The Within-Month Pattern of Medical Care Utilization among SNAP Participants

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Abstract

This paper investigates the implications of the SNAP benefit cycle on medical care consumption. We use the Medical Expenditure Panel Survey (MEPS) from 1996-2013 to empirically examine whether there is any decrease in medical care utilization near the end of the benefit month when benefits are exhausted for some households. To explain the end of the month shift in consumption behavior, we analyze a two-period model of intra-household decision-making. We assume that mothers control SNAP benefits, but those benefits are exhausted towards the end of the month. The fact that cash income must be used to purchase food at the end of the benefit month reduces mothers' power over the budget. We then show that this change in power leads to a cyclical pattern in a household's food and non-food expenditures. To test these theoretical predictions, we disaggregate households into two-parent and single-parent households, and compare the timing of medical care utilization for SNAP participants and eligible non-participants. We aggregate medical treatment visits by week of the month, which allows us to examine whether the likelihood of having any visit will be affected by the exhaustion of SNAP benefits in the last week. To control for the potential endogeneity of SNAP participation, we use instrumental variable methods. In addition, we exploit the panel structure of the MEPS and estimate a correlated random effects specification. Our findings indicate that medical care utilization declines at the end of the benefit month, but that this decline occurs mainly in two-parent SNAP households as opposed to single-parent SNAP households. This result is consistent with our theory model indicating that the SNAP benefit cycle results in substitution away from non-food goods at the end of the benefit month in two-parent households, but not in single-parent households.

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1. Introduction

The Supplemental Nutrition Assistance Program (SNAP, formerly the Food Stamp Program) is the largest public assistance program in the U.S, providing an average of 255 dollars per month to more than 21 million participant households in fiscal year 2016. Although, the program plays a leading role in preventing malnutrition by supplementing food budgets and freeing up income for nonfood expenditures, the benefits last an average of just two to three weeks for most recipients (Castner and Henke 2011). This behavior whereby SNAP participants exhaust their benefits non-uniformly over the course of the month is known as SNAP benefit cycle and has been found to have negative effects on beneficiaries. In this paper we consider whether the SNAP benefit cycle might alter consumption pattern of medical care. In particular, we investigate whether benefit-receiving households change their medical care utilization behavior towards the end of the benefit month.

There is a growing literature demonstrates that receipt timing affects food consumption behavior. For example, Wilde and Ranney (2000) find that many SNAP households, and in particular those who shop infrequently, experience a reduction in food energy intake at the end of the benefit month. SNAP households also purchase food at different locations across the benefit month (Damon, King and Leibtag 2013). In particular, households reduce their purchases of food eaten at home (FAH) from grocery stores and superstores at the end of the month, and purchase more FAH from convenience stores and food eaten away from home (FAFH). These findings suggest that food security and nutrient intake may drop at the end of the month among SNAP households. In support of this hypothesis, Todd (2015) demonstrates that calorie intake declined by as much as 25 percent at the end of the benefit month for SNAP households prior to the increase in SNAP benefits instituted under the American Recovery and Reinvestment Act. Likewise, Hamrick and Andrews (2016) show that SNAP participants have an increasing probability of experiencing a day with no eating occurrences over the benefit month.

Under the permanent income hypothesis framework these results are puzzling, as consumption should be unrelated to when expected income is received. Researchers have put forward alternative hypotheses for the lack of consumption smoothing among benefit-receiving households. In a recent study, Smith et al. (2016) find empirical support for the hypothesis that short-run impatience contributes to the SNAP benefit cycle and that non-fungibility of income can exacerbate the effect of impatience on consumption decisions. On the other hand, prior studies of food stamp households suggest that intra-household resource allocation decisions may have a significant impact on food purchases and nutrition. For example, Breunig and Dasgupta (2005) construct a noncooperative model of intra-household decision-making and use it to demonstrate that food purchases in multiple-adult SNAP households would decrease if their benefits were replaced with a cash transfer.

Although the benefit must be spent on food consumption, the benefit cycle may also have implications on participants' medical care consumption behavior. Conceptually, there are two reasons why medical care utilization may be impacted by SNAP benefit timing. First, the end of month change in nutritional availability and food access have adverse effects on participants' health status and consequently medical care utilization. Second, households may postpone their non-food purchases, such as those for medical care to free up cash income for food purchases when the benefits are exhausted. However, the reduction in the consumption of non-food goods at the end of month is not sufficient to smooth food consumption.

While most recent studies on SNAP households have focused on food-related issues and the role of program on health outcomes, there are relatively few studies on medical care consumption among SNAP participants. For example, Nicholas (2011) investigated whether participation in SNAP can improve diabetes health outcomes, and found no significant change in their medical spending or diet-related outcomes compared to eligible non-participants. In a related study, Heflin, Hodges and Mueser (2016) use administrative data from the Missouri SNAP and Medicaid programs to examine whether the timing of the benefits affects the within-month pattern of emergency room visits for hypoglycemia, and find no evidence of a cyclical pattern. In contrast, Gregory and Deb (2015) find that nonelderly SNAP participants have fewer doctor visits and better self-reported health outcomes than comparable non-participants, but more checkup visits. Likewise, Berkowitz, Seligman and Basu (2017) conclude that SNAP participation is associated with lower subsequent healthcare expenditures. While not restricted on SNAP participants, Seligman et al. (2014) show that inpatient admissions for hypoglycemia increased by 27 percent in the last week of the month relative to the first week for the low-income population.

We use the Medical Expenditure Panel Survey (MEPS) from 1996-2013 to empirically examine whether there is any decrease in medical care utilization near the end of the benefit month among SNAP participants. In order to determine the mechanisms that underlie the relationships observed in the data, we develop a two-period model of intra-household decision making, and use it to investigate the possibility that the benefit cycle influences intra-household distribution of power and consumption behavior in two-parent households. Using an instrumental variable approach, and panel data techniques to control for the potential endogeneity of SNAP participation, we find that participation in SNAP increases the use of medical services among households with children. In accordance with our theory model, our findings suggest that there is a reduction in the probability of seeking medical care at the end of the month in two-parent households, but not single-parent households. The decline in medical utilization of two-parent households over the benefit month is particular to emergency room and outpatient visits. Finally, in order to understand how resources pass-through from parents to children, we estimate our IV model separately for children and adults. While we find that SNAP participation among children in two-parent households increases the probability of having emergency room visits and inpatient stays, the change in medical utilization at the end of the benefit month is not statistically different from zero. In contrast, we find that SNAP participation reduces the probability that an adult in a two-parent household has an emergency room visit at the end of the benefit cycle by 0.6 percentage points.

This article makes two main contributions to the literature. First, we study the consequences of the SNAP benefit cycle on medical care utilization. This provides further evidence that there is a behavioral response to the timing of SNAP benefits. Second, we investigate whether the effect varies by household composition. The latter in conjunction with our theoretical analyses allows us to determine the extent to which intra-household allocation of resources contributes to the end of the month changes in the level of consumption.

The remainder of this article is organized as follows. The second section builds a dynamic model of intra-household decision-making, and outlines the conceptual framework. The third section discusses our empirical framework. We then describe the data. Major empirical results are presented in the fifth section. We conclude in the last section.

2. A theoretical model of intra-household decision-making

To show how changes in power between mothers and fathers in two-parent households can explain shifts in consumption behavior, we analyze a two-period model of intra-household decision-making using the framework proposed by Breunig and Dasgupta (2005).

The utility function for member i is time separable[2] and strictly quasi-concave, and represented by $U_i(C_1,\ C_2, M_1^c, M_2^c, M_{1i}, M_{2i})$, where $i \in \{m\ (mother),\ f\ (father)\}$, C_t is the level of expenditures on food in period t. Food is used for both parents' private food expenditures and some public consumption. M_{ti} is member i's private medical care spending in period t, and M_t^c is the level of expenditure on public medical care consumption, also in period t. A natural interpretation for M_t^c is the amount spent on children's medical care consumption.

A two-parent household with two income earning members receives s amount of SNAP benefit. We assume that mothers have responsibility for purchasing food. In period 1, all the food eaten at home is purchased with the SNAP benefit. In period 2, in addition to the surplus benefit from the first period, parents contribute to the food budget from their own cash income. As a result, the allocation rule is determined collectively in the second period.

