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Abstract

We tested three hypothesis related to food insecurity and the Supplemental Nutrition Assistance Program (SNAP), America's largest anti-food insecurity program. We hypothesized that 1)food insecurity would be associated with increased healthcare expenditures, 2)food insecurity would be associated with increased use of emergency department and inpatient services, and 3) SNAP participation would be associated with lower subsequent healthcare expenditures. We used data from the 2011 National Health Interview Survey linked to the 2012-13 Medical Expenditures Panel Survey. We used zero-inflated negative binomial regression to test the relationship between food insecurity and healthcare cost and use. We evaluated the association between SNAP participation and healthcare expenditures using generalized linear regression modeling, near/far matching instrumental variable analysis using state-level variation in SNAP policy as our instrument, and augmented inverse probability weighting. Those with food insecurity had significantly greater estimated mean annualized healthcare expenditures (\$6,072 vs. \$4,208, p<0.0001), an extra \$1,863 in healthcare expenditure per year, or \$77.5 billion in additional healthcare expenditure annually nation-wide. Further, food insecurity was associated with significantly greater emergency department visits (Incidence Rate Ratio [IRR] 1.47, 95% Confidence Interval [CI] 1.12 – 1.93), inpatient hospitalizations (IRR 1.47, 95% CI 1.14 – 1.88), and days hospitalized (IRR 1.54, 95% CI 1.06 – 2.24). Across several analytic approaches, we found that SNAP participation was associated with reduced subsequent healthcare expenditures (best estimate: -\$1,409; 95% Confidence Interval [CI] -\$2,694 to -\$125). We conclude that food insecurity is associated with increased healthcare costs and use, and SNAP participation is associated with lower subsequent healthcare expenditures.

Executive Summary

Healthcare expenditures in the United States are disproportionately related to preventable chronic conditions due to poor nutrition (i.e., type 2 diabetes)[1], and disproportionately concentrated among the poor.[2] In 2014, food insecurity affected approximately 49 million Americans in 17.4 million U.S. households, or 14% of the population.[3] Food insecurity has been associated with numerous health conditions.[4-23] The relationship between food insecurity and chronic disease is likely bi-directional[24,25]: poor health may make it harder to work, leading to lower income and increasing risk of food insecurity; conversely, food insecurity may incentivize purchases of cheaper but less healthy foods, or trade-offs between medications and healthcare to purchase food[26], leading to chronic disease, worse mental health[13], and poorer disease self-management. The Supplemental Nutrition Assistance Program (SNAP) is the nation's largest anti-food insecurity program, serving approximately 1 in 7 Americans.[27] SNAP is proven to reduce both the duration and severity of food insecurity episodes.[28] Though SNAP is not a health program, there is growing interest in whether social programs, such as SNAP, may offer benefits in the healthcare sector.

In this report, we address the following research questions: 1) What is the association between food insecurity and healthcare expenditures, 2) what is the association between food insecurity and healthcare use, and 3) is SNAP participation associated with reduced healthcare expenditures?

The data for all analyses in this study came from the 2011 National Health Interview Survey (NHIS) linked to the 2012-2013 Medical Expenditure Panel Survey (MEPS). These are nationally-representative surveys used for epidemiologic surveillance. The NHIS and MEPS were administered by trained interviewers in English or Spanish.[35,36]

We sought to evaluate our three hypotheses by conducting a series of related, but independent analyses.

Hypothesis 1: Food insecurity is associated with increased healthcare expenditures

Individuals were categorized as food insecure using a validated 10-item questionnaire with a 30-day look-back period[3,33,34] Using standard scoring, those who answered affirmatively to more than two items were considered food insecure.[33] Our primary outcome for testing this hypothesis was total healthcare expenditure from 2012 through 2013, converted to 2015 U.S. dollars using the Consumer Price Index. Secondary outcomes included expenditures within the following MEPS categories: outpatient expenditures (both office-based and hospital-based outpatient), emergency department expenditures (excluding those resulting in an inpatient admission), inpatient expenditures (including emergency department spending for that admission), and prescription medication expenditures.[26] Because expenditure data is often highly skewed, overdispersed (i.e. the variance is greater than the mean), and inclusive of a high proportion of individuals with no expenditures, we analyzed the data using zero-inflated negative binomial regression.[39-41] This modeling approach considers that two processes may be occurring simultaneously: one that generates expenditures, including zero expenditures in some cases (e.g. illness requiring medical care, or lack thereof), and a separate process that can reduce the likelihood of expenditures even if they would otherwise occur, leading to what is sometimes called 'excess zero' expenditures (e.g. inability to access healthcare). An advantage of this approach, compared with estimating expenditure contingent on having greater than zero spending, is that observations with zero expenditures are still analyzed.

In multivariable regressions adjusted for age, age-squared, race/ethnicity, education, income, rural residence, and health insurance category, those with food insecurity had significantly greater healthcare expenditures: $6,071.60 (95% Confidence Interval [CI]$5,144.92 to $6,998.28) for those with food insecurity, compared with $4,208.43 (95%CI $3,976.07 to $4,437.79) for those without. The adjusted model estimates that food insecurity was associated with an extra $1,863.17 in healthcare expenditure per year ($p<.0001$). This difference in expenditures, multiplied by 41,616,255 food insecure Americans, represents approximately $77.5 billion in additional healthcare costs, compared with what would be expected for demographically similar individuals without food insecurity, if the relationship between food insecurity and expenditures were causal. When examining categories of expenditures, we found significant differences between those with and those without food insecurity. Individuals reporting food insecurity had significantly greater expenditures than food secure individuals for inpatient hospitalizations ($471.48 greater per year, $p=.03$), and prescription medications ($779.36 greater per year, $p<0.0001$). Expenditure differences for food insecure individuals were not statistically significant for outpatient ($42.19 greater per year, $p=0.07$) and emergency department expenditures ($21.87 greater per year, $p=0.18$).

Hypothesis 2: Food insecurity is associated with increased use of emergency department and inpatient services

We assessed food insecurity in the same way as in Hypothesis 1. Because they are often the focus of programs to reduce healthcare use, we evaluated number of emergency department visits (which, in MEPS does not include those that result in a hospital stay), number of inpatient hospital admissions, and number of days spent as a hospital inpatient. We again used zero inflated negative binomial regression to analyze the association between food insecurity and healthcare use.

In zero-inflated negative binomial models (Table 8), adjusted for age, age squared, gender, race/ethnicity, education, income, health insurance, region, and living in a rural area, food insecurity was associated with significantly greater emergency department visits (Incidence Rate Ratio [IRR] 1.47, 95% Confidence Interval [CI] 1.12 – 1.93) (Table 3). Similarly, food insecurity was associated with greater inpatient hospitalizations (IRR 1.47, 95% CI 1.14 – 1.88), and greater number of days hospitalized (IRR 1.54, 95% CI 1.06 – 2.24).

Hypothesis 3: SNAP participation is associated with reduced subsequent healthcare expenditures

SNAP participation was indicated by an affirmative response to the 2011 NHIS item: "At any time during the last calendar year, did you or any family members living here receive SNAP or food stamp benefits?" Those who responded affirmatively were categorized as receiving SNAP, without regard to the duration or amount of benefits received. The primary outcome for evaluating this hypothesis was total healthcare expenditures over the two-year MEPS period (2012 through 2013), the same as for hypothesis 1, and also annualized. To determine the relationship between SNAP receipt and subsequent healthcare expenditures, and to check the robustness of any associations to analytic strategy, we conducted three types of analyses: a standard regression analysis, a matched-pairs instrumental variable (IV) technique called near/far matching, and an augmented inverse probability weighted (AIPW) analysis. While standard regression can adjust for measured confounders, there may be unobserved characteristics that affect SNAP participation and healthcare expenditures. To address potential confounding by unrecorded factors, we conducted a near/far matching analysis.[44,45] In this study, our instrument consisted of variations in state policies regarding SNAP enrollment. SNAP eligibility is set at the federal level, but enrollment policies vary by state, and these policies can make it easier or harder to enroll, thus subtly encouraging or discouraging receipt of SNAP.[46,47] These policies were abstracted from the SNAP policy database[46] and in effect over the 2011 NHIS survey recall period. The policies used were 1)an option for online submission of a SNAP application, 2)presence of a broad-based categorical eligibility policy (which extends SNAP eligibility to those eligible for other assistance programs), and 3) whether the state uses simplified reporting requirements for households with earnings.[46] Finally, as an alternative to the instrumental variable-based analysis, we conducted an analysis using augmented inverse probability weighting (AIPW), a 'doubly-robust' technique to mitigate selection bias by estimating the likelihood of receiving SNAP and then using response-weights to achieve balance in measured covariates between the group that did and did not receive SNAP.[52]

In standard regression analyses adjusted for observed factors, SNAP participation was associated with a significant decrease in estimated expenditures: -$1,409 per year in those who did, versus did not, report SNAP participation (95% CI -$2,694 to -$125, p=0.03). For the near/far matching analysis, our instrument was strongly associated with participation in SNAP, and passed a test of over-identifying restrictions. Interestingly, endogeneity tests suggested that instrumental variable methods may not have been needed (p=0.72). The near/far match resulted in 3676 participants comprising 1838 matched pairs, and the instrument was strong (first-stage partial deviance statistic: 42.5). Analyses using the 2SRI method, adjusted for the same factors as the standard regression, and state spending, demonstrated lower expenditures for SNAP receipt, (-$5,160 per year; 95% CI -$6,924 to -$438). AIPW analyses, conducted on the entire cohort, successfully balanced observed factors, and passed tests of over-identifying restrictions. The AIPW analysis estimated the average treatment effect of SNAP enrollment to be -$931 (95% CI -$2,026 to -$152), again representing lower yearly expenditures with SNAP participation.

Studying individuals in the 2011 NHIS who underwent food insecurity assessment and subsequently enrolled in MEPS, we found that food insecurity was associated with approximately $1,800 higher healthcare expenditures per year, after adjusting for age, gender, race/ethnicity, education, income, insurance, and residence area. Individuals with food insecurity were particularly more likely to incur expenditures for inpatient hospitalizations and prescription medications. The expenditure difference between those with and without food insecurity was even greater in chronic diseases that have been associated with food insecurity: diabetes, hypertension, and heart disease.[21] Further, we found that food insecurity was significantly associated with greater use of healthcare visit types, such as emergency department and inpatient admissions, that are common targets of programs to reduce healthcare use. Going further to examine the relationship between SNAP participation and healthcare expenditures, we found that SNAP participation was associated with lower subsequent healthcare expenditures in low-income adults. Though the estimated amount saved varied by analytic approach, the finding of reduced healthcare expenditures associated with SNAP participation was robust across several different strategies and was estimated to be greater for participants with diet-sensitive conditions previously linked to food insecurity.[21]

The results of this study should be interpreted in light of several limitations. This study relied on self-report of clinical conditions, without laboratory or other clinical confirmation. However, these self-report items are validated and commonly used in epidemiologic surveillance of the conditions of interest.[61] Secondly, because of the nature of the study, those in the most severe social circumstances, including very low food security, may have been less likely to enroll in NHIS and be followed in MEPS. Next, the study may have lacked power to evaluate categories of expenditures. While not all observed differences were statistically significant, the direction of difference was consistent across spending categories. Next, food insecurity was assessed only once, in the 2011 NHIS, and over the preceding 30-day period. Because food insecurity is a dynamic condition, individuals who did not report food insecurity in 2011 may have experienced it during the subsequent period. This may bias estimates of expenditure difference to the null. Similarly, SNAP assessment occurred at a single point in time. Since low-income households often cycle on and off SNAP, this may have resulted in misclassification. However, this misclassification would likely bias estimates to the null. Standard tests of the instruments we used were consistent with their validity, but ultimately instrumental variable approaches rely on some assumptions that cannot be empirically tested. The generalizability of the findings in the near/far analysis may have been limited because we were unable to incorporate survey design information, but since the matching process breaks the geographical link, and since IV analyses do not estimate population-level effects, this may not be a significant issue. Further, these limitations are mitigated by the fact that the standard regression analysis (which is nationally representative because it incorporated survey design information), and the AIPW analysis, neither of which make IV assumptions, produced qualitatively similar results. The limitations of this study are balanced by several strengths. The MEPS methodology allows for highly accurate capture of the healthcare expenditures for a nationally-representative sample of individuals, giving a complete picture of costs borne by the individuals themselves or reimbursed on their behalf. Secondly, the longitudinal design provides strong evidence that exposure to food insecurity, for whatever reason, is likely to be associated with excess subsequent healthcare expenditure.

