# Changes in Supplemental Nutrition Assistance Program Policies and Diabetes Prevalence: Analysis of Behavioral Risk Factor Surveillance System Data From 2004 to 2014

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*Sameed Ahmed M. Khatana,[1,2,3] Nicholas Illenberger,[4] Rachel M. Werner,[3,5,6] Peter W. Groeneveld,[2,3,5,6] and Nandita Mitra[3,4]*

**OBJECTIVE**

**Food insecurity is associated with diabetes. The Supplemental Nutrition Assistance Program (SNAP) is the largest U.S. government food assistance program. Whether such programs impact diabetes trends is unclear. The objective of this study was to evaluate the association between changes in state-level policies affecting SNAP participation and county-level diabetes prevalence.**

**RESEARCH DESIGN AND METHODS**

**We evaluated the association between change in county-level diabetes prevalence and changes in the U.S. Department of Agriculture SNAP policy index—a measure of adoption of state-level policies associated with increased SNAP participation (higher value indicating adoption of more policies associated with increased SNAP participation; range 1–10)—from 2004 to 2014 using g-computation, a robust causal inference methodology. The study included all U.S. counties with diabetes prevalence data available from the Centers for Disease Control and Prevention's U.S. Diabetes Surveillance System.**

**RESULTS**

**The study included 3,135 of 3,143 U.S. counties. Mean diabetes prevalence increased from 7.3% (SD 1.3) in 2004 to 9.1% (SD 1.8) in 2014. The mean SNAP policy index increased from 6.4 (SD 0.9) to 8.2 (SD 0.6) in 2014. After accounting for changes in demographic-, economic-, and health care-related variables and the baseline SNAP policy index, a 1-point absolute increase in the SNAP policy index between 2004 and 2014 was associated with a 0.050 (95% CI 0.042–0.057) percentage point lower diabetes prevalence per year.**

**CONCLUSIONS**

**State policies aimed at increasing SNAP participation were independently associated with a lower rise in diabetes prevalence between 2004 and 2014.**

Diabetes prevalence in the U.S. has steadily climbed over the past several decades, with ∼9% of adults diagnosed with diabetes as of 2014 (1). The burden of diabetes disproportionately falls on low-income individuals, with the prevalence among

*[1]Division of Cardiovascular Medicine, Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA*
*[2]Penn Cardiovascular Outcomes, Quality, & Evaluative Research Center, Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA*
*[3]The Leonard Davis Institute of Health Economics, University of Pennsylvania, Philadelphia, PA*
*[4]Department of Biostatistics, Epidemiology and Informatics, Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA*
*[5]Division of General Internal Medicine, Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA*
*[6]Center for Health Equity Research and Promotion, Michael J. Crescenz Veterans Affairs Medical Center, Philadelphia, PA*

*Corresponding author: Sameed Ahmed M. Khatana, sameed.khatana@pennmedicine.upenn.edu*

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*S.A.M.K. and N.I. contributed equally to this manuscript.*

individuals living in poverty nearly twice that of high-income individuals (2). Food insecurity—the economic and social condition of limited or inadequate consistent access to healthy food—has been associated with diabetes in prior studies (3,4). A recent analysis also suggested a link between food insecurity and cardiovascular mortality (5). Whether policies aimed at reducing food insecurity have also impacted trends in diabetes prevalence is unclear.

The Supplemental Nutrition Assistance Program (SNAP) is the largest U.S. government-funded program providing food assistance to low-income individuals and households. This federally funded and state-administered program provided assistance to >39 million low-income individuals in 2020 (6). In general, households and individuals are required to have an income of ≤130% of the federal poverty limit to be eligible. Previous studies have demonstrated a significant association between SNAP participation and improvements in food security, reductions in poverty, and lower health care expenditures (7–9). There is also some evidence of improvements in self-described health among SNAP participants compared with low-income nonparticipants (10) as well as a possible reduction in premature mortality (11).

Whether SNAP participation has influenced population level trends in diabetes prevalence, however, is uncertain. As diabetes disproportionately impacts lower-income individuals, policies impacting this segment of the population may lead to changes in overall population-level diabetes prevalence. Examining the relationship between SNAP participation and diabetes is challenging given its association with income as well as other socioeconomic variables that are strongly associated with diabetes. However, SNAP participation varies across states based on state-level policies that are independent of individual- or area-level socioeconomic factors, including the ease of application to the SNAP program and which of an individual's assets are used to determine eligibility. Such policies have been found to be significantly associated with SNAP participation rates (12–14). Studying changes in state-level policies that encourage or discourage SNAP participation may therefore allow for the analysis of the relationship between SNAP participation and trends in diabetes.

Our objective was therefore to examine the longitudinal relationship between county-level diabetes prevalence in the U.S. and state-level policies related to SNAP participation. To capture the later, we used the U.S. Department of Agriculture SNAP policy index, which measures implementation of state-level policies that encourage or discourage SNAP participation, between 2004 and 2014.

## RESEARCH DESIGN AND METHODS

Because all data used are publicly available as aggregated data at the state or county level, this analysis was considered exempt by the University of Pennsylvania Institutional Review Board.

### Data Sources

#### *Diabetes Prevalence*

Annual, age-adjusted, county-level prevalence of diagnosed diabetes for adults ≥20 years of age from 2004 to 2014 was obtained from the Centers for Disease Control and Prevention's (CDC's) U.S. Diabetes Surveillance System. County-level estimates of diagnosed diabetes were based on self-reported diabetes from the Behavioral Risk Factor Surveillance System (BRFSS).