The solution to the problem can be thought of as a two-stage process. We analyze the game by first deriving the equilibrium in period 2 for any given first-period allocation of food and non-food expenditures. Thus, each member's optimization program in the second period is:

$$\max_{C_2, M_{2i}, M_2^c} U_i(C_1,\ C_2, M_1^c, M_2^c, M_{1i}, M_{2i}), \tag{1}$$

subject to the budget constraint,

$$C_2 + M_{2i} + M_2^c = w^i + s + c_{1k} + c_{2k} + m_{1k} + m_{2k} - C_1 - M_1^c - M_{1i}, \tag{2}$$

where w^i denotes the wage earned by member i, c_{tk} represents the other income earner's contribution to food purchases in period t, and m_{tk} represents his/her contribution to public medical care expenditures in period t. From the first-order conditions, the solutions to the father's period-2 optimization program are functions of his budget that remains in period 2:

[2] Specifically, we assume that the marginal rate of substitution in period t does not depend on the level of expenditures in other periods.

$$C_2 = g^f\big(w^f + s + c_{1m} + c_{2m} + m_{1m} + m_{2m} - C_1 - M_1^c - M_{1f}\big), \tag{3}$$

$$M_{2f} = h^f\big(w^f + s + c_{1m} + c_{2m} + m_{1m} + m_{2m} - C_1 - M_1^c - M_{1f}\big), \tag{4}$$

$$M_2^c = l^f\big(w^f + s + c_{1m} + c_{2m} + m_{1m} + m_{2m} - C_1 - M_1^c - M_{1f}\big). \tag{5}$$

where $g^f(\cdot)$, $h^f(\cdot)$, and $l^f(\cdot)$ are strictly increasing functions. Similarly, the solution to the mother's optimization problem can be characterized as follows:

$$C_2 = g^m\big(w^m + s + c_{1f} + c_{2f} + m_{1f} + m_{2f} - C_1 - M_1^c - M_{1m}\big), \tag{6}$$

$$M_{2m} = h^m\big(w^m + s + c_{1f} + c_{2f} + m_{1f} + m_{2f} - C_1 - M_1^c - M_{1m}\big), \tag{7}$$

$$M_2^c = l^m\big(w^m + s + c_{1f} + c_{2f} + m_{1f} + m_{2f} - C_1 - M_1^c - M_{1m}\big). \tag{8}$$

where $g^m(\cdot)$, $h^m(\cdot)$, and $l^m(\cdot)$ are strictly increasing on available budget. We also include the following additional constraint for food expenditures, and public medical expenditures in period 2:

$$C_2 = c_{2f} + c_{2m} + s - C_1 + c_{1m} + c_{1f}, \tag{9}$$

$$M_2^c = m_{2f} + m_{2m} + m_{1f} + m_{1m} - M_1^c. \tag{10}$$

Given our non-negativity assumption for each parents' contribution, constraint (9) imposes the restriction that the surplus SNAP benefit from first period must be allocated towards food purchases in the second period. In addition, equations (9) and (10) enforce the restriction that other income earner's contributions to food and public medical care expenditures cannot be allocated for other purposes. The Nash equilibrium in period 2 for any given first-period allocation of food and nonfood expenditures is as follows:

$$C_2^* = C_2(w^f + w^m + s - C_1 - M_{1f} - M_{1m} - M_1^c), \tag{11}$$

$$M_2^{c*} = C_2\big(w^f + w^m + s - C_1 - M_{1f} - M_{1m} - M_1^c\big), \tag{12}$$

$$M_{2f}^{*} = M_2^{f}\left(w^f + w^m + s - C_1 - M_{1f} - M_{1m} - M_1^c\right), \tag{13}$$

$$M_{2m}^{*} = M_2^{m}\left(w^f + w^m + s - C_1 - M_{1f} - M_{1m} - M_1^c\right). \tag{14}$$

We now turn to intra-household allocation in the first period. To determine optimal first period allocations, we assume that the father does not contribute any cash income for first period allocation of food expenditures. As a result, the mother determines the level of food expenditures in period 1 by maximizing her utility function:

$$\max_{C_1, M_{1m}, M_1^c} U_m\left(C_1, M_1^c, M_{1m}, C_2^*(\cdot), M_1^{c*}(\cdot), M_{2m}^*(\cdot)\right), \tag{15}$$

which provides the following first order condition:

$$\begin{aligned}&\frac{\partial U_m(\cdot)}{\partial C_1} + \frac{\partial U_m(\cdot)}{\partial C_2}\frac{\partial C_2^*(\cdot)}{\partial C_1} + \frac{\partial U_m(\cdot)}{\partial M_{2m}}\frac{\partial M_{2m}^*(\cdot)}{\partial C_1} + \frac{\partial U_m(\cdot)}{\partial M_2^c}\frac{\partial M_2^{c*}(\cdot)}{\partial C_1}\\ &\qquad = \frac{\partial U_m(\cdot)}{\partial C_1} + \lambda_m\frac{\partial C_2^*(\cdot)}{\partial C_1} + \lambda_m\frac{\partial M_{2m}^*(\cdot)}{\partial C_1} + \lambda_{\mathrm{m}}\frac{\partial M_2^{c*}(\cdot)}{\partial C_1} = 0.\end{aligned} \tag{16}$$

Likewise, the first-period allocation of budget for member i's private expenditures is determined by the following first-order condition:

$$\begin{aligned}&\frac{\partial U_i(\cdot)}{\partial M_{1i}} + \frac{\partial U_i(\cdot)}{\partial C_2}\frac{\partial C_2^*(\cdot)}{\partial M_{1i}} + \frac{\partial U_i(\cdot)}{\partial M_{2i}}\frac{\partial\, M_{2i}^*(\cdot)}{\partial M_{1i}} + \frac{\partial U_m(\cdot)}{\partial M_2^c}\frac{\partial M_2^{c*}(\cdot)}{\partial M_{1i}}\\ &\qquad = \frac{\partial U_i(\cdot)}{\partial M_{1i}} + \lambda_{\mathrm{i}}\frac{\partial C_2^*(\cdot)}{\partial M_{1i}} + \lambda_{\mathrm{i}}\frac{\partial\, M_{2i}^*(\cdot)}{\partial M_{1i}} + \lambda_{\mathrm{i}}\frac{\partial M_2^{c*}(\cdot)}{\partial M_{1i}} = 0,\end{aligned} \tag{17}$$

where λ_{i} is the Lagrange multiplier for member i's optimization problem in the second period. The first derivatives of the mother's budget constraint provide:

$$\frac{\partial C_2}{\partial C_1} + \frac{\partial M_{2m}}{\partial C_1} + \frac{\partial M_2^c}{\partial C_1} + \frac{\partial C_1}{\partial C_1} = \frac{\partial c_{2f}}{\partial C_1} + \frac{\partial m_{2f}}{\partial C_1}, \tag{18}$$

and

$$\frac{\partial C_2}{\partial M_{1m}} + \frac{\partial M_{2m}}{\partial M_{1m}} + \frac{\partial M_2^c}{\partial M_{1m}} + \frac{\partial M_{1m}}{\partial M_{1m}} = \frac{\partial c_{2f}}{\partial M_{1m}} + \frac{\partial m_{2f}}{\partial M_{1m}}. \tag{19}$$

The first derivative of father's budget constraint yields:

$$\frac{\partial C_2}{\partial M_{1f}} + \frac{\partial M_{2f}}{\partial M_{1f}} + \frac{\partial M_2^c}{\partial M_{1f}} + \frac{\partial M_{1f}}{\partial M_{1f}} = \frac{\partial c_{2m}}{\partial M_{1f}} + \frac{\partial m_{2f}}{\partial M_{1f}}. \tag{20}$$

Combining (16), and (18) , the optimal solution for food expenditures in period 1 satisfies the following condition:

$$\frac{\partial U_m(.)}{\partial C_1} + \lambda_m \frac{\partial c_{2f}}{\partial C_1} + \lambda_m \frac{\partial m_{2f}}{\partial C_1} - \lambda_m = 0. \tag{21}$$

Similarly, combining (17), (19) provides the following expression for the optimal solution for first period allocation of private medical expenditures for the mother:

$$\frac{\partial U_m(.)}{\partial M_{1m}} + \lambda_m \frac{\partial c_{2f}}{\partial M_{1m}} + \lambda_m \frac{\partial m_{2f}}{\partial M_{1m}} - \lambda_m = 0, \tag{22}$$

And the optimal solution for first period allocation of the father's private medical expenditures satisfies the following condition:

$$\frac{\partial U_f(.)}{\partial M_{1f}} + \lambda_f \frac{\partial c_{2m}}{\partial M_{1f}} + \lambda_f \frac{\partial m_{2m}}{\partial M_{1f}} - \lambda_f = 0. \tag{23}$$

