The Effect of SNAP on Obesity in the Presence of Endogenous Misreporting

Augustine Denteh*

November 2, 2017

Abstract

This paper estimates the effect of the Supplemental Nutrition Assistance Program (SNAP) on adult obesity addressing self-selection and endogenous misreporting of participation. There is increasing evidence suggesting that the consequences of reporting errors in program participation may be severe enough to render the sign of the treatment effect not to be identified by standard methods. Using a two-step procedure that accounts for endogenous misreporting of participation, this paper estimates the causal impact of SNAP on obesity using data from the National Longitudinal Survey of Youth–1979 cohort. From a simple partial observability model of participation and misreporting, I predict probabilities of participation which are used to consistently estimate the average effect of SNAP on body mass index (BMI). I rely on exclusion restrictions for program participation and reporting errors for identification. The estimated misreporting model confirms some prior findings in the literature regarding the correlates of reporting error. However, contrary to most previous studies, I do not find any evidence of a statistically significant effect of SNAP on BMI.

Keywords: Misreporting, Endogeneity, Treatment Effects, Obesity
JEL No: C18, C25, I28, I38

*I am grateful to my advisor Rusty Tchernis. I am also thankful for valuable comments from Charles Courtemanche, Pierre Nguimkeu, Ian McCarthy, and Tom Mroz. I also received helpful feedback from participants in seminars at Georgia State University and the Western Economic Association International Graduate Student Workshop (San Diego). I am solely responsible for any errors. Department of Economics, Andrew Young School of Policy Studies, Georgia State University, P.O. Box 3992, Atlanta, GA 30302-3992, E-mail: augidenteh@gmail.com.

1 Introduction

This paper estimates the casual effect of the Supplemental Nutrition Assistance Program (SNAP) on adult Body Mass Index (BMI) when participation is endogenously misreported using an econometric framework developed in Nguimkeu et al. (2016).[1] SNAP is the largest nutrition assistance program in the U.S., serving millions of low-income individuals and households in an effort to reduce food insecurity and support a healthy population. High adult obesity rates coupled with a higher prevalence among low-income households targeted by SNAP motivates a thorough understanding of the relationship between SNAP and obesity.[2] Since obesity remains a public health or policy concern, it is of interest to policymakers to know whether SNAP and any other government program have any unintended consequences for the weight of recipients. For instance, if SNAP affects the weight of recipients, then the size of the negative externalities associated with obesity would need to incorporate these effects (Bhattacharya & Sood 2006, Bailey 2013). Also, knowing whether there are any such effects can inform debates regarding proposals to restructure SNAP.

It is often asserted that SNAP participation reduces food insecurity, lifts millions from poverty, and provides a fiscal boost to the economy during downturns without any significant adverse impact on the health of participants (U.S. Department of Agriculture 2012). However, existing research on the relationship between SNAP participation and obesity is mixed,

[1] SNAP was formerly called the Food Stamp Program (FSP).

[2] Descriptive empirical evidence suggests that lower incomes are associated with higher probabilities of obesity and severe obesity and this gradient is more pronounced for women. For instance, using the 2001-2010 National Health and Nutrition Examination Survey (NHANES) data, Gundersen (2015) finds that obesity rates (BMI$\geq$30) decline from 36.3% to 31.3% moving from below the federal poverty level to above 400% of the federal poverty level, while severe obesity rates (BMI$\geq$35) declines from 19.1% to 13.0%. Also, using NHANES data from 2007-2010, Condon et al. (2015) reports that adult SNAP participants were more likely to be obese compared to income-eligible nonparticipants (43.6% vs. 33.3%) and higher-income nonparticipants (43.6% vs. 31.9%).

inconclusive, and deserves closer examination especially because the low-income households targeted by SNAP are also relatively more vulnerable with respect to obesity risk factors and other negative health conditions (Bitler 2015, Gundersen 2015). Obesity remains one of the leading health problems in the U.S., with an adult, age-adjusted prevalence rate of 37.7% (35% for men and 40.4% for women) as of 2014 (Flegal et al. 2016). Obesity heightens a person's risk of many debilitating diseases and health problems such as diabetes, cardiovascular risk factors, lower quality of life, and many other chronic conditions (Colditz et al. 1995, McGee et al. 2005, Kim & Kawachi 2008). In addition, there are significant health care costs of obesity (Finkelstein et al. 2009, Cawley & Meyerhoefer 2012) as well as negative effects of obesity on labor market outcomes (Bhattacharya & Bundorf 2009).

Estimating the impact of SNAP participation on obesity is complicated by two identification challenges. The first is the non-random selection of people into the program; SNAP participation is a choice and hence endogenous. SNAP participants may differ in systematic unobserved ways from similar income-eligible non-participants. These systematic differences may simultaneously affect SNAP participation and obesity, making it difficult to obtain unbiased estimates of SNAP's effect on obesity. Such factors as current or expected future health, human capital characteristics, financial stability, time and risk preferences, preferences for food and other health inputs, and attitudes toward work are simultaneously related to SNAP participation and health outcomes (Currie 2003, Kreider et al. 2012). Previous researchers have found that SNAP is associated with adverse nutrition-related health outcomes such as worse diets and nutrition intake, obesity, or overweight compared to non-recipients (Currie 2003, Hoynes & Schanzenbach 2015). This may be suggestive of negative selection into SNAP rather than a causal association. The literature has recognized this problem and

some attempts have been made to overcome this selection bias using instrumental variable (IV) estimation and panel data methods such as fixed effects estimation and propensity score matching.

The second identification challenge is non-classical measurement error arising due to the potential misreporting of SNAP status in national surveys. Misreporting is pervasive in survey data and occurs when SNAP participants report receiving no benefits when they actually did (false negatives) or vice versa (false positives). Meyer et al. (2009) provide evidence of extensive under-reporting of program benefits of ten transfer programs in five nationally representative surveys and reports that at least one-third of SNAP benefits are not reported mostly due "to not reporting at all, rather than reporting too little conditional on reporting." Validation studies confirm severe misreporting of program participation, sometimes up to 50%, with the measurement error being possibly correlated with covariates (Meyer et al. 2015). Also, false negative reporting errors tend to be more frequent than false positives, particularly with government programs. In general, misreporting of SNAP participation creates biases whose magnitude and direction are not known without further assumptions (Bound et al. 2001, Kreider et al. 2012). Even so, models that allow one to quantify and sign the resulting bias from a misclassified binary variable are scarce while the few studies that take on the issue of misclassification seriously usually assume that misreporting occurs randomly with fixed or constant probability (Lewbel 2007).

This paper reexamines whether SNAP participation is linked to weight gain in adults when we account for the typical case of false negative reporting errors. This paper makes two contributions. First, using a novel approach proposed in Nguimkeu et al. (2016), this paper informs the longstanding policy discussions and debates regarding the impacts of SNAP on

recipient weight by addressing endogenous participation and misreporting of benefit receipt. Second, the results highlight the consequences of misreporting on estimated treatment effects in empirical work by comparing our approach to standard estimators. I do not find evidence that SNAP participation significantly increases weight for the full sample or separately by gender. This finding departs from most previous studies suggesting positive impacts of SNAP on weight outcomes, especially among females.

The rest of the paper is organized as follows. Section 2 presents background information on SNAP. Section 3 discusses the related literature. Section 4 presents the data. Section 5 presents the methodology. Section 6 discusses the results and Section 7 concludes.

2 Background and Theoretical Framework

2.1 Brief Overview of SNAP

The Food Stamp Program has undergone numerous legislative changes from its establishment under the Food Stamp Act of 1964, through the Food Stamp Act of 1977 (which eliminated the purchase requirement), to the Food, Conservation and Energy Act of 2008 that changed the name of the Food Stamp Act of 1977 to the Food and Nutrition Act of 2008 and renamed the Federal program the Supplemental Nutrition Assistance Program.[3] SNAP is administered by the U.S. Department of Agriculture (USDA) with the objective of increasing food security, reducing hunger, and improving health and well-being of low-income individuals and households by expanding access to food, nutritious diets, and nutrition education (Mabli

[3]The change of name presumably was an attempt to reduce the associated stigma with program participation. Also, see Institute of Medicine and National Research Council (2013) for more detailed discussion of SNAP's historical milestones.

et al. 2013). The Food Stamp Act of 2008 contains national eligibility standards (categorical, financial and non-financial) as well as exceptions to the eligibility criteria. Households are categorically eligible for SNAP if they are receiving Temporary Assistance for Needy Families (TANF), Supplemental Security Income (SSI), or General Assistance (GA) in certain cases (U.S. Department of Agriculture 2017). Households that are not categorically eligible must meet two basic income eligibility standards – a gross income test and a net income test.

Between 2000 and 2014, the number of Americans receiving SNAP benefits has almost tripled from about 17 million to 46 million while total spending on SNAP has more than quadrupled from about $17 billion to almost $75 billion.[4] This translates to about one in seven Americans (or roughly 14% of the total U.S. population) and monthly average benefits of $257 per household, or $125 per person, or $4.11 per person per day in 2014.[5]

Although SNAP has no specific objective to influence obesity directly, obtaining accurate estimates of its effects on health outcomes in general and obesity in particular is critical in the broader ongoing policy debates surrounding its existence and role in the lives of the millions of Americans who benefit from it. For instance, understanding the causal link between SNAP and obesity can help us understand and evaluate the merits of recent proposals aimed at influencing the nutritional choice and well-being of participants.

