.566)	(0.858)
ARRA	3.703***	5.596***	5.478***	5.516***
	(0.626)	(0.940)	(0.987)	(1.692)
Constant	48.270***	67.422***	30.734**	37.701*
	(9.801)	(14.248)	(15.333)	(20.842)
athrho	0.666**	0.594**	0.775***	1.099**
	(0.263)	(0.258)	(0.278)	(0.45)
lnsigma	3.605***	3.786***	3.715***	3.525***
	(0.027)	(0.027)	(0.035)	(0.087)
Log-likl	-4.12E+04	-2.70E+04	-2.09E+04	-6.61E+03
N	7,606	4,780	3,780	1,252

* p<0.10, ** p<0.05, *** p<0.01 Standard Errors in () robust to arbitrary heteroskedasticity and correlation within households.

Table 6. Second-Stage Food Security IV-Probit Marginal Effects, CCER Sample

	Sample 1	Sample 2	Sample 3	Sample 4
Snap per Capita	-0.005***	-0.005***	-0.005***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.003)
Household Income	-0.040***	-0.032***	-0.026***	-0.028***
	(0.005)	(0.005)	(0.005)	(0.006)
Age	0.020***	0.021***	0.020***	0.010
	(0.003)	(0.004)	(0.004)	(0.006)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000**
	0.00000	0.00000	0.00000	0.0000
Married	-0.088***	-0.079***	-0.080***	(0.065)
	(0.028)	(0.029)	(0.028)	(0.042)
Own Home	-0.069***	-0.077***	-0.069***	-0.037
	(0.020)	(0.021)	(0.026)	(0.039)
HS Graduate	-0.022	0.000	-0.010	-0.027
	(0.017)	(0.021)	(0.024)	(0.040)
College Graduate	-0.093***	-0.109***	-0.085**	-0.102*
	(0.024)	(0.032)	(0.034)	(0.055)
Non-white	0.061***	0.067***	0.050*	0.001
	(0.025)	(0.026)	(0.028)	(0.057)
Unemployed	0.116***	0.127***	0.120***	0.131*
	(0.025)	(0.027)	(0.034)	(0.063)
No Children	-0.062***	-0.064**	-0.037	0.007
	(0.027)	(0.028)	(0.029)	(0.051)
Grocery Index	-0.023	-0.033	-0.036	0.078
	(0.083)	(0.105)	(0.108)	(0.195)
HH Size	0.023***	0.010	0.010	0.021
	(0.005)	(0.007)	(0.008)	(0.013)

* p<0.10, ** p<0.05, *** p<0.01 Standard Errors in () robust to arbitrary heteroskedasticity and correlation within households.

Table 7. Second-Stage Food Security IV Probit Marginal Effects, QFAHD Sample

	Sample 1	Sample 2	Sample 3	Sample 4
Snap per Capita	-0.004***	-0.003**	-0.004***	-0.007***
	(0.002)	(0.001)	(0.002)	(0.003)
Household Income	-0.032***	-0.021***	-0.019***	-0.018***
	(0.005)	(0.006)	(0.005)	(0.005)
Age	0.019***	0.021***	0.020***	0.011**
	(0.002)	(0.002)	(0.003)	(0.004)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***
	0.00000	0.00000	0.00000	0.0000
Married	-0.075***	-0.080***	-0.086***	-0.097***
	(0.024)	(0.024)	(0.023)	(0.034)
Own Home	-0.054***	-0.056***	-0.058***	(0.019)
	(0.020)	(0.021)	(0.022)	(0.036)
HS Graduate	-0.029**	-0.017	-0.016	-0.023
	(0.013)	(0.015)	(0.016)	(0.031)
College Graduate	-0.089***	-0.097***	-0.086***	-0.062
	(0.021)	(0.026)	(0.026)	(0.042)
Non-white	0.038***	0.030*	0.019	0.005
	(0.016)	(0.017)	(0.019)	(0.038)
Unemployed	0.090***	0.099***	0.099***	0.125***
	(0.018)	(0.020)	(0.022)	(0.040)
No Children	-0.047**	-0.053**	-0.048**	-0.049
	(0.022)	(0.023)	(0.023)	(0.040)
Thrifty Food Plan Index	-0.057	-0.206*	-0.182	-0.121
	(0.090)	(0.115)	(0.118)	(0.221)
HH Size	0.017***	0.009*	0.006	0.007
	(0.004)	(0.005)	(0.006)	-0.01

* p<0.10, ** p<0.05, *** p<0.01 Standard errors in () robust to arbitrary heteroskedasticity and correlation within households.