Therefore, the Nash equilibrium in period 2 satisfies the followings:

$$\frac{\partial U_m(.)}{\partial C_1} = \lambda_m - \lambda_m \frac{\partial c_{2f}}{\partial C_1} - \lambda_m \frac{\partial m_{2f}}{\partial C_1}, \tag{24}$$

and

$$\frac{\partial U_i(.)}{\partial M_{1i}} = \lambda_i - \lambda_i \frac{\partial c_{2k}}{\partial M_{1i}} - \lambda_i \frac{\partial m_{2k}}{\partial M_{1i}}. \tag{25}$$

In Appendix, we show that $0 < \frac{\partial c_{2f}}{\partial C_1} + \frac{\partial m_{2f}}{\partial C_1} < 1$, and $0 < \frac{\partial c_{2k}}{\partial M_{1i}} + \frac{\partial m_{2k}}{\partial M_{1i}} < 1$, which allow us to identify the following relationship between the first and second period optimal solutions:

$$\frac{\partial U_m(.)}{\partial C_1} < \frac{\partial U_m(.)}{\partial C_2}, \tag{26}$$

$$\frac{\partial U_i(.)}{\partial M_{1i}} < \frac{\partial U_i(.)}{\partial M_{2i}}, \tag{27}$$

which imply the followings:

$$C_1^* > \ C_2^* \ , M_{1i}^* > M_{2i}^*. \tag{28}$$

In words, at the equilibrium point, the level of expenditures on food and private non-food consumption are lower in the second period than the first period. This holds irrespective of parents' preferences for food consumption. We summarize our findings in the following proposition:

Proposition1. Assume that one member has more control over the SNAP payment within a household. Then, the level of expenditures on food and private non-food consumption will go down at the end of benefit month when the benefits are exhausted.

Intuitively, the fact that cash income must be used to purchase food at the end of the month changes the total income individually available, and consequently the balance of power in two-parent households. This change in power leads to a cyclical pattern in a household's food, and non-food expenditures at the end of the benefit month. However, this result does not apply to public medical care expenditure. We are not able to predict the relationship between the first and second period optimal public medical care expenditure in our theory model, but we answer this question empirically when we test whether the SNAP benefit cycle alters medical care consumption among children.

It is worth noting that if intra-household bargaining is a dominant factor for the changes in the level of consumption, single-parent households are expected to smooth their consumption over the course of the month. Through this framework we generate similar predictions on consumption behavior of non-SNAP two-parent households, since the shift in power results from SNAP participation.

3. Empirical Models

Our goal is to test the implications of our theory model using individual-level data on medical service consumption. However, we are not able to fully identify the relationship between data and theory due to the lack of information on food consumption. In order to determine whether the differences in power amongst parents affects intra-household allocations differently towards the end of the benefit cycle, we compare the timing of the medical treatment visits for SNAP participants and those that are eligible for, but do not participate in the program. Since enrollment into SNAP is non-random, we account for this in our empirical strategy using both an instrumental variable approach and panel data techniques (Meyerhoefer and Yang 2011).

3.1. Instrumental variable approach

In order to test whether the likelihood of having treatment visits might be affected by the exhaustion of the SNAP benefits in the last week, we aggregate treatment visits (i.e. emergency room, inpatient, and outpatient visits) by week of the month for each individual. To identify the causal effects of benefit cycle on medical care utilization, we rely on instrumental variables strategy in a recursive bivariate probit model. The recursive structure builds on a first equation for the potentially endogenous SNAP participation status and a second equation determining medical care utilization for each type of medical service among SNAP-eligible individuals using a latent variable approach as follows:

$$\Pr(SNAP_i = 1) = \Phi(\lambda Z_i + X_i\varphi), \tag{29}$$

$$\Pr(m_{iw} = 1) = \Phi(\textstyle\sum_{k=1}^{4} \alpha_k D_k + \beta SNAP_i + \gamma SNAP_i \times wgt_{iw} + X_i\psi), \tag{30}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. Z_i, our instrument for SNAP participation, is a state-level dummy variable indicating whether the state operates call centers. m_{iw} is the binary measure of individual i's utilization of medical care in week w, D_k is a binary variable that indicates the week of the month, $SNAP_i$ is an indicator variable equal to unity if individual i is a SNAP recipient. wgt_{iw} is the probability that week w is the last week in the benefit month for individual i.[3] X_i is a vector of covariates including demographics, insurance coverage, socioeconomic status, self-reported health status and disability. We assume that the error terms $(\varepsilon_{iw}, \upsilon_i)$ is independent of Z_i, and distributed as bivariate normal with mean zero. Each has unit variance, and $\rho = corr(\varepsilon_{iw}, \upsilon_i)$. Under these assumptions, coefficient β represents the causal effect of participation in SNAP on medical care utilization when the recipient is not at the end of the benefit month. Under the same conditions, γ indicates the causal effect of being at the end of the benefit cycle on a SNAP recipient's decision to use medical services.

State-level variables from the SNAP policy database have been widely used in the literature as instruments for SNAP participation (See, for example, Meyerhoefer and Pylypchuk 2008, Yen et al. 2008, Ratcliffe et al. 2011, Gregory and Deb 2015, Almada, McCarthy and Tchernis 2016). The functions of call centers vary widely by state. Most call centers allowed clients to report changes, answered general questions for clients, and provided case information. Few call centers completed initial application interviews and certified cases. Call centers improve program access, as a result, households in states in which call center services are available are more likely to participate in SNAP. As of 2011, 33 states offered call center services compared to only 6 states

[3] We also estimate our models after including wgt in addition to the interaction term, and find similar results. Importantly, the estimated coefficient on wgt is not statistically different from zero.

in 2000, and no states in 1996 based on information in the Economic Research Service's SNAP policy database.

The validity of our results depends on exclusion restriction. However, the exogeneity of instruments is difficult to validate. In addition, policy endogeneity is a concern whenever policies are used as instruments. Because we are concerned that states which operates call centers may differ in important ways from those which do not, we control in our models for a number of state characteristics relating to income, and education. We control for state-level data on per-capita income, poverty rate, unemployment rate and educational attainment obtained from U.S. Census Bureau in order to reduce the potential for the estimates to be confounded by policy endogeneity (see, for example, Cawley, Frizvold and Meyerhoefer 2013). However, it is possible that even controlling for these observed characteristics, there may remain a problem of policy endogeneity that would imply our instrument is invalid. For further investigation, we pursue a second approach that does not require the exclusion restriction.

3.2. Correlated random effects approach

In our second approach, we exploit the longitudinal nature of MEPS to account for non-random selection into the SNAP program in the following specification:

$$\Pr(m_{iwt} = 1) = \Phi(\textstyle\sum_{k=1}^{4} \alpha_k D_k + \beta SNAP_{it} + \gamma SNAP_{it} \times wgt_{iwt} + X_{it}\psi + c_i), \qquad (31)$$

where c_i is a stochastic time-invariant individual specific effect that captures unobserved determinants of medical care utilization. In non-linear specifications when time series dimension of the panel is fixed, estimation of common parameters of interest jointly with c_i as fixed effects usually leads to inconsistent estimates (Cameron and Trivedi, 2005). As an alternative, Chamberlain (1980) proposed a random effects estimator that is consistent when T is fixed and that allows c_i to be correlated with all the regressors in all time periods. Therefore, we assume c_i is correlated with regressors via the following:

$$c_i = \lambda_1 \tilde{X}_{i1} + \lambda_2 \tilde{X}_{i2} + \cdots + \lambda_T \tilde{X}_{iT} + u_i, \tag{32}$$

where $\tilde{X}$ is a vector of all the model regressors for time t, and u_i is assumed to be orthogonal to $\tilde{X}$, and distributed as $N(0, \sigma_u^2)$. Substituting into (31), we have:

$$\Pr(m_{iwt} = 1) = \Phi(\lambda_1 \tilde{X}_{i1} + \lambda_2 \tilde{X}_{i2} + \cdots + (\tilde{\beta} + \lambda_t)\tilde{X}_{it} + \cdots + \lambda_T \tilde{X}_{iT}). \tag{33}$$

We follow Meyerhoefer et al. (2005) and use a two-step procedure to consistently identify the coefficients of interest. First, consistent estimates of the reduced-form parameters are obtained from equation-by-equation estimation of (33), followed by identification of the structural parameters, through minimum distance estimation:

$$\min D(\psi) = (\hat{\pi} - H\psi)'\hat{\Omega}^{-1}(\hat{\pi} - H\psi), \tag{34}$$

where ψ denotes the vector of structural parameters, $\hat{\pi}$ is the vector of reduced-form parameters obtained from the first step, $\hat{\Omega}$ is the estimated variance-covariance matrix of $\hat{\pi}$, and H is a design matrix mapping the structural parameters to the reduced-form estimates.