Gundersen (2015) discusses recent state- and national-level proposals aimed at restricting the food choices of participants and prohibiting the purchase of foods deemed as "unhealthy" or "junk." A much publicized proposal is the State of New York's waiver request to the USDA

[4]SNAP statistics can be found at http://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap. Part of this dramatic SNAP expansion is presumably due to the Great Recession and this is a testament to the importance of SNAP in the social safety net in the U.S.

[5]See Hoynes & Schanzenbach (2015) for a current review of SNAP and other nutrition assistance programs in the U.S.

in 2010 to permit a two-year demonstration project that will ban the use of SNAP benefits to purchase any beverage with more than 10 calories per 8-ounce serving (Gundersen 2015, Kansagra et al. 2015). The State of New York's proposal which would have banned sports drinks, soda, vegetable drinks and iced tea while allowing others such as milk and 100% fruit juices was ultimately denied by the USDA.

Similar state-level proposals have been made by Minnesota, Maine, Wisconsin, and South Carolina although none has been granted by the USDA. At the national level, an amendment sponsored by Senator Tom Coburn in 2013 to prohibit the use of SNAP benefits to purchase junk food was not passed (Gundersen 2015). Without a causal SNAP-obesity link, it is unclear whether any of these proposals restricting consumption choices of SNAP participants will reduce the probability of being obese among low-income households and may in effect lead to unintended consequences such as increased stigma associated with participation and higher transaction and program administration costs.

2.2 Can SNAP Participation Influence BMI?

Theoretically, the impact of SNAP on obesity is ambiguous. This section explores two theoretical links between SNAP participation and obesity: neoclassical economic theory and the "Food Stamp Cycle" hypothesis.

2.2.1 Neoclassical Theory

SNAP participation may affect obesity through its effect on consumption. Does SNAP lead to greater food consumption that could increase the probability of becoming obese? Following the standard Southworth model (Southworth 1945, Bartfeld et al. 2015), individuals allocate

total income (cash income plus SNAP benefits) between food and a composite nonfood good. Since relative prices are unchanged, SNAP benefits can be thought of as a pure income effect with a predicted increase in consumption of all *normal* goods. In this standard framework, the receipt of SNAP benefits merely loosens the budget constraint of participants and affords greater consumption of food and nonfood goods as would any arbitrary increase in disposable income or cash transfer.

However, due to the in-kind nature of SNAP, the Southworth model presented in Figure 2.1 distinguishes between *inframarginal or unconstrained* SNAP participants and *extramarginal or constrained* SNAP participants. Before the receipt of SNAP, the individual chooses the mix of food and nonfood goods such that her utility is maximized and her budget exhausted – point I_1 in Figure 2.1. Upon receipt of SNAP benefits, the individual's budget constraint shifts outward from AD to the kinked budget constraint represented by BE_2D.[6]

Inframarginal SNAP Participants

Households are unconstrained or inframarginal if they receive less in SNAP benefits than they would otherwise spend on food if their total income were solely cash. From Figure 2.1, inframarginal households would choose the new consumption bundle represented by I_2, consuming more of both food and nonfood goods.[7] In this scenario, we can draw on existing research on how changes in income affects obesity to predict the impact of SNAP on obesity. Even so, existing research on the relationship between income and weight (or obesity) is mixed and inconclusive (see, for e.g., Cawley et al. (2010), Schmeiser (2009), Lindahl (2005)).

[6]The triangle marked DE_2C represents consumption bundles that are attainable since SNAP benefits are targeted or in-kind.

[7]Consumption of food goes up by less than the full amount of SNAP benefits.

Extramarginal SNAP Participants

Households are classified as extramarginal or constrained if they receive more in SNAP benefits than they would otherwise have allocated for food if all their income were cash. These consumers may have stronger preferences for relatively lower food consumption and their consumption bundle before SNAP participation is represented by point E_1 in Figure 2.1. After receiving SNAP, the extramarginal consumer spends only her SNAP benefits on food expenditures and chooses the bundle denoted by point E_2 (kink) in Figure 2.1. Such an individual is predicted to spend proportionately more on food with SNAP than an equivalent cash transfer. There is some evidence, possibly plagued by selection bias, that SNAP participants with excess allowances tend to purchase more food than they otherwise would (Fox et al. 2004, Devaney & Moffitt 1991, Fraker et al. 1995). Hoynes & Schanzenbach (2009) provides recent evidence that estimates of the marginal propensity (MPC) to consume food out of SNAP benefits is similar to the MPC of cash income, albeit with dated data from the initial introduction of the program between 1961 and 1975 across about 3000 U.S. counties.

Whether SNAP participants are inframarginal or extramarginal, the increased spending on food can positively or negatively impact obesity depending on the mix of "healthy" and "unhealthy" food purchased and consumed, which ultimately depends on the preferences of households. Descriptive evidence suggests that SNAP participants are less likely to consume appropriate amounts of vitamins and minerals and are more likely to derive energy from solid fats, alcoholic beverages, and added sugars relative to SNAP-eligible households who do not participate in SNAP (Cole & Fox 2008). SNAP households also have lower scores on the

Healthy Eating index (HEI) 2005 than income-eligible nonparticipants and income-ineligible nonparticipants (Cole & Fox 2008).

If SNAP participants are selected from a population with stronger preferences for "unhealthy" food, then one will expect participants to have relatively greater consumption of "unhealthy" foods at all levels of income, leading to weight gain. The converse also holds. Even given the same preferences, the loosening of the budget constraint could lead to spending on goods that increase (decrease) sedentary activities resulting in weight loss (gain). Depending on the proportion of recipient households that are inframarginal versus extramarginal and the types of food purchased, SNAP participation may or may not have anything to do with obesity.

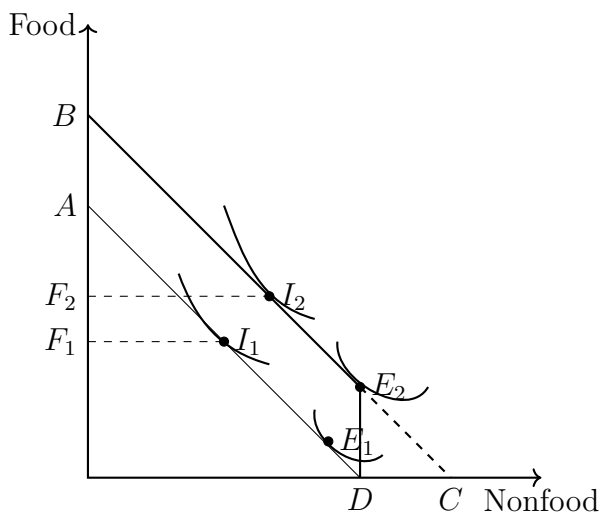

Figure 1: Neoclassical framework for analyzing impact of SNAP on consumption

2.2.2 The Food Stamp Cycle Hypothesis

The Food Stamp Cycle describes the phenomenon where SNAP participants unevenly use SNAP benefits and consume calories during the course of the month. Wilde & Ranney

(2000) and Shapiro (2005) present evidence that SNAP participants' food spending and food energy intake (calories) peaks sharply in the first few days upon receipt of SNAP benefits and declines significantly with weeks, suggesting that the timing of SNAP receipt may induce a preference for immediate consumption. The Food Stamp Cycle thus leads to periods of over-consumption (surpluses) and under-consumption (shortages) that is linked to weight gain in both adults and children (Blackburn et al. 1989, Polivy et al. 1994, Dietz 1995, Fisher & Birch 1999).

3 Literature Review

3.1 Previous Literature on SNAP and Adult Obesity

Using a variety of approaches, a common finding in the literature is that SNAP participation is positively correlated with the probability of being obese or overweight (Townsend et al. 2001, Gibson 2003, Baum 2011, Meyerhoefer & Pylypchuk 2008). For instance, Gibson (2003) uses an individual fixed effects estimator and concludes that SNAP participation increases obesity among women but finds no significant effects for men. Meyerhoefer & Pylypchuk (2008) adopts an individual fixed effects and IV estimation approaches and comes to the same conclusion as Gibson (2003).

Other researchers have found no statistically significant relationship between SNAP participation and obesity (Fan 2010, Almada & Tchernis 2015). Using propensity score matching methods, Fan (2010) finds no significant effect of SNAP on obesity, overweight or BMI. Using partial identification methods to bound the treatment effect of SNAP participation,

Kreider et al. (2012) find that these commonly cited relationships are misleading, concluding that "under the weakest restrictions, there is substantial ambiguity; we cannot rule out the possibility that SNAP increases or decreases poor health."

Nonetheless, the consensus among policy makers is that while SNAP participation does not increase or decrease probability of being obese for children and non-elderly men, it tends to increase the probability of being obese or overweight for non-elderly adult women (U.S. Department of Agriculture 2012).

3.2 The Problem of Misreporting of SNAP Benefits

Misreporting of SNAP participation in national surveys has been well-documented with false negatives being more prevalent than false positives. For instance, false negatives for SNAP are estimated to be around $20-30\%$ in the 2001 and 2005 panels of the Survey of Income and Program Participation (SIPP), 35% in the 2001 American Community Survey (ACS) and up to 50% in the 2002-2005 Annual Social and Economic Supplement (March CPS) (Meyer et al. 2015). Also, Mittag (2013) finds 26% false negatives in the 2008-2010 ACS while Almada et al. (2016) estimate $23-45\%$ false negative rates in the National Longitudinal Survey of Youth (NLSY) - 1979 cohort. However, the corresponding false positive error rates are less than 1.5% (Meyer et al. 2015).

