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Re-evaluating associations between the Supplemental Nutrition Assistance Program participation and body mass index in the context of unmeasured confounders

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ABSTRACT

Objective: To evaluate the association between participation in the Supplemental Nutrition Assistance Program (SNAP) and body mass index (BMI) in the presence of unmeasured confounding.
Methods: We applied new matching methods to determine whether previous reports of associations between SNAP participation and BMI were robust to unmeasured confounders. We applied near-far matching, which strengthens standard matching by combining it with instrumental variables analysis, to the nationally-representative National Household Food Acquisition and Purchasing Survey (FoodAPS, N = 10,360, years 2012–13).
Results: In ordinary least squares regressions controlling for individual demographic and socioeconomic characteristics, SNAP was associated with increased BMI (+1.23 kg/m^2, 95% CI: 0.84, 1.63). While propensity-score-based analysis replicated this finding, using instrumental variables analysis and particularly near-far matching to strengthen the instruments' discriminatory power revealed the association between SNAP and BMI was likely confounded by unmeasured covariates (+0.21 kg/m^2, 95% CI: −3.88, 4.29).
Conclusions: Previous reports of an association between SNAP and obesity should be viewed with caution, and use of near-far matching may assist similar assessments of health effects of social programs.

1. Introduction

Approximately one in seven Americans participate in the Supplemental Nutrition Assistance Program (SNAP, formerly the "Food Stamp Program"), which provides low-income beneficiaries with an electronic debit-type card that can be used to purchase qualified foods. Given the number of participants in SNAP, and the large burden of nutrition-related disease in the United States, epidemiologists have been interested in whether and how the program affects conditions such as obesity. Several previous cross-sectional (Leung et al., 2013; Simmons et al., 2012; Jilcott et al., 2011; Leung and Villamor, 2011) and longitudinal (Schmeiser, 2012; Gibson, 2003), reported associations between SNAP participation and elevated body mass index (BMI), even after adjusting for confounders such as socioeconomic status (see DeBono et al., 2012 for a recent review). Yet many assessments have not addressed unmeasured confounders such as neighborhood factors that may influence both the probability of SNAP participation and obesity risk, such as density and pricing of fresh fruits and vegetables and calorie-dense foods, or additional social and cultural confounders that are difficult to measure (e.g., "local dietary culture"). In addition, previous datasets that have been used to study the SNAP-obesity relationship are limited by lack of administrative confirmation of SNAP participation, which may lead to bias through significant misreporting of SNAP participation status (Kreider et al., 2012).

An ideal experiment to investigate the SNAP-obesity association would be to randomize participation into SNAP, but such an experiment may be unethical (given high food insecurity among

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the SNAP-eligible population, and no natural waiting list or treated control population), illegal (given SNAP is an entitlement for all eligible Americans), and logistically infeasible (given lack of political and administrative support for such research). Therefore two methods of addressing confounding in the absence of a randomized trial have dominated the extant literature: (i) assuming measured confounders can sufficiently block all sources of confounding (ignorability); and (ii) finding an instrumental variable–a variable that effectively encourages individuals into or out of the treatment (SNAP participation) while remaining independent of the outcome (BMI), except through influence on SNAP participation (Baiocchi et al., 2014). Instrumental variable analyses attempt to control for unmeasured confounders by mimicking a randomized trial.

Previous SNAP-BMI studies have generally assumed ignorability–a strong and difficult-to-prove assumption given that SNAP participation and BMI are potentially influenced by many unmeasured factors such as neighborhood poverty (Franco et al., 2008). Alternatively, researchers have used state variations in SNAP enrollment rules as instrumental variables to assess the effect of SNAP on a range of outcomes such as household expenditures (Almada and Nam, 2017), diet quality (Gregory et al., 2012), and food insecurity (Ratcliffe and McKernan, 2010). State variations in SNAP enrollment policies may effectively discourage or encourage individuals from enrolling in SNAP. For example, the requirement of an individual to appear in person and submit a fingerprint may discourage SNAP participation. In FoodAPS, we have access to many of these SNAP policy variables that may vary from state to state ("USDA ERS - Documentation," 2016). A policy variable that is a valid instrument would only be related to BMI through its association with SNAP participation while remaining uncorrelated with any sources of unmeasured confounding in a simple model of BMI as a function of SNAP and other measured confounders, i.e., it is exogenous. Once a valid instrument is identified, researchers typically use it in a two-stage least squares model to estimate the treatment effect of SNAP on BMI.

As with all parametric models, such instrumental variables analysis can produce a treatment effect estimate vulnerable to model specification (i.e., choice of inclusion of different measured covariates), but it is difficult to know if the correct model has been specified (Ho et al., 2007). Instruments can also be "weak" (Todd and Ver Ploeg, 2014); that is, limited in their ability to encourage SNAP participation independent of measured confounders, risking bias (Bound et al., 1995) and sensitivity to unmeasured confounders even with large sample size (Small and Rosenbaum, 2008). 'Weak instrument' bias tends to bias results in the same direction as results from a standard regression approach that adjusts for measured confounders (ordinary least squares, OLS) regression (Pischke, 2016. Chao and Swanson, 2005). Finally, instrumental variable analysis requires parametric adjustment for measured confounders, which may be problematic with skewed data (Ho et al., 2007).

Two recent developments have potentially improved our ability to re-examine the SNAP-BMI relationship. First, the release of the National Food Acquisition and Purchase Survey (FoodAPS) provides a nationally-representative sample of Americans with county-level geocodes and associated covariates, as well as body mass index and administratively-confirmed SNAP participation data. Second, this setting provides an opportunity to test out the relatively new analytical approach of near-far matching (Baiocchi et al., 2010; Rigdon et al., 2017). Prior to fitting any statistical models or conducting any hypothesis tests, near-far matching (Appendix Fig. 1) simultaneously matches groups of participants to be similar in observable characteristics (e.g., age, sex, race, etc.) and maximally different with regard to the level of instrumental variables (e.g., one participant being in a state that encourages SNAP enrollment, and their matched comparator being in a state that discourages SNAP enrollment) (Baiocchi et al., 2010, 2012). The near-far method makes use of instrumental variables' ability to control for unmeasured confounders, while taking advantages of the benefits of matching to examine the distribution of measured confounders. In particular, near-far matching facilitates identification of whether the distributions of measured baseline covariates between treated and untreated subjects are systematically different, which is easier to do than determining whether a model has been correctly specified. Near-far matching can also strengthen 'weak' instruments. Individuals are pair-matched to be near on measured covariates and simultaneously far on the instrument, increasing the chance that within pair differences in treatment assignment are due to differences in the instrument, thus strengthening the instrument. Furthermore, the approach facilitates examination of how changes in the populations selected for analysis by matching can alter the association between treatment and outcome (a sensitivity analysis), and enables nonparametric adjustment for measured confounders through matching (Baiocchi et al., 2010).

Here, we applied near-far matching to the FoodAPS dataset to examine how traditional regression, propensity matching, standard IV analysis, and near-far matching differ in estimating the SNAP-BMI association. This specific case exemplifies a common problem in social epidemiology in which social program exposure and outcomes are potentially explained by unmeasured covariates, and experimental randomization is impossible. We test the hypothesis that associations between SNAP participation and BMI are explained by previously-unmeasured confounders related to county-level covariates.