For all of our models, we calculate the marginal effect of a SNAP participant being at the end of the benefit month on medical care utilization as:

$$ME = Pr(m = 1|SNAP = 1, SNAP \times wgt = 1, X) - Pr(m = 1|SNAP = 1\,, SNAP \times wgt = 0, X). \tag{35}$$

4. Data

The main source of data for our empirical analysis is the 1996-2013 Medical Expenditure Panel Survey (MEPS). The MEPS is a nationally representative survey of households, and their medical care providers. MEPS contains detailed information for each individual in the household on demographic characteristics, socioeconomic status, health status, and health insurance coverage. Respondents are also interviewed about their medical care use over the course of two years through five rounds.

We restrict our sample to households with at least one child under age 18 to be consistent with the assumptions of our theory model. We exclude households with a parent younger than age 20 or older than age 50. In order to test the implications of our theory model, we further disaggregate our sample to single-parent and two-parent households. If the parent was not married, but cohabitated with another adult, we group the household as a two-parent household.

MEPS respondents are asked whether anyone in the household received food stamps in the past year and for how many months. The SNAP participation dummy is set to 1 if the household received food stamps in any of the twelve months, and 0 otherwise. We construct a group of eligible households. To be eligible for the SNAP, a household has to pass gross income, net income, and asset tests. Since our data does not contain information on household assets, we simulate the gross income, and net income tests to determine households' eligibility status.[4] The Gross monthly income limits and net monthly income limits are set at 130, and 100 percent of the poverty level for the household size, respectively (USDA, 2016b).[5] In accordance with eligibility rules, we exempt households from the gross income test if they are an SSI recipient due to a disability or any household member is 60 years of age or older. To pass the net income test, a number of deductions are allowed. Households are able to deduct dependent care expenses and shelter costs (for details, see USDA, 2016a). The MEPS does not contain information on housing costs or child care payments, so we impute this information using state-level market rate amount

[4] When estimating panel data models, we define the eligibility status based on the first-year observation of individuals.
[5] Monthly income eligibility standards for 1996-2003 were obtained from USDA/FNS.

for child care centers from National Women's Law Center (Schulman and Blank 2014) and the average monthly shelter expenses from Center on Budget and Policy Priorities (Rosenbaum, Tenny, and Elkin 2002). Able bodied adults without dependents (ABAWD) are required to work or participate in a work program for at least 20 hours per week in order to receive SNAP benefits for more than 3 months in a 36-month period. States may request to waive the ABAWD time limit in areas with an unemployment rate above 10 percent or a lack of sufficient jobs. We do not have data on ABAWD waivers, so we exclude ABAWDs who work less than 20 hours per week from our sample.

In MEPS, each medical event record includes the date of the visit. As a measure of medical utilization, we aggregate medical treatment visits by week of the month for SNAP participants and eligible non-participants. We drop any events where the date of treatment visit is missing, and define the first seven days of the month as week1 and the last seven days of the month as week 4. The remaining days of the month are split evenly between what we defined as week 2 and week 3, with the extra day added to week 3 as needed.

Not all states issue SNAP benefits on the same day of the month to all households, nor do they all issue benefits at the very beginning of the calendar month. In addition, it is not the case that every household in the state receives benefits on the same day, and some states may choose to spread the distribution of benefits to recipients throughout the month (USDA, 2016b). One limitation of this study is that the MEPS does not include information on the date when each household last received SNAP benefits, so it is impossible to determine the last week of benefit month for all SNAP recipients with certainty. Therefore, using state and county codes in the restricted-use MEPS, we merge the historical monthly SNAP benefit issuance schedule in each state to MEPS to calculate the probability that each calendar week is the last week of the benefit month. We dropped Alabama, Illinois, Missouri, Mississippi and New Mexico from our sample, since their benefit payments have been spread over a large number of days.[6]

We control for a full set of socio-demographic characteristics, health status and insurance coverage variables in our models. Our main control variables include age (dichotomous indicators for age 7–17, 18–30, 31–45, 31–45, 46–60 , 61–75, age 76 and older with age 0–6 being the omitted category), gender, race and ethnicity (Hispanic, Black, and other with White being the omitted category), region (South, Midwest, and West with Northeast omitted), urban residence, education (high school diploma, any college with less than a high school degree omitted), number of children in the household, and log of income earned by family members (normalized by household size), and insurance coverage (Medicare, Medicaid, Private with uninsured omitted). In order to control for health status, we use self-reported mental and physical status and disability status which indicates whether a person has any IADL (Instrumental Activities of Daily Living), ADL (Activities of Daily Living), functional, activity, or sensory limitations in any rounds of interview. Table 1 contains descriptive statistics of all the variables we used in the analysis. The first two column present means for two-parent households by SNAP participation status. The next two columns contain means for single-parent households.

5. Empirical Results

We estimate our models separately for two-parent and single-parent households. In Appendix A, we report full estimation results for two-parent households for our IV model in table A1 as well as the CRE model in table A2.[7] The Standard errors for our IV model are clustered at

[6] Benefits are made available over 20 days in New Mexico and Alabama, 22 days in Missouri, 18 days in Mississippi, and on the 1st, 3rd, 4th, 5th, 6th, 7th, 8th, 9th, 10th, 13th, 17th, and 20th of every month in Illinois.
[7] Complete estimation results from IV model as well as estimation results for the CRE for single-parent households are available from the authors upon request.

the state level, while for the CRE model we calculate standard errors using Balanced Repeated Replication (BRR) in order to account for the complex design of the MEPS. In the CRE model, the random effect capturing unobserved heterogeneity was specified to be correlated with SNAP participation, self-reported physical and mental health variables, disability status, log of family income and insurance coverage.

We present the estimated marginal effect of participation in SNAP, and the marginal effect of being at the end of the benefit cycle on recipient's decision for the use of different types of medical services of two-parent households in Table 2. Similar marginal effects for single-parent households are reported in Table 3. These are reported for cross section models (non-IV and IV) as well as the CRE model.

The impact of SNAP participation on the probability of outpatient visit for two-parent households is imprecisely estimated in the non-IV model. However, the estimated marginal effects from our IV model for two-parent households suggests that SNAP participation increases the likelihood of having any outpatient visit by 3.7 percentage points, or 13.7%. This is consistent with the downward bias of program participation effect on medical care utilization care in non-IV cross section model. This bias is caused by adverse selection of individuals with poorer unobserved SES status and poorer access to medical care, which are positively correlated with participation in SNAP, and negatively correlated with medical care utilization, so failure to capture these un-observables resulted in attenuation bias. Importantly, we find that there is a reduction of 0.6 percentage points in the probability of having an outpatient visit among participants at the end of the benefit month. The marginal effects for emergency-room visits are relatively less sensitive to the choice of model. These suggest that SNAP participants are more likely to have an emergency room visit by at least 0.7 percentage points relative to comparable non-participants, but being at the end of the benefit cycle reduces emergency room utilization by at least 0.4 percentage points among SNAP recipients in two-parent households. In contrast to the marginal effect of the benefit cycle on outpatient and emergency room visits, there is no significant change in the pattern of inpatient visits. Nonetheless, the marginal effect of SNAP participation from IV model on the likelihood of inpatient stays of 0.3 percentage points is statistically significant at 16% level.

The analogous marginal effects of SNAP participation and SNAP benefit cycle on medical care utilization among single-parent households are reported in Table 3. Our results from all three models imply that SNAP participation increases the likelihood of having emergency room visits by at least 0.94 percentage points among single-parent households. While we find no significant impact on the probability of having outpatient visit, the marginal effect of SNAP participation on inpatient stays by single-parent households are more sensitive to the choice of model. Our results from all three models suggest that none of the end of the month effects are statistically different from zero. This result is consistent with our theory model indicating that the SNAP benefit cycle results in substitution away from non-food allocations at the end of the benefit month in two-parent households, but not in single-parent households.

