HHS Public Access
Author manuscript
Ann Intern Med. Author manuscript; available in PMC 2022 June 01.

Published in final edited form as:
Ann Intern Med. 2021 December ; 174(12): 1674–1682. doi:10.7326/M21-1588.

SNAP Participation and Healthcare Use in Older Adults: A Cohort Study

Seth A. Berkowitz, MD MPH[1,2], **Deepak Palakshappa, MD MSHP**[3,4,5], **Joseph Rigdon, PHD**[6], **Hilary K. Seligman, MD MAS**[7,8], **Sanjay Basu, MD PhD**[9,10,11]

[1]Division of General Medicine and Clinical Epidemiology, Department of Medicine, University of North Carolina at Chapel Hill School of Medicine, Chapel Hill, NC

[2]Cecil G. Sheps Center for Health Services Research, University of North Carolina at Chapel Hill, Chapel Hill, NC

[3]Department of Pediatrics, Wake Forest School of Medicine, Winston-Salem, NC

[4]Department of Epidemiology and Prevention, Division of Public Health Sciences, Wake Forest School of Medicine, Winston-Salem, NC

[5]Department of Internal Medicine, Wake Forest School of Medicine, Winston-Salem, NC

[6]Department of Biostatistics and Data Science, Wake Forest School of Medicine, Winston-Salem, NC

[7]University of California San Francisco, Division of General Internal Medicine, San Francisco, CA

[8]Center for Vulnerable Populations at San Francisco General Hospital & Trauma Center, San Francisco, CA

[9]Center for Primary Care, Harvard Medical School, Boston, MA, USA

[10]Institute of Health Policy, Management & Evaluation, University of Toronto

[11]School of Public Health, Imperial College London, London, UK

Abstract

Background: Older adults dually eligible for Medicare and Medicaid have particularly high food insecurity prevalence and healthcare use.

Address for correspondence: Seth A. Berkowitz, MD MPH, 5034 Old Clinic Bldg, CB 7110, Chapel Hill, NC 27599, seth_berkowitz@med.unc.edu, Tel: 919-966-2276.
Author information: SAB conceived of the study and drafted the manuscript. DP, JR, HKS, and SB revised the manuscript critically for intellectual content. All authors give approval of the manuscript version to be submitted.
Seth A. Berkowitz, MD MPH, 5034 Old Clinic Bldg, CB 7110, Chapel Hill, NC 27599
Deepak Palakshappa, MD MSHP, Department of Internal Medicine, Wake Forest School of Medicine, Winston-Salem, NC 27157
Joseph Rigdon, PhD, Department of Biostatistics and Data Science, Wake Forest School of Medicine, Winston-Salem, NC 27157
Hilary K. Seligman, MD MAS, UCSF Box 1339, San Francisco, CA 94143
Sanjay Basu, MD PhD, 85 Bluxome St, San Francisco, CA 94107

Prior Presentation: None

Reproducible Research Statement
Study protocol: Not available.
Statistical code: Available in the Supplement
Data set: Not available owing to terms of the data use agreement

Objective: We sought to determine whether Supplemental Nutrition Assistance Program (SNAP) participation, which reduces food insecurity, is associated with lower healthcare use and cost for older adults dually eligible for Medicare and Medicaid.

Design: Incident user retrospective cohort study. We assessed the association between SNAP participation and healthcare use and cost using outcome regression, supplemented by entropy balancing, matching, and instrumental variable analyses.

Setting: North Carolina, September 2016 through July 2020.

Participants: Older adults (age ≥65 years) dually enrolled in Medicare and Medicaid but initially not enrolled in SNAP.

Measurements: Inpatient admissions (primary outcome), emergency department visits, long-term care admissions, and Medicaid expenditures.

Results: Of 115,868 individuals included, 5093 (4.4%) enrolled in SNAP. Mean follow-up was approximately 22 months. In outcome regression analyses, SNAP enrollment was associated, per 1000 person-years, with fewer inpatient hospitalizations (−24.6, 95% confidence interval [CI] −40.6 to −8.7), emergency department visits (−192.7, 95%CI −231.1 to −154.4), long-term care admissions (−65.2, 95%CI −77.5 to −52.9), and $2360 (95%CI −2649 to −2071) fewer dollars in Medicaid payments per person per year. Results were similar in entropy balancing, matching, and instrumental variable analyses.

Limitations: Single state; no Medicare claims data available; possible residual confounding.

Conclusions: SNAP participation was associated with fewer inpatient admissions and lower healthcare costs for older adults dually eligible for Medicare and Medicaid.

Funding Source: National Institutes of Health

Keywords

Food Insecurity; Healthcare Utilization; Healthcare Costs; Supplemental Nutrition Assistance Program; Socioeconomic Factors; Delivery of Healthcare; Hospitalization; Health Services Research; Dual Medicaid Medicare Eligibility

---

Over 35 million Americans lived in households affected by food insecurity—insufficient or uncertain access to enough food for an active, healthy life—in 2019(1), a number that grew to as many as 54 million during the COVID-19 pandemic.(2) Food insecurity is associated with worse health through a number of pathways, including incentivizing worse diet quality, forcing trade-offs between food, medications, and other basic needs, and increasing psychological distress.(3–12) The negative impact of food insecurity on health is reflected in high use of acute care services (such as inpatient admissions and emergency department visits), and higher healthcare costs.(13–17)

The Supplemental Nutrition Assistance Program (SNAP) is the nation’s largest direct effort to fight food insecurity, reaching almost 40 million Americans.(18) Prior studies have shown that SNAP reduces both the depth and breadth of food insecurity.(19,20) However, many eligible individuals, particularly older adults, do not participate in SNAP.(21) SNAP participation may improve health in several ways, which in turn may be associated with lower healthcare use and cost. SNAP could affect health through a nutrition pathway, though this would likely occur over a relatively long time frame. Further, SNAP's effect, if any, on diet quality is unclear.(22,23) Therefore, particularly in the short-term, other mechanisms may be more salient. SNAP represents a relatively large near-cash transfer for those with lower income.(24) In 2019, the mean SNAP benefit was about $1500 per person, per year.(25) Prior studies have estimated that SNAP lifts approximately 8 million individuals out of poverty each year.(26,27) Income freed up by SNAP may translate into improved medication adherence, reduced stress and depressive symptoms, and the ability to meet other health-related social needs (such as housing and transportation).(8,12)

The relationship between SNAP participation and health has been difficult to study as SNAP participation cannot be randomized. Thus, it can be difficult to account for differences between those who are known to have enrolled in SNAP and those who are eligible for SNAP but do not enroll. Prior studies have suggested that SNAP is associated with lower healthcare use and cost(28–31), but questions about prevalent user designs, residual confounding, and self-reported SNAP status have led to continued uncertainty regarding the effect, if any, of SNAP on health.

