Does SNAP Improve Your Health?

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Abstract. In this study, we examine the effect of SNAP on health quite generally, examining self-assessed health (SAH), healthy time, and basic health utilization measures as outcomes. Our approach is to model outcomes and participation simultaneously, using exogenous variation in state eligibility to identify SNAP participation. We use this approach for both ordered choices (health) and count outcomes (sickdays, office-based visits, outpatient visits), where the former uses maximum likelihood and the latter maximum simulated likelihood. In addition, we control for state-level unobservables that are correlated with both participation and health, which previous studies of this question have neglected. Our results indicate that SNAP has an consistently positive effect on SAH; it significantly increases the probability of reporting excellent or very good health. We also find that SNAP participants spend between 1 and 2 fewer days in bed due to illness each year, and report between 1 and 2 fewer office-based doctor visits and a fraction fewer outpatient visits. Supplementary specifications indicate that, although SNAP participants consume fewer office visits overall, they have more checkups than comparable non-participants.

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1 Introduction

The Supplemental Nutrition Assistance Program (SNAP) is the largest of federal food assistance programs, spending $80 billion on 47 million participants in 2012. The program is intended to reduce the chances that participants experience food insecurity–the condition of having insecure access to enough food for a healthy, active lifestyle. Additionally, it is meant to support low-income households in consumption of a healthy, nutritious diet. While there is some evidence that first of these goals is being accomplished (Yen et al. (2008), DePolt et al. (2009), Ratcliffe et al. (2011), Shaefer and Gutierrez (2012)), evidence on the second is more mixed; for example, a recent study found that SNAP participation increases consumption of whole fruit, but leads to a small decrease in consumption of dark green and orange vegetables (Gregory et al., 2013). Many other studies have yielded similar inconclusive results.[1]

What is the role of the Supplemental Nutrition Assistance Program (SNAP) in promoting health more generally? On the one hand, it is reasonable to assume that, because SNAP reduces food insecurity and gives households extra income, it might also have an ameliorative effect on conditions associated with food hardship and improve health in general. This supposition is supported by the aforementioned literature that has shown that SNAP does indeed reduce food insecurity. It is also supported by the considerable body of research that shows that income is directly (even proportionally) related to health (Deaton, 2002; Deaton and Paxson, 2001). On the other hand, it is not always clear that food insecurity has clear negative effects on health (Bhattacharya et al., 2004), particularly among children, so the ameliorative effect of SNAP food insecurity may not appear in our usual measurements of health. Additionally, some recent research suggests that SNAP is causally related to obesity, itself an "oracle condition" for pressing and costly chronic diseases like diabetes, cancer, and sleep apnea (Meyerhoefer and Pylypchuk, 2008; Ver Ploeg and Ralston, 2008; Gibson, 2003; Zagorsky and Smith, 2009; Townsend et al., 2001; Kaushal, 2007).

The conflicting indications of the empirical research notwithstanding, an additional problem

[1] For example, see the review by Fox et al. (2004).

for understanding the effect of SNAP on health is knowing where to look for its effects. Much of the research has focused on food security, food expenditures and intakes, and obesity–and understandably so.[2] However, there is also a need to understand the effect of SNAP on health broadly conceived. As a transfer program, SNAP frees up income for activities that promote well-being but are not necessarily diet-related or measured by diet-related outcomes. At the same time, extra resources afforded by SNAP participation could ease financial stress beyond that associated with food insecurity. Both of these effects might be missed by conventional examinations of diet-related outcomes, but be captured by other measures of well-being.

One reason that the findings about the relationship between SNAP and obesity are so important is that obesity and its attendant conditions are expensive to treat: by one recent calculation, obese persons spend roughly $2,700 per year more on health costs than non-obese persons (Cawley and Meyerhoefer, 2012). However, the finding that SNAP is associated with increased expenditure does not directly address its affect on health (Meyerhoefer and Pylypchuk, 2008). Although Grossman (1972) argued that health care utilization was increasing in health, this aspect of the human capital model has come under sustained scrutiny, as it has not been borne out by the empirical literature. Recent theoretical work has suggested that the negative association of health with health care utilization could be the result of the fact that people do not adjust the level of health instantaneously, but over time (Galama and Kapteyn, 2011). When people are healthy, they consume *less* health care, and vice versa. With this in mind, we might ask, if SNAP does improve health, what effect can we expect it to have on health care utilization?

A particular problem for understanding the effect of SNAP on health is that selection into SNAP and most measures of health will be correlated with characteristics that are unobserved to the researcher–for example, inter-temporal discount rates could affect both the preference for investment in health and financial management practices, which could affect both SNAP participation and underlying health. In addition, local attitudes toward health and program participation are likely strongly related to person-level outcomes; failure to account for these

[2]For a recent review of this literature, see Meyerhoefer and Yang (2011).

characteristics could lead to biased estimates of program effects.