5.1. Subgroup Analyses

In order to determine the mechanisms that underlie the relationships observed in our data, we estimate our models separately for children and adults. We present the estimated effects in Table 4 for the two-parent sample and in Table 5 for single-parent households. While we find that SNAP participation among children in two-parent households increases the likelihood of having emergency room visits and inpatient stays, there is no significant impact on medical utilization among adults. In contrast, we find that SNAP participation reduces the probability that an adult in a two-parent household has an emergency room visit at the end of the benefit cycle by 0.6

percentage points. The analogous marginal effect for outpatient visit is larger, but it is less precisely estimated. Nonetheless, the end of the benefit cycle effect on outpatient visit of 0.6 percentage point is significant at 13% level. By comparison, our results suggest that the change in medical utilization for children at the end of the benefit month is not statistically different from zero. The fact that medical care utilization by adults, but not children, is reduced at the end of the benefit month is consistent with the protection of child consumption by parents when household resources are diminished. Our results for single-parent households in table 5 are consistent with our results for the pooled sample. As expected, medical care consumption by adults and children does not vary across the SNAP benefit cycle in single-parent households.

5.2. Misreporting of SNAP Participation

An important identification problem that arises in this study is nonrandom measurement error. This is because a large fraction of recipients fail to report their participation in SNAP, and as a result, the rate of SNAP participation in household surveys is lower than the actual participation rate (see, for example, Bollinger and David, 1997). Our findings may be biased if underreporting is more prevalent in single-parent households than in the two-parents, and vice versa. Researchers often estimate misreporting with linked administrative data (see, for example, Meyer and George, 2011). We do not have access to such data. In order to examine the possibility that our results are confounded by measurement error, we use data on state-level rates of SNAP participation from SNAP Data System to correct for under-reporting in the MEPS.[8] Doing so allows us to use state-level variation in SNAP participation to predict individual level participation score in our sample based on individuals' characteristics and the state of residency. We run a state-

[8] Data on state-level SNAP participation are available at: https://www.ers.usda.gov/data-products/supplemental-nutrition-assistance-program-snap-data-system/time-series-data/

level regression to predict the likelihood of SNAP participation using a linear probability model. To this end, we construct state-level demographics and socioeconomic status variables using data from U.S. Census Bureau.[9] We also control for state-level data on unemployment, and poverty rate. In addition, we control for information on state-level SNAP policies relating to eligibility criteria, recertification and reporting requirements, benefit issuance methods, availability of online applications, use of biometric technology (such as fingerprinting), and coordination with other low-income assistance programs. We reclassify the participation status for reported non-participant households with high predicted participation probabilities until the average rate of participation in the MEPS for each year is the same as the rate reported in administrative data (Table 6).[10] We find similar results when we estimate our IV models after this adjustment. We report this result in Table 7 for two-parent sample, as well as single-parent households. While two-parent households reduce their outpatient and emergency room visits when they run out of SNAP benefits, there is no significant change in the pattern of medical care utilization among single-parent households.

6. Discussion and Conclusion

Using panel data techniques and instrumental variables to control for selection into the SNAP, we find that participants who live in two-parent households are more likely to have outpatient and emergency room visits relative to comparable non-participants. Presumably, the higher tendency of medical care use by SNAP participants is due to an increase in discretionary income. We also investigate the pattern of medical consumption over the benefit month. We find

[9] These include age categories, educational attainment (college degree or higher, high school diploma, below high school), race and ethnicity, and per capita income.
[10] Time-series data on individual level rate of SNAP participation available at: https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap

that medical care utilization declines at the end of the benefit month, but that this decline occurs mainly in two-parent SNAP households as opposed to single-parent SNAP households. This result is indicative of within-month change in the total income individually available in two-parent households. In particular, if mothers have primary control over the SNAP benefit, then they may decide to over-spend in period 1 to persuade fathers to contribute more cash income to buy food in period 2. Prior studies on SNAP households find empirical evidences of such food consumption behavior; periods of food surpluses followed by periods of undereating; among participant households (see, for example, Wilde and Ranney, 2000). Our theory model predicts that the change in distribution of power not only leads to a cyclical pattern in a household's food allocation, but also results in substitution away from non-food allocations at the end of the benefit month in two-parent households, but not in single-parent households. Specifically, parents in two-parent households may decide to postpone their medical care consumption. Our results imply that the demand for emergency room visits in two-parent households are more responsive to SNAP participation than outpatient visits, as emergency room visits are a more expensive type of medical care services compared to outpatient visits. This finding is also consistent with descriptive statistics from MEPS indicating that, on average, SNAP participants are less likely to self-report a usual source of care than eligible non-participants. Although, emergency room visits do not require patients to pay upfront for their services, households may decide to substitute cheaper sources of medical care such as urgent care centers.[11] In addition, a growing number of hospitals are requiring emergency room patients with routine medical problems to pay upfront for their services.[12] We

[11] Urgent centers are grouped as office-based visits in MEPS. In MEPS, Office-based visits can occur in a variety of places in, which makes it difficult to observe the end of the month shift for outpatient visits. Because potential substitutions between different types of outpatient visits are omitted when they are aggregated into the same category.

[12] Kaiser Health News at: http://khn.org/news/hospitals-demand-payment-upfront-from-er-patients/.

also find that the reduction in medical care utilization in two-parent households is particular to adults. This provides insight into how the resources pass-through from adults to children, and that the issue we consider that has been largely beyond the scope of empirical food consumption analyses, due to the lack of individual-level data.

We believe that our study has important implications for the SNAP program. First, we provide foundational analysis necessary to determine the extent to which intra-household decision-making determines households' allocations on nonfood goods. Second, we explore the consequences of the SNAP benefit cycle for medical care consumption, an important input in the production of health. Studying the relationship between SNAP participation and the use of medical care provides another piece of evidence for the lack of consumption smoothing in benefit receiving households, and understanding intra-household decision-making is critical to the design of policies that address the negative consequences of the SNAP benefit cycle.

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Tables

Table 1) Descriptive Statistics by SNAP participation Status and Household Composition

	Two-parent		Single-parent	
	SNAP	Non-SNAP	SNAP	Non-SNAP
Age 0_6	0.277	0.232	0.277	0.223
	(0.006)	(0.004)	(0.005)	(0.006)
Age 18_30	0.198	0.169	0.175	0.173
	(0.006)	(0.004)	(0.004)	(0.005)
Age 31_45	0.227	0.271	0.162	0.206
	(0.005)	(0.003)	(0.004)	(0.004)
Age 46_60	0.027	0.041	0.024	0.039
	(0.002)	(0.002)	(0.002)	(0.002)
Age 61_75	0.004	0.008	0.002	0.001
	(0.001)	(0.001)	(<0.001)	(<0.001)
Age over 76	0.001	0.002	0.001	0.001
	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Hispanic	0.375	0.442	0.257	0.273
	(0.035)	(0.015)	(0.017)	(0.013)
Black	0.136	0.087	0.427	0.333
	(0.013)	(0.006)	(0.017)	(0.016)
Other races	0.065	0.062	0.020	0.038
	(0.012)	(0.006)	(0.003)	(0.006)
Female	0.490	0.487	0.645	0.629
	(0.005)	(0.003)	(0.005)	(0.006)
HH members 0-5	1.266	1.022	0.891	0.644
	(0.032)	(0.021)	(0.023)	(0.020)
Midwest	0.16	0.129	0.202	0.167
	(0.019)	(0.012)	(0.016)	(0.014)
South	0.423	0.379	0.381	0.404
	(0.032)	(0.017)	(0.018)	(0.017)
West	0.288	0.343	0.204	0.223
	(0.025)	(0.016)	(0.016)	(0.014)
Urban	0.791	0.838	0.842	0.849
	(0.019)	(0.013)	(0.012)	(0.012)
High school	0.148	0.153	0.128	0.156
	(0.006)	(0.004)	(0.004)	(0.005)
Some college or above	0.076	0.126	0.076	0.125
	(0.004)	(0.004)	(0.003)	(0.004)
Ln(HH income per)	8.864	9.134	8.182	8.345
	(0.041)	(0.029)	(0.038)	(0.061)
Medicaid	0.713	0.375	0.851	0.516
	(0.012)	(0.009)	(0.006)	(0.012)
Medicare	0.003	0.005	0.002	0.002
	(0.001)	(0.001)	(<0.001)	(0.001)