2. Methods

2.1. Data source

We performed secondary data analyses on the National Household Food Acquisition and Purchase Survey (FoodAPS) released in 2015 by the U.S. Department of Agriculture (USDA). FoodAPS is a cross-sectional national survey representative of non-institutionalized U.S. households conducted in 2012–2013, including subpopulations of SNAP participants, eligible non-participants (household incomes <185% of the federal poverty threshold), and higher-income ineligible non-participants. The FoodAPS survey provides data on SNAP participation; self-reported height and weight (from which body mass index is calculated); demographic and socioeconomic variables including age, sex, race/ethnicity, income and distance to primary store where food is acquired; and county-level geocoded data including poverty rate and urban/rural status. FoodAPS additionally includes state-level SNAP enrollment policy variables commonly utilized as instrumental variables (Appendix Table 1).

2.2. Statistical approach

Our statistical approach proceeded in four steps. Each successive step potentially made a stronger effort to control for unmeasured confounding when assessing the impact SNAP participation on BMI. The four procedures are summarized in Appendix Table 2.

First, we fit a standard ordinary least squares (OLS) model of BMI on SNAP participation (coded as a binary variable – participating or not participating), while adjusting for common measured demographic and socioeconomic covariates to mimic prior epidemiologic studies of the SNAP-obesity association. Demographic and socioeconomic covariates are further defined in Table 1, and include age, sex, race (Black), ethnicity (Hispanic), education level, household size, marital status, and household income (percent of the

Table 1
Summary of features of statistical analysis approaches.

	Analytic cohort	
Confounder control	Uses full sample for analysis	Filters cohort from study design perspective, sharpening inferences
Controls for only measured confounders	Approach 1: ordinary least squares (OLS) regression	Approach 2: propensity score match (PSM), then OLS
Controls for measured and unmeasured confounders	Approach 3: two-stage least squares regression (2SLS) using instrumental variable	Approach 4: near-far match using instrumental variable, then 2SLS

federal poverty threshold adjusted for household size).

$$
\begin{aligned}
BMI_i = {} & \beta_0 + \beta_1 1\{SNAP_i = yes\} + \beta_2 age_i + \beta_3 1\{sex_i \\
& = female\} + \beta_4 1\{race_i = black\} + \beta_5 1\{ethnicity_i \\
& = hispanic\} + \beta_6 education_i + \beta_7 pctpovhh_i + \beta_8 hhsize_i \\
& + \beta_9 marital + e_i
\end{aligned} \tag{1}
$$

Second, we conducted a propensity score-matched (PSM) analysis (Rosenbaum and Rubin, 1983), in which SNAP participants were matched to SNAP non-participants in a 1:1 nearest-neighbor match using the R package MatchIt (Ho et al., 2011). Prior to the match, we eliminated the bottom 10% and top 90% of propensity scores to ensure sufficient overlap. The goal of the PSM was to find a suitably matched non-participant for each SNAP participant, in the sense that the non-participant is similar on each of the covariates age, sex, race, ethnicity, education, marital status, and household size to the SNAP participant. The propensity score was the probability of participating in SNAP given the seven variables on the right side of equation (2),

$$
\begin{aligned}
p_i = \Pr[& SNAP_i = yes | age_i,\ sex_i,\ race_i,\ ethnicity_i, \\
& education_i,\ marital_i,\ hhsize_i]
\end{aligned} \tag{2}
$$

and was estimated using logistic regression. The PSM did not include household income as it was imputed when missing by FoodAPS based on SNAP status.

Third, we fit a standard instrumental variables model, using two-stage least squares regression (2SLS). The instrumental variables model included all state level policy variables with notable variation between states. For simplicity and comparison to the near-far match to follow in step 4, state-level policies were combined into a single composite weighted instrument (IVcomb) normalized to the interval [0, 1] where 0 indicates most discouraged from SNAP and 1 indicates most encouraged into SNAP (see Appendix for details). The 2SLS equation took the form:

$$
\begin{aligned}
BMI_i = {} & \beta_0 + \beta_1 \widehat{SNAP}_i + \beta_2 age_i + \beta_3 1\{sex_i \\
& = female\} + \beta_4 1\{race_i = black\} + \beta_5 1\{ethnicity_i \\
& = hispanic\} + \beta_6 education_i + \beta_7 pctpovhh_i + \beta_8 hhsize_i \\
& + \beta_9 marital + e_i
\end{aligned} \tag{3}
$$

where predicted SNAP ($\widehat{SNAP}_i$) was the predicted probability from a logistic regression model for SNAP status as a function of the demographic and socioeconomic factors in (2) plus the combined IV:

$$
\begin{aligned}
logit(SNAP_i) = {} & \gamma_0 + \gamma_1 age_i + \gamma_2 1\{sex_i = female\} + \gamma_3 1\{race_i \\
& = black\} + \gamma_4 1\{ethnicity_i \\
& = hispanic\} + \gamma_5 education_i + \gamma_6 pctpovhh_i \\
& + \gamma_7 hhsize_i + \gamma_8 marital_i + \gamma_9 IVcomb_i
\end{aligned} \tag{4}
$$

All continuous covariates in the models (age, education, and percent poverty in household) were median centered, i.e., the median was subtracted from the variable to provide more interpretable model coefficients. A weak instruments test, a test for overidentifying restrictions, and the Wu-Hausman test for endogeneity were performed for the 2SLS model.

The IVs chosen for our analysis are those that involve state variations in SNAP enrollment policies. Appendix Table 1 provides a systematic review of state variations in SNAP enrollment policies that were considered. We specifically examined the strength of each IV (first-stage F) and variation among states in the IV, as well as correlation to other IVs and relationship to SNAP enrollment. The major, untestable assumption behind IV analysis is that the IV was exogenous to BMI except by way of influencing SNAP enrollment.

To be a valid instrument, a candidate instrument needs to be associated with the exposure or treatment, not be associated with the outcome except through the exposure/treatment, and not share common causes with the outcome. In the case of the SNAP-BMI relationship, state level SNAP policy variations are conceptually valid instruments because they should be associated with receiving SNAP, but there is no reason to think they would be related to BMI except through their effect on SNAP, or share common causes with an individual's BMI. For this reason, prior studies have used state-level SNAP policy variations as an instrument (Almada and Nam, 2017; Gregory et al., 2012), and these studies have consistently supported their validity. Most importantly, these prior studies have shown that more liberal states often have more restrictive SNAP policies, which suggests that less restrictive SNAP policies are not simply a product of a more 'generous' approach to government that offers other more generous health benefits.

Fourth, we fit the same 2SLS model as in equation (3) after executing a near-far match (Baiocchi et al., 2012; Lorch et al., 2012). We pair-matched persons to be simultaneously similar ("near") on all measured covariates shown in Table 1 and different ("far") on the composite instrument IVcomb defined in step 3 above using the nearfar R package (Rigdon et al., 2017). Near-far matching is intended to increase the strength of the composite instrument as measured by a first-stage F test (where an F test value > 10 is typically regarded as strong, see (Nichols, 2016)). To strengthen execute the pair-match and strengthen the instrument, near-far matching eliminates certain individuals from the data set. Two parameters control who gets eliminated: (1) the proportion we are willing to eliminate (percent sinks), and (2) the separation in the instrument below which a strong penalty is applied when considering individuals for a pair match (the cutpoint parameter).

Following (Baiocchi et al., 2012), we initially set the percent sinks to be 50% and the cutpoint to be one standard deviation unit of the combined instrument, then varied these parameters in sensitivity analyses and robustness checks detailed below.

The post-matched sample was then analyzed using the above 2SLS regression (equation (2)). The association of SNAP participation on BMI was represented by both the 2SLS estimate of β_1 and the effect ratio, a non-parametric alternative to 2SLS models which is analogous to the Wald estimator in standard IV analyses (Baiocchi et al., 2010). The near-far match yields pairs of similar individuals, of whom one is encouraged into treatment and one is discouraged from treatment (by the IV). The effect ratio is defined as a ratio of the average effect across the pair-matches of IV encouragement versus not in the outcome variable divided by the average effect across the pair-matches of IV encouragement versus not in the treatment variable, e.g., an effect ratio equal to 1/100 would mean that for every 100 individuals that comply with the IV encouragement, 1 experiences the outcome.