In this study, we examine the effect of SNAP on health quite generally, examining self-assessed health (SAH), healthy time, and basic health utilization measures as outcomes. Our approach is to model outcomes and participation simultaneously, using exogenous variation in state eligibility to identify SNAP participation. In addition, we control for state-level unobservables that are correlated with both participation and health. Our results indicate that SNAP increases the probability of reporting excellent or good health by 6 and 2 percentage points, respectively; SNAP results in between 1 and 2 fewer sick days and office-based provider visits, and a fraction fewer outpatient visits. Additionally, we find evidence that although SNAP participants have fewer office-based visits overall, they have more checkups, and fewer diagnostic or emergency office-based visits.

2 Related Work

While research on SNAP and health has understandably focused on diet-related outcomes, there is a smaller line of research on other measures of health. For example, one recent study examined the possible effect of SNAP on Medicare spending on diabetes (Nicholas, 2011) and found that there was no significant impact of SNAP spending, outpatient utilization, blood sugar, or hospitalizations. Additionally, there are several recent studies that focus on the possible effect of SNAP on SAH and health more generally. Fey-Yensan et al. (2003) looked at a convenience sample of elderly SNAP participants in Connecticut subsidized housing, and found no difference in SAH between participants and non-participants. Gibson (2001) examined the association between SNAP, SAH and four chronic health conditions using a single cross section of adolescents from the NLSY97; this study failed any significant correlation between SNAP participation and health outcomes. Yen et al. (2012) used a switching regression-instrumental variables framework to examine the SAH status of participants in Tennessee's welfare program, Families First. They found that SNAP participation had large negative effects on SAH, reducing the probability of reporting excellent health by over 26 percentage points.

In the context of these studies, the value added of this research is to get estimates of the effect of SNAP on health for a nationally representative sample non-elderly adults, using methods that account for geographic unobservables correlated with health and SNAP participation, selection into the program, and the distribution of outcomes. While Nicholas (2011) uses fixed-effect methods to account for time invariant heterogeneity, the author does not address the distribution of count outcomes (hospitalizations, outpatient episodes) and skewed continuous outcomes (spending). Yen et al. (2012) uses a regression framework suitable for addressing the complex selection issues involved in SNAP and health, but the estimates are for participants in the welfare programs of a single state. None of the studies mentioned above (and few in the literature examining diet-related outcomes) address geographic unobserved heterogeneity that could impact both selection into SNAP and measures of health. We address both modeling challenges and unobserved geographical heterogeneity in this study.

3 Data

The data for our study come from 10 years of the Medical Expenditure Panel Survey (MEPS) (1999-2008), a comprehensive multistage probability sample of the non-institutionalized civilian population of the United States. MEPS is an overlapping panel; the survey is administered five times over two years, with the original second panel being included after one year of data collection on the first panel, and the third panel after a year of the second, just as the first rolled off, and so on. The survey collects detailed information on demographic, labor market, health insurance, health condition, and utilization data for all respondents. In addition to health, disability, and labor market information collected at each of five interviews, MEPS reports full year measures for expenditures, income, and SNAP participation.

Because the question about SNAP participation is fielded yearly, we focus on aggregate yearly measures that we construct or are constructed in the survey. In particular, the question about SAH is asked at each of the five interviews; we use the response in the last interview of each year, since that would be the interview that yearly variables–such as the number of months in the previous twelve that one received SNAP–are also collected.

The SAH variable contains a response to the following question: "In general, compared to other people of your age, would you say that your health is excellent, very good, good, fair, or poor?" We construct the sick days variable from three questions in the activity limitations section of the survey. In particular, we get sick days by summing the number of work days, school days, and days of other activities lost due to illness when the respondent spent at least half of the day in bed.[3] We used the yearly counts of office-based visits and outpatient utilization constructed in the survey.

Our multivariate models control for demographic, employment, condition and health insurance variables. These variables include gender, race, marital status, family size, education level, employment status, Medicaid participation, other public insurance participation, indicator for being without insurance for the entire year, wage income, unemployment income, income from other public assistance programs, number of medical conditions reported, and supplemental security income (SSI). We limit the sample to include persons who are 20 to 64 years old and whose households are at or below 130% of the federal poverty line–the gross income cutoff for SNAP participation.

The summary statistics of the sample are shown in table 1. These measures indicate that SNAP participants are more likely to be Non-Hispanic Black, to have experienced unemployment in the past 12 months and to have participated in Medicaid in the last 12 months. SNAP participants have less wage income, more unemployment income and other public program income (including SSI), and they report more health conditions than non-SNAP participants. They have more office-based visits, outpatient visits, and sick days per year; they are less likely to rate their health as excellent or very good, and more likely to rate their health as fair or poor compared to non-participants.