Table 8. GMM SNAP Per-Capita Exponential Regression

	Sample 1	Sample 2	Sample 3	Sample 4
ARRA	0.239***	0.192***	0.267***	0.199
	(0.061)	(0.062)	(0.088)	(0.371)
Household Income	-0.609***	-0.508***	-0.493***	-0.491**
	-0.052	-0.061	-0.09	-0.192
Age	0.064***	0.066***	0.080***	0.069
	(0.02)	(0.02)	(0.02)	(0.05)
Age Squared	-0.001***	-0.001***	-0.001***	-0.001*
	0.000	0.000	0.000	(0.001)
Married	-0.553***	-0.466***	-0.496***	0.258
	(0.114)	(0.117)	(0.177)	(0.408)
Own Home	-0.438***	-0.429***	-0.582***	-0.729*
	(0.107)	(0.113)	(0.163)	(0.379)
HS Graduate	0.037	0.088	0.146	0.107
	(0.099)	(0.101)	(0.146)	(0.362)
College Graduate	-0.560**	-0.484**	-0.407	-0.761
	(0.231)	(0.238)	(0.293)	(0.556)
Non-white	0.406***	0.346***	0.298**	0.563*
	(0.096)	(0.098)	(0.142)	(0.339)
Unemployed	0.228**	0.236**	0.343**	0.414
	(0.108)	(0.107)	(0.161)	(0.379)
No Children	-0.326**	-0.251*	-0.147	0.380
	(0.135)	(0.134)	(0.174)	(0.447)
Grocery Index	-1.014**	-0.802*	-0.852	-1.989*
	(0.439)	(0.469)	(0.628)	(1.162)
HH Size	0.134***	0.071**	0.048	0.142
	(0.030)	(0.031)	(0.044)	(0.124)

* p<0.10, ** p<0.05, *** p<0.01 Standard Errors in () robust to arbitrary heteroskedasticity and correlation within households.

Table 9. GMM SNAP-Per Capita Exponential Regression QFAHD Sample

	Sample 1	Sample 2	Sample 3	Sample 4
ARRA	0.274***	0.264***	0.351***	0.12
	(0.045)	(0.045)	(0.063)	(0.248)
Household Income	-0.559***	-0.409***	-0.475***	-0.446***
	-0.05	-0.06	-0.057	-0.129
Age	0.052***	0.052***	0.078***	0.055
	(0.01)	(0.01)	(0.02)	(0.04)
Age Squared	-0.001***	-0.001***	-0.001***	-0.001*
	0.000	0.000	0.000	0.000
Married	-0.667***	-0.561***	-0.601***	-0.673**
	(0.089)	(0.090)	(0.133)	(0.307)
Own Home	-0.612***	-0.589***	-0.722***	-0.817***
	(0.088)	(0.091)	(0.128)	(0.273)
HS Graduate	-0.096	-0.069	-0.015	-0.070
	(0.077)	(0.079)	(0.107)	(0.313)
College Graduate	-0.699***	-0.651***	-0.679***	-0.840*
	(0.175)	(0.181)	(0.240)	(0.458)
Non-white	0.272***	0.192**	0.156	0.325
	(0.075)	(0.077)	(0.109)	(0.258)
Unemployed	0.217***	0.246***	0.263**	0.337
	(0.082)	(0.082)	(0.123)	(0.283)
No Children	-0.406***	-0.321***	-0.295**	-0.385
	(0.096)	(0.095)	(0.127)	(0.331)
TFP Index	-1.205**	-1.428**	-0.835	-2.640
	(0.540)	(0.564)	(0.785)	(1.921)
HH Size	0.096***	0.034	0.027	0.070
	(0.023)	(0.024)	(0.036)	(0.092)

* p<0.10, ** p<0.05, *** p<0.01 Standard errors in () robust to arbitrary heteroskedasticity and correlation within households.