Older adults who are dually eligible for Medicare and Medicaid may be especially likely to benefit from SNAP. Owing to a combination of low-income and older age, this group experiences both high rates of food insecurity and high healthcare use and costs.(32–34) Because eligibility requirements are similar, most individuals dually eligible for Medicare and Medicaid are also eligible for SNAP.(35,36) However, many SNAP eligible individuals do not enroll.

We used a unique circumstance to better study the association between SNAP participation and healthcare use and cost. As part of a state program to increase SNAP enrollment, individuals dually eligible for Medicare and Medicaid received outreach for SNAP enrollment. This allowed for previously unavailable linkages between data sets related to SNAP outreach, SNAP participation, and healthcare use and cost. We used these data to estimate the association between gaining SNAP benefits and changes in healthcare use and cost, hypothesizing that SNAP participation would be associated with lower healthcare use and cost.

Methods

Study Design and Setting

This was an 'incident-user', retrospective cohort study using data from two key sources. The first data source was the outreach records of Benefits Data Trust (BDT). BDT is a 501(c)3 charitable organization that provides outreach to help enroll individuals in government programs. In 2017, BDT received a contract from North Carolina to help enroll older individuals (age ≥ 65 years) dually eligible for Medicare and Medicaid ('dual-eligibles') in SNAP.(37) BDT received, on a quarterly basis, information on all dual-eligible individuals in North Carolina not enrolled in SNAP. Many dual-eligibles are eligible for SNAP, but may not have enrolled owing to administrative burdens.(35) Enrollment assistance can increase SNAP enrollment, as demonstrated by a prior randomized trial.(38) BDT provides enrollment assistance consisting of an initial outreach mailing, telephone-based screening, and if the individual chooses, SNAP application filing. BDT data included information on whether outreach occurred, date of contact, whether a SNAP application was submitted, and whether the individual ultimately enrolled in SNAP (confirmed by state administrative records).

The second data source for this study was North Carolina Medicaid claims (we did not have access to Medicare claims). BDT and Medicaid claims data were linked by the North Carolina Department of Health and Human services using unique state benefit ID numbers, along with name, social security number, and birth date. These data were then anonymously coded. The UNC institutional review board approved this study (IRB number 18-1312). Data covered the time period 9/13/16 to 7/31/20 (Appendix Figure 1). All individuals included in the study were assigned an 'index date', defined as the date BDT received their information. Index dates ranged from 9/14/17 to 1/1/20. We used data up to 365 days prior to the index date to calculate baseline variables (such as comorbidity indicators and healthcare utilization and cost in the baseline period). We used all available NC Medicaid data after the index date (up to a study end date of 7/31/20) to calculate study outcomes. Analyses were completed in August 2021.

Participants

Study participants were community-dwelling older adults (age ≥ 65 years) who resided in North Carolina, were dually eligible for Medicaid and Medicare, and were not enrolled in SNAP at the time their information was provided to BDT.

SNAP Participation

SNAP participation was confirmed by the administrative records of the North Carolina Department of Health and Human Services. Any enrollment in SNAP during the study period was classified as SNAP participation, even if the individual subsequently disenrolled.

Outcomes

We examined three outcomes related to healthcare utilization, and two outcomes related to healthcare expenditure. The utilization outcomes were: inpatient hospital admissions (primary outcome), emergency department visits, and long-term care admissions. The first expenditure outcome was the sum of all claims paid by NC Medicaid. Because those included were dually eligible, this does not equal the total cost of care in the study period, as Medicare also bore some costs. Next, the claims data indicate the highest amount that Medicaid could have paid for a given claim, had the individual not also had Medicare coverage. The total of these 'allowable expenditures' was a secondary outcome.

Covariates

We considered several covariates that may confound the association between SNAP participation and health services use and cost, at both individual and area levels. At the individual level, covariates from Medicaid claims data were: age, gender, race/ethnicity (categorized as: non-Hispanic Black, non-Hispanic White, Hispanic, and other), indicators for five common comorbidities associated with food insecurity (hypertension, diabetes, depression, chronic kidney disease, and coronary heart disease)(8,39–41), the Gagne comorbidity index(42), and healthcare use and cost during the baseline period. Because some types of Medicare-Medicaid dual eligibility provide only partial Medicaid coverage (which affects which claims Medicaid pays), we distinguished between full and partial Medicaid coverage using CMS categories of dual eligibility.(43) As the study outcomes were related to use of health services, we selected the hospital service area (HSA), based on home address at the index date, as the relevant level.(44) Area-level covariates included mean HSA-level SNAP enrollment in the study cohort(45), and three indicators of healthcare service use and morbidity at the HSA level (taken from the most recently available Dartmouth Atlas data for each variable)(44): hospital discharges per 1000 Medicare enrollees in 2015, total Medicare reimbursements per enrollee in 2017, and the age, sex, and race adjusted total mortality among Medicare enrollees in 2017.

Statistical Analysis

We conducted descriptive statistics, and estimated intraclass correlation coefficients (ICC) at different geographic levels (HSA, along with ZIP Code, and hospital referral region [HRR] as alternative geographic areas) to better understand the variation in SNAP enrollment and study outcomes across geographic areas.

Because of the overlap between Medicaid and SNAP eligibility, an estimand that would be useful for policymakers is the average treatment effect (ATE) of SNAP enrollment on healthcare use and cost. The ATE in this case represents the difference in healthcare use and cost if all dual eligibles enrolled in SNAP, compared with the counterfactual scenario where none enrolled in SNAP.