There is a growing literature suggesting that the estimated effect of a misclassified binary explanatory variable may be substantially biased (Aigner 1973, Bollinger & David 1997, Hausman et al. 1998, Black et al. 2000, Frazis & Loewenstein 2003, Brachet 2008, Kreider et al. 2012, Kreider 2010). When a binary explanatory variable is misclassified, the measure-

ment error is necessarily nonclassical and without additional assumptions about the nature of the measurement error, Gundersen & Kreider (2008) find wide bounds on the resulting bias. This resulting bias persists even when misclassification is completely random or exogenous. Examining the consequences of infrequent arbitrary errors in a binary explanatory variable, Kreider (2010) finds that even with misclassification error rates of 2%, the confidence intervals from the contaminated data that the researcher observes and the true error-free data might not overlap.

Methods for estimating the treatment effects of an endogenous and possibly misreported binary regressor remains an active area of research. Obviously, the OLS estimator inconsistent for the average treatment effect of SNAP participation and may even assume a "wrong sign" in special cases (see for e.g., Hu et al. (2015) and Nguimkeu et al. (2016) for sign-reversal results). Traditional IV methods have also been shown to be inconsistent (Black et al. 2000, Frazis & Loewenstein 2003).[8]

Existing methods for addressing misreporting in a right-hand side binary variable have focused on the case of exogenous or random misreporting. For instance, Frazis & Loewenstein (2003) provide a Generalized Method of Moments (GMM) estimator when instruments are available and provide bounds when the misclassified variable is endogenous. Following Mahajan (2006), Lewbel (2007) also considers the estimation of the treatment effect of a misclassified binary regressor in nonparametric and semiparametric regression and achieves identification using an "instrument-like" variable.[9] More recently, Almada et al. (2016) pursue various parametric and non-parametric approaches to identify the effects of SNAP on

[8]For instance, Black et al. (2000) show that, under appropriate assumptions, the parameter estimate of a mismeasured independent variable may be asymptotically bounded between the OLS and IV estimators and provide a method-of-moments estimator for the case of binary or discrete variables.

[9]See Nguimkeu et al. (2016) for some evidence on the performance of Lewbel's estimator

the probability of being obese or overweight. In addition to not finding any significant effects for SNAP's effects on the probability of being obese, Almada et al. (2016) caution that instrument-based estimators are overstated and exceed nonparametric upper bounds under reasonable assumptions of the treatment selection and misreporting probabilities.

When both participation and response error are endogenous, the estimation approach employed in this paper is a reasonable attempt to overcome the difficulties of consistently estimating the average treatment effect of interest.

4 Data

This study uses data from the National Longitudinal Survey of Youth - 1979 Cohort (NLSY79), which is a nationally representative sample of 12,686 men and women surveyed annually from 1979 and biennially after 1994. The NLSY79 is comprised of three sub-samples: a cross-sectional sample of 6,111 respondents representing the non-institutionalized population, a supplemental sample of 5,295 civilian Hispanic or Latino, black, and economically disadvantaged non-black/non-Hispanic population, and a sample of 1,280 military youth. The analysis sample is limited to the 1996, 1998, 2000, 2002, and 2004 waves in part due to the availability of state-level policy variables from the SNAP Policy Database, which are used to instrument SNAP participation (U.S. Department of Agriculture (USDA) 2016).[10] The respondents were between 14 and 22 years old in 1979, thus, the ages of the respondents in the analysis sample range from 31 to 39 years.

[10]The Economic Research Service (ERS) of the USDA maintains the SNAP Policy Database which contains state-level SNAP policy choices for all 50 states and the District of Columbia from 1996 to 2011 as of October, 2016.

The dependent variable of interest is respondents' body weight as measured by BMI, which is constructed from the self-reports of weight and height. I restrict the sample to observations with non-missing values of weight and height biennially from 1996 to 2004.[11]

The treatment indicator of interest is a dummy that equals 1 for SNAP participation in at least one month of the past calendar year and zero otherwise. In the final analysis sample, 16.26% of the survey respondents reported SNAP participation in at least one month of the previous calendar year. Out of this reported participation, about 72.36% participated during every month of the year. It is a more complicated process to determine which respondents are eligible in the NLSY79 and almost any other nationally representative survey because of the inadequacy of the income and asset data required for such an exercise. In general, individuals must meet gross income, net income, and asset tests. Although these criteria are determined at the federal level, many exceptions exist and individual states can make exemptions in certain cases.

As a result, the majority of studies have resorted to using some cutoff that is determined as a percent of the federal poverty line after adjusting for household size. While some studies use the gross income cutoff of 130% of the federal poverty line to determine SNAP eligibility, other studies have used higher thresholds of up to 250% of the federal poverty line. Using just the gross income test to determine eligibility can result in comparisons with individuals that are not truly eligible for SNAP. Also, since eligibility is based on gross and net *monthly* income, using a more restrictive threshold might miss those who become eligible for only certain portions of the year (Meyerhoefer & Pylypchuk 2008, Mykerezi & Mills 2010). Thus,

[11] Weight is reported in pounds in the survey years 1981, 1982, 1985, 1986, 1988, 1989, 1990, 1992, 1993, 1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012 and 2014. However, height in inches is only reported in 1981, 1982, and 1985. Following the prior literature, I use height in 1985 to calculate each respondent's BMI as weight in kilograms divided by height in meters squared.

I restrict the final analysis sample to respondents at or less than 250% of the federal poverty level who are observed in at least two waves from 1996 to 2004. Doing so captures about 96% of reported SNAP participation.

The NLSY79 permits the construction of demographic variables such as race, gender, and marital status. It also contains information on household characteristics such as the age of household members, household size, family income, information on labor market activities, and educational attainment of respondents and their mothers. Educational attainments for respondents and their mothers are measured by dummies for completing of high school or more. Labor market activity is captured by weekly hours worked in the past calendar year as well as current employment status. Also, the NLSY79 collects post-interview information from interviewers include demographic characteristics and other remarks about the interview process such as the respondents' general attitude and the presence of third parties during the interview. Section 5 discusses how I exploit these additional interview and interviewer characteristics in the estimation strategy.

The final data set consists of 2,798 persons and 8,502 person-year observations. Table 1 reports the means and standard deviations of the variables used in the regressions for the full sample and by participation status. The average BMI for SNAP participants is 29.39 while it is 27.94 for nonparticipants. The summary statistics indicate that SNAP participants are negatively selected on a variety of observable dimensions. For instance, SNAP recipients belong to households with lower family incomes ($15,147.11 vs. $24,522.59), work for fewer average weekly hours (20.67 vs. 34.38), have slightly larger household sizes (3.70 vs. 3.43) with more children (2.07 vs. 1.69), are less likely to be married (0.25 vs. 0.47), are less likely to have a high school diploma or higher (0.72 vs. 0.84), are more likely to have mothers have

graduated from high school (0.41 vs. 0.52), and are more likely to participate in WIC (0.21 vs. 0.06) relative to nonparticipants.

5 Methodology

The objective of this study is to estimate the average treatment effect of SNAP participation on BMI, accounting for selection bias and possible misreporting of participation. As previously discussed, self-selection into SNAP along unobservable dimensions as well as the possible misclassification of participation status renders a naive regression of weight status on the binary SNAP participation indicator an inconsistent estimator for the average treatment effect of interest. In fact, although standard linear IV estimators may address the self-selection problem, they are inconsistent for the treatment effect of interest in light of the nonclassical nature of misreported participation (Black et al. 2000, Nguimkeu et al. 2016).

In the remainder of this section, I present the econometric framework, developed in Nguimkeu et al. (2016), which addresses these problems by simultaneously modeling SNAP participation and misreporting decisions in relation to the evolution of BMI. For concreteness, suppose we are interested in the causal effect of participating in SNAP on BMI in the linear treatment effects model

$$y_{it} = \boldsymbol{x'_{it}}\boldsymbol{\beta} + T^*_{it}\alpha + \epsilon_{it}, \tag{1}$$

where y_{it} is the outcome of interest for individual i at time t, T^*_{it} is individual i's true unobserved (to the researcher) SNAP participation status in year t, $\boldsymbol{x_{it}}$ is a vector of observed characteristics, $\boldsymbol{\beta}$ is a k-parameter vector, and ϵ_{it}, is the error term. Our interest lies in estimating the treatment effect denoted by α.