Table 10. GMM Food Insecurity Linear Model, CCER Sample

	Sample 1	Sample 2	Sample 3	Sample 4
Snap per Capita	-0.005*	-0.005	-0.004	-0.003
	(0.003)	(0.003)	(0.004)	(0.003)
Household Income	-0.035***	-0.030***	-0.023***	-0.012***
	(0.010)	(0.010)	(0.008)	(0.004)
Age	0.018***	0.023***	0.021***	0.006
	(0.003)	(0.004)	(0.005)	(0.005)
Age Squared	-0.000***	-0.000***	-0.000***	0.000
	0.00	0.00	0.00	0.00
Married	-0.102**	-0.098*	-0.094*	(0.063)
	(0.046)	(0.054)	(0.052)	(0.047)
Own Home	-0.086***	-0.101**	-0.113**	(0.017)
	(0.033)	(0.040)	(0.048)	(0.039)
HS Graduate	-0.026	0.000	(0.031)	(0.035)
	(0.020)	(0.026)	(0.030)	(0.040)
College Graduate	-0.105***	-0.130***	-0.123***	-0.092*
	(0.031)	(0.044)	(0.047)	(0.054)
Non-white	0.059	0.077*	0.056	-0.023
	(0.038)	(0.047)	(0.044)	(0.043)
Unemployed	0.154***	0.177***	0.140**	0.164**
	(0.046)	(0.056)	(0.065)	(0.068)
No Children	-0.069*	-0.074*	(0.017)	(0.017)
	(0.039)	(0.044)	(0.041)	(0.049)
Grocery Index	-0.003	-0.017	-0.036	0.182
	(0.100)	(0.140)	(0.143)	(0.198)
HH Size	0.026***	0.012	0.022*	0.023
	(0.008)	(0.009)	(0.011)	(0.014)

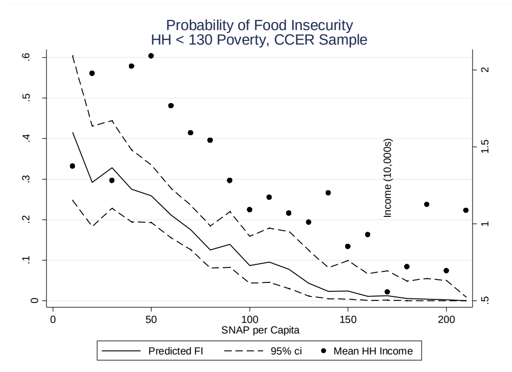
* p<0.10, ** p<0.05, *** p<0.01 Standard errors in () robust to arbitrary heteroskedasticity and correlation within households.

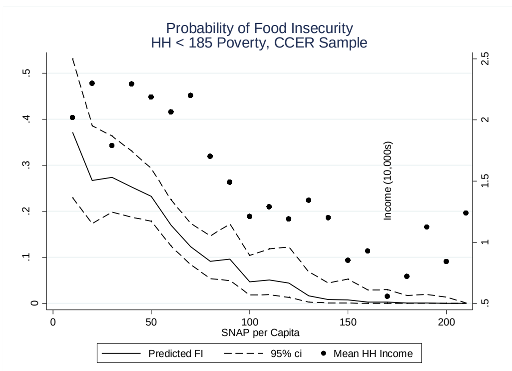
Table 11. GMM Food Insecurity Linear Model, QFAHD Sample