[3]Questions about work days lost were asked only of those who were employed in the reference period; those about school were only asked of those who were enrolled in school; questions about other activities were asked only of those who were not employed or in school. Since the period of time covered by each set of interviews may be different for each person–a little more or less than one year–we included a variable that measured the total time in days covered by each persons interviews.

4 Methods

The problem facing us in estimating the effect of SNAP on health is that there are likely to be unobserved factors that affect both SNAP and health–however measured–simultaneously. Multivariate regression models that control for observed factors may suggest that health hardships for SNAP participants are not quite as severe as the summary statistics indicate, but if we want to better understand the causal effects of the program, we need to have a way to account for selection into SNAP and for person level unobserved heterogeneity simultaneously.

For this application, we adopt a treatment effects approach, using likelihood and simulated likelihood approaches and estimating treatment and outcomes simultaneously. In particular, we use two methods, one for the ordinal outcome (SAH) and one for the count outcomes (sick days, office-based visits, outpatient visits). For the first, we begin with the following model:

$$\begin{aligned} S_i^* &= X_i\beta_S + Z_i\delta + \varepsilon_i \\ H_i^* &= X_i\beta_H + S_i\zeta + \upsilon_i. \end{aligned} \tag{1}$$

S^* and H^* are latent variables representing the random utility associated with SNAP participation and underlying health status; S is binary and H is ordered, as described above. X contains the covariates outlined above, state and year fixed effects; Z are variables exogneous to health outcomes that determine SNAP participation. We assume that ε and υ have a bivariate normal distribution and estimate equations representing these choice processes simultaneously. $S_i = 1$ if $X_i\beta_S + Z_i\delta + \varepsilon_i > 0$ and 0 otherwise; and $H_i = 1$ if $X_i\beta_H + S_i\zeta + \upsilon_i < \mu_1$; $H_i = 2$ if $\mu_1 \leq X_i\beta_H + S_i\zeta + \upsilon_i < \mu_2$, and so on, up to $J = 4$ with the final condition being $H_i = 5$ if $X_i\beta_H + S_i\zeta + \upsilon_i > \mu_4$. β, δ, and ζ are parameters.[4]

While the model for the above outcomes is aided by the assumption that unobservables are distributed jointly bivariate normally, convenient assumptions about joint distributions of error terms is not available for count outcomes models. We handle these by modeling a common

[4]Greene and Hensher (2010) elaborate this model, absent the identifying exogneous variables, the semi-ordered bivariate probit. (See Greene and Hensher, 2010).

latent factor structure in the error terms for the treatment and outcome equations. To fix ideas, let

$$\begin{aligned} S_i^* &= X_i\beta_S + Z_i\delta + l_i\lambda + \epsilon_i \\ E(C_i|X_i, S_i, l_i) &= g(X_i\beta_C + S_i\zeta + l_i\lambda). \end{aligned} \tag{2}$$

$S^*, S, X, Z, \beta, \delta,$ and ζ are defined as above. C_i is the count outcome and l_i is the latent (unobserved) characteristic that underlies the correlation between selection and the outcome. $S_i = 1$ if $X_i\beta_S + Z_i\delta + l_i\lambda + \epsilon_i > 0$ and 0 otherwise; g is a negative-binomial 1 density.[5]

The main problem in this model is accounting for the l_i, which are unobserved. In general, if we assume that l_i have a normal distribution, we could estimate the maximum likelihood estimates of the parameters of the joint distribution of $(C_i, S_i|X_i, Z_i)$ by integrating over the distribution of l_i:

$$Pr(C_i, S_i|X_i, Z_i) = \int\{f(X_i\beta_C + S_i\zeta + l_i\lambda) \times \Phi(X_i\beta_S + Z_i\delta + l_i\lambda)\phi(l_i)dl_i\}. \tag{3}$$

In this case Φ and ϕ are the standard normal cumulative distribution function and density function, respectively. However, the computational burden for accomplishing this estimate is considerable, as it does not have a closed-form solution. Instead, we rely on simulated likelihood methods, in which we average over draws from a normal distribution in estimating the likelihood function.

$$ln\ell(C_i, S_i|X_i, Z_i) \approx \sum_{i=1}^{N} ln[\frac{1}{S}\sum_{i=1}^{S}\{f(X_i\beta_C + S_i\zeta + \tilde{l}_{is}\lambda) \times \Phi(X_i\beta_S + Z_i\delta + \tilde{l}_{is}\lambda)\}]. \tag{4}$$

$\tilde{l}_i$ are draws from a standard normal distribution. We use $S = 400$ quasirandom Halton sequence draws, which are known to have efficiency properties over standard quasi random draws, for each model.[6]

[5]Tests of model fit using negative binomial 2 and negative binomial 1 densities uniformly showed that the latter did better than the former using Bayes' Information Criterion.