Although this study focused on healthcare expenditures, SNAP is a food insecurity and nutrition program, not a healthcare program. SNAP's purpose is not to reduce healthcare expenditures, and we are of the opinion that its funding is justified without regard to any impact on healthcare costs.

Food insecurity is an all-too-common problem for many Americans. Food insecurity is associated with increased healthcare spending, particularly in those with common and costly conditions such as diabetes, hypertension, and heart disease, and increased use of healthcare services such as emergency department visits and hospitalizations. For this reason, there is significant potential for food insecurity interventions to improve health and reduce healthcare costs among vulnerable populations. In an analysis of the nation's largest food insecurity reduction program (SNAP), and across several analytic approaches, including an instrumental variable approach that accounts for unmeasured confounding, SNAP participation was associated with lower subsequent healthcare expenditures for low-income adults. Ultimately, our success at achieving the triple aim of healthcare will depend on our ability to address social, along with genetic and behavioral, determinants of health.

Introduction

Healthcare expenditures in the United States are disproportionately related to preventable chronic conditions due to poor nutrition (i.e., type 2 diabetes)[1], and disproportionately concentrated among the poor.[2] In 2014, food insecurity affected approximately 49 million Americans in 17.4 million U.S. households, or 14% of the population.[3] Food insecurity has been associated with numerous health conditions.[4-23] The relationship between food insecurity and chronic disease is likely bi-directional[24,25]: poor health may make it harder to work, leading to lower income and increasing risk of food insecurity; conversely, food insecurity may incentivize purchases of cheaper but less healthy foods, or trade-offs between medications and healthcare to purchase food[26], leading to chronic disease, worse mental health[13], and poorer disease self-management.

The Supplemental Nutrition Assistance Program (SNAP) is the nation's largest anti-food insecurity program, serving approximately 1 in 7 Americans.[27] SNAP is proven to reduce both the duration and severity of food insecurity episodes.[28] Though SNAP is not a health program, there is growing interest in whether social programs, such as SNAP, may offer benefits in the healthcare sector. For example, the Centers for Medicare & Medicaid Services' Accountable Health Communities intervention program will evaluate whether linking those with food insecurity to resources such as SNAP will affect healthcare expenditures.[29] The conceptual model of the relationship between food insecurity and health noted above[30] suggests several ways that programs to address food insecurity might reduce healthcare costs. In the long-term, alleviating food insecurity may help reduce the incidence of chronic diet-sensitive conditions such as obesity and diabetes, and thus reduce their attendant effects on morbidity and mortality. In the short-term, however, the prevalence of diabetes, obesity, coronary heart disease, and other chronic conditions is much greater than their incidence. Therefore, in the short-term, SNAP is most likely to improve healthcare expenditures by enhancing disease self-management, for example by facilitating adherence to recommended diets, making available financial resources that can be spent on medications, reducing stress over subsistence needs, and freeing up cognitive 'bandwidth' to attend to self-care.

In this report, we address the following research questions: 1) What is the association between food insecurity and healthcare expenditures, 2) what is the association between food insecurity and healthcare use, and 3) is SNAP participation associated with reduced healthcare expenditures?

We believe these questions are highly policy relevant as ongoing healthcare reforms are heavily focused on reducing overall system-level costs, particularly among low-income populations.[31] Upstream investment in programs to prevent chronic disease or its complications can be highly-cost effective.[32] However, policymakers increasingly wish to determine the "return on investment" for safety net programs such as SNAP, or novel clinic-based programs to reduce food insecurity. To determine the potential for 'return on investment', it is necessary to identify health care utilization and expenditures associated with high food insecurity, and whether the nation's largest program designed to reduce food insecurity can indeed mitigate excess healthcare costs. To date, this issue has been largely unaddressed.

Data

The data for all analyses in this study came from the National Health Interview Survey (NHIS) linked to the Medical Expenditure Panel Survey (MEPS). NHIS is a cross-sectional, nationally-representative survey used for epidemiologic surveillance, conducted by the Centers for Disease Control and Prevention's National Center for Health Statistics.[36] In 2011, NHIS first asked questions about food insecurity. A nationally-representative subset of NHIS participants are selected to participate, for the two years after their NHIS participation, in MEPS, a longitudinal survey conducted by the Agency for Healthcare Research and Quality to gather national healthcare expenditure data.[35]. The NHIS and MEPS were administered by trained interviewers in English or Spanish.[35,36]

The Human Research Committee at Partners Healthcare exempted this analysis of de-identified data from human subjects review.

Research Methods

We sought to evaluate our three hypotheses by conducting a series of related, but independent analyses.

Hypothesis 1: Food insecurity is associated with increased healthcare expenditures

Measures

Individuals were categorized as food insecure using a validated 10-item questionnaire with a30-day look-back period, which the USDA sponsored for inclusion in the NHIS to help understand the relationship between food insecurity and health.[3,33,34] As examples, items queried, "if the family was worried about food running out before there was money to buy more" or "if the food purchased just didn't last until there was money to buy more" (full questionnaire available at: ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Survey_Questionnaires/NHIS/2011/English/qfamily.pdf).[33] Using standard scoring, those who answered affirmatively to more than two items were considered food insecure.[33]

Outcomes

Our primary outcome for testing this hypothesis was total healthcare expenditure from 2012 through 2013, converted to 2015 U.S. dollars using the Consumer Price Index (http://data.bls.gov/cgi-bin/cpicalc.pl). Total healthcare expenditure is defined as the actual amount spent by individuals or paid by third parties on their behalf: "expenditures in MEPS are comprised of direct payments for care provided during the year, including out-of-pocket payments and payments by private insurance, Medicaid, Medicare, and other sources."[35] Secondary outcomes included expenditures within the following MEPS categories: outpatient expenditures (both office-based and hospital-based outpatient), emergency department expenditures (excluding those resulting in an inpatient admission), inpatient expenditures (including emergency department spending for that admission), and prescription medication expenditures.[26]

Demographic, Socioeconomic, and Clinical Variables

We included several covariates in our multivariable regressions of food insecurity and healthcare expenditures to account for factors potentially associated with food insecurity, healthcare expenditures, or both, and to try to isolate, to the extent possible, the role of food insecurity (rather than poverty more broadly). Age, in years as a continuous variable, was taken from NHIS data; because health and healthcare expenditures may have a curvilinear relationship with age[37], we also included an age-squared term. Other covariates collected from the NHIS dataset included gender (male or female), race/ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and Asian/multi-racial/other), educational attainment (less than high school diploma, high school diploma, greater than high school diploma), and household income (expressed as a percentage of the federal poverty level, which accounts for household size), and health insurance categorized as: private, Medicare (not including Medicare-Medicaid 'dual eligibles'), other public (including Medicaid, 'dual eligibles', and coverage through the Department of Veterans Affairs), and uninsured. Because place of residence is associated with variation in healthcare spending[38], we also included an indicator of living in a rural versus urban area (defined by living in a Metropolitan Statistical Area).

MEPS includes detailed questions regarding several 'priority' health conditions, including diabetes, hypertension, and heart disease.[35] Because these conditions are thought to be closely related to food insecurity[21], we conducted pre-specified subgroup analyses focusing on individuals who reported these conditions using validated self-report items in MEPS.[35] Diabetes was defined as self-report of having been diagnosed with diabetes by a doctor. Hypertension was defined as self-report of having been diagnosed with high blood pressure by a doctor. Heart disease was defined as having been diagnosed with coronary heart disease, angina, myocardial infarction, or other unspecified heart disease by a doctor. Owing to issues of age penetrance, MEPS only asks these questions of respondents aged > 17 years, so analyses of these conditions were restricted to adults.

Statistical Analysis

We first conducted descriptive statistics, applying sampling weights to estimate population-representative numbers. Differences in health care expenditures between individuals who did and did not report food insecurity were examined using chi-square testing for dichotomous variables and Wilcoxon testing for continuous variables.

Because expenditure data is often highly skewed, overdispersed (i.e. the variance is greater than the mean), and inclusive of a high proportion of individuals with no expenditures, we analyzed the data using zero-inflated negative binomial regression.[39-41] This modeling approach considers that two processes may be occurring simultaneously: one that generates expenditures, including zero expenditures in some cases (e.g. illness requiring medical care, or lack thereof), and a separate process that can reduce the likelihood of expenditures even if they would otherwise occur, leading to what is sometimes called 'excess zero' expenditures (e.g. inability to access healthcare). An advantage of this approach, compared with estimating expenditure contingent on having greater than zero spending, is that observations with zero expenditures are still analyzed. Zero-inflated negative binomial regression models estimate the probability of having 'excess zero' healthcare expenditures (using a logistic model), and the expenditure count (using a negative binomial model). Thus there are two results to consider—an odds ratio (OR) that estimates the probability of having 'excess zero' expenditures (that is, not being able to generate expenditures in some circumstances) and an incidence rate ratio that compares the incidence rate of expenditures between two groups.

To aid understanding of the data, we estimated adjusted annualized expenditures and per-year difference in healthcare expenditures for individuals at different levels of food insecurity using the regression models, and estimated total annual excess costs in the U.S[42]. Finally, we evaluated the possibility of an interaction between food insecurity and health insurance, and conducted sensitivity analyses restricted to adults.

A p-value <0.05 indicated statistical significance. Analyses were conducted in SAS Version 9.4 (SAS Institute, Cary, NC) and STATA/SE Version 14.0 (StataCorp LP, College Station, TX).

Hypothesis 2: Food insecurity is associated with increased use of emergency department and inpatient services

Food Insecurity

We assessed food insecurity in the same way as in Hypothesis 1.

Healthcare Use

Information on healthcare expenditures and use that occurred in 2012 and 2013 was taken from MEPS. Because they are often the focus of programs to reduce healthcare use, we evaluated number of emergency department visits (which, in MEPS does not include those that result in a hospital stay), number of inpatient hospital admissions, and number of days spent as a hospital inpatient. For consistency, we converted all expenditures to 2015 dollars, using the Consumer Price Index http://data.bls.gov/cgi-bin/cpicalc.pl). Owing to lower numbers of children and low use of emergency department and inpatient services by children, our analyses for hypothesis 2 were restricted to adults (age > 18 years at time of NHIS completion).