We summarized the balance in the data both pre- and post-match in terms of mean standardized difference (Appendix Tables 3a and 3b). In sensitivity analyses, we repeated the near-far match with 75% of the data retained (25% sinks), and again with the requirement of a two standard deviation difference in the combined instrument variable to assess robustness of our results.

Finally, we repeated the above OLS, PSM, 2SLS, and near-far plus 2SLS procedures with the inclusion of county covariates captured in FoodAPS: distance to primary food store (in miles), urban versus rural county (by U.S. Census Bureau definition), and percent of county under the federal poverty threshold adjusted for household size. Specifically, we re-fit the models to the data set with the inclusion of these three covariates (including in the PSM match), where the two continuous covariates (distance to primary store and percent of county in poverty) were median-centered. We specifically hypothesized that the OLS, PSM, and 2SLS models would converge to be more similar to the near-far model estimates of the SNAP-obesity association once county-related covariates, unmeasured in the previous analyses, were considered. As a sensitivity analysis, we developed a second combined instrument (IVcomb2) that only included state level policies with substantial between-state variation (see Appendix). As a final sensitivity analysis, we included two additional propensity score matches with more covariates, both at the individual and household level and the county level. A summary of all modeling approaches is included in Appendix Table 2.

Statistical analyses were conducted in *R* version 3.3.2 (R Core Team, 2016), using the statistical code provided in the Appendix. Missing data were not imputed, as <1% of data for any given variable were missing. To provide a comparable analysis cohort to similar studies, we only included individuals 16 years of age or older.

Survey weights were not taken into account in the OLS and PSM given prior studies suggesting exclusion of weights when comparing OLS and PSM estimates (Gelman, 2007), and to provide comparability to results from IV and near-far matches, which attempt to estimate a local average treatment effect. We applied cluster robust standard errors to the OLS (Cameron et al., 2011) and 2SLS (White, 1982) models to adjust for clustering of individuals within households in FoodAPS.

3. Results

3.1. Characteristics of the study sample

Table 2 summarizes the demographic, socioeconomic, and county level differences between SNAP non-participants and SNAP participants in the overall FoodAPS sample. Compared to SNAP non-participants, SNAP participants were younger (mean age of 28.1 versus 35.1, $P < 0.0001$), more likely to be female (54.0% versus 51.6%, $P = 0.006$), more likely to be of Black race (23.3% versus 11.9%, $P < 0.0001$), more likely to be of Hispanic ethnicity (30.6% versus 22.8%, $P < 0.0001$), less educated (46.1% had some college versus 65.2%, $P < 0.0001$), had lower household income (mean 123.6% versus 304.7% of the federal poverty threshold, adjusted for household size, $P < 0.0001$), were further from a primary food store (0.12 miles versus 0.11, $P = 0.15$), less likely to be in a rural location (24.4% versus 26.9%, $P = 0.001$), and in counties with higher poverty (16% versus 14% of the county below the federal poverty threshold, $P < 0.0001$).

3.2. Results of statistical analyses

Table 3 summarizes the estimates of the association between SNAP participation and BMI. In the ordinary least squares regression controlling for individual demographic and socioeconomic characteristics (first row of Table 3), SNAP participation was associated with increased body mass index (+1.35 kg/m^2, 95% CI: 0.96, 1.74).

In the PSM controlling for individual demographic and socioeconomic characteristics (second row of Table 3), SNAP participation was similarly associated with increased body mass index (+1.34 kg/m^2, 95% CI: 0.89, 1.78). The standardized differences between the SNAP and matched non-SNAP subjects were all less than or equal to 0.05, indicating that the covariates were balanced according to the rule of thumb of having a standardized difference <0.2 (Appendix Table 3a). In a second PSM controlling for additional covariates, the association of SNAP on BMI was +0.96 kg/m^2 (95% CI: 0.49, 1.43).

Fig. 1 shows a directed acyclic graph representing our study and Fig. 2 displays the state-level policy data and the combined instrument. A standard 2SLS instrumental variables analysis (third row of Table 3) produced a larger effect size estimate, but with wider confidence intervals around the estimate (+2.26 kg/m^2 BMI associated with SNAP participation, 95% CI: −0.52, 5.04).

Using near-far matching produced a similar effect size estimate as OLS but with widened the confidence intervals (+1.37 kg/m^2 increase, 95% CI: −2.58, 5.33). The standardized differences between the SNAP and matched non-SNAP subjects were small (near 0) after the match (Appendix Table 3a).

3.3. Adjustment for county-level characteristics

The second column of Table 3 provides estimates of the association between SNAP participation and BMI after adjustment for county-level variables in addition to demographic and socioeconomic variables.

In the ordinary least squares regression controlling for individual demographic and socioeconomic characteristics as well as county level covariates (first row of Table 3), the increased body mass index associated with SNAP participation was only slightly attenuated from the estimate that excluded county-level covariates (from +1.35 kg/m^2 increase without county characteristics to +1.23 kg/m^2 increase with county characteristics, 95% CI: 0.84, 1.63).

The effect size was also attenuated in the PSM, from +1.34 kg/m^2 without county covariates to +1.15 kg/m^2 with county characteristics (95% CI: 0.71, 1.60; Table 3). The effect size was also attenuated in the PSM that adjusted for additional covariates, from +0.96 kg/m^2 without county covariates to +0.74 kg/m^2 (95% CI: 0.27, 1.21).

The effect size was more profoundly attenuated and confidence intervals widened in the 2SLS model, from +2.26 kg/m^2 when

Table 2
Summary of individual, household, and county level characteristics for the National Household Food Acquisition and Purchasing Survey (nationally-representative survey of United States, years 2012–13) by SNAP participation for individuals 16 years of age or older. Means (±standard deviations) for continuous variables and N (%) for categorical variables.

	SNAP non-participants n = 6835	SNAP participants n = 3525	Total n = 10,360	P-value[a]
Demographic and Socioeconomic variables				
Age (years)	43.4 (±18.2)	39.4 (±16.5)	42.0 (±17.8)	<0.0001
Sex				<0.0001
Male	3275 (47.9%)	1496 (42.4%)	4771 (46.1%)	
Female	3560 (52.1%)	2029 (57.6%)	5589 (53.9%)	
Black race				<0.0001
Yes	783 (11.5%)	783 (22.2%)	1566 (15.1%)	
No	6040 (88.4%)	2741 (77.8%)	8781 (84.8%)	
Missing	12 (0.2%)	1 (0.0%)	24 (0.1%)	
Hispanic ethnicity				<0.0001
Yes	1442 (21.1%)	965 (27.4%)	2407 (23.2%)	
No	5390 (78.9%)	2557 (72.5%)	7947 (76.7%)	
Missing	3 (0.0%)	3 (0.1%)	6 (0.1%)	
Education				<0.0001
High school or less	256 (3.7%)	200 (5.7%)	456 (4.4%)	
Some college	769 (11.3%)	798 (22.6%)	1567 (15.1%)	
College or more	5791 (84.7%)	2493 (70.7%)	8284 (80.0%)	
Missing	19 (0.3%)	34 (1.0%)	53 (0.5%)	
Marital status				<0.0001
Married	3407 (49.8%)	966 (27.4%)	4373 (42.2%)	
Widowed	354 (5.2%)	178 (5.0%)	532 (5.1%)	
Divorced	739 (10.8%)	592 (16.8%)	1331 (12.8%)	
Separated	135 (2.0%)	227 (6.4%)	362 (3.5%)	
Never married	2190 (32.0%)	1559 (44.2%)	3749 (36.2%)	
Missing	10 (0.1%)	3 (0.1%)	13 (0.1%)	
Household size	3.3 (±1.8)	4.1 (±2.1)	3.6 (±1.9)	<0.0001
Household %income	319.3 (±298.8)	132.8 (±171.5)	255.9 (±277.0)	<0.0001
County variables				
Distance to primary store (miles)	0.1145 (±0.0387)	0.1159 (±0.0390)	0.1150 (±0.0388)	0.080
Rural				0.022
Yes	1847 (27.0%)	879 (24.9%)	2726 (26.3%)	
No	4988 (73.0%)	2646 (75.1%)	7634 (73.7%)	
Fraction of county under federal poverty threshold	0.1451 (±0.0476)	0.1626 (±0.0475)	0.1511 (±0.0483)	<0.0001

[a] Wilcoxon rank sum test for continuous variables and Fisher's exact test for categorical variables.