Our primary analytic approach was outcome regression. For the outcome regression analyses, we fit generalized linear mixed models with a random intercept term for the HSA. For utilization outcomes, we used negative binomial regression models. For expenditure outcomes, which often have a large point mass at zero and skewed right tails (i.e., a few individuals with very high expenditures), we used a gamma error distribution and a log link function.(46) These models adjusted for the individual-level and area-level covariates described above. They also adjusted for the number of follow-up days (to account for differing risks of experiencing study outcomes), and the index date (to account for secular trends regarding healthcare use and cost). We adjusted for race/ethnicity variables in the analyses because these variables may indicate the experience of racism, which worsens health and may affect healthcare use and cost. These models adjust for the baseline version of the outcome (e.g., baseline inpatient admissions in models with inpatient admission is the outcome), which helps account for unmeasured time-invariant confounding. To make results more interpretable, we then used predictive margins(47) to estimate marginal means, and their difference as an estimate of the ATE. This standardizes the estimate of the association between the treatment and outcome over the distribution of covariates included in the model.

Because all analytic strategies have strengths and limitations, we supplemented our primary analyses with three additional approaches. Each of these approaches makes different assumptions than the others, and is susceptible to bias in different ways. We reasoned that if four different analytic approaches, each of which makes different assumptions and thus would be unlikely to be biased in the same way, yield similar results, we could have greater confidence in the study's findings.

The second set of analyses used a weighting based approach called entropy balancing.(48–51) Whereas outcome regression models the association between exposure and outcome, entropy balancing is similar to inverse probability weighting in that it uses weights to balance covariates between those who do and do not enroll in SNAP, removing their confounding effect in a weighted pseudopopulation.(48) We used the same covariates to estimate the entropy balancing weights as adjusted for in the outcome regression models, again targeting the ATE estimand (Supplement). After estimating the balancing weights, we then estimated the association between SNAP and the study outcomes in weighted regression models (negative binomial models for count outcomes and log-gamma models for cost outcomes).

The third set of analyses used a matching based approach. This approach estimated a propensity score (the probability of enrolling in SNAP) using individual-level characteristics, and then matched participants on the basis of the propensity score within the participants' HSA (meaning a participant who enrolled in SNAP was matched to participants who did not enroll in SNAP from their same HSA). Matching within HSA has the effect of accounting for HSA-level confounding.(52) After matching, we fit regression models identical to the models used in the outcome regression analysis, but in the matched subset of the study sample (Supplement for details).(53)

The final set of analyses used were instrumental variable analyses. The association between receipt of SNAP benefits and healthcare use and cost could be confounded by factors that are not measured in claims data, such as interest in receiving government assistance. To avoid bias caused by this confounding, we made use of a unique feature of the BDT dataset. Because of the large number of potentially SNAP eligible individuals to contact, not all individuals could receive outreach at the same time. To ensure a fair chance to receive outreach that did not rely on characteristics of the participants, each individual was assigned an outreach group at random. Thus, although enrolling in SNAP may be correlated with study outcomes, receipt of outreach was not, and can thus be considered an instrumental variable. For instrumental variable analyses, we used the two-stage residual inclusion (2SRI, also called the 'control function') approach.(54–56) We describe the rationale for instrumental variable analyses, testing of assumptions, and analytic procedures in detail in the Supplement and Appendix Tables 1–2. However, while outreach was strongly associated with treatment (5.3% of those who received outreach enrolled in SNAP, compared with 0.7% of those who did not receive outreach; $p < .001$), the low overall enrollment in SNAP even with outreach means that weak instrument bias in the instrumental variable results cannot be excluded.(57)

To formally test the sensitivity of the outcome regression analyses to unmeasured confounding, we used the EValue approach to quantify the strength of association an unmeasured confounder would need to have with both SNAP enrollment and the outcome for a given analysis in order to render the observed association null.(58) Because type of dual eligibility may affect the claims data available to us, we also fit outcome regression models identical to those used for the main analyses, but among the subset of study participants who had full Medicaid benefits, as their claims information is most complete. Further sensitivity analyses are described in the Supplement.

We considered the outcome regression analysis examining inpatient hospitalization the primary analysis. As data missingness was very low, we did not pursue imputation (Supplement Table 1). A p-value < 0.05 indicated statistical significance. Analyses were conducted in SAS 9.4, Stata 16.1, and R 3.6.0.

Role of the Funding Source

This study was funded by the National Institutes of Health, which had no role in the study's design, conduct, or reporting.

Results

BDT records for 105 individuals could not be matched to Medicaid records and were excluded; records for 115,868 individuals could be matched and were included as the final study sample. The mean age was 74.2 years (SD: 7.6), 67.4% were women, and 34.5% were identified as non-Hispanic black in the administrative records (Table 1). The mean duration of follow-up was 664 days (SD: 308), or approximately 22 months. 5093 (4.4%) individuals enrolled in SNAP at any time during the study period. There were participants from all 96 North Carolina HSAs (codes 34001 – 34102). Table 2 and Supplement Figures 1–5 present data on the study outcomes. ICC's showed that little variation was explained at various geographic levels (Supplement Table 2).

Outcome Regression Results

In generalized linear mixed models with a random intercept term for HSA and adjustment for individual- and area-level covariates, SNAP enrollment was associated with reduced healthcare utilization and cost for all outcomes (Table 3 and full models in Supplement Tables 3–7). SNAP enrollment was associated with 24.6 fewer (95% CI −40.6 to −8.7) inpatient hospitalizations per 1000 person-years, 192.7 fewer (95%CI −231.1 to −154.4) emergency department visits per 1000 person-years, and 65.2 fewer (95%CI −77.5 to −52.9) long term care admissions per 1000 person-years. SNAP enrollment was associated with an estimated $2360 fewer (95%CI −2649 to −2071) dollars in Medicaid expenditures per person per year. Results were similar in the subset of individuals who were full dually eligible (Supplement Table 8).

Entropy Balancing Results

Entropy balancing weights produced exact balance on all covariates (Supplement Table 9). Results from entropy balancing analyses (Table 3) were similar to results from the outcome regression analyses. For example, SNAP enrollment was associated with 47.4 fewer (95% CI −67.4 to −27.4) inpatient hospitalizations per 1000 person-years, and 101.9 fewer (95%CI −187.3 to −16.6) emergency department visits per year.

Matching Results

All but 3 (5090/5093, 99.9%) of those who enrolled in SNAP were matched, to 50887 individuals who did not enroll in SNAP but resided in the same HSA. Matching produced excellent balance (SMD < 0.02) for all covariates (Supplement Table 10). Results from the matching analyses were similar to results from the outcome regression analyses. For example, SNAP enrollment was associated with 22.8 fewer (95% CI −39.0 to −6.5) inpatient hospitalizations per 1000 person-years, and 186.8 fewer (95%CI −227.3 to −146.2) emergency department visits per year (Table 3).