Other Measures

We considered several factors that may confound the relationship between food insecurity and healthcare expenditure and use. We used data from the 2011 NHIS to determine the participants age (at time of NHIS completion), gender, race/ethnicity (categorized as non-Hispanic white, non-Hispanic black, Hispanic, and other), education (less than high school diploma, high school diploma, greater than high school diploma), income expressed as a percentage of federal poverty level which accounts for inflation and household size, health insurance (private, Medicare, other public insurance which includes Medicaid, Medicare and Medicaid dual eligibles, and coverage through the Department of

Veterans' Affairs, and no health insurance). Because area of residence is associated with variation in healthcare expenditure and use, we used data from MEPS to assess census region of residence (Northeast, Midwest, South, or West) and urban vs. rural residence. Also, because healthcare organizations commonly use condition-based programs to target high healthcare users, we assessed the presence of 4 common conditions (heart disease, diabetes mellitus, respiratory illness [asthma, emphysema, or chronic bronchitis], and hypertension), using self-report items from MEPS.

Statistical Analysis

We first performed descriptive statistics, and created our percentile groups. We then tested the association between food insecurity and subsequent healthcare use. Because healthcare use often has a large number of observations without any use, we used zero-inflated negative binomial regression. We conducted both unadjusted analyses, and analyses adjusted for the covariates described above. Analyses were conducted SAS version 9.4 (SAS Institute, Cary, NC) and Stata SE 14.1 (StataCorp, College Station, Tx). All analyses accounted for survey design information (sampling strata and weights).

Hypothesis 3: SNAP participation is associated with reduced subsequent healthcare expenditures

SNAP Participation

The primary indicator of SNAP participation in this study was an affirmative response to the 2011 NHIS item: "At any time during the last calendar year, did you or any family members living here receive SNAP or food stamp benefits?" Those who responded affirmatively were categorized as receiving SNAP, without regard to the duration or amount of benefits received.

Healthcare Expenditures

The primary outcome for evaluating this hypothesis was total healthcare expenditures over the two-year MEPS period (2012 through 2013), the same as for hypothesis 1. To aid understanding, we present annualized results in 2015 U.S. dollars (using the Consumer Price Index http://data.bls.gov/cgi-bin/cpicalc.pl). In MEPS, total healthcare expenditures are the actual amount of money either paid on behalf of the individual by a third-party (costs, not charges), or spent by an individual as out-of-pocket costs.[35] As in analyses for hypothesis 2, we restricted our analyses to adults owing to low numbers of children and because MEPS does not measure comorbidity in children in the same way as adults, making it impossible to pool estimates.

Demographic, Socioeconomic, and Clinical Variables

We considered several factors that could confound the relationship between SNAP participation and healthcare expenditures. Age (in years), was taken from NHIS data; to account for a curvilinear relationship between age and healthcare expenditures[37], we also included an age-squared variable. Also from the NHIS data, we extracted information on gender, race/ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and Asian/multi-racial/other), household income as a percentage of the federal poverty level, educational attainment (less than high school diploma, high school diploma, greater than high school diploma), and disability status (yes or no, based on application for supplemental income).[4,5] We categorized health insurance as private, Medicare (not including Medicare-Medicaid 'dual eligibles'), other public (including Medicaid, 'dual eligibles', and Department of Veterans Affairs), and uninsured. To account for area variation in healthcare spending[38], we also included variables for census region (Northeast, Midwest, South, or West), and rural or urban location.

Because our conceptual model posited that the short-term effect, if any, of SNAP on healthcare expenditures would relate to improving disease control, we also included, from MEPS, self-reported presence/absence of several clinical conditions: obesity (based on body mass index > 30 kg/m^2), hypertension, coronary heart disease, diabetes mellitus, stroke, arthritis, and chronic obstructive pulmonary disease. Finally, we included an indicator of death during the study period.

Statistical Analysis

We first conducted descriptive statistics. Then, to determine the relationship between SNAP receipt and subsequent healthcare expenditures, and to check the robustness of any associations to analytic strategy, we conducted three types of analyses: a standard regression analysis, a matched-pairs instrumental variable (IV) technique called near/far matching, and an augmented inverse probability weighted (AIPW) analysis.

For the standard regression analysis, we adjusted for the observed covariates listed above. Because healthcare expenditure data generally contains many observations without any expenditures, and also has a few observations with very high expenditures, we followed the approach proposed by Manning et al. to determine the appropriate functional form for regression analysis, using a modified Park test.[43] This led to selecting generalized linear regression with a gamma distribution and log link. For these analyses, we used the survey strata and sampling weights for NHIS-MEPS.

While standard regression can adjust for measured confounders, there may be unobserved characteristics that affect SNAP participation and healthcare expenditures. To address potential confounding by unrecorded factors, we conducted a near/far matching analysis.[44,45] A more detailed description of this approach is contained in the Appendix, but in general near/far matching can be thought of as filtering a cohort to find its most informative pairs—those who are very similar on measured characteristics ('near') but are dissimilar ('far') on the values of an instrumental variable. An instrumental variable is one that, in some way, allocates 'treatment' independently of the likelihood of experiencing the outcome, and thus is analogous to a randomized clinical trial. In this study, our instrument consisted of variations in state policies regarding SNAP enrollment. SNAP eligibility is set at the federal level, but enrollment policies vary by state, and these policies can make it easier or harder to enroll, thus subtly encouraging or discouraging receipt of SNAP.[46,47] These policies were abstracted from the SNAP policy database[46] and in effect over the 2011 NHIS survey recall period. The policies used were 1)an option for online submission of a SNAP application, 2)presence of a broad-based categorical eligibility policy (which extends SNAP eligibility to those eligible for other assistance programs), and 3) whether the state uses simplified reporting requirements for households with earnings.[46] These instruments have been validated and used in prior studies[47,48], and we describe their justification and testing in more detail in Hypothesis 3: Supporting Information. In addition to variables used in the standard regression, the near/far match included information on per-enrollee state healthcare expenditures in the year prior to MEPS[49], to help account for other state-level factors that would be reflected in participants' healthcare expenditures. After creation of the matched cohort, we performed an instrumental variable analysis using the two-stage residual inclusion (2SRI) approach[50,51], adjusting for covariates, with a logit model to estimate SNAP receipt, a gamma regression model to estimate expenditures, and bias-corrected bootstrapped confidence intervals (500 replications).

Finally, as an alternative to the instrumental variable-based analysis, we conducted an analysis using augmented inverse probability weighting (AIPW), a 'doubly-robust' technique to mitigate selection bias by estimating the likelihood of receiving SNAP and then using response-weights to achieve balance in measured covariates between the group that did and did not receive SNAP.[52] This approach does not rely on instrumental variable assumptions, but may not be able to achieve balance on unmeasured confounders. To justify this approach, we examined post-weighting balance between covariates and conducted tests of overidentifying restrictions.[53] We again calculated replication based confidence intervals (bias-corrected confidence intervals using 500 bootstrap replications).

For interpretation, we expressed results as the average treatment effect (local average treatment effect in the case of the instrumental variable near/far analysis), reported in the difference in US dollars spent per year, using the postestimation predictive margins command in Stata (or from the procedure itself in the case of AIPW). The standard regression and AIPW analyses used the entire study sample, while the near/far analysis was conducted on those residing in the 29 most-populous states, as AHRQ does not release state-level codes for the other states owing to privacy concerns (eTable 2 for list of included states). Survey design information could not be incorporated into the near/far or AIPW analyses.

Finally, to determine whether there was support for our conceptual model which posited that the short-term effects of SNAP participation would result from making illnesses easier to manage, we examined predicted differences in healthcare expenditures for hypertension and coronary heart disease, two conditions where SNAP participation is particularly likely to affect management, using marginal predictions from our standard regression model. We expected that differences between those who did and did not participate in SNAP would be greater for these conditions.

A p-value <0.05 indicated statistical significance. Analyses were conducted in SAS Version 9.4 (SAS Institute, Cary, NC), Stata Version 14.0 (StataCorp LP, College Station, TX), and in R version 3.3.1 (https://cran.r-project.org/), using the package 'nearfar' (https://cran.r-project.org/web/packages/nearfar/index.html).

Results

Hypothesis 1

Of 16,663 individuals eligible for analysis, 14.0% reported food insecurity in the 2011 NHIS, representing approximately 41,616,255 Americans. Food insecurity was more common among younger individuals, racial/ethnic minorities, those with lower education and income, and those with public health insurance or who lacked insurance (Table 1). The mean and median annualized total expenditures among all individuals were $4,113.30 (standard error [SE] $115.36) and $1,108.17 (interquartile range [IQR] $219.09 to $3,993.07), respectively. Overall, 9.2% of individuals had no healthcare expenditures during the study period (food insecure 13.2%, food secure 8.6%, p<0.0001). Unadjusted annualized mean and median healthcare expenditures were $4,382.64 (SE $329.98) and $1,648.19 (IQR $284.12 to $7,050.56) for food insecure individuals versus $4,070.48 (SE $113.24) and $2,296.63 (IQR $523.67 to $8,100.38) for food secure individuals, respectively. Annually, an estimated $182.4 billion in healthcare spending occurred among individuals with food insecurity.

In multivariable regressions (Table 2) adjusted for age, age-squared, race/ethnicity, education, income, rural residence, and health insurance category, those with food insecurity had significantly greater healthcare expenditures: $6,071.60 (95% Confidence Interval [CI]$5,144.92 to $6,998.28) for those with food insecurity, compared with $4,208.43 (95%CI $3,976.07 to $4,437.79) for those without. The adjusted model estimates that food insecurity was associated with an extra $1,863.17 in healthcare expenditure per year (p<.0001). This difference in expenditures, multiplied by 41,616,255 food insecure Americans, represents approximately $77.5 billion in additional healthcare costs, compared with what would be expected for demographically similar individuals without food insecurity, if the relationship between food insecurity and expenditures were causal. We did not observe evidence that food insecure individuals were prevented from generating healthcare expenditures (OR of 'excess zero' expenditures 0.93, 95% CI 0.72 to 1.21) when adjusting for other factors. Results restricted to adults (age > 18 years) were similar (Tables 5a-5b). We found no evidence of an interaction between food insecurity status and health insurance coverage (p=0.84).

When examining categories of expenditures, we found significant differences between those with and those without food insecurity (Table 3). Individuals reporting food insecurity had significantly greater expenditures than food secure individuals for inpatient hospitalizations ($471.48 greater per year, p=.03), and prescription medications ($779.36 greater per year, p<0.0001). Expenditure differences for food insecure individuals were not statistically significant for outpatient ($42.19 greater per year, p=0.07) and emergency department expenditures ($21.87 greater per year, p=0.18).

Among those with conditions previously associated with food insecurity, food insecure individuals with diabetes had $4,413.61 higher estimated annualized total healthcare expenditures than food secure individuals with diabetes (annualized total expenditure $13,035.16 vs. $8,621.55, p=0.004) (Table 4). Similarly, food insecure individuals with hypertension had $2,175.51 higher annualized costs than food secure individuals with hypertension (annualized total expenditure $8,134.71 vs. $5,959.21, p=0.003) and food insecure individuals with heart disease had $5,144.05 higher annualized costs than food secure individuals with heart disease (annualized total expenditure $12,984.17 vs. $7,840.12, p=<.0001).