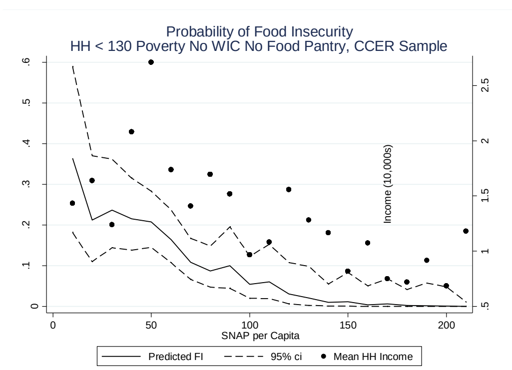
	Sample 1	Sample 2	Sample 3	Sample 4
Snap per Capita	-0.003	-0.003	-0.003*	-0.005
	(0.002)	(0.002)	(0.002)	(0.004)
Household Income	-0.025***	-0.019***	-0.017***	-0.012***
	(0.006)	(0.006)	(0.005)	(0.004)
Age	0.015***	0.018***	0.017***	0.008**
	(0.002)	(0.002)	(0.003)	(0.004)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***
	0.00	0.00	0.00	0.00
Married	-0.079***	-0.088***	-0.093***	-0.091**
	(0.029)	(0.031)	(0.029)	(0.043)
Own Home	-0.056**	-0.061**	-0.062**	(0.007)
	(0.023)	(0.026)	(0.026)	(0.034)
HS Graduate	-0.027*	-0.015	-0.015	-0.024
	(0.014)	(0.017)	(0.017)	(0.029)
College Graduate	-0.084***	-0.095***	-0.085***	-0.059
	(0.023)	(0.029)	(0.028)	(0.044)
Non-white	0.034*	0.028	0.015	(0.006)
	(0.019)	(0.020)	(0.020)	(0.034)
Unemployed	0.112***	0.121***	0.122***	0.160***
	(0.026)	(0.030)	(0.033)	(0.053)
No Children	-0.048*	-0.056**	-0.053**	-0.041
	(0.025)	(0.027)	(0.026)	(0.042)
TFP Index	-0.048	-0.219*	-0.199	-0.110
	(0.093)	(0.129)	(0.125)	(0.213)
HH Size	0.019***	0.011*	0.007	0.009
	(0.005)	(0.006)	(0.007)	(0.011)

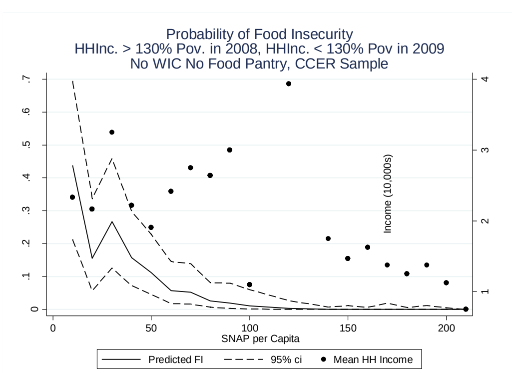
* p<0.10, ** p<0.05, *** p<0.01 Standard errors in () robust to arbitrary heteroskedasticity and correlation within households.

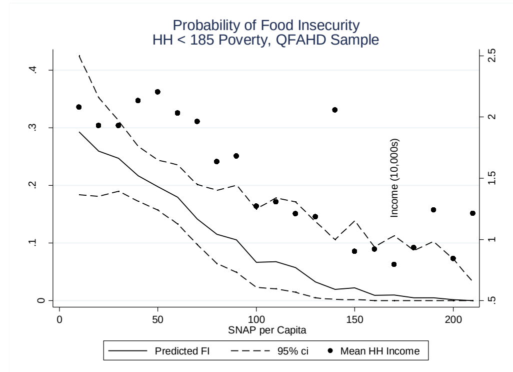
Figure 1: Food Insecurity Probability & 95% CI