Two-Stage Residual Inclusion Results

In 2SRI analyses, SNAP enrollment was associated with significantly lower healthcare utilization and lower costs for all outcomes (Table 3, full models in Supplement Tables 11–16).

Sensitivity Analyses

Results were robust across several types of analyses examining sensitivity to violations of instrumental variable assumptions, different modeling specifications, or unmeasured confounding (Supplement Tables 17–18). For the primary analysis (outcome regression of the inpatient admission outcome), the EValue approach suggests that an unmeasured confounder that was associated with both the treatment and the outcome with a risk ratio of 1.50 each, after adjustment for the measured confounders, would explain away the observed association; the confidence interval could be moved to include the null by an unmeasured confounder that was associated with both the treatment and the outcome by a risk ratio of 1.21, after adjustment for the measured confounders.(58) EValues for other outcomes and analytic approaches are presented in Appendix Table 3. Overall, moderate to strong unmeasured confounding would be needed to explain away the observed associations.

Discussion

In this cohort study of older adults dually eligible for Medicare and Medicaid, we found that SNAP enrollment was associated with fewer inpatient admissions, emergency department visits, and long-term care admissions over approximately 22 months of follow-up. SNAP enrollment was also associated with approximately $2360 lower annual Medicaid spending per person. Further, these findings were similar across several analytic approaches that make different methodological assumptions. Despite this, enrollment in SNAP was low overall, suggesting that there is substantial room for improvement with regard to individuals accessing benefits for which they are eligible.

The results of this study are consistent with and expand prior literature on the topic of SNAP and health. A prior randomized trial in Pennsylvania demonstrated that outreach could significantly increase SNAP uptake, but did not examine health outcomes.(38) Several prior studies have also suggested that SNAP enrollment may be associated with lower healthcare cost and use, and at least one study has associated SNAP enrollment with decreased mortality.(28–31,59) This study adds to the literature by using a dataset with observation before and after SNAP enrollment (to account for unmeasured time-fixed characteristics), administrative confirmation of SNAP enrollment (rather than self-report), and making use of a situation in which SNAP outreach is known not to be correlated with study outcomes.

The findings of this study have several important implications. First, the low SNAP participation rate suggests that we should increase efforts to boost enrollment. Coordination between different agencies within state governments may help.(35) However, we should also reassess the administrative burdens of means-tested programs.(60,61) Even if barriers to enrollment can be overcome with outreach, these burdens may not need to be present in the first place. Lengthening re-certification periods and streamlining social assistance by moving from multiple programs with similar eligibility criteria (e.g., SNAP, the Housing Choice Voucher Program, Low Income Home Energy Assistance Program) to a single more comprehensive program deserves consideration. So do more universal social assistance programs that focus on categorical eligibility rather than means-testing. Future research should explore the health effects of alternate approaches to social assistance, and also investigate how soon benefits may accrue.

Study findings should be considered in the context of several limitations. First, we did not have access to Medicare data. While this is unlikely to affect assessment of healthcare utilization outcomes, as virtually all of these care episodes will be reflected in Medicaid claims, it does preclude a more comprehensive analysis of healthcare spending. However, our findings were very similar in the subset of participants who were fully Medicaid eligible, which suggests that the lack of Medicare data is unlikely to meaningfully affect the study's findings. Second, this study included only older adults dually eligible for Medicare and Medicaid in North Carolina, and there was low SNAP enrollment even with outreach. Thus, how the results generalize to other settings is not known. Finally, as an observational study, bias caused by residual confounding cannot be excluded. However, all four analytic approaches, which each made different assumptions, yielded similar results, which helps increase confidence in the findings.

Conclusions

SNAP is a vital part of the US safety net, and addresses both food insecurity and poverty for millions of Americans. In this study, we find that SNAP is also associated with meaningfully lower healthcare use and cost. This is important, as lower use of healthcare services like inpatient admission and emergency department visits may indicate better overall health. However, we should distinguish between studying changes in healthcare utilization as indicators of health, and viewing SNAP as a program to produce a 'return on investment' by reducing healthcare costs. We view SNAP as a program that provides critical nutrition and income support to millions of Americans, rather than a cost containment strategy for the healthcare system.(62) Given the clear connection between income and health, programs, like SNAP, that provide nutrition and income support to individuals made vulnerable by the political economy are a key tool for advancing health equity.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments:

We greatly appreciate the efforts of Karin Szymanski, Lisa Dillman, David O'Malley, Matthew Wakeman, and the data team Benefits Data Trust, for providing data and information on BDT's outreach process and program for this study. They were not compensated for their efforts. We also greatly appreciate the team at the North Carolina Department of Health and Human Services that provided and linked the data necessary for this project. They were not compensated for their efforts. Finally, we greatly appreciate the assistance of Lily Wang at UNC for her assistance in preparing the data files for analysis. She was compensated for her efforts.

Funding Information:

Funding for SAB's role on the study was provided by the National Institute of Diabetes And Digestive And Kidney Diseases of the National Institutes of Health under Award Number K23DK109200. DP's work on this project was supported by the National Heart, Lung, and Blood Institute of the National Institutes of Health under Award Number K23HL146902. Funding for HKS's role on the study was provided by the Centers for Disease Control and Prevention under Cooperative Agreement Number 5U48DP00498-05. Medicaid claims data were made available through the Carolina Cost and Quality Initiative, a collaborative partnership between UNC's Gillings School of Global Public Health and the Cecil G. Sheps Center for Health Services Research. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health or Centers for Disease Control and Prevention.

Disclosures:

SAB reports receiving personal fees from the Aspen Institute, outside the submitted work. All other authors report no disclosures.