Table 1: Summary Statistics by SNAP Participation Status

	Full Sample	Nonparticipants	Participants
Body Mass Index	28.13	27.94	29.39
	(0.17)	(0.16)	(0.42)
Age	38.71	38.79	38.21
	(0.08)	(0.08)	(0.19)
Female	0.58	0.55	0.75
	(0.01)	(0.01)	(0.02)
Hispanic	0.09	0.08	0.11
	(0.01)	(0.01)	(0.02)
Black	0.23	0.21	0.35
	(0.03)	(0.03)	(0.04)
Household Size	3.46	3.43	3.70
	(0.05)	(0.06)	(0.08)
Married	0.44	0.47	0.25
	(0.02)	(0.02)	(0.02)
Mother's education (High school graduate or higher)	0.51	0.52	0.41
	(0.02)	(0.02)	(0.03)
High school graduate or higher	0.82	0.84	0.72
	(0.01)	(0.01)	(0.02)
Number of children	1.74	1.69	2.07
	(0.05)	(0.05)	(0.08)
Household with child (< 5 years)	0.17	0.17	0.22
	(0.01)	(0.01)	(0.02)
Lives in Urban Area	0.66	0.66	0.70
	(0.03)	(0.03)	(0.03)
WIC	0.08	0.06	0.21
	(0.00)	(0.00)	(0.02)
SSI	0.09	0.06	0.27
	(0.01)	(0.01)	(0.02)
AFDC/TANF	0.07	0.01	0.40
	(0.01)	(0.00)	(0.03)
Household in poverty	0.31	0.26	0.65
	(0.01)	(0.01)	(0.02)
Average Weekly Hours worked (Past Calendar Year)	32.55	34.38	20.67
	(0.50)	(0.51)	(0.92)
Household with elderly (> 65 years)	0.07	0.07	0.05
	(0.01)	(0.01)	(0.01)
Employed	0.83	0.86	0.65
	(0.01)	(0.01)	(0.02)
Total Net Family Income (2004 dollars)	23,267.58	24,522.59	15,147.11
	(484.88)	(518.98)	(446.10)
Observations	8502	7120	1382

Standard errors in parentheses are adjusted for the complex design survey design of the NLSY79. Based on the 1996-2004 biennial waves of the NLSY79, restricted to individuals or households with income lower than 250% of the federal poverty line.

In the empirical analyses, $\boldsymbol{x_{it}}$ includes demographic characteristics such as respondent's age, race, gender, marital status. It also includes family characteristics such as household size, number of children, logarithm of income and human capital characteristics such as educational attainment and mother's education. Other variables included in $\boldsymbol{x_{it}}$ are labor market activity measured by average weekly hours worked in past calendar year and current employment status as well as indicators for living in an urban area, receiving WIC benefits, AFDC/TANF receipt, SSI receipt, and indicators for having an infant ($\leq$5 years) and an elderly person ($\geq$ 65 years) living in the home.

To address self-selection into the program, an individual's true SNAP participation decision is modeled following the usual latent utility formulation as

$$T_{it}^{*} = \mathbf{1}\left(\boldsymbol{z_{it}'}\boldsymbol{\theta} + v_{it} \geq 0\right), \tag{2}$$

where $\boldsymbol{z_{it}}$ is a vector of observed covariates related to the decision to participate in SNAP, $\boldsymbol{\theta}$ is a q-parameter vector, and v_{it} is the error term. The endogeneity of true participation arises due to the self-selection mechanism in equation (2) and the correlation of the error terms in equations (1) and (2).

In equation (2), $\boldsymbol{z_{it}}$ includes $\boldsymbol{x_{it}}$ in addition an exclusion restriction, namely, the percentage of SNAP benefits issued by the state via electronic benefit (EBT) cards. Theoretically, this state-level exclusion restriction should affect the probability of take-up but should not directly influence BMI in equation (1) or the propensity to misreport in equation (3) below. The Personal Responsibility and Work Opportunity Reconciliation Act of August 22, 1996 (PRWORA) mandated all states to implement EBT systems by the year 2012 which allows

recipients to authorize their SNAP benefits to be electronically transferred unto their EBT accounts monthly.[12] States that mail benefits by direct mail (as opposed to using EBT cards), increase the costs associated with participation but there is no reason to expect that these state-level policies should influence BMI. The number of states implementing EBT systems grew from 15 in 1996, 37 in 1998, 42 in 2000, 49 in 2002, to all states by 2004.[13]

Since true SNAP participation, T_{it}^*, is unobserved (due to possible misreporting), the researcher observes a surrogate, T_{it} that is generated as

$$T_{it} = \begin{cases} T_{it}^* & \text{if} \quad R_{it} = 1 \\ 0 & \text{if} \quad R_{it} = 0, \end{cases} \tag{3}$$

where R_{it} is a reporting dummy variable characterized by

$$R_{it} = \mathbf{1}\left(\boldsymbol{w}_{\boldsymbol{it}}'\boldsymbol{\gamma} + u_{it} \geq 0\right), \tag{4}$$

where $\boldsymbol{w}_{\boldsymbol{it}}$ is a vector of observed covariates related to the decision to correctly (or incorrectly) report program participation, $\boldsymbol{\gamma}$ is a p-parameter vector, and u_i is the error term. Again, the endogeneity of misreporting arises because of the mechanism described by equation (4) and the fact that the error terms in equations (1) and (4) are allowed to be correlated.

Equations (2) and (4) together form a complete model of SNAP participation and report-

[12] Other major changes that came along with PRWORA included removing eligibility for most legal immigrants, limiting benefit receipt to 3 out of 36 months for individuals classified as able-bodied adults without dependents (ABAWDs), and setting the maximum allotments at 100 percent of the change in the Thrifty Food Plan (TFP). A complete description of the changes effected by PRWORA can be found at https://www.fns.usda.gov/snap/short-history-snap.

[13] Also, I initially used other state-level policies such as whether the state requires biometric identification, whether the state operates a call center, and the proportion of SNAP units with and without earnings with 1-3 month re-certification periods. None of these policies significantly predicted participation in this sample.

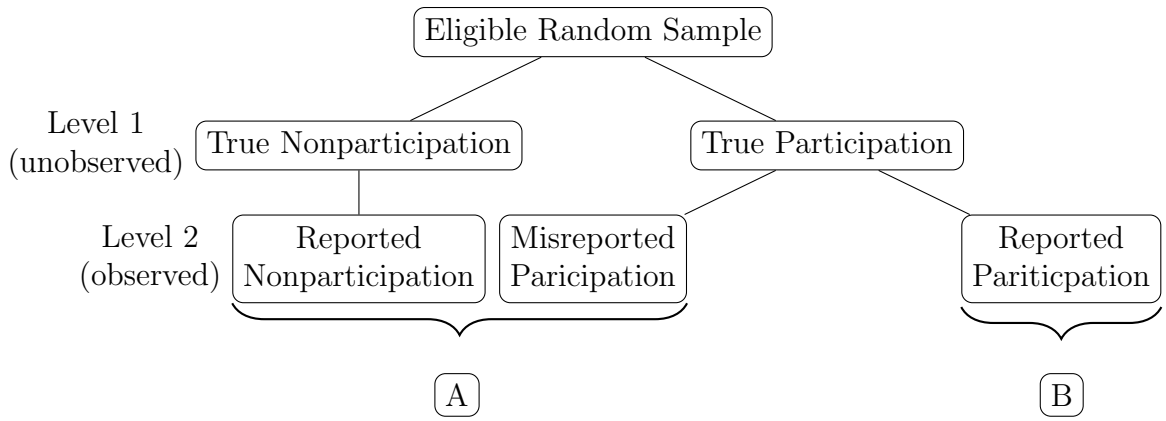

Figure 2: First Stage (Partial Observability Model)

ing although T_{it} and R_{it} are unobserved. The observation mechanism in equation (3) can also be expressed as $T_i = T_i^* \times R_i$. It is immediately obvious that misreporting is unidirectional and captures only false negatives since an individual *correctly* reports her participation only if $R_i = 1$ and reports non-participation otherwise.[14]

Figure (2) graphically illustrates the partial observability inherent in equation (3). If we suppose that we have a random sample of eligible participants, then Figure (2) shows two levels of data observability. In Level 1, the data is split into two distinct classes, namely the class of true participants and true participants. Level 1 is not observable to the researcher but only the individual respondent. Level 2 describes the observed data which are split into two cases, A and B. Case A consists of two observationally indistinguishable cases, namely, true reports of nonparticipation and false reports of nonparticipation (false negatives). These two scenarios under Case A are observationally equivalent because the researcher only observed $T_{it} = 0$ in both instances. In the second case denoted by B in Figure (2), true participants (correctly) report participation. These distinct groups of observations (A and B) motivate

[14]This framework abstracts away from false positives because of their low prevalence is validation studies. In other words, we assume that nonparticipants always correctly report their program participation. Also, introducing two-way misreporting introduces complications in the statistical estimation.

the maximum likelihood estimation of the partial observability model described in equations (3) and (4).

In equation (4), $\boldsymbol{w_{it}}$ includes $\boldsymbol{x_{it}}$ and additional regressors that are hypothesized to be associated with one's probability of accurately reporting participation. These extra covariates need to be excluded from equation (2) but need not be excluded from the outcome equation. The exclusion restrictions in equations (2) and (4) may come from different data sources. Although exclusion restrictions for misreporting are hard to find in practice, I use a set of interview and interviewer characteristics available in the NLSY79 as predictors of the misreporting mechanism.[15]

As previously mentioned, the NLSY79 interviewers participate in a survey after the interview process where information is collected on their perceptions regarding the interview process and their interaction with interviewees such as the respondent's general attitude during the interview and whether a third party was present with the primary respondent during the interview. Thus, I use indicators for the interview mode, indicators of the respondent's attitude during the interview based on the interviewer's remarks in the post-interview survey as well as the gender and race of the interviewer as the excluded predictors of misreporting in equation (4). Collectively, these variables are in the spirit of the "cooperativeness hypothesis" in Bollinger & David (2001) who find favorable evidence for the hypothesis that respondents with high propensity to cooperate with the survey are more likely to truthfully report their participation. For example, respondents who are impatient, restless, or hostile during the interview are less cooperative with the survey and are more likely to respond inaccurately,

[15] Although the covariates z_i and w_i may overlap, it is required that they be different in general, at least to avoid the local identification problems discussed in Poirier (1980).

all other things being equal. I expect these characteristics to be strongly associated with the probability to misreport participation but should not affect one's participation decision or the evolution of body weight.