[6]For more details on this kind of maximum simulated likelihood model, see Deb and Trivedi (2006), Train

In both models, we use an indicator variable for whether the state in which the household resides has semi-annual or simplified reporting for households with earnings for Z. For this to be a valid instrument it should be correlated with the treatment–SNAP participation–and it should not be with correlated the outcome–self-assessed health, sick days, or doctor visits–except through the treatment. The first of these can be tested: we show the results of the significance tests of this instrument in the results below. The second cannot be directly tested, although we have estimated models in which this variable was included in the outcome equation and we found that it was not related to the outcomes we are looking at.

5 Results

5.1 Parameter Estimates

Table 2 shows the parameter estimates for each of the models described above. In the leftmost column are the results for the SAH model, while in the rightmost 3 columns are the results for the sick days, office-based visits, and outpatient visits models.

Turning first to the SAH model, we note that the covariates in the participation equation have the expected signs. Increased education reduces the probability of being on SNAP as does being married; women and black persons are more likely to participate in SNAP; being unemployed any time in the previous year, having more health conditions, participating in Medicaid, having unemployment income or income from public assistance programs, receiving SSI, and family size all increase the probability of participating in SNAP. Persons in states with simplified reporting are more likely to participate in SNAP as well. In terms of SAH, the signs of the coefficients only tell us about the direction that the variable is moving the distribution–to the left (negative coefficients: better health) or to the right (positive coefficients: worse health). We note that more education and higher wage income are associated with a leftward shift in the distribution, while unemployment, Medicaid participation, getting insurance from other public programs, being uninsured all year, public assistance and social security, and more

(2009), and Gourieroux and Monfort (1996).

health conditions are associated with a rightward shift in the distribution. The coefficient on SNAP participation is negative and highly significant, indicating that it shifts the distribution of the self-assessed to the left–toward better health.

The coefficients in the count models indicate that Blacks are more likely and Hispanics less likely to participate in SNAP. Being married reduces the probability of participation as does more education. Medicaid and public health insurance receipt, unemployment income, other program income, being uninsured all year, more health conditions and a larger family size are all correlated with participation in SNAP. Persons in states with simplified reporting requirements are more likely to participate in SNAP. In the outcome equations, we note that women and Hispanics have fewer sick days, office visits, and outpatient visits. Married persons have fewer sick days, but more office visits and outpatient visits. Education is correlated with more sick days, office visits and outpatient visits in general, while college graduates have fewer sick days. People who have been unemployed, participated in Medicaid, have unemployment income, have been uninsured for the entire year, have more health conditions, larger families, or receive public assistance report more sick days, office based visits, and outpatient visits.

The parameters ρ and λ represent the different measures of correlation between the unobservables in the selection equation and the outcome equation for self-assessed health and the count outcomes, respectively. The value of the parameter ρ–the correlation between bivariate normal errors in the two equations–indicates that SNAP participants are more likely to report worse health "before" entering SNAP–that is, selection is adverse rather than beneficial. This parameter is highly statistically significant. The parameter λ represents the loading factor on the unobservables in the two equations in the count models; as it is normalized to be one in the treatment equation, the value in table 2 can be understood to indicate the correlation between the unobservables in the outcome with unobservables in the selection equation. The values of λ indicate that the unobservables in the SNAP participation equation are positively correlated with sick days and outpatient visits in general, and negatively correlated with office-based visits.

5.2 Marginal Effects

Table 3 shows the marginal effects of SNAP on SAH. As noted above, the parameter estimate on SNAP is large, negative and significant, indicating that SNAP participation moves the distribution of SAH to the left–that is, toward better health. The marginal effects calculation clarifies the effect of SNAP on the probabilities of being reporting each level of health. The probability of reporting excellent health is increased by 6.4 percentage points, of very good health by 2.8 percentage points. At the same time, the probability of reporting good, fair, and poor health decrease by 2.1, 4.3, and 2.7 percentage points, respectively.

Because of the highly skewed distribution of predicted (and observed) outcomes in the count models, we show the entire distribution of marginal effects in the figure 1. We calculate these differences by computing the expected value of the outcomes given our model under the counterfactuals that all respondents are SNAP participants (μ_1) and then non-participants (μ_0); the marginal effects are $\mu_1 - \mu_0$.[7] We report median (rather than mean) marginal effects and show the most compact part of the support for predicted values and differences.

All of the graphs in figure 1 suggest that SNAP is related to a decrease in utilization of medical care. The median values of marginal effects for sick days, office-based visits, and outpatient visits are -1.54, -1.63, and -.08. Our model predicts that these values are less than zero at a very high level of probability.