Hypothesis 2:

There were 11,781 adults included in the study. Of these, 13.2% (n=2056, percentage is weighted) belong to households that reported food insecurity in 2011. Those in food insecure households were more likely to be younger, racial/ethnic minorities, and be poorer, compared with those in food secure households (Table 6).

Among study participants, unadjusted utilization analyses showed a highly right-skewed distribution with most participants having no utilization in these categories (Table 7). This supports the use of zero-inflated modeling. In zero-inflated negative binomial models (Table 8), adjusted for age, age squared, gender, race/ethnicity, education, income, health insurance, region, and living in a rural area, food insecurity was associated with significantly greater emergency department visits (Incidence Rate Ratio [IRR] 1.47, 95% Confidence Interval [CI] 1.12 – 1.93) (Table 3). Similarly, food insecurity was associated with greater inpatient hospitalizations (IRR 1.47, 95% CI 1.14 – 1.88), and greater number of days hospitalized (IRR 1.54, 95% CI 1.06 – 2.24). In particular, the difference between food insecure and food secure participants, adjusting for other factors, was large for those with Medicare (difference in emergency department visits 0.42: p=0.01; difference in inpatient admissions: 0.25 admissions, p = 0.01; difference in days hospitalized: 1.93, p=0.04) and other public insurance, which includes Medicaid and 'dual eligibles' (difference in emergency department visits: 0.39 p<.0001; difference in inpatient admissions: 0.10 admissions, p = 0.005; difference in days hospitalized: 0.62 , p=0.03).

Zero inflated negative binomial models, adjusted for the same factors as above and adding adjustment for four clinical conditions commonly used in care management programs (heart disease, diabetes mellitus, respiratory illness, and hypertension), showed similar results. Food insecurity remained associated with greater ED visits (IRR 1.41, 95% CI 1.12 – 1.78), inpatient admissions (IRR 1.28 95% CI 1.01 – 1.61) and days hospitalized (IRR 1.61, 95% CI 1.12 – 2.31).

Hypothesis 3

There were 4447 patients who met inclusion criteria (age > 18 years, income < 200% of federal poverty level and information on SNAP receipt). Overall there were significant demographic differences between those who did and did report SNAP participation (Table 9), with SNAP participants generally being younger, more likely to be a racial/ethnic minority, and poorer.

Unadjusted analyses, likely confounded by sociodemographics and selection issues, showed the annual mean expenditures for those who reported SNAP participation to be $4,825, compared with $4,417among those who did not report participation (difference $408, 95% Confidence Interval [CI] -$877 to $1,692, p=0.53) (Table 10).

In standard regression analyses adjusted for observed factors, SNAP participation was associated with significantly less estimated expenditures: -$1,409 per year in those who did, versus did not, report SNAP participation (95% CI -$2,694 to -$125, p=0.03). The full model is reported in Table 11.

For the near/far matching analysis, our instrument was strongly associated with participation in SNAP, and passed test of overidentifying restrictions. Interestingly, endogeneity tests suggested that instrumental variable methods may not have been needed (p=0.72). The near/far match resulted in 3676 participants who comprised 1838 matched pairs, and the instrument was strong (first-stage partial deviance statistic: 42.5) (see Hypothesis 3: Supporting Information). Analyses using the 2SRI method, adjusted for the same factors as the standard regression, and state spending, demonstrated lower expenditures for SNAP receipt, (-$5,160 per year; 95% CI -$6,924 to -$438) (full model in Table 12).

AIPW analyses, conducted on the entire cohort, successfully balanced observed factors (Table 13), and passed tests of overidentifying restrictions. The AIPW analysis estimated the average treatment effect of SNAP enrollment to be -$931 (95% CI -$2,026 to -$152) (full model in Table 14), again representing lower yearly expenditures with SNAP participation.

Figure 1 presents a comparison of the effect estimates from the different analytic strategies.

Using our standard regression model, estimated differences in healthcare expenditures between those who did and did not participate in SNAP were even greater in those with hypertension (-$2,654, 95% CI -$5,089 to -$220) and coronary heart disease (-

$4,109, 95% CI -$7,947to -$272). To help understand policy implications of changing SNAP enrollment, we also evaluated the difference in expenditures between SNAP participation and non-participation for those who are disabled (-$3,958, 95% CI -$7,772 to -$143) and those who receive non-Medicare public health insurance, such as Medicaid (-$2,544, 95% CI -5,017 to -$71).

Discussion

Studying individuals in the 2011 NHIS who underwent food insecurity assessment and subsequently enrolled in MEPS, we found that food insecurity was associated with approximately $1,800 higher healthcare expenditures per year, after adjusting for age, gender, race/ethnicity, education, income, insurance, and residence area. Individuals with food insecurity were particularly more likely to incur expenditures for inpatient hospitalizations and prescription medications. The expenditure difference between those with and without food insecurity was even greater in chronic diseases that have been associated with food insecurity: diabetes, hypertension, and heart disease.[21] Further, we found that food insecurity was significantly associated with greater use of healthcare visit types, such as emergency department and inpatient admissions, that are common targets of programs to reduce healthcare use. Going further to examine the relationship between SNAP participation and healthcare expenditures, we found that SNAP participation was associated with lower subsequent healthcare expenditures in low-income adults. Though the estimated amount saved varied by analytic approach, the finding of reduced healthcare expenditures associated with SNAP participation was robust across several different strategies, and was estimated to be greater for participants with diet-sensitive conditions previously linked to food insecurity.[21]

For several reasons, we believe that the standard regression model estimate of approximately -$1400 dollars per year per person, across the population of low-income adults, is the best estimate of the average treatment effect of SNAP enrollment. First, the near/far analysis estimates the effect of SNAP enrollment in the 'marginal' case where the instrument made the difference in SNAP enrollment, and the analysis could include only the 29 most populous states. Second, the savings estimate for the standard regression model is contained within the confidence interval for the near/far estimate. Third, endogeneity tests did not strongly indicate residual confounding beyond the factors adjusted for in the standard regression model. Finally, if there was residual confounding, the estimates from the near/far analysis indicate it was likely to be in the direction of reducing the savings associated with SNAP, making the standard regression estimate the conservative one. For comparison, the average per person SNAP benefit across the US is $129 per month, or $1548 over a 12-month period.[62]

This study is consistent with prior work and enhances our understanding of food insecurity and health. A recent cross-sectional study conducted in Ontario, Canada[54] found an association between food insecurity and healthcare costs similar in magnitude to what we observed in this study. Because of universal healthcare coverage in Ontario, those findings are likely more comparable to an insured US population than the entire US population. While the data in our study were mainly collected before implementation of the Affordable Care Act's health insurance coverage mandate[55], results from the Canadian study suggest that improvements in health insurance coverage in the U.S. are unlikely to close the gap in healthcare expenditures between those with and without food insecurity.

Another recent study[56] found that increases in Medicaid spending for those in Massachusetts with conditions thought to be related to food insecurity, including diabetes and malnutrition, declined after a temporary increase in Supplemental Nutrition Assistance Program (SNAP) benefits, a federal nutrition program known to reduce the depth, breadth, and severity of food insecurity.[27,57] Because the study was ecological in nature, however, it is unknown whether the decreased spending occurred in those experiencing food insecurity or enrolled in the SNAP program. Still, these results are consistent with our finding that food insecurity is associated with significant increases in health care expenditures, and suggest that addressing food insecurity may lead to healthcare savings. Regarding SNAP participation, it has been unclear if food insecurity interventions could reduce healthcare costs. We believe that this finding fits into an emerging body of evidence that suggests interventions targeting food insecurity can improve clinical outcomes such as cardio-metabolic risk factors, which supports a potential mechanism (improved clinical control of chronic disease) for the observed findings.[63,64]

The results of this study have significant implications for public health and health policy. With decades of research demonstrating that 'social determinants of health', including food insecurity, have a profound influence on health and healthcare costs, policy makers and healthcare providers are increasingly seeking actionable 'levers' to help individuals and populations pursue better health, better patient experience, and lower costs.[29,58] The finding that food insecurity is particularly associated with inpatient and prescription medication expenditures is consistent with the idea that people facing food insecurity may defer attending to their health in the presence of pressing immediate needs, which in turn leads their health conditions to worsen. As such, food insecurity interventions have the potential to improve health not only by improving dietary quality, but also by improving mental health, medication adherence, and by freeing up financial and cognitive resources for health maintenance and chronic disease management. With regard to healthcare use, the ability to predict who will have higher use of expensive services in the subsequent two years is highly relevant for population health management efforts. We should note, however, that it is certainly true that emergency department visits or inpatient admissions are not necessarily to be avoided in all situations. Often they represent appropriate care. But given the clear association between food insecurity and these types of healthcare use, which are often disruptive to patients and represent worsening of clinical conditions, interventions to determine whether addressing food insecurity can help alter healthcare use in a way beneficial for both patients and the healthcare system is certainly warranted. Even if these interventions do not change, or even increase, this type of healthcare use, identifying food insecurity may yet help target resources to those most in need of them. With regard to our SNAP analysis, since the instrumental variables used were actual policy differences enacted in some states, but not others, prioritizing ways to make it easier for eligible Americans to enroll in SNAP is likely to be a feasible way to help reduce healthcare costs. This may be of particular interest to states because of differences in the funding source between SNAP and healthcare costs. As an entitlement program, SNAP benefits are paid for by the federal government, while Medicaid, which would likely see some of the savings if healthcare costs are reduced, is paid for jointly by states and the federal government.[65] Therefore, state policies regarding SNAP enrollment may help offload state Medicaid budgets.

The results of this study should be interpreted in light of several limitations. This study relied on self-report of clinical conditions, without laboratory or other clinical confirmation. However, these self-report items are validated and commonly used in epidemiologic surveillance of the conditions of interest.[61] Secondly, because of the nature of the study, those in the most severe social circumstances, including very low food security, may have been less likely to enroll in NHIS and be followed in MEPS. Next, the study may have lacked power to evaluate categories of expenditures. While not all observed differences were statistically significant, the direction of difference was consistent across spending categories. Next, food insecurity was assessed only once, in the 2011 NHIS, and over the preceding 30-day period. Because food insecurity is a dynamic condition, individuals who did not report food insecurity in 2011 may have experienced it during the subsequent period. This may bias estimates of expenditure difference to the null. Similarly, SNAP assessment occurred at a single point in time. Since low-income households often cycle on and off SNAP, this may have resulted in misclassification. However, this misclassification would likely bias estimates to the null. Standard tests of the instruments we used were consistent with their validity, but ultimately instrumental variable approaches rely on some assumptions that cannot be empirically tested. The generalizability of the findings in the near/far analysis may have been limited because we were unable to incorporate survey design information, but since the matching process breaks the geographical link, and since IV analyses do not estimate population-level effects, this may not be a significant issue. Further, these limitations are mitigated by the fact that the standard regression analysis (which is nationally representative because it incorporated survey design information), and the AIPW analysis, neither of which make IV assumptions, produced results qualitatively similar.