Finally, the joint trivariate distribution of the error terms in equations (1), (2), and (4) is given by

$$(\epsilon_i, u_i, v_i) \sim N(0, \Sigma), \quad \text{with} \quad \Sigma = \begin{pmatrix} \sigma^2 & \varphi_u \sigma & \varphi_v \sigma \\ \varphi_u \sigma & 1 & \rho \\ \varphi_v \sigma & \rho & 1 \end{pmatrix}, \tag{5}$$

where σ^2 is the variance of ϵ_i; φ_u, φ_v and ρ are the correlations between ϵ_i and u_i, ϵ_i and v_i, and u_i and v_i, respectively.

5.1 Two-Step Estimation Procedure

The estimation of the model presented above proceeds in two steps. The first stage is estimated as a partial observability model following Poirier (1980), which is followed by ordinary least squares regression in the second stage (regression with a proxy variable). Notice that, from equations (3) and (4), we can write the double-index model for observed participation, T_{it}, as

$$T_{it} = T_{it}^* \times R_{it} = \mathbf{1}\left(\boldsymbol{z}_{\boldsymbol{it}}'\boldsymbol{\theta} + v_{it} \geq 0,\ \boldsymbol{w}_{\boldsymbol{it}}'\boldsymbol{\gamma} + u_{it} \geq 0\right). \tag{6}$$

If we denote the joint cumulative density function (CDF) of $(-u, -v)$ by

$$F(\underline{u}, \underline{v}, \rho) = \Pr[-u_i \leq \underline{u},\ \ -v_i \leq \underline{v}], \quad \text{for any } -\infty < \underline{u},\ \underline{v} < +\infty, \tag{7}$$

then the parameters θ (equation (2)), γ (equation (4)), and ρ (equation (5)) may be consistently estimated in the first stage. I estimate the following partial observability binary choice model by maximum likelihood

$$\Pr[T_{it} = 1|\boldsymbol{w_{it}}, \boldsymbol{z_{it}}] = \Pr\left[-u_{it} \leq \boldsymbol{w'_{it}}\gamma, \quad -v_{\{}it\} \leq \boldsymbol{z'_{it}}\theta\right] = F\left(\boldsymbol{w'_{it}}\gamma, \boldsymbol{z'_{it}}\theta, \rho\right) = P_i(\gamma, \theta, \rho), \tag{8}$$

where the log-likelihood function of the model is given by

$$L_n(\gamma, \theta, \rho) = \sum_{i=1}^{n} T_i \ln P_i(\gamma, \theta, \rho) + (1 - T_i) \ln\left(1 - P_i(\gamma, \theta, \rho)\right).$$

In the second step, each person's predicted probability of true participation, $\hat{T}^*_{it}$, is obtained as $\hat{T}^*_{it} = \Phi(\boldsymbol{z'_{it}}\hat{\theta})$ using the estimates of θ from the first stage. The predicted values, $\hat{T}^*_{it}$, which are free from self-selection and nonclassical measurement error are substituted for T^*_{it} in the outcome equation in the new model given by

$$y_{it} = \boldsymbol{x'_{it}}\beta + \hat{T}^*_{it}\alpha_{2S} + \eta_{it}, \tag{9}$$

where α_{2S} denotes the average treatment effect of SNAP on BMI and η_i is the associated disturbance term. It can be shown that the above two-step procedure is a consistent and asymptotically normal estimator of the treatment effect of interest (Nguimkeu et al. 2016).

6 Results and Discussion

I present estimates from the first step estimation of the partial observability model in equation (6) followed by the second step results from equation (9).

6.1 First Step Estimation

Table 2 reports the maximum likelihood estimates of the parameters of the excluded regressors in the true participation and reporting equations for females. The analogous results for the full and male samples are reported in the Appendix.[16] Panels A and B in Table 2 correspond with equations (2) and (4), respectively.

The econometric framework adopted in this paper requires two sets of covariates that need to be distinguished: (a) instruments for true participation ($\boldsymbol{z_{it}}$), and (b) predictors of misreporting ($\boldsymbol{w_{it}}$). Although these sets of covariates may overlap, they must be different for identification purposes (Nguimkeu et al. 2016). In other words, at least one excluded variable (exclusion restriction) in either the participation or reporting equation suffices for identification. All regressions also include the additional covariates from the outcome equation.

As previously mentioned, the state-level policy variable that is used to instrument for true participation is the percentage of SNAP benefits issued by the state via EBT cards. Panel A in Table 2 shows that the percentage of SNAP benefits issued by the state via electronic benefit (EBT) cards is positive and statistically significantly correlated with the true participation probability for females. The likelihood ratio test of excluded instrument

[16]The discussion of the results in the main text focuses on females partly because most of positive associations between SNAP participation and obesity have been reported for females.

Table 2: Partial Observability Probit Model of Reported Participation (Females)

	Female Sample
Panel A: True Participation Equation	
Percentage of Benefits issued via EBT Card	0.467***
	(0.108)
Observations	5036
Likelihood Ratio Test of Excluded Instruments	19.05***
Panel B: True Reporting Equation	
Interview Mode Dummies	
Any Adult Present During Interview	0.073
	(0.140)
Phone Interview	-0.203
	(0.137)
Respondent's Attitude Dummies	
Not Interested But Cooperative	-0.345***
	(0.129)
Impatient/Restless/Hostile	-0.128
	(0.238)
Interviewer Characteristics	
Same Gender Dummy (Interviewer & Interviewee)	-1.128**
	(0.497)
Same Race Dummy (Interviewer & Interviewee)	-1.065*
	(0.579)
Interaction of Same-gender & Same-race Dummy (Interviewer & Interviewee)	1.049*
	(0.582)
Observations	5036
Likelihood Ratio Test of Excluded Instruments	22.61***

Standard errors in parentheses. Results are based on the 1996-2004 biennial waves of the NLSY79, restricted to individuals or households with income below 250% of the federal poverty line. The excluded category for the interview mode dummies is "In person (alone)" and that for the respondent attitude dummies is "Friendly and Interested." Regressors not reported in here include respondentss age, race, household size, number of children, weekly hours worked in the past calendar year, current employment status, educational attainment, mothers education, marital status, log of income, time fixed effects, and indicators for living in an urban area, receiving WIC benefits, receiving AFDC/TANF, receiving SSI benefits, and indicators for having an infant ($\leq$5 years) and an elderly person ($\geq$ 65 years) living in the home.
$*p < 0.10, **p < 0.05, ***p < 0.010$

also suggests that EBT card benefit issuance is a strong predictor of participation.

Panel B in Table 2 presents coefficient estimates of the excluded predictors of misreporting in the reporting equation (4). I rely on the NLSY79 interview and interviewer characteristics as excluded covariates driving the reporting process. It is noteworthy that these covariates only need to be excluded from the true participation equation but not the outcome equation. The set of excluded predictors in equation (4) describing the reporting mechanism are interview mode, descriptors for respondents' attitude during the interview, gender of the in-

terviewer, and race of the interviewer. I expect these covariates to influence one's probability of misreporting participation without affecting the probability of participation.

The interview mode is a categorical variable with three levels describing features of the interview process. These 3 levels are: 1=in-person and alone, 2=in-person with third party present, and 3=phone interview. The excluded category in the regressions is level 1 (in-person and alone). Also, the NLSY79 interviewers were surveyed after each interview and asked to indicate their perception of the respondent's attitude during the interview. Responses were grouped on a 3-point scale: 1=Friendly and interested, 2=Cooperative but not particularly interested, and 3=Impatient, restless, or hostile. This attitude variable is included as a set of dummy variables in the regressions with the excluded category being level 1 (Friendly and interested). Finally, I include a dummy variable for whether the interviewee and the interviewer are of the same gender, whether the interviewee and the interviewer are of the same race, and an interaction of these two dummy variables.

Due to a lack of a general theory of misreporting, I do not have strong *a priori* expectations about the directions of the effects of these interview and interviewer characteristics. Nonetheless, one can draw on a related literature studying the relationship between the probability of misreporting in surveys and both interview and interviewer characteristics for insights in discussing the results herein (e.g., Bruckmeier et al. (2015), OMuircheartaigh & Campanelli (1998), Schober & Conrad (1997), Suchman & Jordan (1990)).

The estimates in Panel B of Table 2 suggest that the interview, interviewee, and interviewer characteristics are correlated with the probability of true participation in equation (4). A large body of literature has considered measurement error in survey responses to *sensitive* questions, especially when the answers may be stigmatized or not viewed as socially

desirable. For instance, Tourangeau & Yan (2007) report substantial error in responses to sensitive questions and also notes that such inaccurate responses vary significantly with the mode of administering the survey. I find that having an adult present during the interview is positively associated with the probability of truthfully reporting participation status, relative to being interviewed alone in person, albeit not statistically significant for females (see Table 2).[17] This finding is similar to Bruckmeier et al. (2015) who find that survey respondents are more likely to give truthful answers on welfare receipt when a third person is present. However, I do not find statistically significant association between being in a phone interview relative to being interviewed alone in person.