References

1. Coleman-Jensen A, Rabbitt MP, Gregory CA, Singh A. Household Food Security in the United States in 2019 [Internet]. [cited 2020 Nov 3]. Available from: http://www.ers.usda.gov/publications/pub-details/?pubid=99281
2. Gundersen C, Hake M, Dewey A, Engelhard E. Food Insecurity during COVID-19. Appl Econ Perspect Policy. 2020 Oct 2;
3. Seligman HK, Berkowitz SA. Aligning Programs and Policies to Support Food Security and Public Health Goals in the United States. Annu Rev Public Health. 2019 Apr 1;40:319–37. [PubMed: 30444684]
4. Leung CW, Epel ES, Ritchie LD, Crawford PB, Laraia BA. Food insecurity is inversely associated with diet quality of lower-income adults. J Acad Nutr Diet. 2014 Dec;114(12):1943–1953.e2. [PubMed: 25091796]
5. Orr CJ, Keyserling TC, Ammerman AS, Berkowitz SA. Diet quality trends among adults with diabetes by socioeconomic status in the U.S.: 1999-2014. BMC Endocr Disord. 2019 May 31;19(1):54. [PubMed: 31151439]
6. Morales ME, Berkowitz SA. The Relationship Between Food Insecurity, Dietary Patterns, and Obesity. Curr Nutr Rep. 2016 Mar 1;5(1):54–60. [PubMed: 29955440]
7. Arenas DJ, Thomas A, Wang J, DeLisser HM. A Systematic Review and Meta-analysis of Depression, Anxiety, and Sleep Disorders in US Adults with Food Insecurity. J Gen Intern Med. 2019 Aug 5;
8. Leung CW, Epel ES, Willett WC, Rimm EB, Laraia BA. Household Food Insecurity Is Positively Associated with Depression among Low-Income Supplemental Nutrition Assistance Program Participants and Income-Eligible Nonparticipants. J Nutr. 2015 Mar 1;145(3):622–7. [PubMed: 25733480]
9. Silverman J, Krieger J, Kiefer M, Hebert P, Robinson J, Nelson K. The Relationship Between Food Insecurity and Depression, Diabetes Distress and Medication Adherence Among Low-Income Patients with Poorly-Controlled Diabetes. J Gen Intern Med. 2015 Oct;30(10):1476–80. [PubMed: 25917659]
10. Berkowitz SA, Seligman HK, Choudhry NK. Treat or eat: food insecurity, cost-related medication underuse, and unmet needs. Am J Med. 2014 Apr;127(4):303–310.e3. [PubMed: 24440543]

11. Gundersen C, Ziliak JP. Food Insecurity And Health Outcomes. Health Aff Proj Hope. 2015 Nov;34(11):1830–9.
12. Wilder ME, Kulie P, Jensen C, Levett P, Blanchard J, Dominguez LW, et al. The Impact of Social Determinants of Health on Medication Adherence: a Systematic Review and Meta-analysis. J Gen Intern Med. 2021 Jan 29;
13. Tarasuk V, Cheng J, Oliveira C de, Dachner N, Gundersen C, Kurdyak P. Association between household food insecurity and annual health care costs. CMAJ. 2015 Oct 6;187(14):E429–36. [PubMed: 26261199]
14. Garcia SP, Haddix A, Barnett K. Incremental Health Care Costs Associated With Food Insecurity and Chronic Conditions Among Older Adults. Prev Chronic Dis. 2018 Aug 30;15:E108. [PubMed: 30171678]
15. Berkowitz SA, Basu S, Meigs JB, Seligman HK. Food Insecurity and Health Care Expenditures in the United States, 2011-2013. Health Serv Res. 2017 Jun 13;
16. Berkowitz SA, Seligman HK, Meigs JB, Basu S. Food insecurity, healthcare utilization, and high cost: a longitudinal cohort study. Am J Manag Care. 2018 Sep;24(9):399–404. [PubMed: 30222918]
17. Dean EB, French MT, Mortensen K. Food insecurity, health care utilization, and health care expenditures. Health Serv Res. 2020;55(S2):883–93. [PubMed: 32187388]
18. Supplemental Nutrition Assistance Program (SNAP) | USDA-FNS [Internet]. [cited 2020 Feb 19]. Available from: https://www.fns.usda.gov/snap/supplemental-nutrition-assistance-program
19. Ratcliffe C, McKernan S-M. How Much Does Snap Reduce Food Insecurity? [Internet]. [cited 2020 Jul 3]. Available from: http://www.ers.usda.gov/publications/pub-details/?pubid=84335
20. Swann CA. Household history, SNAP participation, and food insecurity. Food Policy. 2017;73(C):1–9.
21. US Department of Agriculture Food and Nutrition Service. Trends in SNAP Participation Rates: Fiscal Year 2010-2017 [Internet]. [cited 2021 Apr 1]. Available from: https://www.fns.usda.gov/snap/trends-supplemental-nutrition-assistance-program-participation-rates-fiscal-year-2010
22. Gregory CA, Ploeg MV, Margaret, rews, Coleman-Jensen A. Supplemental Nutrition Assistance Program (SNAP) Participation Leads to Modest Changes in Diet Quality [Internet]. [cited 2021 Feb 9]. Available from: http://www.ers.usda.gov/publications/pub-details/?pubid=45062
23. Hastings J, Kessler R, Shapiro JM. The Effect of SNAP on the Composition of Purchased Foods: Evidence and Implications. Am Econ J Econ Policy [Internet]. [cited 2021 Feb 9]; Available from: 10.1257/pol.20190350&&from=f
24. Chart Book: SNAP Helps Struggling Families Put Food on the Table [Internet]. Center on Budget and Policy Priorities. [cited 2021 Feb 9]. Available from: https://www.cbpp.org/research/food-assistance/chart-book-snap-helps-struggling-families-put-food-on-the-table
25. SNAP Data Tables | USDA-FNS [Internet]. [cited 2021 Mar 9]. Available from: https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap
26. The Positive Effect of SNAP Benefits on Participants and Communities [Internet]. Food Research & Action Center. [cited 2021 Feb 9]. Available from: programs/supplemental-nutrition-assistance-program-snap/positive-effect-snap-benefits-participants-communities
27. Wheaton L, Tran V. The Antipoverty Effects of the Supplemental Nutrition Assistance Program [Internet]. Urban Institute. 2018 [cited 2021 Feb 9]. Available from: https://www.urban.org/research/publication/antipoverty-effects-supplemental-nutrition-assistance-program
28. Berkowitz SA, Seligman HK, Rigdon J, Meigs JB, Basu S. Supplemental Nutrition Assistance Program (SNAP) Participation and Health Care Expenditures Among Low-Income Adults. JAMA Intern Med. 2017 Nov 1;177(11):1642–9. [PubMed: 28973507]
29. Samuel LJ, Szanton SL, Cahill R, Wolff JL, Ong P, Zielinskie G, et al. Does the Supplemental Nutrition Assistance Program Affect Hospital Utilization Among Older Adults? The Case of Maryland. Popul Health Manag. 2017 Jul 6;
30. Szanton SL, Samuel LJ, Cahill R, Zielinskie G, Wolff JL, Thorpe RJ, et al. Food assistance is associated with decreased nursing home admissions for Maryland's dually eligible older adults. BMC Geriatr. 2017 Jul 24;17(1):162. [PubMed: 28738897]