The limitations of this study are balanced by several strengths. The MEPS methodology allows for highly accurate capture of the healthcare expenditures for a nationally-representative sample of individuals, giving a complete picture of costs borne by the individuals themselves or reimbursed on their behalf. Secondly, the longitudinal design provides strong evidence that exposure to food insecurity, for whatever reason, is likely to be associated with excess subsequent healthcare expenditure.

There are many questions that remain unanswered in this area, and represent promising directions for future work. It is important to develop a deeper understanding of the mechanism by which food insecurity, (and SNAP and other food insecurity assistance programs), could lead to changes in health and healthcare expenditures. It is important to evaluate whether effects persist over longer periods of time, and whether longer evaluation periods can detect clinical changes, such as reduced incidence of diabetes or cardiovascular events. Should more than one food insecurity intervention prove effective, comparing and evaluating interactions between their effects would likely also be worth pursuing.

Although this study focused on healthcare expenditures, SNAP is a food insecurity and nutrition program, not a healthcare program. SNAP's purpose is not to reduce healthcare expenditures, and we are of the opinion that its funding is justified without regard to any impact on healthcare costs.

Conclusion

Food insecurity is an all-too-common problem for many Americans. Food insecurity is associated with increased healthcare spending, particularly in those with common and costly conditions such as diabetes, hypertension, and heart disease, and increased use of healthcare services such as emergency department visits and hospitalizations. For this reason, there is significant potential for food insecurity interventions to improve health and reduce healthcare costs among vulnerable populations. In an analysis of the nation's largest food insecurity reduction program (SNAP), and across several analytic approaches, including an instrumental variable approach that accounts for unmeasured confounding, SNAP participation was associated with lower subsequent healthcare expenditures for low-income adults. Ultimately, our success at achieving the triple aim of healthcare will depend on our ability to address social, along with genetic and behavioral, determinants of health.

Table 1: Demographics

	Total	Food Secure	Food Insecure	p-value
	% (n) or mean (se)	% (n) or mean (sd)	% (n) or mean (sd)	
Age (y)	37.1 (0.3)	37.9 (0.4)	32.1 (0.6)	<.0001
Age Categories				<.0001
0 - 17	23.5 (4604)	22.9 (3611)	27.6 (991)	
18-64	63.8 (10235)	63.2 (8335)	66.9 (1896)	
65 and greater	12.7 (1551)	13.9 (1390)	5.5 (160)	
Female	51.5 (8769)	51.3 (7068)	52.7 (1695)	0.21
Race/Ethnicity				<.0001
Non-Hispanic White	64.1 (5815)	66.1 (5095)	51.7 (719)	
Non-Hispanic Black	12.4 (3542)	11.3 (2665)	18.9 (875)	
Hispanic	16.9 (5664)	15.4 (4286)	26.1 (1374)	
Asian/multi-/other	6.7 (1612)	7.3 (1482)	3.3 (130)	
Educational Attainment				<.0001
< High School Diploma	30.5 (5966)	28.6 (4490)	42.6 (1473)	
High School Diploma	21.6 (3202)	20.9 (2577)	25.7 (625)	
> High School Diploma	47.9 (5891)	50.4 (5203)	31.7 (687)	
Income				<.0001
<100% FPL[a]	15.1 (3692)	11.5 (2327)	36.9 (1362)	
100-199% FPL	18.9 (3462)	16.5 (2564)	34.0 (898)	
≥200% FPL	66.0 (7823)	72.1 (7235)	29.1 (587)	
Census Region				0.16
Northeast	17.7 (2790)	17.7 (2296)	17.5 (491)	
Midwest	21.7 (2955)	22.0 (2446)	19.6 (508)	
South	37.2 (6092)	36.4 (4809)	42.3(1281)	
West	23.4 (4784)	23.9 (3967)	20.5 (816)	
Rural Residence	14.3 (2005)	13.9 (1587)	16.9 (418)	0.17
Insurance				<.0001
Private	63.0 (7920)	67.6 (7226)	34.1 (692)	
Medicare	7.7 (1108)	7.7 (880	8.1 (228)	
Other Public	14.1 (3725)	11.6 (2592	29.5 (1131)	
Uninsured	15.3 (3317)	13.2 (2404	28.3 (911)	
Health Conditions[b]				
Diabetes	8.5 (1160)	7.9 (892)	11.7 (268)	<.0001
Hypertension	35.5 (4224)	35.1 (3410)	38.0 (814)	0.12
Heart Disease	15.7 (1630)	15.2 (1302)	18.6 (327)	0.02

% presented are weighted, not directly calculable from N

[a]FPL = Federal Poverty Level

[b]Restricted to individuals aged > 17 years

Table 2: Total Expenditures							
	Odds of 'Excess Zero' Expenditures		Incidence Rate of Expenditures		Expenditure Estimates		
	OR	95% Confidence Interval	IRR (95% CI)	p-value	Annualized Estimated Expenditures	95% Confidence Interval	Annualized Difference
Food Insecure	0.93	0.72 – 1.21	1.44 (1.24 to 1.67)	P<0.0001	$6,071.60	$5,144.92 to $6,998.28	$1,863.17
Food Secure	ref	--	ref	--	$4,208.43	$3,976.07 to $4,437.79	--

Estimates adjusted for: age, age squared, gender, race/ethnicity, education, income, rural residence, and insurance. Estimated expenditures in 2015 dollars.
Interpretation note: an odds ratio greater than 1 represents evidence of a process that prevents expenditures (e.g. inability to access healthcare). An incidence rate ratio greater than 1 represents evidence of greater expenditures in a group, compared with a referent group. Information from both models is used to estimate annual expenditures.
Ref=Reference category

Table 3: Estimated Expenditures by Spending Category

	Outpatient			Emergency Department			Inpatient			Prescription medication		
	Annualized Estimated Expenditure (95% CI), $	Annualized Difference, $	p-value	Annualized Estimated Expenditure (95% CI), $	Annualized Difference, $	p-value	Annualized Estimated Expenditure (95% CI), $	Annualized Difference, $	p-value	Annualized Estimated Expenditure (95% CI), $	Annualized Difference, $	p-value
Food Insecure	576.60 (417.22to 735.99)	154.34	0.07	271.96 (201.74 to 342.18)	91.46	0.512	1587.49 (1149.85 to 2025.14)	**493.41**	.03	1776.59 (1472.03 to 2081.15)	**779.36**	<0.0001
Food Secure	422.26 (377.42 to 467.10)	--		180.50 (164.58 to 196.42)	--		1094.09 (958.73 to 1229.44)	--		997.23 (897.52 to 1096.95)	--	

Estimates adjusted for: age, age squared, gender, race/ethnicity, education, income, rural residence, and insurance. Estimated expenditures expressed in 2015 dollars.
Bold indicates significant at p<0.05

Table 4: Total Expenditures by condition

	Odds of 'Excess Zero' Expenditures	Incidence Rate of Expenditures	Expenditure Estimates		
	OR(95% CI)	IRR (95% CI)	Annualized Estimated Expenditure (95% CI)	Annualized Difference	p-value
Diabetes Mellitus[a]					
Food Insecure	2.69 (0.57 to 12.73)	1.52 (1.14 to 2.02)	$13,035.16 ($9,527.01 to $16,543.30)	$4,413.61	0.004
Food Secure	Ref	Ref	$8,621.55 ($7,274.23 to $9,968.87)	--	--
Hypertension[a]					
Food Insecure	0.63 (0.29 to 1.36)	1.35 (1.11 to 1.65)	$8,134.71 ($6,596.09 to $9,673.34)	$2,175.50	0.003
Food Secure	Ref	Ref	$5,959.21 ($5,462.33 to $6,456.09)	--	--
Heart Disease[a]					
Food Insecure	0.72 (0.26 to 2.01)	1.65 (1.29 to 2.10)	$12,984.17 ($9,988.35 to $15,979.99)	$5,144.05	<0.0001
Food Secure	Ref	Ref	$7,840.12 ($6,813.83 to $8,866.41)	--	--

OR = odds ratio. IRR = Incident Rate Ratio. Estimates adjusted for: age, age squared, gender, race/ethnicity, education, income, and insurance. Estimated expenditures in 2015 dollars.
a=analysis conducted among those reporting the condition
Interpretation note: an odds ratio greater than 1 represents evidence of a process that prevents expenditures (e.g. inability to access healthcare). An incidence rate ratio greater than 1 represents evidence of greater expenditures in a group, compared with a referent group. Information from both models is used to estimate annual expenditures.
Ref=Reference category

Table 5: Annualized Expenditures, restricted to adults (age ≥18 years)

	Expenditure Estimates			
	Annualized Estimated Expenditures	95% Confidence Interval	Annualized Difference	p-value
Food Insecure	$6,148.53	$5,091.22 to $7,205.84	$1965.56	<0.0001
Food Secure	$4,182.96	$3,934.14 to $4,431.79	--	

Estimates adjusted for: age, age squared, gender, race/ethnicity, education, income, rural residence, and insurance. Estimated expenditures in 2015 dollars.

Table 5: Total Expenditures, restricted to adults (age ≥18 years)

	Logistic Model		Negative Binomial Model	
	OR	95%CI	IRR	95%CI
Food Insecure	0.95	0.73 to 1.22	1.47	1.24 to 1.73
Food Secure	Ref	--	Ref	--
Age (y)	1.01	0.98 to 1.05	1.03	1.01 to 1.05
Age Squared	1.00	1.00 to 1.00	1.00	1.00 to 1.00
Female	0.33	0.28 to 0.39	1.32	1.19 to 1.48
Race/Ethnicity				
Non-Hispanic White	Ref	--	Ref	--
Non-Hispanic Black	1.63	1.26 to 2.11	0.88	0.75 to 1.04
Hispanic	2.14	1.69 to 2.70	0.75	0.64 to 0.87
Asian/multi-/other	2.59	1.91 to 3.51	0.78	0.64 to 0.94
Educational Attainment				
< High School Diploma	Ref	--	Ref	--
High School Diploma	0.87	0.68 to 1.11	1.04	0.88 to 1.23
> High School Diploma	0.60	0.46 to 0.78	1.05	0.90 to 1.22
Income				
<100% FPL	Ref	--	Ref	--
100-199% FPL	0.97	0.77 to 1.22	1.01	0.84 to 1.21
≥200% FPL	0.68	0.54 to 0.86	0.93	0.79 to 1.09
Rural Residence	0.74	0.55 to 1.01	1.04	0.89 to 1.23
Insurance				
Private	Ref	--	Ref	--
Medicare	0.68	0.30 to 1.54	1.38	1.20 to 1.60
Other Public	1.12	0.81 to 1.54	1.03	0.84 to 1.26
Uninsured	2.80	2.20 to 3.56	0.54	0.46 to 0.63

OR = odds ratio. IRR = Incident Rate Ratio. FPL = Federal Poverty Level. 95% CI= 95% Confidence Interval

Estimates adjusted for: age, age squared, gender, race/ethnicity, education, income, rural residence, and insurance.