Bollinger & David (1997, 2001) discuss the so-called "cooperator hypothesis" where survey respondents may or may not cooperate with the survey in terms of giving accurate responses. They provide evidence in support of the hypothesis that cooperators have a tendency to give more accurate responses (Bollinger & David 2001, 2005). I find evidence that the respondent's attitude during the interview is associated with the probability of truthfully reporting participation. The results suggest that interviewees who are impatient, restless or hostile during the interview are less likely to truthfully report participation and this association is statistically significant for the full and male samples (see Table A1). For females, respondents who are not interested are less likely to report participation truthfully (Table 2).

Finally, a related literature studies how interviewers (for e.g., interviewer demographic characteristics) affects the accuracy of survey responses. One might expect interviewers'

[17] However, the coefficient estimate on having an adult present during the interview is positive and statistically significant for males (see Table A1).

gender and race to affect survey responses when respondents know or can perceive the demography of the interviewer.[18] I include three variables controlling for interviewer effects: a same-gender indicator variable that takes on 1 if both respondent and interviewer are of the same sex and 0 otherwise, a same-race indicator variable that assumes 1 if both respondent and interviewer are of the same race (i.e., either black, hispanic, or non-black/non-hispanic) and 0 otherwise, and an interaction of these two dummy variables. From Table 2, I find that, for females, being interviewed by someone of the same sex is negatively correlated with the propensity of truthfully reporting participation and this effect varies statistically significantly by race.[19]

Overall, the results from the first step of the two-step estimator used in this paper suggest that the instruments for true participation and predictors of participation are strongly correlated with the observed, reported SNAP participation.

6.2 Second Step Estimation

Table 3 reports the estimated average treatment effect of interest using the two-step estimator (2S) in equation (9) for females. I do not find a statistically significant effect of SNAP participation on BMI for the full sample or by gender. The estimated treatment effect of SNAP participation on BMI for females of -1.973 implies a weight loss of approximately 12 pounds, albeit not statistically significant (Table 3).[20] For the full and male samples, the estimated coefficients are statistically insignificant and imply a weight gain of about 3

[18]See Weisberg (2009) for a more detailed review of the literature on interviewer effects in surveys.

[19]I do not find statisticaly signifcant effects of such gender and race combinations for the full and male samples (see Table 2).

[20]The mean height in the final data set is 65.75 inches, suggesting that relative to the average height, a one BMI unit change translates into a weight change of 6.12 pounds.

pounds and 7.7 pounds, respectively (see Table A2).

For robustness, I also performed the analysis for alternative SNAP eligibility criteria. As previously mentioned, qualifying for SNAP is based on financial, non-financial and categorical eligibility rules. I initially restricted the analysis sample to respondents below 250% of the federal poverty line since the literature recognizes that the federal gross income eligibility threshold of 130% is too restrictive (Mykerezi & Mills 2010, Almada et al. 2016). Thus, I re-estimated the model with the sample restricted to 185% and 130% of the federal poverty level for females. Table A4 presents the results for these alternative eligibility criteria and shows that pattern of results is unchanged. The estimated effect of SNAP on BMI remains negative and statistically insignificant for females although the magnitude suggests smaller weight reductions of about 8.3 pounds and 2.6 pounds for 185% and 130% of the federal poverty line, respectively.

For the purposes of comparison with the two-step (2S) estimator, Table 3 also presents estimates of SNAP's effect on BMI using ordinary least squares (OLS) and standard instrumental variable (IV) estimators. From Tables 3 and A2, the OLS estimates of SNAP's effects are positive and statistically significant, with participation being associated with an increase in weight of about 5.1 pounds and 4.8 pounds for the full sample and females, respectively. The effect is slightly smaller in magnitude for males but is not statistically significant.

The IV estimator uses the same instrument for participation (i.e., the percentage of SNAP benefits issued by the state via electronic benefit cards) as the two-step estimator adopted in this paper. The first stage results for the IV estimator are summarized in Table A3, showing high and statistically significant F-statistics. From Table 3, the IV estimates are negative and statistically insignificant but with magnitudes implying weight reductions

Table 3: Effects of SNAP participation on BMI (Females)

Dependent Variable: BMI			
	Estimator		
	OLS	IV	2S
Female Sample			
SNAP Participation	0.794*	-1.180	-1.973
	(0.428)	(7.782)	(1.632)
Observations	5036	5036	5036

Standard errors in parentheses and are bootstrapped (200 replications) for the two-step (2S) estimation. Results are based on the 1996-2004 biennial waves of the NLSY79, restricted to individuals or households with income lower than 250% of the federal poverty line. Regressors not reported in here include respondentss age, race, household size, number of children, weekly hours worked in the past calendar year, current employment status, educational attainment, mothers education, marital status, log of income, time fixed effects, and indicators for living in an urban area, receiving WIC benefits, receiving AFDC/TANF, receiving SSI benefits, and indicators for having an infant ($\leq$5 years) and an elderly person ($\geq$ 65 years) living in the home.
$*p < 0.10, **p < 0.05, ***p < 0.010$

of about 7.2 pounds for females and notably implausible weight reductions of almost 100 pounds for males (see Table A2).

Summarizing, the results of the two-step estimator adopted here suggest no statistically significant effect of SNAP on BMI for the full sample and also by gender. The two-step estimates also suggest that the estimated average treatment effect of SNAP is not bounded between the OLS and IV estimates as has been suggested elsewhere when misreporting is exogenous.

Moreover, the findings of this paper depart from previous studies suggesting positive associations between SNAP participation and obesity, especially for females (Townsend et al. 2001, Gibson 2003, Chen et al. 2005, Kaushal 2007, Meyerhoefer & Pylypchuk 2008, Baum 2011). For instance, Chen et al. (2005) find that SNAP participation is associated with an

increase of 3.61 BMI units, implying a weight increase of almost 22 pounds. In particular, although not statistically significant, I find a reduction in BMI for females that is linked to SNAP participation. Thus, the estimated coefficients in this study do not support the hypothesis that SNAP participation increases BMI for females.

7 Conclusion

The Supplemental Nutrition Assistance Program remains the largest nutrition assistance program in the United States and currently influences the diets of about 1 in 7 Americans. The existing literature which mostly finds a positive impact of SNAP on the probability of being obese, especially for females, has inadequately addressed the high misreporting rates in reported participation in national surveys. Not only is SNAP participation subject to severe misreporting but such measurement error may be endogenous. Although the prevalence of misreporting is not new, few researchers have examined its consequences for estimating the impacts of SNAP. This paper estimates the casual effect of SNAP on adult body weight in the presence of endogenous misreporting using a novel identification strategy that explicitly addresses both the endogeneity of participation and the systematic nature of misreporting (Nguimkeu et al. 2016). In contrast to most previous studies, I find that SNAP participation is associated with reductions of approximately 2 BMI units (about 7% on average) for females but these changes are not statistically different from zero.

The econometric framework models the evolution of body weight, true participation, and the misreporting mechanism jointly. The first equation is the usual treatment effects model relating BMI to an unobserved SNAP participation indicator and other contributing

factors. To address selection bias, the second equation models true SNAP participation as a function of observed covariates such as those in the outcome equation and exclusion restrictions. Finally, the third equation describes an individual's probability to misreport her true SNAP participation status as a function of observed covariates including demographic and survey/interviewer characteristics.

I use predicted probabilities of true participation from a first stage estimation which are free from self-selection and measurement error to estimate the causal effect of SNAP participation on BMI. In addition to functional form assumptions, I employ exclusion restrictions for participation and predictors of misreporting such as interview and interviewer characteristics to strengthen identification. I show that when the researcher can access variables that are correlated with the propensity to misreport participation, the effects of SNAP on obesity can be consistently estimated. I do not find evidence of a statistically significant effect of SNAP on weight status for females with the estimated effect suggesting reductions in BMI. Even when SNAP participation is positively associated with BMI such as for males and the full sample, the magnitude of the effects is not large enough to cause people of normal weight to become obese.

This study has a few limitations. This study focused on false negative reporting errors which are the more prevalent case of reporting errors. Future work should address bidirectional reporting error. As pointed out by other researchers, there are more accurate measures of fatness besides BMI used in this study (Burkhauser & Cawley 2008).