31. Sonik RA, Parish SL, Mitra M. Inpatient Medicaid Usage and Expenditure Patterns After Changes in Supplemental Nutrition Assistance Program Benefit Levels. Prev Chronic Dis. 2018 Oct 4;15:E120. [PubMed: 30289106]

32. Keohane LM, Stevenson DG, Freed S, Thapa S, Stewart L, Buntin MB. Trends In Medicare Fee-For-Service Spending Growth For Dual-Eligible Beneficiaries, 2007-15. Health Aff Proj Hope. 2018 Aug;37(8):1265–73.

33. Madden JM, Shetty PS, Zhang F, Briesacher BA, Ross-Degnan D, Soumerai SB, et al. Risk Factors Associated With Food Insecurity in the Medicare Population. JAMA Intern Med. 2019 Sep 30;

34. Berkowitz SA, Terranova J, Hill C, Ajayi T, Linsky T, Tishler LW, et al. Meal Delivery Programs Reduce The Use Of Costly Health Care In Dually Eligible Medicare And Medicaid Beneficiaries. Health Aff Proj Hope. 2018 Apr;37(4):535–42.

35. McKethan A, Berkowitz SA, Cohen M. Focusing on Population Health at Scale - Joining Policy and Technology to Improve Health. N Engl J Med. 2019 Jan 10;380(2):113–5. [PubMed: 30625065]

36. Opportunities for States to Coordinate Medicaid and SNAP Renewals [Internet]. Center on Budget and Policy Priorities. 2016 [cited 2018 Jun 28]. Available from: https://www.cbpp.org/research/health/opportunities-for-states-to-coordinate-medicaid-and-snap-renewals

37. NC Department of Health and Human Services. Pilot Program Increase Access to Public Benefits For Older Dual Eligible Seniors [Internet]. [cited 2021 Feb 9]. Available from: https://files.nc.gov/ncdhhs/SL-2017-57-Section-11C.8.-b--Dual-Eligibles-2020.pdf

38. Finkelstein A, Notowidigdo MJ. Take-Up and Targeting: Experimental Evidence from SNAP*. Q J Econ. 2019 Aug 1;134(3):1505–56.

39. Berkowitz SA, Berkowitz TSZ, Meigs JB, Wexler DJ. Trends in food insecurity for adults with cardiometabolic disease in the United States: 2005–2012. PloS One. 2017;12(6):e0179172. [PubMed: 28591225]

40. Seligman HK, Laraia BA, Kushel MB. Food Insecurity Is Associated with Chronic Disease among Low-Income NHANES Participants. J Nutr. 2010 Feb;140(2):304–10. [PubMed: 20032485]

41. Crews DC, Kuczmarski MF, Grubbs V, Hedgeman E, Shahinian VB, Evans MK, et al. Effect of food insecurity on chronic kidney disease in lower-income Americans. Am J Nephrol. 2014;39(1):27–35. [PubMed: 24434743]

42. Gagne JJ, Glynn RJ, Avorn J, Levin R, Schneeweiss S. A combined comorbidity score predicted mortality in elderly patients better than existing scores. J Clin Epidemiol. 2011 Jul;64(7):749–59. [PubMed: 21208778]

43. Centers for Medicare & Medicaid Services. LIST AND DEFINITION OF DUAL ELIGIBLES [Internet]. [cited 2021 Feb 9]. Available from: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MedicareEnrpts/downloads/Buy-InDefinitions.pdf

44. Dartmouth Atlas of Health Care [Internet]. Dartmouth Atlas of Health Care. [cited 2021 May 24]. Available from: https://www.dartmouthatlas.org/

45. Begg MD, Parides MK. Separation of individual-level and cluster-level covariate effects in regression analysis of correlated data. Stat Med. 2003;22(16):2591–602. [PubMed: 12898546]

46. Deb P, Norton EC. Modeling Health Care Expenditures and Use. Annu Rev Public Health. 2018 Apr 1;39:489–505. [PubMed: 29328879]

47. Graubard BI, Korn EL. Predictive margins with survey data. Biometrics. 1999 Jun;55(2):652–9. [PubMed: 11318229]

48. Hainmueller J Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. Polit Anal. 2012 ed;20(1):25–46.

49. Zhao Q, Percival D. Entropy Balancing is Doubly Robust. J Causal Inference [Internet]. 2017 Mar 1 [cited 2021 May 24];5(1). Available from: 10.1515/jci-2016-0010/html

50. Josey KP, Berkowitz SA, Ghosh D, Raghavan S. Transporting experimental results with entropy balancing. Stat Med. 2021 May 20;

51. Basu S, Akers M, Berkowitz SA, Josey K, Schillinger D, Seligman H. Comparison of Fruit and Vegetable Intake Among Urban Low-Income US Adults Receiving a Produce Voucher in 2 Cities. JAMA Netw Open. 2021 Mar 1;4(3):e211757. [PubMed: 33749765]