As mentioned above, we identify the effect of SNAP through both assumptions about the distributions of the unobservables and exogenous policy variables–in this case, simplified reporting for earners participating in SNAP. In order for this instrument to be valid, it has to be correlated with the treatment that we're interested in–SNAP participation–but not with the outcome variable. The first can be checked by a test of the instruments strength in the participation equation: this is shown in table 2 by χ^2_{IV}. The values reported in the table are 13.370, 7.276, 12.02, and 10.70 for the SAH, sick days, office visits, and outpatient visits models, respectively. These are all highly significant, and are at or near the rule of thumb threshold for

[7] We show the top 90% of the distribution of differences; the fit of a non-linear model based on a highly skewed distribution is not guaranteed to work well for tail values of the distribution; our models perform poorly for about 8 percent of observations.

strong instruments in linear models (Staiger and Stock, 1997). Although the latter supposition cannot be checked, as in informal means of checking its validity, we have estimated all of the models with the instruments in the outcome equations and found none of them statistically significant. Thus, we are confident that the instrument is contributing to the identification of SNAP's effect on health and health care utilization.

6 Additional Evidence

In addition to the total number of office-based visits, we looked at the composition of visits based on their purpose. While SNAP might improve participants' overall sense of health and reduce their utilization of medical care on the whole, the income effect might also prompt participants to engage in more preventative care. MEPS provides a classification for each office based visit; for the purposes of making models tractable, we use the following division: general checkup, diagnosis or treatment, and other.[8] We show the results of these models in figure 2.

SNAP participants have fewer follow-up or other visits, but they have a higher number of office-based checkup visits than non-participants. Although the median difference is only .13 visit, this represents about a 30 percent increase from the median value of about .33 visit for this population. The total number of diagnostic visits is smaller by a fraction– -.05–at the median, although the mean difference is -2.22. The median difference in the number of diagnostic visits is smaller for SNAP participants by about 1.3.

7 Discussion

Does SNAP affect health? The research that has approached this question outside of the context of diet-related outcomes has been inconclusive and is characterized by limitations in data and methodology. This study contributes to this literature by looking at a nationally representative sample of non-elderly adults using models that account for selection into SNAP and for state-

[8]In MEPS, this category includes psychotherapy, emergency, surgical or other follow-up, immunization, vision, laser eye surgery and other. The unweighted number of cases for these categories is often very small, making model estimation in our framework difficult, so we aggregated them.

level unobservables that are correlated with both SNAP and health outcomes. We find that SNAP improves health as measured by SAH, sick days, office-based visits and outpatient visits. We also find evidence that SNAP increases participants use of office based check-up visits while other kinds of visits decrease.

One might argue that the effect measured by SNAP in the utilization models is as an index of material hardship: of course, poorer people consume fewer health resources. However, that would not explain the strong result that we get for self-assessed health or sick days. Moreover, other covariates in our model that represent receipt of public assistance or insurance (other public program income, social security income, medicaid) are all positively correlated with health care usage. Also, one of the types of utilization that might be considered a "luxury" to low-income persons–a checkup–is more likely among SNAP participants than non-participants. Further, recent theoretical work has established a good reason to expect good health to be correlated with less rather than more health care utilization in general: Galama and Kapteyn (2011) argue that people don't adjust their levels of health capital instantaneously as suggested by Grossman (1972); people who find that their current level of health capital is above their optimal threshold refrain from using health care as a way of recalibrating the health capital that they hold.

While we have not taken advantage of the panel aspect of the data here, we have estimated models dropping one of the two observations for each person in the sample and found no difference in the results. Moreover we have estimated these models for other utilization measures and found results that are similar to those shown here and/or consistent with these results. Finally, we note that we have estimated these models without controlling for state-level unobservables and found that the signs and magnitudes of the coefficients on the SNAP indicators are sometimes flipped, indicating to us the importance of controlling for these effects in studies of program effects on health.

While we think these results are a contribution to the literature on the effect of SNAP on health, the mechanism by which SNAP is working in our models is less clear. As we suggested above, it could be that extra income frees up SNAP participants to participate in non-diet-related activities that nonetheless improve their well being. Many kinds of recreation–including but not limited to exercise–might be the agent in this case. Or, SNAP could help to relieve stress that includes but goes beyond that associated with food insecurity. As the literature suggests, stress is a significant contributor to health outcomes (Juster et al., 2010). We think that these possibilities, as well as others, will be fruitful avenues for further research.

8 Figures and Tables

Table 1: Summary Statistics, Estimation Sample

	Non SNAP	SNAP
Female	0.45	0.34
	(0.00)	(0.01)
Black	0.17	0.29
	(0.00)	(0.01)
Hispanic	0.25	0.20
	(0.00)	(0.00)
Other Race	0.05	0.05
	(0.00)	(0.00)
Age	39.10	37.66
	(0.12)	(0.14)
Married	0.39	0.31
	(0.00)	(0.01)
HSGrad	0.54	0.55
	(0.00)	(0.01)
College Grad	0.07	0.02
	(0.00)	(0.00)
Grad Deg	0.08	0.04
	(0.00)	(0.00)
Unemployed in Last 12 Months	0.51	0.68
	(0.00)	(0.01)
Medicaid in Last 12 Months	0.22	0.63
	(0.00)	(0.01)