	Two-parent		Single-parent	
	SNAP	Non-SNAP	SNAP	Non-SNAP
Private	0.097	0.353	0.07	0.277
	(0.008)	(0.010)	(0.004)	(0.011)
all good MH	0.354	0.351	0.317	0.321
	(0.011)	(0.009)	(0.007)	(0.008)
Missing MH	0.012	0.011	0.013	0.009
	(0.001)	(0.001)	(0.001)	(0.001)
all excellent MH	0.257	0.295	0.27	0.283
	(0.009)	(0.008)	(0.008)	(0.009)
poor/fair MH	0.106	0.06	0.128	0.104
	(0.006)	(0.003)	(0.005)	(0.005)
some excellent MH	0.528	0.577	0.548	0.571
	(0.011)	(0.009)	(0.008)	(0.009)
all poor health	0.062	0.041	0.062	0.047
	(0.003)	(0.002)	(0.003)	(0.003)
some poor health	0.174	0.122	0.168	0.143
	(0.006)	(0.004)	(0.005)	(0.005)
some excellent health	0.432	0.482	0.47	0.478
	(0.011)	(0.008)	(0.008)	(0.009)
all excellent health	0.186	0.215	0.215	0.209
	(0.008)	(0.007)	(0.007)	(0.007)
Missing health	0.012	0.011	0.012	0.009
	(0.001)	(0.001)	(0.001)	(0.001)
all good health	0.386	0.387	0.357	0.374
	(0.011)	(0.007)	(0.007)	(0.008)
any disability	0.119	0.08	0.124	0.103
	(0.006)	(0.003)	(0.004)	(0.004)
State-level poverty rate	14.185	13.637	13.754	13.362
	(0.169)	(0.103)	(0.122)	(0.132)
State-level unemp. rate	6.744	6.242	6.449	6.029
	(0.106)	(0.071)	(0.092)	(0.076)
State-leve per capita income	35.679	35.542	35.641	34.762
	(0.395)	(0.243)	(0.288)	(0.273)
State-level bachelor attainment	26.363	26.881	26.375	26.573
	(0.186)	(0.154)	(0.188)	(0.194)
Pr. of outpatient visit per week	0.296	0.256	0.307	0.276
	(0.006)	(0.005)	(0.005)	(0.005)
Pr. of ER visit per week	0.047	0.031	0.056	0.041
	(0.002)	(0.001)	(0.002)	(0.002)
Pr. of inpatient stays per week	0.024	0.018	0.023	0.018
	(0.001)	(0.001)	(0.001)	(0.001)

Note: Means are weighted to be nationally representative. Standard deviations in parentheses.

Table 2) Marginal effects from probit, biprobit , and correlated random effect, two-parent households with children under age 18

	Outpatient			Emergency Room			Inpatient		
	probit	IV	CRE	probit	IV	CRE	probit	IV	CRE
SNAP	0.011	0.037*	0.017*	0.010***	0.007**	0.009***	0.001	0.003	0.001
	(0.008)	(0.02)	(0.009)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)
SNAP×wgt	-0.017**	-0.006*	<0.001	-0.011**	-0.004**	-0.010**	0.001	<0.001	0.002
	(0.009)	(0.003)	(0.01)	(0.005)	(0.002)	(0.004)	(0.003)	(0.001)	(0.003)
F statistic	-	11.45	-	-	11.45	-	-	11.45	-
N(T)	178,320	178,320	164,944	178,320	178,320	164,944	178,320	178,320	164,944

Note: Standard errors in parentheses for cross section non-IV were computed using the delta method and are adjusted for the complex design of the MEPS, for cross section IV were computed using the delta method and are clustered at state-level, and for the CRE are adjusted for the complex survey design of the MEPS using balanced repeated replication (BRR). Models include cross-section non-IV, cross section IV and correlated random effects (CRE) probit regressions. Control variables include age, gender, race and ethnicity, region (Northeast, South, Midwest, and West), urban residence, years of education completed before entering the survey, number of children in the household, and log of income earned by family members (normalized by household size), mental and physical status, insurance coverage and disability status. In biprobit specification, we also include state-level variables.

Significance level:

***$p < 0.01$.

**$p < 0.05$.

*$p < 0.1$.

Table 3) Marginal effects from probit, biprobit, and correlated random effect, single-parent households with children under age 18

	Outpatient			Emergency Room			Inpatient		
	probit	IV	CRE	probit	IV	CRE	probit	IV	CRE
SNAP	0.010	-0.098	0.012	0.010***	0.009*	0.013***	-0.001	0.009**	0.002
	(0.007)	(0.288)	(0.010)	(0.003)	(0.006)	(0.003)	(0.001)	(0.004)	(0.002)
SNAP×wgt	-0.001	-0.001	-0.001	0.001	0.001	0.006	0.001	<0.001	0.001
	(0.010)	(0.004)	(0.012)	(0.005)	(0.002)	(0.007)	(0.003)	(0.002)	(0.004)
F statistic	-	7.14	-	-	7.14	-	-	7.14	-
N(T)	126,440	126,440	105,200	126,440	126,440	105,200	126,440	126,440	105,200

Note: Standard errors in parentheses for cross section non-IV were computed using the delta method and are adjusted for the complex design of the MEPS, for cross section IV were computed using the delta method and are clustered at state-level, and for the CRE are adjusted for the complex survey design of the MEPS using balanced repeated replication (BRR). Models include cross-section non-IV, cross section IV and correlated random effects (CRE) probit regressions. Control variables include age, gender, race and ethnicity, region (Northeast, South, Midwest, and West), urban residence, years of education completed before entering the survey, number of children in the household, and log of income earned by family members (normalized by household size), mental and physical status, insurance coverage and disability status. In biprobit specification, we also include state-level variables.

Significance level:

***p < 0.01.

**p < 0.05.

*p < 0.1.

Table 4) Marginal effects from cross section IV, two-parent households with children under age 18

	Outpatient		Emergency Room		Inpatient	
	Adults	Children	Adults	Children	Adults	Children
SNAP	0.028	0.024	0.004	0.007***	-0.001	0.003**
	(0.018)	(0.027)	(0.005)	(0.003)	(0.004)	(0.001)
SNAP×wgt	-0.006	-0.005	-0.006**	-0.003	0.002	-0.001
	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)
N(T)	79,316	99,004	79,316	99,004	79,316	99,004

Note: Standard errors in parentheses were computed using the delta method, and clustered at state-level.

Significance level:

***p < 0.01.

**p < 0.05.

*p < 0.1.

Table 5) Marginal effects from cross section IV, single-parent households with children under age 18

	Outpatient		Emergency Room		Inpatient	
	Adults	Children	Adults	Children	Adults	Children
SNAP	0.034	-0.152	0.025**	0.006	0.022***	<0.001
	(0.203)	(0.141)	(0.011)	(0.006)	(0.003)	(0.004)
SNAP×wgt	0.008	-0.006	0.005	-0.002	>-0.001	<0.001
	(0.007)	(0.005)	(0.005)	(0.003)	(0.005)	(0.001)
N(T)	43,220	83,220	43,220	83,220	43,220	83,220

Note: Standard errors in parentheses were computed using the delta method, and clustered at state-level.
Significance level:
***p < 0.01.
**p < 0.05.
*p < 0.1.

Table 6) Times series rate of SNAP participation from administrative data and rate of SNAP participation in MEPS from 1996-2013

Year	SNAP Participation in administrative data (%)	Self-reported SNAP Participation in MEPS (%)
1996	9.7	6.7
1997	8.5	5.9
1998	7.3	5.8
1999	6.8	5.1
2000	6.2	4.5
2001	6.1	4.6
2002	6.6	5.0
2003	7.3	5.7
2004	8.2	6.2
2005	8.7	6.3
2006	9.0	6.2
2007	8.7	6.8
2008	9.3	7.7
2009	10.9	9.5
2010	13.1	9.4
2011	14.4	10.3
2012	14.8	11.3
2013	15.1	12.2

Note: SNAP participation in MEPS are weighted to be nationally representative.

Table 7) Marginal effects from IV model after adjustment for misclassification of SNAP participation, households with children under age 18

	two-parent			single-parent		
	Outpatient	Emergency Room	inpatient	Outpatient	Emergency Room	inpatient
SNAP	0.041*	0.006*	0.001	0.054	0.014****	0.011***
	(0.023)	(0.004)	(0.002)	(0.075)	(0.005)	(0.003)
SNAP×wgt	-0.007**	-0.004**	0.001	>-0.001	>-0.001	0.001
	(0.004)	(0.002)	(0.001)	(0.005)	(0.003)	(0.002)
N(T)	178,320	178,320	178,320	126,440	126,440	126,440

Note: Standard errors in parentheses were computed using the delta method, and clustered at state-level.
Significance level:
***p < 0.01.
**p < 0.05.
*p < 0.1.