52. Page LC, Lenard MA, Keele L. The Design of Clustered Observational Studies in Education. AERA Open. 2020 Jul 1;6(3):2332858420954401.
53. Ho DE, Imai K, King G, Stuart EA. Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference. Polit Anal. 2007 ed;15(3):199–236.
54. Terza JV, Basu A, Rathouz PJ. Two-stage residual inclusion estimation: addressing endogeneity in health econometric modeling. J Health Econ. 2008 May;27(3):531–43. [PubMed: 18192044]
55. Terza JV. Two-Stage Residual Inclusion Estimation in Health Services Research and Health Economics. Health Serv Res. 2018 Jun;53(3):1890–9. [PubMed: 28568477]
56. Wan F, Small D, Mitra N. A general approach to evaluating the bias of 2-stage instrumental variable estimators. Stat Med. 2018;37(12):1997–2015. [PubMed: 29572890]
57. Rosenbaum PR. Design of Observational Studies. 2nd ed. 2020 edition. S.l.: Springer; 2021. 576 p.
58. VanderWeele TJ, Ding P. Sensitivity Analysis in Observational Research: Introducing the E-Value. Ann Intern Med [Internet]. 2017 Jul 11 [cited 2017 Aug 10]; Available from: 10.7326/M16-2607
59. Heflin CM, Ingram SJ, Ziliak JP. The Effect Of The Supplemental Nutrition Assistance Program On Mortality. Health Aff Proj Hope. 2019 Nov;38(11):1807–15.
60. Targeting Unrath M., Screening, and Retention: Evidence from California's Food Stamps Program [Internet]. [cited 2021 Feb 9]. Available from: https://www.capolicylab.org/wp-content/uploads/2021/02/CalFresh-Working-Paper.pdf
61. Venkataramani AS, O'Brien R, Tsai AC. Declining Life Expectancy in the United States: The Need for Social Policy as Health Policy. JAMA. 2021 Feb 16;325(7):621–2. [PubMed: 33591352]
62. Lantz PM. "Super-Utilizer" Interventions: What They Reveal About Evaluation Research, Wishful Thinking, and Health Equity. Milbank Q. 2020 Mar;98(1):31–4. [PubMed: 32030820]

Table 1:

Characteristics of study participants

	Overall	By SNAP Status		
		Did not receive SNAP	Received SNAP	SMD
	N=115868	N=110775	N=5093	
Demographic information				
Mean age (SD), years	74.23 (7.61)	74.24 (7.63)	74.00 (7.28)	0.033
Female, n (%)	78124 (67.4)	74512 (67.3)	3612 (70.9)	0.079
Hispanic, n (%)	5571 (4.8)	5478 (4.9)	93 (1.8)	0.173
Non-Hispanic Black, n (%)	39963 (34.5)	38027 (34.3)	1936 (38.0)	0.077
Non-Hispanic White, n (%)	56880 (49.1)	54198 (48.9)	2682 (52.7)	0.075
Other race/ethnicity, n (%)	6074 (5.2)	5827 (5.3)	247 (4.8)	0.019
Partially Dual-Eligible, n (%)	95047 (82.0)	91111 (82.2)	3936 (77.3)	0.124
Baseline healthcare utilization and costs				
Mean inpatient admissions per year during baseline period (SD)	0.15 (0.50)	0.15 (0.50)	0.11 (0.41)	0.09
Mean emergency department visits per year during baseline period (SD)	0.49 (1.63)	0.50 (1.65)	0.31 (1.08)	0.137
Mean long term care admissions per year during baseline period (SD)	0.05 (0.37)	0.05 (0.38)	0.02 (0.20)	0.11
Mean actual Medicaid costs per year during baseline period (SD)	3421.09 (8917.83)	3480.73 (9020.35)	2124.06 (6146.29)	0.176
Mean allowed Medicaid costs per year during baseline period (SD)	6328.72 (13280.07)	6427.90 (13388.99)	4171.59 (10408.43)	0.188
Baseline clinical characteristics				
Mean comorbidity score* (SD)	1.27 (2.51)	1.29 (2.52)	0.90 (2.09)	0.165
History of coronary heart disease, n (%)	14898 (12.9)	14379 (13.0)	519 (10.2)	0.087
History of chronic kidney disease, n (%)	12130 (10.5)	11687 (10.6)	443 (8.7)	0.063
History of depression, n (%)	10061 (8.7)	9679 (8.7)	382 (7.5)	0.045
History of diabetes mellitus, n (%)	26002 (22.4)	25087 (22.6)	915 (18.0)	0.117
History of hypertension, n (%)	50798 (43.8)	48995 (44.2)	1803 (35.4)	0.181
Baseline area-level characteristics				
Proportion of study participants who enrolled in SNAP at HSA level (SD)	0.04 (0.01)	0.04 (0.01)	0.05 (0.03)	0.174
Mean discharges per 1000 Medicare enrollees at HSA level (SD)	260.57 (43.51)	260.46 (43.41)	262.85 (45.62)	0.054
Percent mortality of Medicare enrollees at HSA level (SD)	4.55 (0.49)	4.55 (0.49)	4.58 (0.49)	0.062

	Overall	By SNAP Status		
		Did not receive SNAP	Received SNAP	SMD
	N=115868	**N=110775**	**N=5093**	
Mean Medicare reimbursement per enrollee at HSA level (SD)	9271.77 (719.61)	9269.25 (719.22)	9326.56 (725.91)	0.079
Distribution of participant observation time				
Mean follow-up days (SD)	664.14 (308.28)	660.88 (310.67)	735.21 (239.92)	0.268
Mean days observed during baseline period (SD)	335.95 (74.74)	336.02 (74.77)	334.44 (74.14)	0.021

SNAP = Supplemental Nutrition Assistance Program

HSA = Hospital Service Area

SMD = standardized mean difference

* Comorbidity score ranges from −2 to 26 with higher scores indicating greater comorbidity

Table 2:

Unadjusted Description of Utilization and Cost Outcomes Per Person

	Overall	By SNAP Status	
		Did not receive SNAP	**Received SNAP**
	N=115868	**N=110775**	**N=5093**
Mean number of inpatient admissions per person during follow-up period (SD)	0.28 (0.75)	0.29 (0.75)	0.22 (0.68)
Median number of inpatient admissions per person during follow-up period [25th percentile, 75th percentile]	0 [0, 0]	0 [0, 0]	0 [0, 0]
Mean number of emergency department visits per person during follow-up period (SD)	0.82 (2.55)	0.84 (2.58)	0.55 (1.92)
Median number of emergency department visits per person during follow-up period [25th percentile, 75th percentile]	0 [0, 0]	0 [0, 1]	0 [0, 0]
Mean number of long term care admissions per person during follow-up period [25th percentile, 75th percentile]	0.13 (0.64)	0.13 (0.65)	0.06 (0.36)
Median number of long term care admissions per person during follow-up period [25th percentile, 75th percentile]	0 [0, 0]	0 [0, 0]	0 [0, 0]
Mean actual Medicaid costs per person during follow-up period (SD)	9942 (25083)	10110 (25371)	6307 (17308)
Median actual Medicaid costs per person during follow-up period [25th percentile, 75th percentile]	1930 [0, 4465]	1984 [0, 4522]	204 [0. 3461]
Mean allowed Medicaid costs per person during follow-up period (SD)	16163 (33717)	16405 (34030)	10903 (25439)
Median allowed Medicaid costs per person during follow-up period [25th percentile, 75th percentile]	3121 [0, 14006]	3191 [0, 14292]	513 [0, 8483]