Appendix A Tables

Table A1: Partial Observability Probit Model of Reported Participation

	Full Sample	Female	Male
Panel A: True Participation Equation			
Percentage of Benefits issued via EBT Card	0.452***	0.467***	0.451***
	(0.088)	(0.108)	(0.173)
Observations	8502	5036	3466
Likelihood Ratio Test of Excluded Instruments	30.23***	19.05***	2.92*
Panel B: True Reporting Equation			
Interview Mode Dummies			
Any Adult Present During Interview	0.166	0.073	0.597**
	(0.176)	(0.140)	(0.255)
Phone Interview	-0.152	-0.203	-0.0437
	(0.166)	(0.137)	(0.186)
Respondent's Attitude Dummies			
Not Interested But Cooperative	-0.330	-0.345***	-0.188
	(0.213)	(0.129)	(0.234)
Impatient/Restless/Hostile	-0.485**	-0.128	-1.053**
	(0.216)	(0.238)	(0.433)
Interviewer Characteristics			
Same Gender Dummy (Interviewer & Interviewee)	-0.093	-1.128**	0.419
	(0.280)	(0.497)	(0.358)
Same Race Dummy (Interviewer & Interviewee)	-0.233	-1.065*	-0.281
	(0.257)	(0.579)	(0.231)
Interaction of Same-gender & Same-race Dummy (Interviewer & Interviewee)	-0.007	1.049*	-0.413
	(0.240)	(0.582)	(0.503)
Observations	8502	5036	3466
Likelihood Ratio Test of Excluded Instruments	21.39***	22.61***	20.23***

Standard errors in parentheses. Results are based on the 1996-2004 biennial waves of the NLSY79, restricted to individuals or households with income lower than 250% of the federal poverty line. The excluded category for the interview mode dummies is "In person (alone)" and that for the respondent attitude dummies is "Friendly and Interested" Regressors not reported in here include respondentss age, race, gender, household size, number of children, weekly hours worked in the past calendar year, current employment status, educational attainment, mothers education, marital status, log of income, time fixed effects, and indicators for living in an urban area, receiving WIC benefit (female-only regressions), receiving AFDC/TANF, receiving SSI benefits, and having an infant living in home.
$*p < 0.10, **p < 0.05, ***p < 0.010$

Table A2: Effects of SNAP participation on BMI

Dependent Variable: BMI			
	Estimator		
	OLS	IV	2S
Full Sample			
SNAP Participation	0.835***	-6.040	0.490
	(0.334)	(5.856)	(1.498)
Observations	8052	8052	8052
Female Sample			
SNAP Participation	0.794*	-1.180	-1.973
	(0.428)	(7.782)	(1.632)
Observations	5036	5036	5036
Male Sample			
SNAP Participation	0.649	-16.261	1.265
	(0.510)	(9.831)	(1.531)
Observations	3466	3466	3466

Standard errors in parentheses and are bootstrapped (200 replications) for the two-step (2S) estimation. Results are based on the 1996-2004 biennial waves of the NLSY79, restricted to individuals or households with income lower than 250% of the federal poverty line. Regressors not reported in here include respondentss age, race, gender, household size, number of children, weekly hours worked in the past calendar year, current employment status, educational attainment, mothers education, marital status, log of income, time fixed effects, and indicators for living in an urban area, receiving WIC benefits (female-only regressions), receiving AFDC/TANF, receiving SSI benefits, and indicators for having an infant ($\leq$5 years) and an elderly person ($\geq$ 65 years) living in the home. $*p < 0.10, **p < 0.05, ***p < 0.010$

Table A3: First Stage IV Estimates

Dependent Variable: SNAP Participation			
	Full Sample	Female	Male
Percentage of Benefits issued via EBT Card	0.046***	0.048***	0.0425***
	(0.009)	(0.014)	(0.013)
F- statistics	22.54***	11.93***	10.73***
Observations	8052	5036	3466

Standard errors in parentheses. Results are based on the 1996-2004 biennial waves of the NLSY79, restricted to individuals or households with income lower than 250% of the federal poverty line. Regressors not reported in here include respondentss age, race, gender, household size, number of children, weekly hours worked in the past calendar year, current employment status, educational attainment, mothers education, marital status, log of income, time fixed effects, and indicators for living in an urban area, receiving WIC benefits (female-only regressions), receiving AFDC/TANF, receiving SSI benefits, and indicators for having an infant ($\leq$5 years) and an elderly person ($\geq$ 65 years) living in the home.
$*p < 0.10, **p < 0.05, ***p < 0.010$

Table A4: Effects of SNAP participation on BMI with Alternative Eligibility (Females)

Dependent Variable: BMI			
	Estimator		
	OLS	IV	2S
250% FPL			
SNAP Participation	0.794*	-1.180	-1.973
	(0.428)	(7.782)	(1.632)
Observations	5,036	5,036	5,036
185% FPL			
SNAP Participation	0.851*	-3.237	-1.354
	(0.450)	(6.887)	(1.756)
Observations	3,554	3,554	3,554
130% FPL			
SNAP Participation	0.868*	-2.241	-0.435
	(0.521)	(6.590)	(2.289)
Observations	2,313	2,313	2,313

Standard errors in parentheses and are bootstrapped (200 replications) for the two-step (2S) estimation. Results are based on the 1996-2004 biennial waves of the NLSY79, restricted to individuals or households with income lower than 250% of the federal poverty line. Regressors not reported in here include respondentss age, race, gender, household size, number of children, weekly hours worked in the past calendar year, current employment status, educational attainment, mothers education, marital status, log of income, time fixed effects, and indicators for living in an urban area, receiving WIC benefits, receiving AFDC/TANF, receiving SSI benefits, and indicators for having an infant ($\leq$5 years) and an elderly person ($\geq$ 65 years) living in the home.
$*p < 0.10, **p < 0.05, ***p < 0.010$

References

Aigner, D. J. (1973), 'Regression with a binary independent variable subject to errors of observation', *Journal of Econometrics* **1**(1), 49–59.

Almada, L., McCarthy, I. & Tchernis, R. (2016), 'What can we learn about the effects of food stamps on obesity in the presence of misreporting?', *American Journal of Agricultural Economics* p. aaw017.

Almada, L. & Tchernis, R. (2015), Measuring effects of snap on obesity at the intensive margin, Technical report, Working Paper.

Bailey, J. (2013), 'Who pays for obesity? evidence from health insurance benefit mandates', *Economics Letters* **121**(2), 287–289.

Bartfeld, J., Gundersen, C., Smeeding, T. & Ziliak, J. (2015), *SNAP matters: how food stamps affect health and well-being*, Stanford University Press.

Baum, C. L. (2011), 'The effects of food stamps on obesity', *Southern Economic Journal* **77**(3), 623–651.

Bhattacharya, J. & Bundorf, M. K. (2009), 'The incidence of the healthcare costs of obesity', *Journal of health economics* **28**(3), 649–658.

Bhattacharya, J. & Sood, N. (2006), Health insurance and the obesity externality, *in* K. Bolin & J. Cawley, eds, 'The Economics of Obesity (Advances in Health Economics and Health Services Research, Volume 17', Emerald Group Publishing Limited, pp. 279–318.

Bitler, P. M. (2015), The health and nutrition effects of snap: Selection into the program and a review of the literature on its effects, *in* J. Bartfeld, C. Gunderson, M. T. Smeeting & P. J. Ziliak, eds, 'SNAP Matters: How Food Stamps Affect Health and Well Being', Redwood City, CA: Stanford University Press.

Black, D. A., Berger, M. C. & Scott, F. A. (2000), 'Bounding parameter estimates with non-classical measurement error', *Journal of the American Statistical Association* **95**(451), 739–748.

Blackburn, G. L., Wilson, G. T., Kanders, B. S., Stein, L. J., Lavin, P. T., Adler, J. & Brownell, K. D. (1989), 'Weight cycling: the experience of human dieters', *The American journal of clinical nutrition* **49**(5), 1105–1109.

Bollinger, C. R. & David, M. H. (1997), 'Modeling discrete choice with response error: Food stamp participation', *Journal of the American Statistical Association* **92**(439), 827–835.

Bollinger, C. R. & David, M. H. (2001), 'Estimation with response error and nonresponse: food-stamp participation in the sipp', *Journal of Business & Economic Statistics* **19**(2), 129–141.

Bollinger, C. R. & David, M. H. (2005), 'I didn't tell, and i won't tell: dynamic response error in the sipp', *Journal of applied econometrics* **20**(4), 563–569.

Bound, J., Brown, C. & Mathiowetz, N. (2001), 'Measurement error in survey data', *Handbook of econometrics* **5**, 3705–3843.

Brachet, T. (2008), 'Maternal smoking, misclassification, and infant health', *Misclassification, and Infant Health (September 16, 2008)* .

Bruckmeier, K., Müller, G. & Riphahn, R. T. (2015), 'Survey misreporting of welfare receipt respondent, interviewer, and interview characteristics', *Economics Letters* **129**, 103–107.

Burkhauser, R. V. & Cawley, J. (2008), 'Beyond bmi: the value of more accurate measures of fatness and obesity in social science research', *Journal of health economics* **27**(2), 519–529.

Cawley, J. & Meyerhoefer, C. (2012), 'The medical care costs of obesity: an instrumental variables approach', *Journal of health economics* **31**(1), 219–230.

Cawley, J., Moran, J. & Simon, K. (2010), 'The impact of income on the weight of elderly americans', *Health Economics* **19**(8), 979–993.

Chen, Z., Yen, S. T. & Eastwood, D. B. (2005), 'Effects of food stamp participation on body weight and obesity', *American Journal of Agricultural Economics* **87**(5), 1167–1173.

Colditz, G. A., Willett, W. C., Rotnitzky, A. & Manson, J. E. (1995), 'Weight gain as a risk factor for clinical diabetes mellitus in women', *Annals of internal medicine* **122**(7), 481–486.

Cole, N. & Fox, M. K. (2008), 'Diet quality of americans by food stamp participation status: Data from the national health and nutrition examination survey, 1999-2004. fsp-08-nh.', *Office of Research and Analysis, Nutrition Food and Nutrition Service, US Department of Agriculture* .