Table 3
Results of alternative methods for estimating the association between SNAP participation on BMI in the FoodAPS data set (nationally-representative survey of the United States, years 2012–2013), where the units of the effect estimate (95% CI) are BMI in kg/m^2, i.e., 1.00 indicates a one unit increase in BMI in kg/m^2 due to SNAP participation.

Type of analysis	Individual and household covariates			Individual and household covariates plus county covariates		
	N	Estimate	95% CI	N	Estimate	95% CI
Ordinary least squares (OLS)	9961	1.35	0.96, 1.74	9328	1.23	0.84, 1.63
Propensity score match then OLS	5396	1.34	0.89, 1.78	4956	1.15	0.71, 1.60
2SLS with full cohort	9961	2.26	−0.52, 5.04	9328	1.61	−1.33, 4.55
2SLS after near-far match	4980	1.37	−2.58, 5.33	4664	0.21	−3.88, 4.29

excluding the county covariates to +1.61 kg/m^2 when including the county covariates (95% CI: −1.33, 4.55).

The effect size was essentially null when including county covariates in the near/far match, from +1.37 kg/m^2 without county covariates, to +0.21 kg/m^2 (95% CI: −3.88, 4.29) when including county covariates.

3.4. Sensitivity analysis of near-far matching

When changing the proportion of the sample in the near-far match from 50% to 75%, and when changing the required difference in matched subjects on values of the combined instrument from one standard deviation to two standard deviations, we found that the treatment effect estimate of SNAP on obesity was consistently above +2 kg/m^2, but with consistently wide confidence intervals ranging from −0.8 to +6.1 kg/m^2 (Appendix Table 4). When using the non-parametric effect ratio estimate instead of the parametric treatment effect estimate, the effect ratio was also consistently wide, varying from −0.62–2.11 kg/m^2 with confidence intervals from −2.2 to +5.5 kg/m^2. The range of confidence was not substantially affected by including the county covariates (Appendix Table 5), or by repeating all of the instrument variable analyses (both pre- and post-near-far match) using an alternative combined instrument (Appendix Tables 4 and 5).

4. Discussion

Many questions in social epidemiology involve the study of social programs or policies for which a randomized trial is practically or ethically infeasible. Studying the effects of the largest nutrition program in the U.S., the SNAP program, poses such a conundrum. Mean weight gain in the United States is 1–2 pounds per year (Hutfless et al., 2013), and SNAP has been previously associated with increased BMI even over short-term periods (Leung

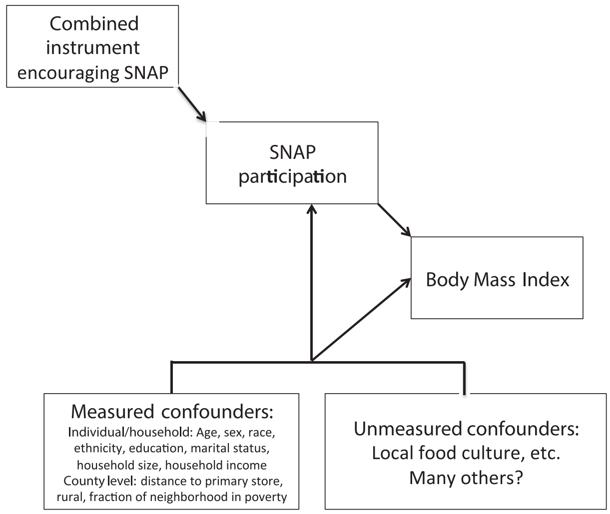

Fig. 1. Directed Acyclic Graph (DAG) representation of relationships between instrument, SNAP participation, and BMI.

and Villamor, 2011). Here, we examined how traditional OLS regression, matching with propensity scores, and IV analysis methods including near-far matching, differed in estimating the SNAP-BMI association. We tested the hypothesis that associations between SNAP participation and BMI are potentially explained by previously-unmeasured confounders related to county-level covariates. Our approach included common regression methods, refining the data set using matching, using a weak instrument for analysis, and finally refining both the data set and the instrument simultaneously. We repeated this four-pronged strategy both with and without the inclusion of county-level characteristics to take advantage of our geocoded data, as most analyses of the SNAP-BMI relationship have not included geographic covariates.

We observed that using ordinary least squares (OLS) with adjustment for measured confounders, applied to both the unmatched data and the propensity score matched (PSM) refined (smaller) data set, could potentially produce a very confident estimate of a positive 'average treatment effect' (ATE) of SNAP participation on BMI. By contrast, IV-based estimators, which focus on a subset of people and thus estimate a 'local average treatment effect' (LATE) (Baiocchi et al., 2014), are much less confident, with very wide confidence intervals and even more sensitivity to county covariates. One possibility is that ATE estimated by OLS/PSM is from a larger sample size and therefore more confidently estimated. This possibility could reflect the "bias-variance trade-off", in which a larger non-randomized sample yields a potentially biased estimate with smaller variance than a smaller filtered (pseudo-randomized) sample that yields a possibly less biased estimate with larger variance. But the fact that the IV-based estimation produces both diminished effect size estimates and wide confidence intervals revealed sensitivity to model specification as well, suggesting that the OLS/PSM may be over-confident in ignoring unmeasured confounders.

One larger implication for social epidemiology is that the common situation in which social program exposures cannot be randomized may render it difficult to have confidence in OLS and