SNAP = Supplemental Nutrition Assistance Program

Table 3:

Healthcare Utilization and Cost Outcomes

	Estimated annual utilization or cost if everyone had received SNAP (95% CI)	Estimated annual utilization or cost if no one had received SNAP (95% CI)	Difference * (95% CI)	P
Inpatient admissions, per 1000 person years				
Outcome Regression Analysis	216.6 (199.3 to 233.9)	241.2 (232.7 to 249.8)	−24.6 (−40.6 to −8.7)	0.004
Entropy Balancing Analysis	168.7 (149.6 to 187.8)	216.1 (210.0 to 222.2)	−47.4 (−67.4 to −27.4)	<.001
Matching Analysis	204.3 (185.4 to 223.2)	227.0 (213.6 to 240.5)	−22.8 (−39.0 to −6.5)	0.009
Two Stage Residual Inclusion Instrumental Variable Analyses	209.5 (193.8 to 233.4)	266.9 (260.1 to 272.8)	−57.4 (−74.2 to −33.2)	<.001
Emergency department visits, per 1000 person years				
Outcome Regression Analysis	517.6 (472.0 to 563.1)	710.3 (671.0 to 749.6)	−192.7 (−231.1 to −154.4)	<.001
Entropy Balancing Analysis	467.5 (383.2 to 551.8)	569.4 (555.9 to 583.0)	−101.9 (−187.3 to −16.6)	0.03
Matching Analysis	460.1 (409.0 to 511.3)	646.9 (590.1 to 703.7)	−186.8 (−227.3 to −146.2)	<.001
Two Stage Residual Inclusion Instrumental Variable Analyses	421.6 (383.3 to 479.2)	651.9 (630.4 to 671.2)	−230.2 (−269.5 to −171.5)	<.001
Long term care admissions, per 1000 person years				
Outcome Regression Analysis	77.4 (65.1 to 89.6)	142.5 (133.7 to 151.3)	−65.2 (−77.5 to −52.9)	<.001
Entropy Balancing Analysis	40.7 (31.0 to 50.4)	117.4 (112.6 to 122.2)	−76.7 (−87.5 to −65.8)	<.001
Matching Analysis	69.5 (56.5 to 82.4)	122.9 (109.5 to 136.3)	−53.4 (−66.6 to −40.2)	<.001
Two Stage Residual Inclusion Instrumental Variable Analyses	64.0 (53.0 to 77.9)	150.2 (144.1 to 156.0)	−86.2 (−97.6 to −71.8)	<.001
Actual Medicaid costs, $ per person per year				
Outcome Regression Analysis	3443 (3155 to 3732)	5804 (5589 to 6019)	−2360 (−2649 to −2071)	<.001
Entropy Balancing Analysis	4441 (4022 to 4859)	5530 (5453 to 5607)	−1090 (−1515 to −664)	<.001
Matching Analysis	4536 (3932 to 5139)	7367 (6560 to 8174)	−2831 (−3348 to −2314)	<.001
Two Stage Residual Inclusion Instrumental Variable Analyses	5986 (5560 to 6502)	7829 (7645 to 7991)	−1843 (−2251 to −1336)	<.001
Allowed Medicaid costs, $ per person per year				
Outcome Regression Analysis	6525 (5981 to 7069)	10652 (10276 to 11027)	−4126 (−4670 to −3583)	<.001
Entropy Balancing Analysis	7639 (7021 to 8256)	9698 (9562 to 9834)	−2059 (−2692 to −1427)	<.001
Matching Analysis	6865 (6112 to 7618)	10510 (9688 to 11332)	−3645 (−4335 to −2955)	<.001

	Estimated annual utilization or cost if everyone had received SNAP (95% CI)	Estimated annual utilization or cost if no one had received SNAP (95% CI)	Difference * (95% CI)	P
Two Stage Residual Inclusion Instrumental Variable Analyses	5471 (5026 to 5833)	8878 (8701 to 9050)	−3406 (−3857 to −3062)	<.001

SNAP = Supplemental Nutrition Assistance Program

*Differences are Average Treatment Effect (ATE) for Outcome Regression Analyses and Entropy Balancing Analyses, Average Treatment Effect in the Matched sample (ATM) for the Matching Analyses, and Local Average Treatment Effect (LATE) for the Two Stage Residual Inclusion Instrumental Variable Analyses

Count outcomes used negative binomial models and cost outcomes used generalized linear models with gamma error distribution and log link.

Estimates and confidence bounds are from predictive margins.

Utilization is expressed per 1000 person-years, and cost is expressed as per person per year

Outcome regression analyses adjusted for: age, gender, race/ethnicity, hypertension, diabetes, depression, chronic kidney disease, coronary heart disease, the Gagne comorbidity index, index date, length of follow-up, pre-index observation time, whether an individual was a partial versus full Medicaid beneficiary, the baseline level of the outcome for each model, hospital discharges per 1000 Medicare enrollees in 2015 at the HSA level, total Medicare reimbursements per enrollee in 2017 at the HSA level, and the age, sex, race adjusted total mortality among Medicare enrollees in 2017 at the HSA level, and mean SNAP enrollment in the study sample at the HSA level. Generalized linear mixed models with a random intercept term for the HSA were fit to produce the presented results.

Entropy balancing analyses were weighted for the same factors as were adjusted for in the outcome regression models but did not include covariates in the regression.

Matching analysis results are from regression models adjusted for the same factors as the outcome regression analyses, but in the subset of sample that was matched, within HSA, following the procedure described in the technical appendix. Generalized linear mixed models with a random intercept term for the HSA were fit to produce the presented results.

Two stage residual inclusion analyses adjust for index date, follow-up time, and whether an individual was a partial versus full Medicaid beneficiary.

P-values from beta coefficient for SNAP term in outcome regression analyses; from beta coefficient for SNAP term in weighted regression model for entropy balancing analyses; from beta coefficient for SNAP term in regression model fit in matched subset for matching analyses; and from beta coefficient for SNAP term in second stage model for two stage residual inclusion analyses following the method proposed by Terza.