Appendix A

Table A1) Cross section IV estimation result for outpatient utilization, two-parent households

	SNAP participation	Outpatient
week1 dummy	-	0.054***
		(0.009)
week2 dummy	-	0.224***
		(0.018)
week3 dummy	-	0.137***
		(0.018)
SNAP participation	-	0.371**
		(0.202)
SNAP×wgt		
0	-	0.021
		(0.022)
1	-	-0.036
		(0.036)
Age 7_17	0.098***	-0.344***
	(0.031)	(0.027)
Age 18_30	0.381***	-0.391***
	(0.03)	(0.033)
Age 31_45	0.338***	-0.423***
	(0.027)	(0.029)
Age 46_60	0.114*	-0.381***
	(0.061)	(0.042)
Age 61_75	-0.198	-0.655***
	(0.147)	(0.101)
Age 76 and older	-0.273	-0.68***
	(0.264)	(0.139)
Hispanic	-0.218***	-0.136***
	(0.077)	(0.043)
Black	0.211**	-0.342***
	(0.101)	(0.051)
Other race	0.038	-0.365***
	(0.084)	(0.058)
Female	-0.057***	0.239***
	(0.014)	(0.013)
HH memebers 0-5	0.157***	-0.012
	(0.034)	(0.012)
Midwest	0.071	-0.006
	(0.093)	(0.046)
South	0.007	-0.086**
	(0.106)	(0.041)

	SNAP participation	Outpatient
West	-0.123	-0.125***
	(0.125)	(0.044)
Urban	-0.16***	0.011
	(0.051)	(0.05)
High school	-0.098***	0.106***
	(0.037)	(0.028)
Some college	-0.283***	0.324***
	(0.046)	(0.028)
ln(HH income per adult equiv.)	-0.048**	0.016
	(0.019)	(0.01)
Medicaid	0.703***	0.483***
	(0.044)	(0.047)
Medicare	0.321	0.795***
	(0.217)	(0.113)
Private	-0.488***	0.553***
	(0.05)	(0.046)
All good MH	-0.056	-0.067
	(0.092)	(0.046)
Missing MH	-0.493	0.666**
	(0.488)	(0.333)
All excellent MH	-0.034	0.089***
	(0.036)	(0.021)
poor/fair MH	0.164**	0.076*
	(0.085)	(0.043)
some excellent MH	-0.079	-0.015
	(0.08)	(0.057)
All poor health	-0.008	0.178***
	(0.057)	(0.034)
Poor/fair health	0.196***	0.191***
	(0.056)	(0.066)
Some excellent health	0.041	-0.232***
	(0.056)	(0.063)
All excellent health	0.012	-0.102***
	(0.038)	(0.029)
Missing health	0.392	-1.079***
	(0.513)	(0.352)
All good health	0.121**	-0.08
	(0.055)	(0.05)
Any disability	0.092***	0.413***
	(0.029)	(0.024)
State-level poverty	0.025	-0.003
	(0.018)	(0.005)
State-level unemployment	0.034	-0.004
	(0.022)	(0.008)
State-level icome per capita	-0.009	-0.008***

	SNAP participation	Outpatient
	(0.007)	(0.002)
State-level bach. attainment	-0.009	0.018***
	(0.013)	(0.004)
Instrument (call center)	0.262**	-
	(0.105)	
_cons	-0.44	-1.173***
	(0.382)	(0.212)

Table A2) The CRE estimation result, two-parent households

	Outpatient	Emergency Room	Inpatient
constant	-1.39***	-2.4***	-2.981***
	(0.158)	(0.172)	(0.162)
week 1 dummy	0.047***	-0.009	0.087**
	(0.014)	(0.023)	(0.039)
week 2 dummy	0.218***	0.09***	0.162***
	(0.014)	(0.026)	(0.045)
week 3 dummy	0.15***	0.013	0.126***
	(0.013)	(0.024)	(0.045)
Age	-0.009***	-0.005***	0.005***
	(0.001)	(0.001)	(0.001)
Hispanic	-0.121***	-0.167***	-0.017
	(0.03)	(0.034)	(0.032)
Black	-0.322***	-0.045	-0.065
	(0.035)	(0.033)	(0.046)
Other race	-0.296***	-0.259***	-0.233***
	(0.051)	(0.063)	(0.066)
Female	0.212***	0.029	0.371***
	(0.014)	(0.018)	(0.028)
HH memebers 0-5	0.024	0.000	0.181***
	(0.015)	(0.015)	(0.015)
Midwest	-0.047	0.121**	-0.036
	(0.059)	(0.056)	(0.059)
South	-0.096**	0.112**	0.073
	(0.041)	(0.045)	(0.052)
West	-0.135***	0.015	-0.06
	(0.039)	(0.047)	(0.056)
Urban	-0.008	0.026	-0.04
	(0.038)	(0.038)	(0.036)
High school	0.117***	0.093***	0.221***
	(0.029)	(0.035)	(0.043)
Some college	0.329***	0.073*	0.182***
	(0.031)	(0.039)	(0.044)
ln(HH income per adult equiv.)	-0.011*	-0.026***	-0.042***
	(0.007)	(0.009)	(0.008)
All good MH	0.111	0.17*	-0.106
	(0.076)	(0.095)	(0.138)
All excellent MH	0.03	-0.004	-0.086*
	(0.021)	(0.035)	(0.05)
poor/fair MH	0.21***	0.134	-0.161
	(0.072)	(0.09)	(0.13)
Some excellent MH	0.16**	0.196**	-0.031

	Outpatient	Emergency Room	Inpatient
	(0.073)	(0.093)	(0.133)
All poor health	0.141***	0.159***	0.136**
	(0.041)	(0.053)	(0.061)
Some poor health	0.264***	0.359***	0.264***
	(0.054)	(0.079)	(0.096)
Some excellent health	0.038	0.237***	0.077
	(0.061)	(0.087)	(0.102)
All excellent health	-0.034	0.025	-0.066
	(0.027)	(0.048)	(0.061)
All good health	0.124*	0.309***	0.128
	(0.064)	(0.088)	(0.106)
Any disability	0.207***	0.061*	0.131***
	(0.037)	(0.034)	(0.049)
Medicaid	0.46***	0.086*	0.292***
	(0.038)	(0.036)	(0.053)
Medicare	0.286	-0.028	-0.191
	(0.419)	(0.419)	(0.426)
Private	0.306***	-0.155***	0.000
	(0.046)	(0.053)	(0.053)
SNAP	0.056**	0.144***	0.012
	(0.028)	(0.035)	(0.042)
SNAP×wgt	-0.005	-0.128**	0.044
	(0.034)	(0.052)	(0.079)

Correlated random effects

Log family income pr. 1 λ	0.013	All poor health pr. 1 λ	-0.052
	(0.01)		(0.038)
Log family income pr. 2 λ	0.024**	All poor health pr. 2 λ	0.035
	(0.01)		(0.038)
All good MH pr. 1 λ	-0.117**	Some poor/ fair health pr.1 λ	-0.008
	(0.057)		(0.05)
All good MH pr. 2 λ	-0.014	Some poor/ fair health pr. 2 λ	0.159***
	(0.094)		(0.057)
All excellent MH pr. 1 λ	0.066***	Some excellent health pr. 1 λ	-0.162***
	(0.024)		(0.052)
All excellent MH pr.2 λ	0.056**	Some excellent health pr. 2 λ	-0.054
	(0.024)		(0.06)
poor/ fair MH pr. 1 λ	-0.085	All excellent health pr. 1 λ	-0.061**
	(0.056)		(0.028)
poor/ fair MH pr. 2 λ	-0.025	All excellent health pr. 2 λ	-0.043
	(0.087)		(0.029)
Some excellent MH period 1	-0.128***	All good health pr. 1 λ	-0.121**
	(0.049)		(0.054)
Some excellent MH period 2	0.026	All good health pr. 2 λ	0.016

Correlated random effects			
	(0.094)		(0.067)
Medicare pr. 1 $\boldsymbol{\lambda}$	0.300	Medicare pr. 2 λ	0.153
	(0.265)		(0.262)
Medicaid pr. 1 $\boldsymbol{\lambda}$	0.062*	Medicaid pr. 2 λ	0.078*
	(0.032)		(0.036)
Any disability pr. 1 $\boldsymbol{\lambda}$	0.136***	Private pr. 1 λ	0.057*
	(0.028)		(0.034)
Any disability pr. 2 $\boldsymbol{\lambda}$	0.113***	Private pr. 2 λ	0.202***
	(0.034)		(0.038)
SNAP pr. 1 $\boldsymbol{\lambda}$	-0.009	SNAP pr. 2 λ	-0.023
	(0.025)		(0.024)

Appendix B

We need to show that:

$$0 < \frac{\partial c_{2f}}{\partial C_1} + \frac{\partial m_{2f}}{\partial C_1} < 1.$$

First we derive $\frac{\partial c_{2f}}{\partial C_1}$.