Condon, E., Drilea, S., Jowers, K., Lichtenstein, C., Mabli, J., Madden, E. & Niland, K. (2015), Diet quality of americans by snap participation status: Data from the national health and nutrition examination survey, 2007-2010, Technical report, Prepared by Wal-

ter R. McDonald & Associates Inc. and Mathematica Policy Research for the Food and Nutrition Service.

Currie, J. (2003), Us food and nutrition programs, *in* 'Means-tested transfer programs in the United States', University of Chicago Press, pp. 199–290.

Devaney, B. & Moffitt, R. (1991), 'Dietary effects of the food stamp program', *American Journal of Agricultural Economics* **73**(1), 202–211.

Dietz, W. H. (1995), 'Does hunger cause obesity?', *Pediatrics* **95**(5), 766–767.

Fan, M. (2010), 'Do food stamps contribute to obesity in low-income women? evidence from the national longitudinal survey of youth 1979', *American Journal of Agricultural Economics* .

Finkelstein, E. A., Trogdon, J. G., Cohen, J. W. & Dietz, W. (2009), 'Annual medical spending attributable to obesity: payer-and service-specific estimates', *Health affairs* **28**(5), w822–w831.

Fisher, J. O. & Birch, L. L. (1999), 'Restricting access to palatable foods affects children's behavioral response, food selection, and intake', *The American journal of clinical nutrition* **69**(6), 1264–1272.

Flegal, K. M., Kruszon-Moran, D., Carroll, M. D., Fryar, C. D. & Ogden, C. L. (2016), 'Trends in obesity among adults in the united states, 2005 to 2014', *JAMA* **315**(21), 2284–2291.

Fox, M. K., Hamilton, W. & Lin, B.-H. (2004), 'Effects of food assistance and nutrition programs on nutrition and health', *Food Assistance and Nutrition Research Report* **19**(4).

Fraker, T. M., Martini, A. P. & Ohls, J. C. (1995), 'The effect of food stamp cashout on food expenditures: An assessment of the findings from four demonstrations', *Journal of human resources* pp. 633–649.

Frazis, H. & Loewenstein, M. A. (2003), 'Estimating linear regressions with mismeasured, possibly endogenous, binary explanatory variables', *Journal of Econometrics* **117**(1), 151–178.

Gibson, D. (2003), 'Food stamp program participation is positively related to obesity in low income women', *The Journal of nutrition* **133**(7), 2225–2231.

Gundersen, C. (2015), Snap and obesity, *in* J. Bartfeld, C. Gunderson, M. T. Smeeting & P. J. Ziliak, eds, 'SNAP Matters: How Food Stamps Affect Health and Well Being', Redwood City, CA: Stanford University Press.

Gundersen, C. & Kreider, B. (2008), 'Food stamps and food insecurity what can be learned in the presence of nonclassical measurement error?', *Journal of Human Resources* **43**(2), 352–382.

Hausman, J. A., Abrevaya, J. & Scott-Morton, F. M. (1998), 'Misclassification of the dependent variable in a discrete-response setting', *Journal of Econometrics* **87**(2), 239–269.

Hoynes, H. W. & Schanzenbach, D. W. (2009), 'Consumption responses to in-kind transfers: Evidence from the introduction of the food stamp program', *American Economic Journal: Applied Economics* **1**(4), 109–39.

Hoynes, H. W. & Schanzenbach, D. W. (2015), U.s. food and nutrition programs, Working Paper 21057, National Bureau of Economic Research.

Hu, Y., Shiu, J.-L. & Woutersen, T. (2015), 'Identification and estimation of single-index models with measurement error and endogeneity', *The Econometrics Journal* **18**(3), 347–362.

Institute of Medicine and National Research Council (2013), *Supplemental Nutrition Assistance Program: Examining the Evidence to Define Benefit Adequacy*, Washington, DC: The National Academies Press.

Kansagra, S. M., Kennelly, M. O., Nonas, C. A., Curtis, C. J., Van Wye, G., Goodman, A. & Farley, T. A. (2015), 'Reducing sugary drink consumption: New york citys approach', *American journal of public health* **105**(4), e61–e64.

Kaushal, N. (2007), 'Do food stamps cause obesity?: Evidence from immigrant experience', *Journal of Health Economics* **26**(5), 968–991.

Kim, D. & Kawachi, I. (2008), 'Obesity and health-related quality of life', *Obesity Epidemiology* pp. 234–260.

Kreider, B. (2010), 'Regression coefficient identification decay in the presence of infrequent classification errors', *The Review of Economics and Statistics* **92**(4), 1017–1023.

Kreider, B., Pepper, J. V., Gundersen, C. & Jolliffe, D. (2012), 'Identifying the effects of snap (food stamps) on child health outcomes when participation is endogenous and misreported', *Journal of the American Statistical Association* **107**(499), 958–975.

Lewbel, A. (2007), 'Estimation of average treatment effects with misclassification', *Econometrica* **75**(2), 537–551.

Lindahl, M. (2005), 'Estimating the effect of income on health and mortality using lottery prizes as an exogenous source of variation in income', *Journal of Human resources* **40**(1), 144–168.

Mabli, J., Ohls, J., Dragoset, L., Castner, L. & Santos, B. (2013), Measuring the effect of supplemental nutrition assistance program (snap) participation on food security, Technical report, Mathematica Policy Research.

Mahajan, A. (2006), 'Identification and estimation of regression models with misclassification', *Econometrica* **74**(3), 631–665.

McGee, D. L., Collaboration, D. P. et al. (2005), 'Body mass index and mortality: a meta-analysis based on person-level data from twenty-six observational studies', *Annals of epidemiology* **15**(2), 87–97.

Meyer, B. D., Goerge, R. & Mittag, N. (2015), 'Errors in survey reporting and imputation and their effects on estimates of food stamp program participation', *Unpublished Manuscript* .

Meyer, B. D., Mok, W. K. & Sullivan, J. X. (2009), 'The under-reporting of transfers in household surveys: its nature and consequences', *National Bureau of Economic Research* .

Meyerhoefer, C. D. & Pylypchuk, Y. (2008), 'Does participation in the food stamp program increase the prevalence of obesity and health care spending?', *American Journal of Agricultural Economics* **90**(2), 287–305.

Mittag, N. (2013), 'A method of correcting for misreporting applied to the food stamp program', *US Census Bureau Center for Economic Studies Paper No. CES-WP-13-28* .

Mykerezi, E. & Mills, B. (2010), 'The impact of food stamp program participation on household food insecurity', *American Journal of Agricultural Economics* **92**(5), 1379–1391.

Nguimkeu, P., Denteh, A. & Tchernis, R. (2016), 'On the estimation of treatment effects with endogenous misreporting', *Andrew Young School of Policy Studies Research Paper Series No. 16-11* . Available at SSRN: https://ssrn.com/abstract=2832257orhttp://dx.doi.org/10.2139/ssrn.2832257.

OMuircheartaigh, C. & Campanelli, P. (1998), 'The relative impact of interviewer effects and sample design effects on survey precision', *Journal of the Royal Statistical Society: Series A (Statistics in Society)* **161**(1), 63–77.

Poirier, D. J. (1980), 'Partial observability in bivariate probit models', *Journal of Econometrics* **12**, 209–217.

Polivy, J., Zeitlin, S. B., Herman, C. P. & Beal, A. L. (1994), 'Food restriction and binge eating: a study of former prisoners of war.', *Journal of abnormal psychology* **103**(2), 409.

Schmeiser, M. D. (2009), 'Expanding wallets and waistlines: the impact of family income on the bmi of women and men eligible for the earned income tax credit', *Health economics* **18**(11), 1277–1294.

Schober, M. F. & Conrad, F. G. (1997), 'Does conversational interviewing reduce survey measurement error?', *Public opinion quarterly* pp. 576–602.

Shapiro, J. M. (2005), 'Is there a daily discount rate? evidence from the food stamp nutrition cycle', *Journal of public Economics* **89**(2), 303–325.

Southworth, H. M. (1945), 'The economics of public measures to subsidize food consumption', *Journal of Farm Economics* **27**(1), 38–66.

Suchman, L. & Jordan, B. (1990), 'Interactional troubles in face-to-face survey interviews', *Journal of the American statistical Association* **85**(409), 232–241.

Tourangeau, R. & Yan, T. (2007), 'Sensitive questions in surveys.', *Psychological bulletin* **133**(5), 859.

Townsend, M. S., Peerson, J., Love, B., Achterberg, C. & Murphy, S. P. (2001), 'Food insecurity is positively related to overweight in women', *The Journal of nutrition* **131**(6), 1738–1745.

U.S. Department of Agriculture (2012), Building a healthy america: A profile of the supplemental nutrition assistance program, Technical report, Office of Research and Analysis, Food and Nutrition Service, U.S. Department of Agriculture.

U.S. Department of Agriculture (2017), *Supplemental Nutrition Assistance Program (SNAP): Eligibility*. https://www.fns.usda.gov/snap/eligibility.

U.S. Department of Agriculture (USDA) (2016), *Economic Research Service (ERS) SNAP Policy Database*. http://www.ers.usda.gov/data-products/snap-policy-database.aspx.

Weisberg, H. F. (2009), *The total survey error approach: A guide to the new science of survey research*, University of Chicago Press.

Wilde, P. E. & Ranney, C. K. (2000), 'The monthly food stamp cycle: Shooping frequency and food intake decisions in an endogenous switching regression framework', *American Journal of Agricultural Economics* **82**(1), 200–213.