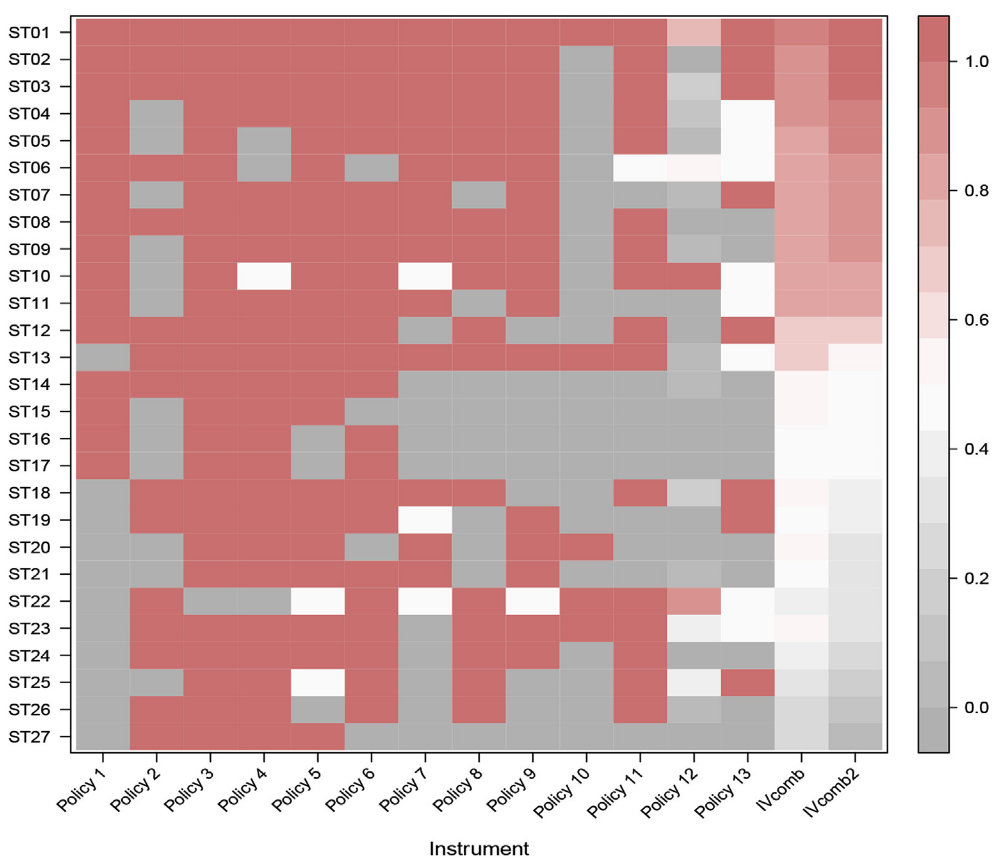

Fig. 2. Heatmap of state level variation for each of 13 potential IVs (columns) for the 27 participating states in FoodAPS (nationally-representative survey of the United States, years 2012–2013) sorted by the first combined IV such that the most encouraging (into SNAP) state appears at the top. Per dissemination rules, IVs policies are randomly named in this figure to avoid identifiability of states, but Appendix Table 1 provides the specific policies and descriptions.

PSM models, and similarly difficult with IV models that are not consistent across specifications. The large and meaningful differences between the standard 2SLS IV analysis and the near-far matched IV analysis suggest that near-far matching can produce estimates that are not simply equivalent to IV analyses with regression adjustment; rather, the matching process that focuses on differences in IV measures simultaneously with similarity in observed covariates produced much more conservative effect size estimates. While we cannot know which estimates are 'true', the lack of consistency across estimators would suggest that we should not have confidence in the SNAP-obesity association.

Our findings should be interpreted in the context of their limitations. First, BMI was self-reported in FoodAPS. Self-reported data could contain inaccuracies but we do not expect there to be differences in BMI self-reporting bias by SNAP status. Second, our findings rely on cross-sectional data. Specifically, we address the question of how BMI is impacted at the current moment by participation in SNAP in the past year. We cannot account for the amount of SNAP participation, longitudinal variation in BMI and SNAP participation, or prior exposure to adverse social conditions. Time-varying confounding could exist and be unaccounted for, as current SNAP participants may have had prior episodes of food insecurity that both led to obesogenic changes in diet and prompted them to enroll in SNAP. Third, we did not adjust for survey weights, opting for comparability and simplicity across alternative model specifications. In the OLS and PSM we aimed to estimate the 'average treatment effect', but near-far matching eliminates both treated and untreated units, changing our target of estimation to the 'local average treatment effect'. Fourth, we chose to use the same functional form as prior analyses that did not adjust for correlations within households. This is a limitation of all of our analyses, but we note that further adjustment for correlation structure would be expected to widen the confidence intervals and thus strengthen our primary conclusion regarding the large uncertainty in effect size estimates. Furthermore, county-level analyses are known to suffer from the modifiable area unit problem and place heterogeneity issues, with emerging datasets attempting to define neighborhoods by multiple levels—a feature unavailable in the data we used here (Clark and Williams, 2016).

We note that there are strengths and limitations to each of the methodological approaches included here. Standard OLS regression was the most efficient (smallest confidence intervals). Propensity score matching could not handle unmeasured confounding. Instrumental variable analysis could handle unmeasured confounding, but relied on assumptions that cannot be empirically proven, including the idea that the instruments can help meaningfully influence people into or out of the exposure, and that the instruments only influence the outcome through exposure to SNAP (though there may be remaining state-level confounding influencing both SNAP rules and BMI). The near-far method had the advantage of combining both matching methods to help provide a more balanced comparison between exposed and unexposed persons in observed covariates, as well as using instrumental variables for control of unmeasured confounders. Near-far matching loses sample size and therefore generalizability, and loses efficiency in this context, in exchange for attempting to control for the unmeasured confounders. In our experiment, the demographics of the post-match cohort were similar to those of the pre-match cohort on variables age, sex, and rural status but significantly different on variables race, ethnicity, education, marital status, household size, household income, distance to supermarket, and county poverty rate, questioning the generalizability of our findings (see Appendix Table 6).

In future work, similar methodology could be applied to other difficult problems in social epidemiology that can be characterized as weak instrument problems—that is, settings where randomization is unethical or infeasible, and researchers must rely on potentially weak instruments to control for some unmeasured confounders. Applying near-far matching in these settings may help to study the robustness of standard instrumental variable results.

Further study is needed on the implications for power when using near-far matching as near-far matching can considerably reduce sample size. An additional current limitation of the near-far matching method is that it is computationally intensive for samples greater than 1000 and when the number of covariates to make "near" in the match is greater than 3. Future work should focus on identifying algorithms that can execute the near/far matching procedure more efficiently. Additional future work could extend the capability of near-far matching to include more than one instrument as only one instrument is required in its current form.

In the current analysis, we observed a lack of consistency across estimation approaches and sensitivity of estimation to alternative specifications. This suggests that previous reports of an association between SNAP and obesity should be viewed with caution.

Acknowledgements

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Appendix

A combined instrument was formed from the 14 available instruments as follows:

1. Each state level instrument was recoded to map to the interval [0, 1] where 0 would indicate most discouraged into SNAP and 1 would indicate most encouraged into SNAP. For example, oapp was originally coded in 3 categories where 0 = no, 1 = yes, and 2 = yes, in some parts of the state and was recoded such that 0 = no, 0.5 = yes, in some parts of the state, and 1 = yes. The only continuous variable, outreach, was recoded as a proportion of the maximum spend by any state. Many variables did not have to be recoded. The policy variable ebtissuance, the proportion of dollar value SNAP benefits accounted for by EBT, was removed from analysis because was equal to 1 for all states (no variation across states).
2. For each of the 13 recoded variables from step 1, a logistic regression of SNAP participation ~ IV was fit. The deviance, d_i, was recorded for IV $i = 1, \ldots, 13$. Deviance is the amount of reduction in the residual deviance due to that IV. In place of a Z-score, deviance was used as a proxy of the discriminatory power of each IV.
3. The combined instrument was constructed as a weighted average of all the IVs by their partial deviances. That is, $IVcomb = (d_1IV_1 + \ldots + d_{13}IV_{13})/(d_1 + \ldots + d_{13})$.

As mentioned in the main text, a second combined instrument was also developed. To only include instruments with sufficient between state variation, steps 1–3 were repeated above with only those instruments with standard deviation greater than 0.4 included in step 2 in developing the combined instrument.

Appendix Table 1
Potential IVs considered for the FoodAPS data set.