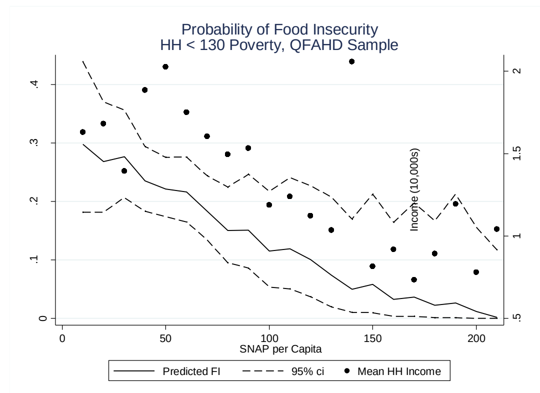


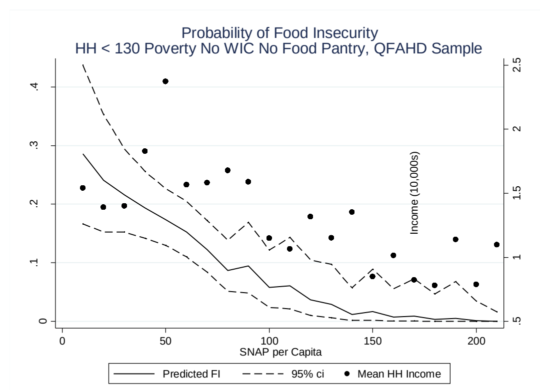












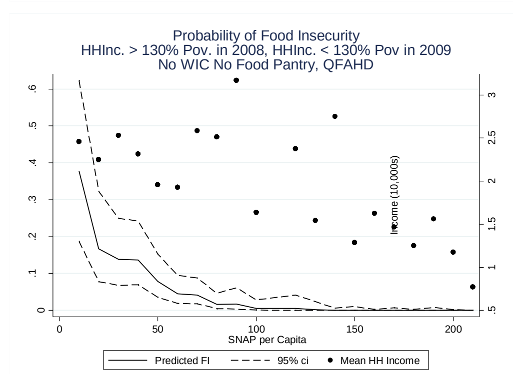
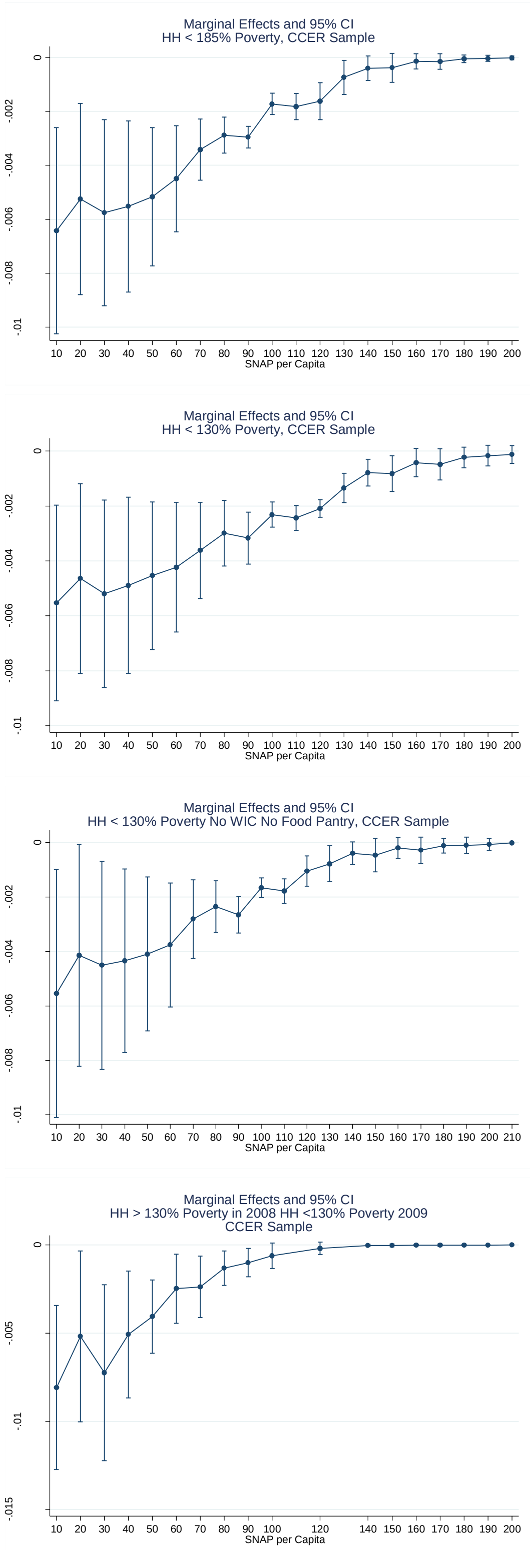