From father's optimization problem in the second period:

$$\frac{C_2}{\mathrm{I_f}} = x_f, \frac{\mathrm{M_2^c}}{\mathrm{I_f}} = y_f, \frac{M_{2f}}{\mathrm{I_f}} = 1 - x_f - \mathrm{y_f} \Rightarrow \frac{\partial \mathrm{M_2^c}}{\partial C_1} = \frac{y_f}{x_f}\frac{\partial C_2}{\partial C_1}$$

And his available budget in the second period:

$$I_f = w^f + s + c_{1m} + c_{2m} + m_{2m} - C_1 - M_{1f} - m_{1f}$$

And, he make his decision to allocate this budget between C_2 and M_{2m}:

$$C_2^* = x_f * (w^f + s + c_{1m} + c_{2m} + m_{2m} - C_1 - M_{1f} - m_{1f})$$

$$c_{2m} = \frac{C_2^*}{x_f} - w^f - s - c_{1m} - m_{2m} + C_1 + M_{1f} + m_{1f}$$

We substitute our finding for c_{2m} in the following additional constraint for food allocation in second period:

$$C_2 = c_{2f} + \frac{C_2^*}{x_f} - w^f - s - c_{1m} - m_{2m} + C_1 + M_{1f} + m_{1f} + s - C_1 + c_{1m} + c_{1f}$$

This simplifies to:

$$C_2 - \frac{C_2^*}{x_f} = c_{2f} - w^f - m_{2m} + M_{1f} + m_{1f} + c_{1f}$$

Now we take derivative w.r.t. C_1:

$$0 = \frac{\partial c_{2f}}{\partial C_1} - \frac{\partial m_{2m}}{\partial C_1} + (\frac{1}{x_f} - 1)\frac{\partial C_2}{\partial C_1}$$

As a result:

$$\frac{\partial c_{2f}}{\partial C_1} = \left(1 - \frac{1}{x_f}\right)\frac{\partial C_2}{\partial C_1} + \frac{\partial m_{2m}}{\partial C_1} \tag{I}$$

Substitute (I) into $\frac{\partial c_{2f}}{\partial C_1} + \frac{\partial m_{2f}}{\partial C_1}$, we have:

$$\frac{\partial c_{2f}}{\partial C_1} + \frac{\partial m_{2f}}{\partial C_1} = \left(1 - \frac{1}{x_f}\right)\frac{\partial C_2}{\partial C_1} + \frac{\partial m_{2m}}{\partial C_1} + \frac{\partial m_{2f}}{\partial C_1}$$

Now we need to find the following:

$$\frac{\partial m_{2m}}{\partial C_1} + \frac{\partial m_{2f}}{\partial C_1} = ?$$

From the father's problem:

$$M^{c^*}_{\ 2} = y_f * (w^f + s + c_{1m} + c_{2m} + m_{2m} - C_1 - M_{1f} - m_{1f})$$

Similarly, from mother's problem:

$$M^{c^*}_{\ 2} = y_m * (w^m + s + c_{1f} + c_{2f} + m_{2f} - C_1 - M_{1m} - m_{1m})$$

Combining these two equations, we have the following:

$$\frac{M^{c^*}_{\ 2}}{y_f} + \frac{M^{c^*}_{\ 2}}{y_m} = w^f + 2s + \mathrm{c}_{1\mathrm{m}} + c_{1f} + c_{2m} + c_{2f} + m_{2m} + m_{2f} - 2C_1 - M_{1f} - M_{1m} - m_{1f} - m_{1m}$$

We simplify this equation using the additional constraint for the food budget:

$$\frac{M^{c^*}_{\ 2}}{y_f} + \frac{M^{c^*}_{\ 2}}{y_m} = w^f + s + m_{2m} - C_1 - M_{1f} - m_{1f} + w^m + C_2 + m_{2f} - M_{1m} - m_{1m}$$

Now we take derivative w.r.t. C_1:

$$\frac{\partial M_2^c}{\partial C_1}\left(\frac{1}{y_m} + \frac{1}{y_f}\right) = \frac{\partial m_{2m}}{\partial C_1} + \frac{\partial m_{2f}}{\partial C_1} - 1 + \frac{\partial C_2}{\partial C_1}$$

$$\frac{\partial m_{2m}}{\partial C_1} + \frac{\partial m_{2f}}{\partial C_1} = \frac{\partial M_2^c}{\partial C_1}\left(\frac{1}{y_m} + \frac{1}{y_f}\right) + 1 - \frac{\partial C_2}{\partial C_1}$$

Substituting this finding into $\left(1-\frac{1}{x_f}\right)\frac{\partial C_2}{\partial C_1}+\frac{\partial m_{2m}}{\partial C_1}+\frac{\partial m_{2f}}{\partial C_1}$:

$$\frac{\partial c_{2f}}{\partial C_1}+\frac{\partial m_{2f}}{\partial C_1}=\left(1-\frac{1}{x_f}\right)\frac{\partial C_2}{\partial C_1}+\frac{\partial M_2^c}{\partial C_1}\left(\frac{1}{y_m}+\frac{1}{y_f}\right)+1-\frac{\partial C_2}{\partial C_1}$$

We know that $\frac{\partial M_2^c}{\partial C_1}=\frac{y_f}{x_f}\frac{\partial C_2}{\partial C_1}$, so we have:

$$\frac{\partial c_{2f}}{\partial C_1}+\frac{\partial m_{2f}}{\partial C_1}=\left(1-\frac{1}{x_f}\right)\frac{\partial C_2}{\partial C_1}+\frac{\partial M_2^c}{\partial C_1}\left(\frac{1}{y_m}+\frac{1}{y_f}\right)+1-\frac{\partial C_2}{\partial C_1}=1+\frac{y_f}{y_m x_f}\frac{\partial C_2}{\partial C_1}=1+\frac{1}{x_m}\frac{\partial C_2}{\partial C_1}$$

Since $\frac{\partial C_2}{\partial C_1}<0$, $x_m>0$, we conclude that:

$$\frac{\partial c_{2f}}{\partial C_1}+\frac{\partial m_{2f}}{\partial C_1}<1 \qquad \text{(II)}$$

We also need to show that $\frac{\partial c_{2f}}{\partial C_1}+\frac{\partial m_{2f}}{\partial C_1}>0$:

Consider the following constraint for public medical expenditure:

$$M_2^c+M_1^c=m_{2m}+m_{2f}+m_{1m}+m_{1f}$$

As a result, we have:

$$\frac{\partial m_{2m}}{\partial C_1}+\frac{\partial m_{2f}}{\partial C_1}=\frac{\partial M_2^c}{\partial C_1}$$

We substitute our finding into $\frac{\partial c_{2f}}{\partial C_1}+\frac{\partial m_{2f}}{\partial C_1}=\left(1-\frac{1}{x_f}\right)\frac{\partial C_2}{\partial C_1}+\frac{\partial m_{2m}}{\partial C_1}+\frac{\partial m_{2f}}{\partial C_1}$ to get:

$$\frac{\partial c_{2f}}{\partial C_1}+\frac{\partial m_{2f}}{\partial C_1}=\left(1-\frac{1}{x_f}\right)\frac{\partial C_2}{\partial C_1}+\frac{\partial M_2^c}{\partial C_1}=\left(1-\frac{1}{x_f}\right)\frac{\partial C_2}{\partial C_1}+\frac{y_f}{x_f}\frac{\partial C_2}{\partial C_1} \qquad \text{(III)}$$

$$=\frac{\partial C_2}{\partial C_1}\left(x_f+y_f-1\right)>0$$

From II, III:

$$0<\frac{\partial c_{2f}}{\partial C_1}+\frac{\partial m_{2f}}{\partial C_1}<1.$$