IV name	Description
bbce	The State uses broad-based categorical eligibility to increase or eliminate the asset test and/or to increase the gross income limit for virtually all SNAP applicants.
bbce_asset	The State eliminates the asset test under broad-based categorical eligibility.
call	The State operates call centers, and whether or not call centers service the entire State or select regions within the State.
cap	The State operates a Combined Application Project for recipients of Supplemental Security Income (SSI), so that SSI recipients are able to use a streamlined SNAP application process.
compdq	The State disqualifies SNAP applicants or recipients who fail to perform actions required by other means-tested programs, primarily Temporary Assistance for Needy Families (TANF).
	The proportion of the dollar value of all SNAP benefits that are accounted for by EBT (electronic benefit transfer).
faceini	The State has been granted a waiver to use a telephone interview in lieu of a face-to-face interview at initial certification, without having to document household hardship.
facerec	The State has been granted a waiver to use a telephone interview in lieu of a face-to- face interview at recertification, without having to document household hardship.
fingerprint	The State requires fingerprinting of SNAP applicants.
noncitadultfull	All legal noncitizen adults (age 18–64) who satisfy other SNAP eligibility requirements such as income and asset limits are eligible for Federal SNAP benefits or State-funded food assistance.
oapp	The State allows households to submit a SNAP application online.
outreach	The sum of Federal, State, and grant outreach spending in nominal dollars ($1,000s)
reportsimple	For households with earnings, the State uses the simplified reporting option that reduces requirements for reporting changes in household circumstances.
vehexclall	The State excludes all vehicles in the household from the SNAP asset test.

Note about creating a combined instrumental variable.

Appendix Table 2a
Absolute standardized differences (ASD) by SNAP participation status, pre- and post-propensity score match, including all individual and household variables.

	Pre-Match			Post-Match		
	SNAP no N = 6573	SNAP yes N = 3388	ASD	SNAP no N = 2698	SNAP yes N = 2698	ASD
Age (years)	43.41	39.29	0.24	39.39	39.96	0.03
Sex (% female)	51.88	57.62	0.12	55.78	56.49	0.01
Race (% black)	11.51	22.40	0.29	16.79	17.31	0.01
Ethnicity (% hispanic)	20.52	27.18	0.16	28.02	27.21	0.02
Education (years)	20.16	18.76	0.50	19.17	19.11	0.02
Household %income[a]	320.51	133.34	0.76	271.08	139.36	0.60
% Married	49.96	27.45	0.48	30.43	31.36	0.02
Household size	3.27	4.07	0.42	3.62	3.68	0.04

[a] Variable not included in match as SNAP status was used to impute missing values in defining this variable.

Appendix Table 2b
Absolute standardized differences by SNAP participation status, pre- and post-propensity score match, including all individual, household, and county variables.

	Pre-Match			Post-Match		
	SNAP no N = 6180	SNAP yes N = 3148	ASD	SNAP no N = 2478	SNAP yes N = 2478	ASD
Age (years)	43.36	39.22	0.24	39.46	39.87	0.02
Sex (% female)	51.91	57.47	0.11	56.13	56.09	0.00
Race (% black)	11.76	22.49	0.29	16.91	16.42	0.01
Ethnicity (% hispanic)	20.94	27.38	0.15	27.97	27.68	0.01
Education (years)	20.17	18.78	0.50	19.13	19.10	0.01
Household %income[a]	320.06	133.93	0.76	261.26	143.19	0.52
% Married	49.97	27.95	0.46	32.00	32.24	0.01
Household size	3.29	4.08	0.41	3.68	3.74	0.03
Distance to primary store (miles)	3.30	3.19	0.02	3.16	3.15	0.00
Rural (%)	27.30	25.22	0.05	26.59	25.83	0.02
Fraction of county under federal poverty threshold	14.53	16.29	0.37	15.57	15.63	0.01

[a] Variable not included in match as SNAP status was used to impute missing values in defining this variable.

Appendix Table 3a
Absolute standardized differences by level of instrumental variable, pre- and post-near-far match with 50% sinks and one standard deviation of separation in the first combined instrument (IVcomb) for individual and household confounders only.

	Pre-Match[a]			Post-Match		
	Encouraged N = 4945	Discouraged N = 5016	ASD	Encouraged N = 2490	Discouraged N = 2490	ASD
IVcomb	0.44	0.87	4.88	0.42	0.85	4.08
Age (years)	41.53	42.49	0.05	41.94	42.02	0.00
Sex (% female)	53.25	54.41	0.02	53.82	53.82	0.00
Race (% black)	15.67	14.75	0.03	8.23	8.23	0.00
Ethnicity (% hispanic)	20.93	24.62	0.09	16.35	16.35	0.00
Education (years)	19.73	19.64	0.03	19.90	19.90	0.00
Household %poverty	258.04	255.67	0.01	285.85	275.25	0.04
% married	42.18	42.42	0.00	49.40	49.40	0.00
Household size	3.59	3.50	0.05	3.46	3.44	0.00

[a] pre-match, data are separated into encouraged (less than the median of IVcomb) and discouraged (greater than or equal to the median of IVcomb).

Appendix Table 3b
Absolute standardized differences by level of instrumental variable, pre- and post-near-far match with 50% sinks and one standard deviation of separation in the first combined instrument (IVcomb) for individual, household, and county confounders.

	Pre-Match[a]			Post-Match		
	Encouraged N = 4658	Discouraged N = 4670	ASD	Encouraged N = 2332	Discouraged N = 2332	ASD
IVcomb	0.44	0.87	4.85	0.43	0.84	3.44
Age (years)	41.57	42.35	0.04	42.23	42.28	0.00
Sex (% female)	53.09	54.48	0.03	53.22	53.22	0.00
Race (% black)	15.80	14.97	0.02	9.34	9.34	0.00
Ethnicity (% hispanic)	21.51	24.71	0.08	18.05	18.05	0.00
Education (years)	19.74	19.65	0.03	19.94	19.94	0.00
Household %income	259.31	255.18	0.01	285.59	274.95	0.04
% Married	42.66	42.42	0.00	47.73	47.56	0.00
Household size				3.46	3.44	0.01
Distance to primary store (miles)	3.28	3.24	0.01	3.34	3.23	0.02
Rural (%)	26.71	26.49	0.00	27.02	27.02	0.00
Fraction of county under federal poverty threshold	14.79	15.46	0.14	14.83	14.77	0.01

[a] pre-match, data are separated into encouraged (less than the median of IVcomb) and discouraged (greater than or equal to the median of IVcomb).

Appendix Table 4
Results of all models with individual and household covariates only. Italicized results also appear in Table 3. Percent sinks refer to percent of sample lost as unsuitable match.

Study design	N	F (p-value);	Wu-Hausman (p-value)	Model effect	95% CI	Effect ratio	95% CI
OLS	*9961*	*NA*		*1.35*	*0.96, 1.74*	*NA*	
Propensity score match + OLS	*5396*	*NA*		*1.34*	*0.89, 1.78*	*NA*	
Propensity score match 2 + OLS[a]	5274	NA		0.96	0.49, 1.43	NA	
Instrument 1							
Pre-match 2SLS	*9961*	*174.618 (<2e-16)*	*0.573 (0.449)*	*2.26*	*−0.52, 5.04*	*NA*	
25% sinks; one SD	7470	133.540 (<2e-16)	0.432 (0.511)	2.32	−0.89, 5.52	0.89	−2.71, 4.47
50% sinks; one SD	*4980*	*77.82 (<2e-16)*	*0.00 (0.998)*	*1.37*	*−2.58, 5.33*	*−0.62*	*−5.02, 3.60*
25% sinks; two SDs	7470	134.625 (<2e-16)	0.521 (0.471)	2.23	−0.94, 5.40	1.48	−1.71, 4.71
50% sinks; two SDs	4980	122.331 (<2e-16)	0.361 (0.548)	2.15	−1.17, 5.46	1.36	−1.89, 4.65
Instrument 2							
Pre-match 2SLS	9961	149.347 (<2e-16)	0.444 (0.505)	2.22	−0.80, 5.23	NA	
25% sinks; one SD	7470	111.203 (<2e-16)	0.347 (0.556)	2.29	−1.23, 5.82	1.44	−2.21, 5.12
50% sinks; one SD	4980	65.796 (6.25e-16)	0.045 (0.831)	1.03	−3.34, 5.40	−0.13	−4.81, 4.39
25% sinks; two SDs	7470	122.419 (<2e-16)	0.512 (0.474)	2.30	−1.00, 5.60	1.67	−1.48, 4.86
50% sinks; two SDs	4980	109.394 (<2e-16)	0.543 (0.461)	2.53	−1.02, 6.07	2.11	−1.18, 5.48