Figure 2. Marginal Effects of SNAP Benefits



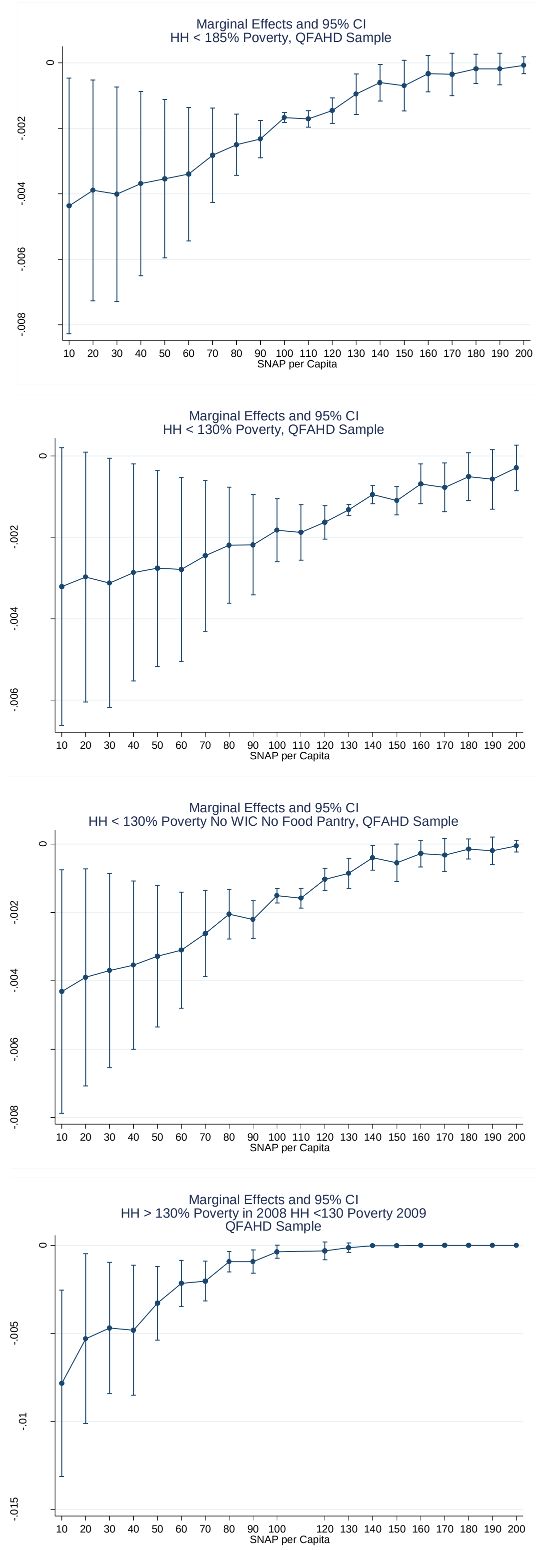


Table 12. The Marginal Effect of Food Prices on Food Insecurity

	Sample 1	Sample 2	Sample 3	Sample 4
IV-Probit Estimates				
CCER Index	.0813***	.0923**	.0697*	0.1592
	(0.029)	(0.044)	(0.041)	(0.111)
QFAHD Index	.0376*	.01300*	0.0138	0.0658
	(0.020)	(0.007)	(0.011)	(0.056)
System GMM Estimates				
CCER Index	0.0768	0.0910	0.0614	0.0582
	(0.056)	(0.080)	(0.073)	(0.078)
QFAHD Index	0.0493	0.0794	0.0465	0.1192
	(0.040)	(0.062)	(0.052)	(0.126)

* p<0.10, ** p<0.05, *** p<0.01 Standard errors in () robust to arbitrary heteroskedasticity and correlation within households.

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