Continued

Table 1: Summary Statistics, Estimation Sample

	Non SNAP	SNAP
Uninsured All Year	0.39	0.26
	(0.00)	(0.01)
Public Insurance	0.02	0.02
	(0.00)	(0.00)
Number of Health Conditions	3.25	4.52
	(0.03)	(0.05)
Wage Income ($)	6199.11	4261.07
	(59.86)	(69.83)
Unemployent Income	88.29	123.33
	(5.67)	(8.40)
Other Program Income	21.18	490.94
	(2.14)	(15.88)
Social Security Income ($)	362.25	1016.25
	(13.03)	(29.49)
Family Size	2.86	3.44
	(0.01)	(0.02)
Excellent Health	0.19	0.13
	(0.00)	(0.00)
Very Good Health	0.27	0.20
	(0.00)	(0.00)
Good Health	0.32	0.33
	(0.00)	(0.01)
Fair Health	0.15	0.22
	(0.00)	(0.00)

Continued

Table 1: Summary Statistics, Estimation Sample

	Non SNAP	SNAP
Poor Health	0.06	0.12
	(0.00)	(0.00)
Total Sick Days	9.80	17.90
	(0.29)	(0.54)
Office Based Visits	4.64	6.73
	(0.10)	(0.17)
Outpatient Visits	0.46	0.89
	(0.03)	(0.07)
N	33423	

Summary statistics from estimation sample, persons aged 20 to 64 years old and below 130% of the federal poverty line. Standard errors in parenthesis.

Continued

Table 2: Parameter Estimates from Ordered and Count Models

	SAH	Sick Days	OB Visits	OP Visits
	SNAP Participation Equation			
Female	0.024	-0.005	0.017	0.035
	(0.017)	(0.026)	(0.026)	(0.025)
Black	0.269***	0.384***	0.335***	0.368***
	(0.03)	(0.032)	(0.034)	(0.033)
Hispanic	-0.072***	-0.124***	-0.099***	-0.129***
	(0.17)	(0.035)	(0.034)	(0.034)
Other Race	-0.011	0.043	0.013	-0.032
	(0.043)	(0.058)	(0.068)	(0.060)
Married	-0.240***	-0.384***	-0.338***	-0.349***
	(0.02)	(0.027)	(0.027)	(0.027)
HS Grad	-0.072***	-0.089***	-0.090***	-0.102***
	(0.02)	(0.026)	(0.028)	(0.025)
Colgrad	-0.464***	-0.693***	-0.557***	-0.669***
	(0.05)	(0.067)	(0.069)	(0.071)
Graddeg	-0.296***	-0.355***	-0.364***	-0.410***
	(0.04)	(0.059)	(0.057)	(0.056)
Unemployed	0.154***	0.172***	0.212***	0.232***
	(0.02)	(0.036)	(0.034)	(0.034)
Medicaid	1.106***	1.540***	1.473***	1.567***
	(0.02)	(0.035)	(0.035)	(0.034)
Public Ins	0.469***	0.443***	0.668***	0.661***
	(0.07)	(0.097)	(0.096)	(0.094)

Continued

Table 2: Parameter Estimates from Ordered and Count Models

	SAH	Sick Days	OB Visits	OP Visits
#Conditions	0.032***	0.037***	0.050***	0.047***
	(0.004)	(0.003)	(0.004)	(0.003)
Wage Income	0.005	0.006	0.008**	0.009***
	(0.00)	(0.004)	(0.004)	(0.003)
UE Income	0.034***	0.046***	0.047***	0.050***
	(0.01)	(0.006)	(0.006)	(0.006)
UninsAllYr	0.458***	0.666***	0.601***	0.661***
	(0.03)	(0.035)	(0.034)	(0.034)
Public Inc	0.132***	0.180***	0.181***	0.187***
	(0.00)	(0.005)	(0.005)	(0.005)
SSI Income	0.029***	0.025***	0.025***	0.026***
	(0.00)	(0.004)	(0.005)	(0.004)
Famsize	0.156***	0.214***	0.212***	0.218***
	(0.01)	(0.007)	(0.007)	(0.007)
Simplify	0.124***	0.134***	0.152***	0.147***
	(0.04)	(0.047)	(0.045)	(0.047)
		Outcome Equation		
Female	0.114***	-0.168***	-0.358***	-0.242***
	(0.02)	(0.040)	(0.031)	(0.036)
Black	0.085***	0.246***	-0.228***	-0.050
	(0.02)	(0.043)	(0.032)	(0.041)
Hispanic	0.047***	-0.577***	-0.005	-0.102**
	(0.02)	(0.051)	(0.031)	(0.045)