[a] PSM 2 included the additional individual and household covariates participation in a nutrition education event, any household member dieting, household gets food by hunting or fishing, household has vegetable garden, household went to a food pantry, household description of food sufficiency, food ran out in last 30 days question, any household member eligible for WIC, and anyone in household is migrant or seasonal worker.

Appendix Table 5
Results of all models with individual, household, and county level covariates. Italicized results also appear in Table 3. Percent sinks refer to percent of sample lost as unsuitable match.

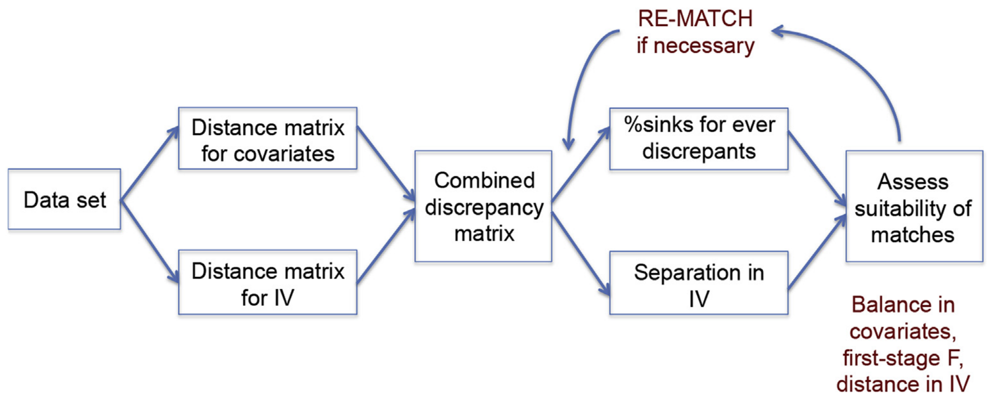
Study design	N	F (p-value)	Wu-Hausman p-value	Model effect	95% CI	Effect ratio	95% CI
OLS	*9328*	*NA*		*1.23*	*0.84, 1.63*	*NA*	
Propensity score match + OLS	*4956*	*NA*		*1.15*	*0.71, 1.60*	*NA*	
Propensity score match 2 + OLS[a]	4854	NA		0.74	0.27, 1.21	NA	
Instrument 1							
Pre-match 2SLS	*9328*	*154.381 (<2e-16)*	*0.087 (0.768)*	*1.61*	*−1.33, 4.55*	*NA*	
25% sinks; one SD	6996	108.084 (<2e-16)	0.529 (0.467)	2.54	−1.02, 6.09	2.66	−1.52, 7.00
50% sinks; one SD	*4664*	*78.348 (<2e-16)*	*0.133 (0.715)*	*0.21*	*−3.88, 4.29*	*0.86*	*−3.77, 5.55*
25% sinks; two SDs	6996	137.476 (<2e-16)	1.205 (0.272)	2.62	−0.50, 5.75	3.24	0.24, 6.39
50% sinks; two SDs	4664	94.57 (<2e-16)	0.06 (0.806)	1.39	−2.28, 5.05	1.76	−1.84, 5.49
Instrument 2							
Pre-match 2SLS	9328	134.749 (<2e-16)	0.053 (0.818)	1.55	−1.61, 4.70	NA	
25% sinks; one SD	6996	90.043 (<2e-16)	0.297 (0.586)	2.22	−1.69, 6.14	3.28	−1.26, 8.09
50% sinks; one SD	4664	57.577 (3.9e-14)	0.087 (0.767)	0.23	−4.55, 5.01	1.30	−3.71, 6.39
25% sinks; two SDs	6996	120.219 (<2e-16)	0.893 (0.345)	2.47	−0.89, 5.82	2.58	−0.46, 5.73
50% sinks; two SDs	4664	67.406 (<2.83e-16)	0.016 (0.898)	0.60	−3.81, 5.01	1.50	−2.70, 5.83

[a] PSM 2 included the additional individual and household covariates participation in a nutrition education event, any household member dieting, household gets food by hunting or fishing, household has vegetable garden, household went to a food pantry, household description of food sufficiency, food ran out in last 30 days question, any household member eligible for WIC, and anyone in household is migrant or seasonal worker plus the additional county covariates secondary store source, primary store travel mode, primary store source, primary store driving dist, primary store driving time, and primary store type.

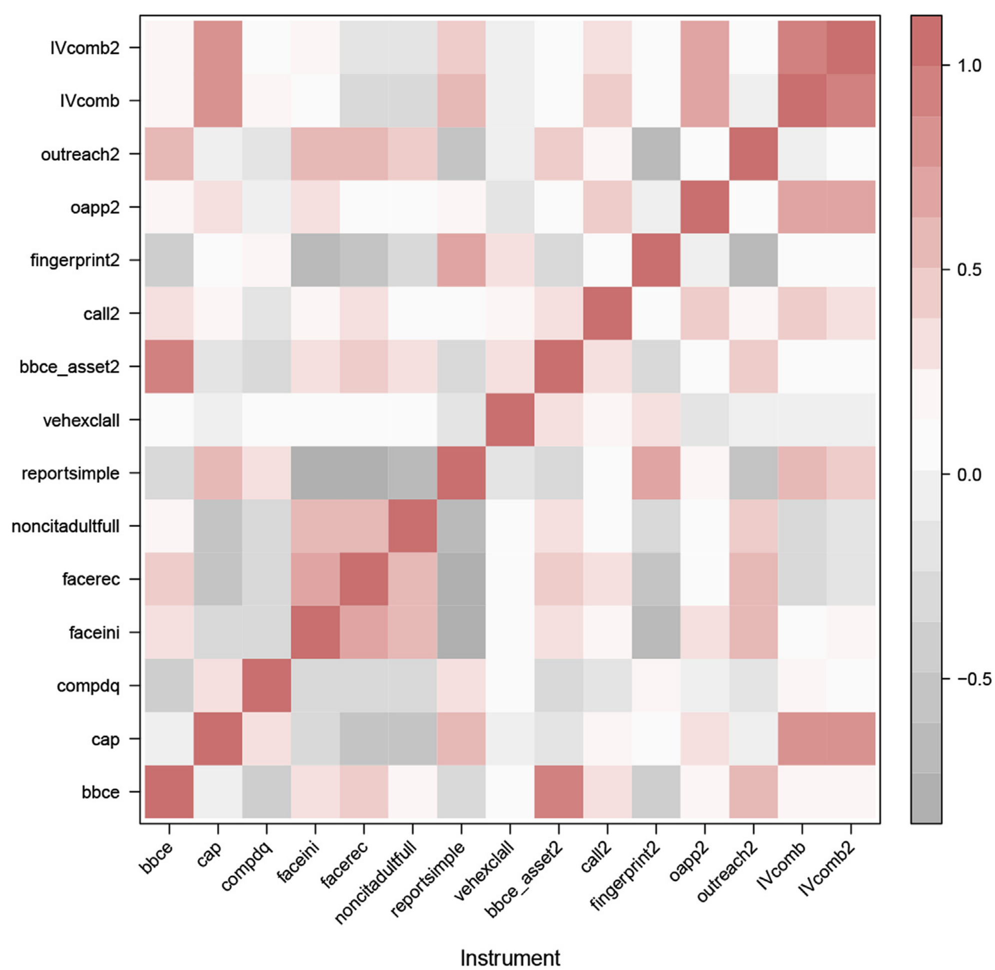
Appendix Table 6
Summary of individual, household, and county level characteristics by inclusion in near-far match from bottom right cell of Table 3. Means (±standard deviations) for continuous variables and N (%) for categorical variables.