Ref=referent category

Table 6: Demographics

	Food Secure % (N) or mean (SE) N=9725	Food Insecure % (N) or mean (SE) N=2056	P
Age, years	47.06 (0.32)	41.52 (0.54)	<.0001
Female	51.80 (5190)	53.43 (1169)	0.1803
Race/Ethnicity			<.0001
Non-Hispanic white	68.89 (4033)	54.91 (537)	
Non-Hispanic black	10.43 (1851)	18.36 (585)	
Hispanic	13.33 (2712)	23.49 (842)	
Asian/Multi-/Other	7.35 (1129)	3.24 (92)	
Education			<.0001
<HS Diploma	12.35 (1818)	25.52 (708)	
HS Diploma	25.66 (2564)	33.28 (621)	
> HS Diploma	61.99 (5201)	41.20 (687)	
Income			<.0001
<100% FPL[a]	9.99 (1324)	35.04 (839)	
100-199% FPL	15.14 (1700)	33.76 (597)	
≥200% FPL	74.88 (5672)	31.20 (438)	
Census Region			0.1261
Northeast	18.27 (1711)	18.00 (335)	
Midwest	22.12 (1731)	19.18 (328)	
South	35.99 (3472)	42.08 (852)	
West	23.62 (2802)	20.75 (539	
Rural Residence	13.94 (1139)	16.80 (274)	0.1665
Insurance			<.0001
Private	68.31 (5559)	34.95 (507)	
Medicare	9.86 (863)	11.16 (228)	
Other Public	6.67 (1046)	19.15 (490)	
Uninsured	15.16 (2096)	34.74 (778)	
Health Conditions			
Heart Disease	15.62 (1291)	19.49 (325)	0.0077
Diabetes	8.30 (891)	12.46 (266)	<.0001
Respiratory illness	10.91 (978)	19.25 (331)	<.0001
Hypertension	36.23 (3401)	39.59 (805)	0.0749

% presented are weighted, not directly calculable from N
[a]FPL = Federal Poverty Level

Table 7: Healthcare Utilization		
	Food Secure	Food Insecure
Emergency Department Visits*		
Mean	0.35	0.71
Median	0	0
25th percentile	0	0
75th percentile	0	0.52
Inpatient Admissions*		
Mean	0.20	0.26
Median	0	0
25th percentile	0	0
75th percentile	0	0
Hospital Days*		
Mean	0.93	1.26
Median	0	0
25th percentile	0	0
75th percentile	0	0
Healthcare Expenditures, 2015 $*		
Mean	9778.92	11075
Median	3139.99	2486.21
25th percentile	689.19	290.47
75th percentile	10495.00	9796.69
90th percentile	25667.00	29686.00
95th percentile	40879.00	53770.00
98th percentile	65674.00	82936.00
99th percentile	88706.00	123605.00
*Over 2-year MEPS period		

Table 8: Healthcare Utilization

	Emergency Department Visits			Inpatient Admissions			Hospital Days		
	IRR (95% CI)	Difference in Events/year	p	IRR (95% CI)	Difference in Events/year	p	IRR (95% CI)	Difference in Events/year	p
Food Insecure	1.47 (1.12 – 1.93)	0.14	0.006	1.47 (1.14 – 1.88)	0.04	0.003	1.54 (1.06 – 2.24)	0.29	0.02
Food Secure									

*all results from zero-inflated negative binomial regression model adjusted for age, age squared, gender, race/ethnicity, education, income, health insurance, region, and rurality , and accounting for survey design characteristics

Table 9: Demographics of included study participants, by receipt of Supplement Nutrition Assistance Program (SNAP) benefit

	No SNAP % or mean (SE) N=2,558	SNAP % or mean (SE) N=1,889	P
Age (y)	44.81 (0.67)	40.22 (0.59)	<.0001
Female	51.53	59.46	<.0001
Race/Ethnicity			<.0001
Non-Hispanic White	53.04	43.02	
Non-Hispanic Black	11.88	26.09	
Hispanic	26.81	26.60	
Asian/multi-/other	8.27	4.29	
Educational Attainment			<.0001
< High School Diploma	26.20	36.78	
High School Diploma	31.09	33.60	
> High School Diploma	42.71	29.62	
Income			<.0001
<100% FPL[a]	32.1	62.6	
100-149% FPL	29.3	24.4	
150-199% FPL	38.7	12.9	
Census Region			0.0010
Northeast	15.03	17.51	
Midwest	18.60	23.08	
South	40.46	42.62	
West	25.91	16.79	
Rural Residence	15.17	19.31	0.0540
Insurance			<.0001
Private	30.03	15.14	
Medicare	17.74	6.87	
Other Public	14.89	44.58	
Uninsured	37.34	33.40	
Died during study period	3.42	1.45	0.0080
Reports disability	10.16	22.70	<.0001
Obesity	31.08	37.59	0.0088
Hypertension	36.21	39.74	0.0625
Heart Disease	17.17	17.89	0.6351
Diabetes	9.98	11.99	0.0983
Stroke	5.07	6.39	0.2383
Arthritis	29.66	30.56	0.6960
Chronic Obstructive Pulmonary Disease	2.73	4.68	0.0548

[a]Federal Poverty Level

Table 10: Effect Estimates

	Estimated Annual Expenditures, 2015 $	Estimated Annual Difference, 2015 $	95% Confidence Interval of Annual Difference, 2015 $
Unadjusted			
SNAP	4825.11	407.69	-876.73 to 1692.09
No SNAP	4417.42	--	--
'Standard' Regression[a]			
SNAP	4421.37	-1409.44	-2693.73 to -125.15
No SNAP	5830.81	--	--
'Near/far' IV analysis[b]			
SNAP	2115.79	-5,160.16	-6923.70 to -437.85
No SNAP	7275.95	--	--
AIPW analysis[c]			
SNAP	3215.20	-930.58	-2026.06 to -152.19
No SNAP	4145.78	--	--

[a]Standard regression estimates from generalized linear model with gamma distribution and log link, incorporating survey design information, and adjusted for age, age squared, gender, race/ethnicity, region, rurality, insurance, education, income, disability, comorbidity, and death in study period. Full model in eAppendix.

[b]'Near/far' estimates from post-match dataset with instrumental variable estimation using the two stage residual inclusion method in a generalized linear model with gamma distribution and log link, adjusted for age, age squared, gender, race/ethnicity, region, rurality, state Medicare spending, insurance, education, income, disability, comorbidity, and death in study period. Full model in eAppendix.

[c]Augmented Inverse Probability Weighted (AIPW) estimates with linear regression model, adjusted for age, age squared, gender, race/ethnicity, region, rurality, insurance, education, income, disability, comorbidity, and death in study period. Full model in eAppendix.

Table 11: ‘Standard’ Regression, full model

	β	Standard Error	P	95% CI Lower	95% CI Upper
SNAP	-0.27671	0.123321	0.026	-0.5199288	-0.03348
Age	-0.00761	0.019378	0.695	-0.0458239	0.030613
Age Squared	0.000125	0.000186	0.504	-0.0002423	0.000492
Female	0.485189	0.119815	<.0001	0.248882	0.721496
Race/ethnicity					
Non-Hispanic White	Reference	--	--	--	--
Non-Hispanic Black	-0.23553	0.128266	0.068	-0.4885058	0.017444
Hispanic	-0.26699	0.158689	0.094	-0.5799668	0.045987
Asian/multi-/other	-0.40676	0.210805	0.055	-0.8225273	0.008999
% Federal Poverty Level	0.050526	0.03032	0.097	-0.0092732	0.110325
Rural	0.346176	0.197889	0.082	-0.044113	0.736466
Northeast	0.167307	0.151833	0.272	-0.1321491	0.466763
Midwest	0.383049	0.179933	0.035	0.0281737	0.737925
South	0.085328	0.142547	0.55	-0.195812	0.366469
Died	0.951147	0.460975	0.04	0.0419825	1.860312
Insurance					
Private	0.608314	0.180358	0.001	0.252599	0.964028
Medicare	0.39253	0.17477	0.026	0.0478369	0.737223
Other Public	0.81397	0.128968	<.0001	0.5596103	1.06833
Uninsured	Reference	--	--	--	--
Educational Attainment					
< High School Diploma	Reference	--	--	--	--
High School Diploma	0.007068	0.134297	0.958	-0.2578015	0.271937
> High School Diploma	0.095854	0.150446	0.525	-0.2008652	0.392573
Obese	-0.00772	0.111718	0.945	-0.2280609	0.212616
HTN	0.282779	0.108835	0.01	0.0681267	0.497432
Stroke	0.191746	0.180082	0.288	-0.1634246	0.546917
CAD	0.782025	0.150553	<.0001	0.4850943	1.078955
Diabetes	0.646371	0.123672	<.0001	0.4024565	0.890286
Arthritis	0.585317	0.127068	<.0001	0.3347054	0.835928
COPD	0.276941	0.240333	0.251	-0.1970601	0.750943
Disability	0.515666	0.115145	<.0001	0.288569	0.742762

Results from a generalized linear model with gamma distribution and log link, accounting for survey design information, and adjusted for all variables in table

Table 12: post-'Near/Far' Matching Two stage residual inclusion model

	β Coefficient	Lower 95% Confidence Interval	Upper 95% Confidence Interval
First Stage Model: Logistic Regression of SNAP receipt			
Age	0.0142	-0.0115	0.0399
Age squared	-0.0004	-0.0007	-0.0002
State 2011 Per Enrollee Medicare Spending, $	0.0000	-0.0002	0.0001
Female	0.2613	0.0992	0.4233
Non-Hispanic White Race/ethnicity	0.4694	0.1037	0.8351
Non-Hispanic Black Race/ethnicity	1.1213	0.7586	1.4839
Hispanic Race/ethnicity	0.3142	-0.0214	0.6497
Private Insurance	-0.6542	-0.8964	-0.4119
Medicare Insurance	0.0715	-0.3213	0.4644
Other Public Insurance	1.1540	0.9552	1.3529
High School Diploma Education	-0.3704	-0.5654	-0.1755
> High School Diploma Education	-0.1971	-0.4068	0.0126
Income as % Federal Poverty Level	-0.3569	-0.4011	-0.3127
Rural Residence	0.1675	-0.0858	0.4208
Northeast Residence	-0.3328	-0.7195	0.0539
Midwest Residence	0.2125	-0.1703	0.5954
South Residence	-0.1061	-0.4834	0.2712
Obesity	0.2084	0.0347	0.3822
Hypertension	0.1525	-0.0602	0.3651
Heart Disease	0.0500	-0.2236	0.3235
Diabetes	0.2790	-0.0142	0.5722
Stroke	0.2807	-0.2074	0.7688
Chronic Obstructive Pulmonary Disease	0.2601	-0.3910	0.9112
Arthritis	0.1422	-0.0987	0.3830
Died during Study Period	-0.7316	-2.3483	0.8852
Disability	0.3289	0.0656	0.5922
Instrumental Variable	1.4581	0.9869	1.9292
Model Constant	-0.3197	-1.5501	0.9108
Second Stage Model: Generalized Linear Regression (gamma distribution, log link) of healthcare expenditures			
SNAP	-1.2351	-3.0280	-0.0621
Age	0.0061	-0.0294	0.0399
Age squared	0.0000	-0.0003	0.0004
State Per Enrollee Medicare Spending, 2011	-0.0002	-0.0003	0.0000
Female	0.6574	0.3430	0.8615