Continued

Table 2: Parameter Estimates from Ordered and Count Models

	SAH	Sick Days	OB Visits	OP Visits
Other Race	0.016	0.021	-0.272***	-0.193**
	(0.03)	(0.068)	(0.085)	(0.087)
Married	0.004	-0.408***	0.259***	0.094**
	(0.02)	(0.040)	(0.028)	(0.037)
HS Grad	-0.201***	0.068*	0.125***	0.084**
	(0.03)	(0.040)	(0.035)	(0.033)
Colgrad	-0.517***	-0.569***	0.318***	-0.050
	(0.03)	(0.067)	(0.061)	(0.094)
Graddeg	-0.383***	0.013	0.347***	0.137**
	(0.03)	(0.088)	(0.051)	(0.063)
Unemployed	0.086***	0.136**	0.139***	0.138***
	(0.02)	(0.060)	(0.034)	(0.049)
Medicaid	0.216***	1.126***	-0.293***	0.109*
	(0.03)	(0.053)	(0.034)	(0.063)
Public Ins	0.133***	0.096	-0.305***	0.134
	(0.05)	(0.111)	(0.079)	(0.094)
# Conditions	0.139***	0.267***	0.165***	0.111***
	(0.001)	(0.004)	(0.005)	(0.006)
Wage Income	-0.019***	-0.003	-0.008**	-0.017***
	(0.001)	(.006)	(0.004)	(0.005)
UE Income	0.079***	0.022***	-0.012**	0.003
	(0.003)	(0.006)	(0.005)	(0.008)
UninsAllYr	0.180***	0.283***	-0.854***	-0.608***

Continued

Table 2: Parameter Estimates from Ordered and Count Models

	SAH		Sick Days	OB Visits	OP Visits
	(0.02)		(0.052)	(0.031)	(0.051)
Public Inc	0.016***		0.117***	-0.059***	0.020**
	(0.004)		(0.008)	(0.005)	(0.008)
SSI Income	0.029***		0.027***	-0.006	0.002
	(0.002)		(0.005)	(0.005)	(0.005)
Famsize	-0.0177***		0.073***	-0.125***	-0.053***
	(0.005)		(0.010)	(0.008)	(0.012)
SNAP	-0.270***		-2.153***	1.544***	-0.257**
	(0.08)		(0.044)	(0.029)	(0.130)
ρ	0.201***	λ	2.113***	-1.310***	0.324***
	(0.05)		(0.021)	(0.020)	(0.107)
μ_1	-0.746***	$ln(\delta)$	1.311***	-0.204**	1.900***
	(0.22)		(0.062)	(0.090)	(0.075)
μ_2	0.0801				
	(0.22)				
μ_3	1.136***				
	(0.22)				
μ_4	2.120***				
	(0.22)				
χ^2_{IV}	13.370***		7.276**	12.202***	10.070***
	(.008)		(.026)	(.002)	(.007)
N			33278		

Continued

Table 2: Parameter Estimates from Ordered and Count Models

SAH	Sick Days	OB Visits	OP Visits

Parameters from models described in text. State and year fixed effects, intercepts, and coefficient on exposure not shown. Standard errors are in parenthesis. ***p<.01, **p<.05, *p<.10.

Table 3: Marginal Effects of SNAP on SAH, 130% FPL

Parameter (se) : -.227*** (.08)				
Excellent	Very Good	Good	Fair	Poor
0.064***	.028***	-.023***	-.041***	-.036***
(.026)	(.010)	(.008)	(.014)	(.013)
N		33278		

Average marginal effects of SNAP on SAH, calculated from treatment effects ordered probit as described in text.