	Not in match n = 4664	In match n = 4664	Total n = 9328	P-value[a]
Demographic and Socioeconomic variables				
Age (years)	41.7 (±17.2)	42.3 (±18.3)	42.0 (±17.8)	0.30
Sex				0.28
Male	2129 (45.6%)	2182 (46.8%)	4311 (46.2%)	
Female	2535 (54.4%)	2482 (53.2%)	5017 (53.8%)	
Black race				<0.0001
Yes	999 (21.4%)	436 (9.3%)	1435 (15.4%)	
No	3665 (78.6%)	4228 (90.7%)	7893 (84.6%)	
Hispanic ethnicity				<0.0001
Yes	1314 (28.2%)	842 (18.1%)	2156 (23.1%)	
No	3350 (71.8%)	3822 (81.9%)	7172 (76.9%)	
Education				<0.0001
High school or less	252 (5.4%)	139 (3.0%)	391 (4.2%)	
Some college	787 (16.9%)	616 (13.2%)	1403 (15.0%)	
College or more	3625 (77.7%)	3909 (83.8%)	7534 (80.8%)	
Marital status				<0.0001
Married	1746 (37.4%)	2222 (47.6%)	3968 (42.5%)	
Widowed	245 (5.3%)	220 (4.7%)	465 (5.0%)	
Divorced	741 (15.9%)	463 (9.9%)	1204 (12.9%)	
Separated	207 (4.4%)	109 (2.3%)	316 (3.4%)	
Never married	1725 (37.0%)	1650 (35.4%)	3375 (36.2%)	
Household size	3.7 (±2.0)	3.4 (±1.8)	3.6 (±1.9)	<0.0001
Household %income	234.2 (±261.1)	280.3 (±293.7)	257.2 (±278.8)	<0.0001
County variables				
Distance to primary store (miles)	0.1145 (±0.0387)	0.1159 (±0.0390)	0.1150 (±0.0388)	0.002
Rural				0.37
Yes	1221 (26.2%)	1260 (27.0%)	2481 (26.6%)	
No	3443 (73.8%)	3404 (73.0%)	6847 (73.4%)	
Fraction of county under federal poverty threshold	0.1545 (±0.0520)	0.1480 (±0.0452)	0.1513 (±0.0488)	<0.0001

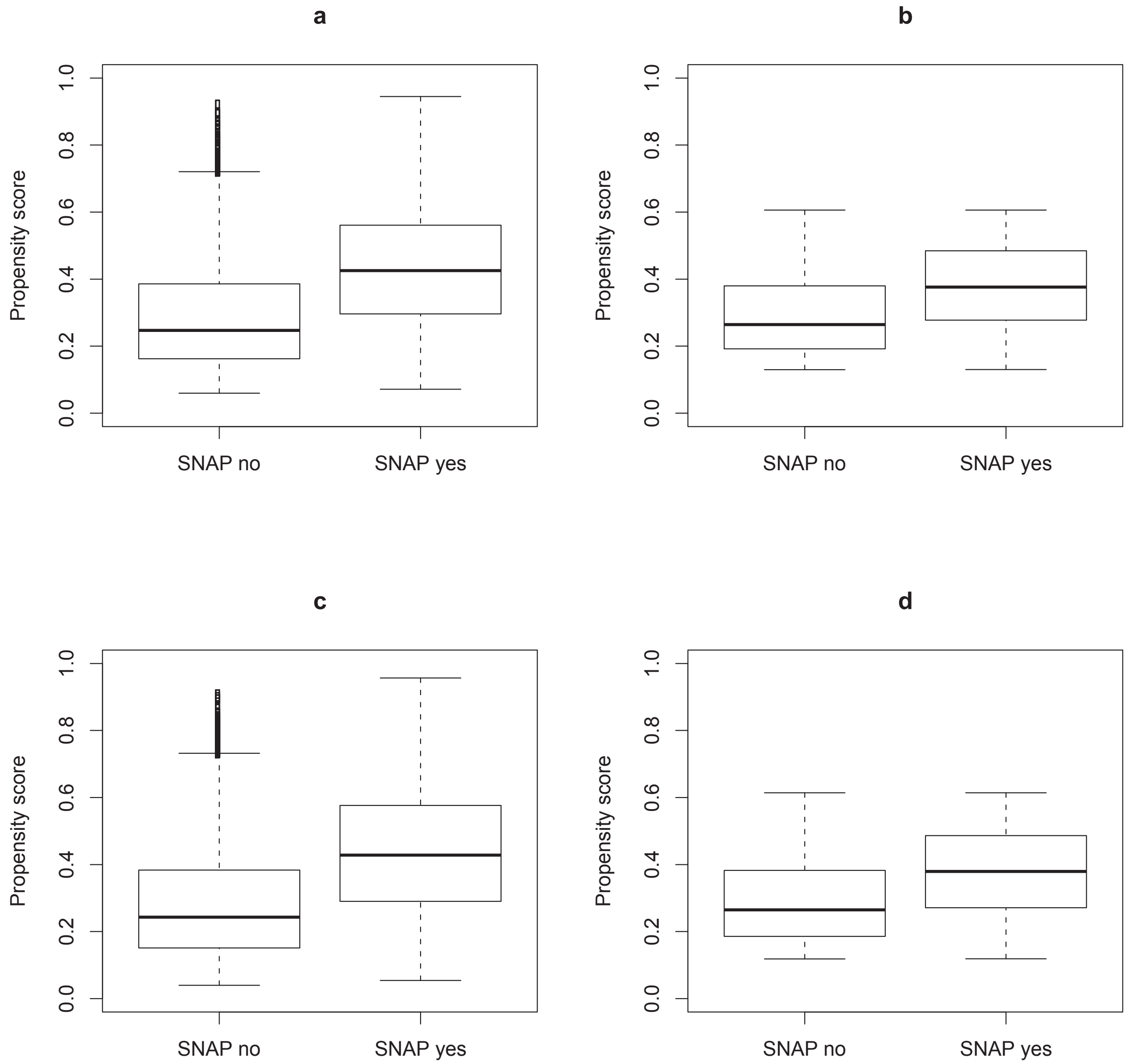
[a] Wilcoxon rank sum test for continuous variables and Fisher's exact test for categorical variables.



Appendix Fig. 1. Schematic of near-far matching procedure.



Appendix Fig. 2. Heatmap of correlations between instrumental variables (2 indicates recode).



Appendix Fig. 3. Propensity score balance (a) for full data set of individual and household variables; (b) for post-10/90 cut of individual and household variables; (c) for full data set of individual, household, and county variables; and (d) for post-10/90 cut of individual, household, and county variables.

Appendix of Statistical code

All code used to execute statistical analyses contained in this manuscript can be found at the following link: https://github.com/joerigdon/SNAP-BMI-nearfar.

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