Non-Hispanic White	0.7511	0.3691	1.2103
Non-Hispanic Black	0.5601	0.0799	1.0856
Hispanic	0.3191	-0.0587	0.7435
Private	0.4280	0.1149	0.7983
Medicare	0.4248	0.0915	0.7296
Other Public	0.8785	0.5181	1.2937
High School Diploma	0.1258	-0.1096	0.4020
> High School Diploma	0.0897	-0.2050	0.4377
Income as % Federal Poverty Level	-0.0221	-0.1605	0.0846
Rural Residence	0.2456	-0.1510	0.6638
Northeast Residence	0.4307	0.0987	0.7975
Midwest Residence	0.4780	0.0610	0.9860
South Residence	0.5131	0.0150	0.9322
Obesity	0.0069	-0.2288	0.2218
Hypertension	0.5043	0.2507	0.7608
Heart Disease	0.6915	0.4489	0.9852
Diabetes	0.6533	0.3667	0.9212
Stroke	0.3270	-0.1061	0.6790
Chronic Obstructive Pulmonary Disease	0.1917	-0.2836	0.5181
Arthritis	0.3328	0.0927	0.5476
Died during Study Period	-0.8834	-2.2756	0.1852
Disability	0.6606	0.4300	0.9515
First Stage Residual	0.7731	-0.3715	2.5608
Model Constant	8.0036	6.3549	9.7676

Table 13: Balance statistics and over-identifying restrictions test for augmented inverse probability weighted analyses

	Standardized differences (values closer to 0 represent better balance)		Variance ratio (values closer to 1 represent better balance)	
	Raw	Weighted	Raw	Weighted
Age	-.1904464	.040384	.8136129	1.096444
Age squared	-.20052	.0517001	.7360837	1.186927
Female	.1865776	.0056819	.9356206	.9983576
Race/Ethnicity				
Non-Hispanic White				
Non-Hispanic Black	.4066883	.0135829	1.557532	1.014918
Hispanic	-.1369969	-.0126716	.9533653	.9954143
Asian/multi-/other	-.1906064	.0650038	.5186053	1.210807
Educational Attainment				
< High School Diploma				
High School Diploma	.0295217	-.0061007	1.023929	.9949781
> High School Diploma	-.2310974	-.0266195	.8296893	.9795665
Income (as % of federal poverty level)	-.7753642	.0140216	.8544885	1.025691
Census Region				
Northeast	.0827734	.0045639	1.162505	1.008478
Midwest	.1117232	-.0083641	1.228365	.9844889
South	.0879722	-.0287469	1.032809	.9882156
West				
Rural Residence	.1197136	-.0242665	1.265335	.9527688
Insurance				
Private	-.4253892	-.0094037	.4864964	.986345
Medicare	-.2158266	.0549826	.5225464	1.152112
Other Public	.6797021	-.0017013	1.699563	.9984802
Uninsured				
Died during study period	-.0376257	.0084814	.6128734	1.105798
Obesity	.1753457	-.0081076	1.116208	.9944992
Hypertension	.1523917	-.0059545	1.092679	.9963328
Heart Disease	.0792404	-.0158846	1.17876	.9669949
Diabetes	.0824979	.0001572	1.224196	1.000359
Asthma	.2196648	-.0007727	1.711926	.9980225
Cancer	-.0266049	-.0119199	.9123387	.9575479
Chronic Obstructive Pulmonary Disease	.0967024	.0026392	1.904168	1.018058
Arthritis	.1196742	-.0078693	1.14302	.9911282
Over-identification test[a]	P=0.7111			

[a]Null hypothesis is that covariates are balanced so higher p-values represents less evidence to reject null

Table 14: Auxiliary equations for augmented inverse probability weighting analyses

	β Coefficient	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Average Treatment Effect Estimate			
SNAP (compared with No SNAP) (two-year estimate)	-1861.15	-4052.11	-304.37
Potential Outcome Mean Estimate			
No SNAP (two-year estimate)	8291.55	6827.60	10224.87
Auxiliary Equations			
Untreated Potential Outcome Equation			
Age	-41.90	-362.72	189.14
Age squared	0.14	-2.42	4.38
Female	569.09	-1914.33	2551.68
Race/ethnicity			
Non-Hispanic White	Referent	--	--
Non-Hispanic Black	-460.40	-3451.52	2526.26
Hispanic	-1183.46	-3332.95	985.32
Asian/multi-/other	534.46	-4019.92	9652.16
Health Insurance			
Uninsured	Referent	--	--
Private	1947.30	-14.07	4263.45
Medicare	15.98	-5339.30	4013.55
Other Public	3351.54	522.84	7328.61
Income as % Federal Poverty Level	-224.69	-958.23	217.98
Education			
< High School Diploma	Referent	--	--
High School Diploma	1697.39	-92.92	3521.06
> High School Diploma	2164.64	172.58	4600.28
Rural Residence	221.96	-2518.49	4018.17
Northeast Residence	974.21	-1218.64	3713.78
Midwest Residence	-132.17	-2481.92	3298.75
South Residence	597.76	-1596.29	4371.85
Obesity	-11.27	-2095.38	1848.98
Hypertension	441.70	-2652.54	3198.17
Heart Disease	11638.60	6384.61	20098.73
Diabetes	6345.61	2087.54	10499.17
Asthma	1296.67	-2562.33	4963.15

Arthritis	4630.79	991.66	9943.60
Cancer	5502.77	558.37	10932.25
Chronic Obstructive Pulmonary Disease	4224.76	-3763.91	17236.73
Stroke	-483.40	-7335.07	4913.90
Died during Study Period	5345.19	-6927.20	28733.24
Disability	8393.79	2850.37	16299.53
Model Constant	2064.63	-4364.70	8973.98
Treated Potential Outcome Equation			
Age	-466.70	-921.48	-124.87
Age squared	6.61	2.22	12.20
Female	458.79	-1614.58	2274.93
Race/ethnicity			
Non-Hispanic White	Referent	--	--
Non-Hispanic Black	-3978.39	-6198.79	-1231.65
Hispanic	-2125.77	-4632.61	740.98
Asian/multi-/other	951.38	-5914.88	12871.56
Health Insurance			
Uninsured	Referent	--	--
Private	3571.15	727.53	7044.33
Medicare	-1143.65	-6913.24	7461.07
Other Public	2974.45	1512.25	4738.22
Income as % Federal Poverty Level	-178.58	-711.35	297.90
Education			
< High School Diploma	Referent	--	--
High School Diploma	112.63	-1874.66	1971.42
> High School Diploma	426.10	-1648.52	2847.93
Rural Residence	1843.96	-1006.21	5692.62
Northeast Residence	2812.31	-553.66	7230.71
Midwest Residence	361.45	2651.56	2827.96
South Residence	-1164.34	-3943.40	802.81
Obesity	-288.64	-2115.48	1470.49
Hypertension	3452.02	1269.89	5729.02
Heart Disease	6879.11	2488.05	12294.64
Diabetes	5166.46	1415.40	10535.20
Asthma	718.91	-1863.54	4336.88
Arthritis	2682.16	-1007.73	5661.81
Cancer	-585.02	-5087.81	4439.41
Chronic Obstructive Pulmonary Disease	220.88	-6908.89	7995.38
Stroke	6859.88	-355.82	13156.78
Died during Study Period	39484.41	-10719.36	102110.90

Disability	6051.96	3209.58	9773.55
Model Constant	8704.02	1765.86	16364.06
Probability of Treatment Equation			
Age	0.01	-0.01	0.02
Age squared	0.00	0.00	0.00
Female	0.12	0.04	0.21
Race/ethnicity			
Non-Hispanic White	Referent	--	--
Non-Hispanic Black	0.35	0.23	0.48
Hispanic	-0.07	-0.19	0.05
Asian/multi-/other	-0.24	-0.44	-0.08
Health Insurance			
Uninsured	Referent	--	--
Private	-0.30	-0.43	-0.18
Medicare	0.05	0.14	0.27
Other Public	0.67	0.56	0.77
Income as % Federal Poverty Level	-0.20	-0.23	-0.18
Education			
< High School Diploma	Referent	--	--
High School Diploma	-0.17	-0.29	-0.07
> High School Diploma	-0.29	-0.40	-0.19
Rural Residence	0.17	0.04	0.30
Northeast Residence	0.23	0.10	0.38
Midwest Residence	0.39	0.22	0.54
South Residence	0.25	0.14	0.39
Obesity	0.10	0.00	0.18
Hypertension	0.16	0.04	0.27
Heart Disease	0.02	-0.12	0.15
Diabetes	0.11	-0.05	0.27
Asthma	0.19	0.05	0.32
Cancer	-0.09	-0.26	0.10
Arthritis	0.13	0.00	0.25
Chronic Obstructive Pulmonary Disease	0.26	-0.05	0.58
Died during Study Period	-0.13	0.84	0.45
Model Constant	0.21	-0.10	0.56

β Coefficients are in 2-year dollars for outcome equations; for treatment equation they are from probit model used in estimating probability of receiving SNAP

Figure 1

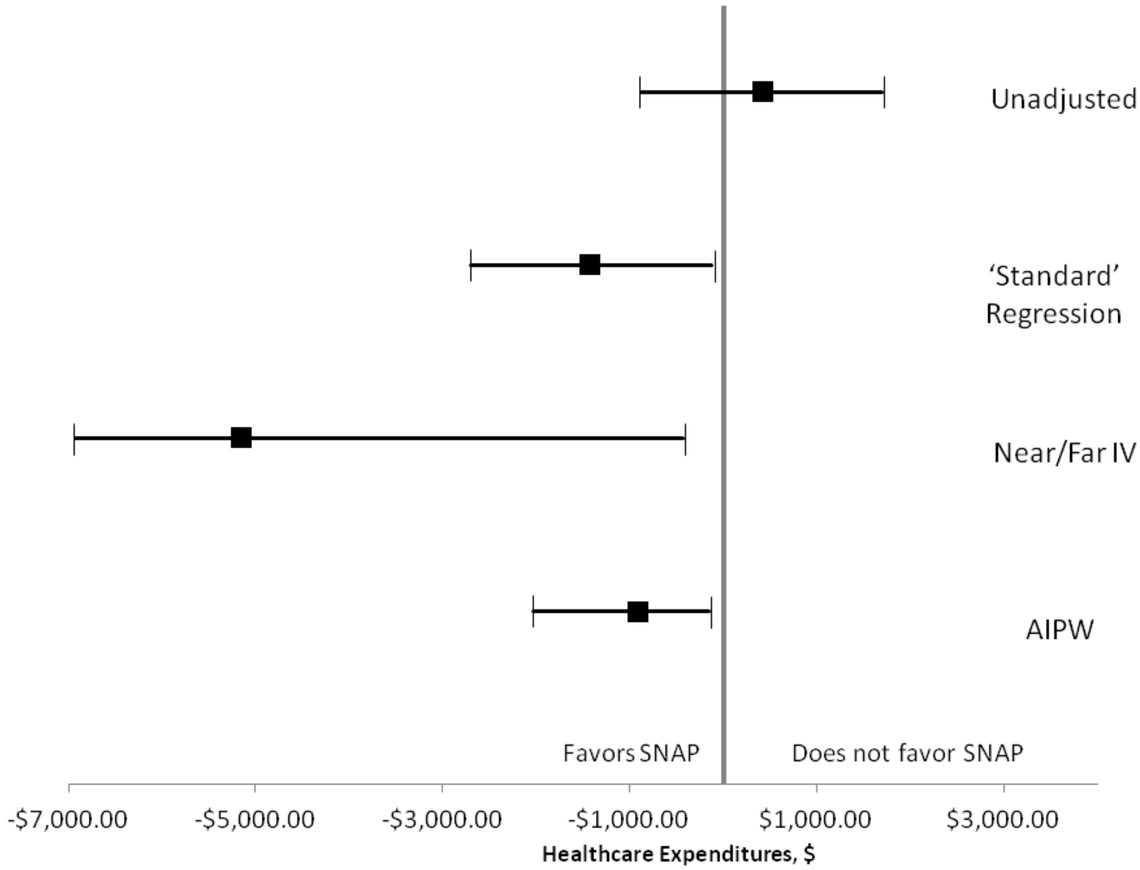

Figure 1 Legend; Forest Plot comparing the difference in estimated mean health expenditures for those who did and did not receive Supplemental Nutrition Assistance Program (SNAP) benefits. Note that standard regression and augmented inverse probability weighting (AIPW) estimate average treatment effect (i.e. the effect of enrolling in SNAP for the entire population of adults with income <200% federal poverty), while near/far instrumental variable (IV) analysis estimates local average treatment effect (i.e. the effect in the marginal case where the instrument made the difference in receipt of SNAP).