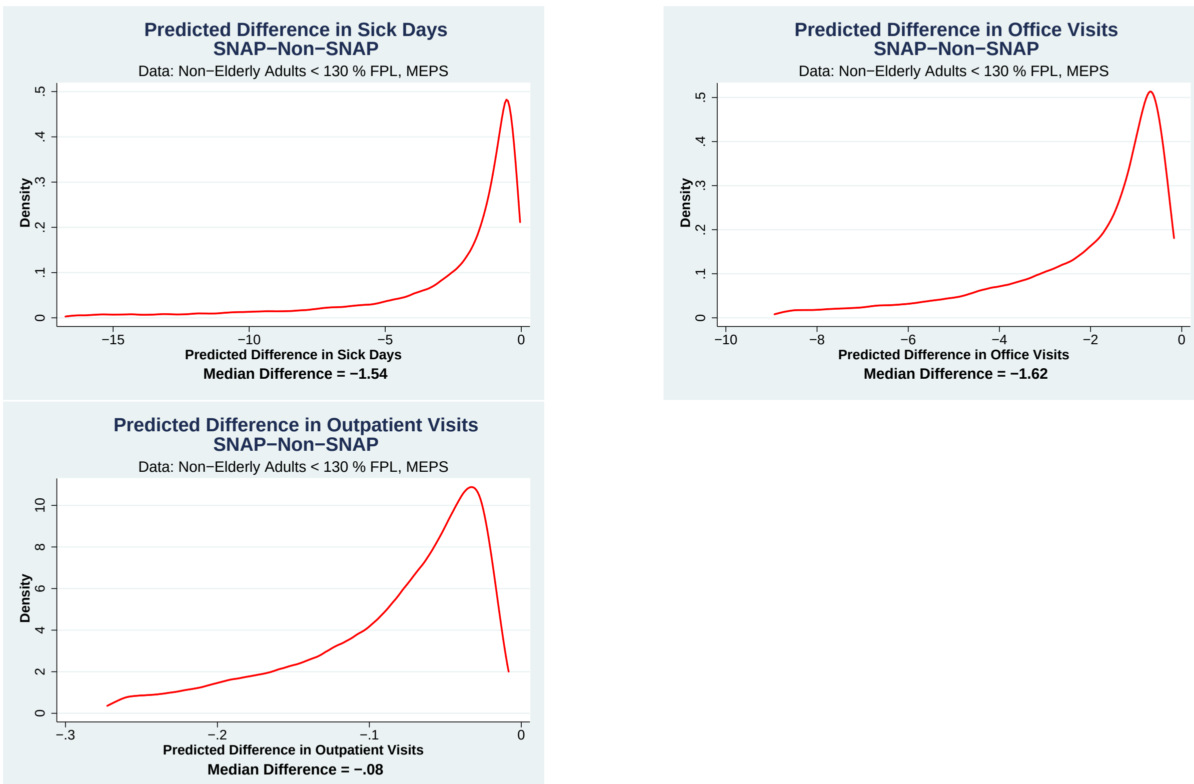

Figure 1: Distribution of Marginal Effects: Count Outcomes in MEPS

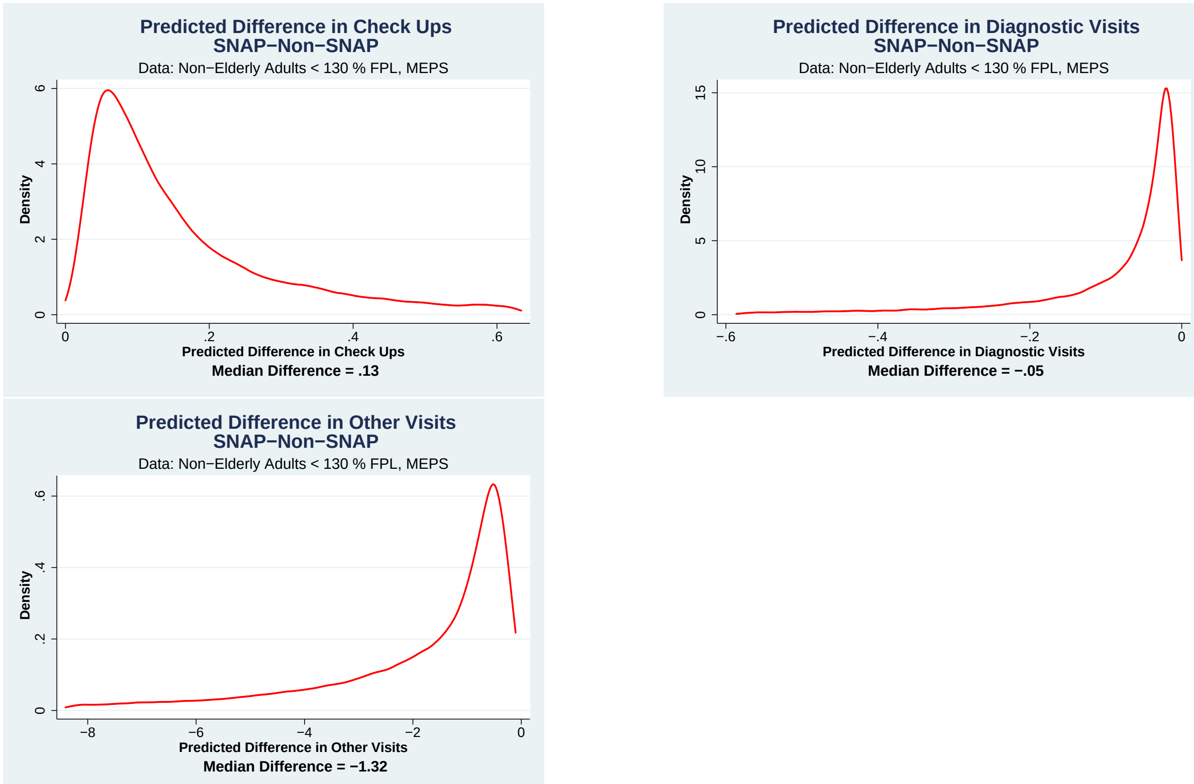

Figure 2: Distribution of Marginal Effects: Types of Office Visits in MEPS

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