Technical Appendix: Description of the near/far matching method

Near/Far Matching

A major concern in evaluating the effect of SNAP participation on healthcare expenditures is selection bias—those who choose to enroll in SNAP may be different from similarly eligible individuals who do not. Some of that difference is likely due to observable factors such as age, income, health insurance, and illness, but other factors that drive enrollment may remain unobserved. To address selection bias, we used an instrumental variable approach called near/far matching.[1-3] Instrumental variable analysis uses instruments to help overcome issues of selection bias related unobservable factors. A suitable instrument is one that a) influences receipt of the treatment, and b) where all causal pathways between the instrument and the outcome, other than through the treatment of interest, can be blocked or do not exist. In other words, an instrument should, conditional on observable factors, affect the outcome only by influencing the receipt of the treatment. This functions analogously to treatment allocation in a randomized clinical trial. In this study, our instruments were policy variables that make it easier or harder to enroll in SNAP when one is eligible. While SNAP eligibility is broadly similar at a national level, SNAP is administered by each state, and differences in state policy, such as the presence of an online application, or the requirement to provide fingerprints when enrolling, can influence the ease of SNAP enrollment. In this sense, these instruments serve as 'nudges', or forms of 'encouragement' or 'discouragement', that may help or hinder an eligible individual considering applying for SNAP. Because state-level variation in how easy or hard it is to sign up for SNAP should influence whether one signs up for SNAP, but should not otherwise be related to healthcare expenditures, conditional on observable features about the states and individuals, these policy variations are theoretically justified instruments. Further, these instruments have been used and validated in prior studies of SNAP.[4,5] The 'near/far' matching type of instrumental variable analysis combines elements of nearest neighbor matching and traditional instrumental variable techniques. Using a probabilistic simulated annealing algorithm, and prior to examining the outcome, study participants are matched, using the Mahalanobis distance of the vector of their covariates, to be as similar as possible ('near') on observable characteristics that may influence the outcome, but as dissimilar as possible ('far') on the values of the instrument.[3] This essentially filters a cohort to reveal its most informative pairs—those who are socio-demographically and clinically as similar as possible, but who differ on whether they were 'encouraged' or 'discouraged' to enroll in SNAP. This design uses differences in receipt of 'encouragement' to enroll in SNAP to yield an effect estimate for SNAP receipt that is not confounded by unmeasured factors which influence both SNAP receipt and healthcare expenditures, and thus mirrors a matched-pairs randomized clinical trial.

To test the instrumental variables, we examined their association with SNAP receipt in a logistic regression model and checked they were not correlated with other state-level factors that may affect the outcome, such as per beneficiary Medicaid expenditures[6] or state Temporary Aid to Needy Families benefit generosity.[7] We conducted Sargan and Basmann tests of over-identifying restrictions, which test whether the residuals in the first stage model are correlated with the instruments (they should be uncorrelated to be valid instruments). Because weak instruments can lead to biased effect estimates, we also evaluated the first-stage statistic of the instruments, using a cut-off > 13 to indicate a sufficiently strong instrument. Finally, we conducted the Durbin-Wu-Hausman test for endogeneity, to determine whether instrumental variable methods were truly needed. To examine the precision of the match, we evaluated absolute standardized differences between the means of the covariates in those ‘encouraged’ vs. ‘discouraged’ to enroll in SNAP. An absolute standardized difference > 0.2 represented a concerning imbalance in matching.

Hypothesis 3: Supporting Information

For our instrumental variable (IV), an index of SNAP policies in place in a given state as of 1/1/2010 (i.e. in place at the beginning of the lookback period regarding SNAP receipt in 2011 NHIS), weighted by their partial f-statistic from a model predicting SNAP receipt, we conducted several tests of the instrumental variable assumptions, summarized in the table below. Because our IV used state level SNAP policy information, we wanted to examine other state level factors that may be correlated with the IV, to lend confidence to the assumption that the IV is associated with the outcome only through receipt of SNAP (we also adjusted for state-level fixed effects in both stages of the IV analysis to account for this as well). We first calculated an intraclass correlation (ICC) between individual-level healthcare expenditures and the states those individuals lived in. This revealed that that state of residence, apart from individual-level factors like health insurance or SNAP receipt, explained little variation in healthcare expenditures—only 0.6% (95% confidence interval 0.3% to 1.2%). We next examined whether the IV was correlated with state level Medicaid spending per beneficiary, using Medicaid expenditure data from the Kaiser Family Foundation, or maximum Temporary Aid for Needy Families (TANF) benefit for a single parent caring for 2 children, an indicator of state TANF generosity. Unlike SNAP where benefits are set at the federal level, states have broad leeway in setting TANF levels, and so this can indicate the 'generosity' of TANF, and potentially other, social service programs in the state. Using Spearman correlations, the IV was weakly and not statistically significantly correlated with these factors, giving confidence in the idea that the IV operated through SNAP receipt and not other state level factors.

Next, we conducted tests of the instrument itself, assessing whether it was associated with receipt of SNAP in a logistic regression model that included the other covariates adjusted for in our main analysis and accounted for the survey design information. We also assessed the first-stage partial F statistic (in this case, a partial R-squared owing to the logistic model), both before and after the 'near/far' match, in order to determine the strength of the instrument (< 13 would indicate an instrument too weak to use). We also used over-identification tests to help assess the validity of the instruments (for this test, higher p-values are better, with $p < 0.05$ indicating potentially invalid instruments). The instrument met all these tests.

Finally, we calculated tests of endogeneity, which indicate whether IV analysis is truly needed, although, owing to questions regarding the power of these tests, some experts recommend proceeding with IV analysis even if the endogeneity tests do not suggest the need for IV analysis (which could be interpreted as a false negative situation). For these tests, a p-value < 0.05 generally indicates a 'positive' result, i.e., that IV analysis is needed. Interestingly, the endogeneity tests indicated that IV methods may not be needed, which suggests the 'standard' regression model may have adequately accounted for confounding on its own.

Supporting information Table A: Tests of IV

	Result
Intraclass correlation between individual healthcare expenditures grouped by state of residence in MEPS	0.0061 (95% CI 0.0029 to 0.0129)
Spearman Correlation between instrumental variable and Medicaid spending per beneficiary[a]	0.10592 (p=0.464)
Spearman Correlation between instrumental variable and maximum TANF benefit[b]	0.11265 (p= 0.436)
First Stage Partial R-square, before 'near/far' match	33.2
First Stage Partial R-square, after 'near/far' match	42.5
Overidentifying	
Sargan (2SLS)	p = 0.307
Basmann (2SLS)	p = 0.310
Endogeneity	
Durbin (2SLS)	p = 0.724
Wu-Hausman F (2SLS)	p = 0.725
Residual (2SRI)	p = 0.298

[a]Medicaid data from Kaiser Family Foundation http://kff.org/medicaid/state-indicator/medicaid-spending-per-enrollee/view/print/?currentTimeframe=0&print=true

[b]TANF data from Congressional Research Service TANF report http://greenbook.waysandmeans.house.gov/sites/greenbook.waysandmeans.house.gov/files/R43634_gb_0.pdf

Supporting information Table B: List of included states

Alabama
Arizona
California
Colorado
Connecticut
Florida
Georgia
Illinois
Indiana
Kentucky
Louisiana
Massachusetts
Maryland
Michigan
Minnesota
Missouri
North Carolina
New Jersey
New York
Ohio
Oklahoma
Oregon
Pennsylvania
South Carolina
Tennessee
Texas
Virginia
Washington

Supporting information Table C: post-'Near/Far' matching demographics, by 'encouragement' status

	'Discouraged' % (n) or mean (SE) N=1838	'Encouraged' % (n) or mean (SE) N=1838	Absolute Standardized Difference
Age (y)	40.77693 (.3959409)	40.38901 (.382705)	0.0232383
Female	58.81 (1,081)	58.54 (1,076)	0.0055231
Race/Ethnicity			
Non-Hispanic White	21.82 (401)	21.49 (395)	0.0079234
Non-Hispanic Black	25.84 (475)	25.84 (475)	0.0000000
Hispanic	45.38 (834)	45.65 (839)	0.0054613
Asian/multi-/other	6.96 (128)	7.02 (129)	n/a
Educational Attainment			
< High School Diploma	6.64 (122)	5.98 (110)	n/a
High School Diploma	61.70 (1,134)	62.51 (1,149)	0.0168186
> High School Diploma	31.66 (582)	31.50 (579)	0.0035103
Income (categorized as percentage of federally poverty level)	3.829706 (.0451396)	3.818825 (.0446944)	0.0056506
Census Region			
Northeast	15.18 (279)	19.80 (364)	0.1219256
Midwest	14.31 (263)	15.45 (284)	0.0320989
South	41.57 (764)	41.19 (757)	0.0077308
West	28.94 (532)	23.56 (433)	n/a
Rural Residence	11.53 (212)	11.59 (213)	0.0017010
Insurance			
Private	18.99 (349)	18.50 (340)	0.0125440
Medicare	8.65 (159)	8.11 (149)	0.0196323
Other Public	29.92 (550)	30.25 (556)	0.0071158
Uninsured	42.44 (780)	43.14 (793)	n/a
Died	0.71 (13)	0.33 (6)	0.0531158
Disabled	13.44 (247)	13.28 (244)	0.0047967
Obesity	34.49 (634)	34.98 (643)	0.0102813
Hypertension	34.49 (634)	34.49 (634)	0.0000000
Heart Disease	10.55 (194)	10.17 (187)	0.0095687
Diabetes	13.60 (250)	13.28 (244)	0.0124919
Stroke	3.81 (70)	3.92 (72)	0.0056450
Arthritis	24.05 (442)	24.21 (445)	0.0200404
COPD	2.01 (37)	1.74 (32)	0.0038137
2011 State adjusted per capita healthcare spending	9892.758 (20.30371)	9858.425 (21.61006)	0.0381945

n/a = not directly calculated due to 'dummy' coding categorical variables for the matching process

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