#### *SNAP Policy Index*

State-level SNAP policies that encourage or discourage participation were measured using the U.S. Department of Agriculture SNAP policy index (15). The SNAP policy index consists of 10 state policies that fall into four categories: eligibility, transaction costs, other program costs, and outreach (Supplementary Table 1). The index is calculated by adding or subtracting a point based on whether a policy is expected to increase or decrease SNAP participation. A score between 0 and 1 is added for policies that are based on the proportion of households impacted by a particular policy (i.e., proportion of households with short recertification periods and the proportion with benefits issued by Electronic Benefit Transfer cards). This score is then scaled from 1 to 10, with a higher score indicating greater implementation of policies that encourage SNAP participation in a given state in a given year. A score of 10 indicates that a state has enacted all policies that increase SNAP participation and no policies that decrease participation.

The SNAP policy index is strongly correlated with SNAP participation, with a 1-unit increase in the index associated with a 0.1 percentage point (pp) increase in the probability of an individual using SNAP during that time period (15). Additionally, the association between the probability of SNAP participation was greater when using the index compared with each individual policy, suggesting that the index performs better as an instrument for SNAP participation compared with each individual policy (15). Because SNAP participation is largely limited to low-income individuals, who are also more likely to have diabetes, the relationship between actual SNAP participation in an area and changes in diabetes trends would be confounded by the prevalence of low socioeconomic status in that area.

#### *Other Variables*

Other annual, county-level demographic-, economic-, and health care-related variables were obtained from different public sources. Poverty rate (≥18 years of age), inflation-adjusted median household income, number of residents (18–64 years of age) without health insurance, and proportion of county residents (≥20 years of age) in different subgroups were obtained from the U.S. Census Bureau. The adult unemployment rate was obtained from the Bureau for Labor Statistics. Physical inactivity and obesity rates (≥20 years of age) were obtained from the CDC's U.S. Diabetes Surveillance System, which is based on the BRFSS. The number of primary care providers per 100,000 county residents was obtained from the Area Health Resources File. Adult prevalence of cigarette smoking was obtained from estimates derived by Dwyer-Lindgren et al. (16) using BRFSS data.

### Outcomes

The primary outcome was the county-level annual age-adjusted prevalence of diagnosed diabetes among adults ≥20 years of age. An alternative falsification outcome was annual age-adjusted prevalence of cigarette smoking (daily or nondaily). Cigarette smoking was chosen as a potential falsification outcome, because it is likely not directly involved in the casual pathway between food assistance and diabetes prevalence, but as a recognized important component of a healthy lifestyle, it may indicate healthy behaviors in a community (17).

### Missing Data

Of the 3,135 counties with available data on diabetes prevalence in each year from 2004 to 2014, some covariates were missing in some years, as listed in Supplementary Table 2. Multiple imputation was used as described in the STATISTICAL METHODS to account for missing data. The eight counties that were excluded due to lack of diabetes prevalence data are listed in Supplementary Table 3.

### Statistical Methods

Counties were first divided into quartiles based on the absolute change in the SNAP policy index (for the state in which the county was located) from 2004 to 2014. Annual population-weighted diabetes prevalence and mean annual percentage change (APC) were calculated for each quartile. To assess the association between change in the SNAP policy index and change in county-level annual diabetes prevalence, we used a longitudinal g-computation approach to estimate the parameters in a marginal structural model. The g-computation procedure is a robust causal inference method that, in contrast to traditional regression methods, can account for time-dependent confounding in the underlying data (18). Briefly, g-computation uses a counterfactual framework to calculate outcomes under all possible treatment possibilities, which is then used to estimate the marginal causal effect of the predictor on the outcome (19). Longitudinal extension of this method involves simulating counterfactual outcomes under possible treatment trajectories based on maximum likelihood estimates of components within the data-generating mechanism. Standard regression of counterfactual outcomes on the exposure trajectory and time can be then used to estimate the treatment effect. This procedure accounts for confounding not just at a given time point but also at previous time points. Additional details on the g-computation methodology are available in Supplementary Approaches.

The longitudinal g-computation models accounted for baseline SNAP policy index in 2004, county metropolitan status, state fixed effects, and the following time-varying covariates: physical inactivity prevalence, median household income, unemployment rate, poverty rate, health insurance coverage, per capita number of primary care providers, and the proportion of county residents who are female, non-Hispanic Black, and Hispanic. As all variables used in the model were aggregated at the county level, to account for the different population sizes that these estimates are derived from, and because the variance of an aggregate point estimate is a function of its underlying population size (20), we weighted the model by the county population. The hierarchical nature of the data (i.e., nesting of county estimates within states) is accounted for by state fixed effects. The g-computation procedure accounts for the longitudinal nature of the data by assuming that county-level observations at each time point are a function of the previous time point's observed values. In the marginal structural model, the key variable of interest was the interaction between year and absolute change in the SNAP policy index between 2004 and 2014, which indicates the additional change in diabetes prevalence per year associated with a 1-unit greater increase in the SNAP policy index between 2004 and 2014. Baseline and change in the SNAP policy index were included as continuous variables in the model.

Because diabetes prevalence may differ by sex, in subgroup analyses, diabetes prevalence among men and women was analyzed separately. To assess whether the association between change in the SNAP policy index and diabetes prevalence may differ by region or by baseline level of the index, we also performed stratified analyses where the g-computation models were refit after stratifying for the following: county metropolitan status, U.S. Census regions, and quartile of the baseline SNAP policy index in 2004.

To assess whether the association between change in the SNAP policy index and diabetes is affected by trends in obesity, a potential mediator of the relationship between SNAP participation and diabetes, or smoking prevalence, these were also included as time-varying covariates into the g-computation model as a sensitivity analysis. As there were changes in the methodology of the BRFSS in 2011, to assess whether our findings were sensitive to these changes, we refit the primary g-computation model but only with data from 2004 to 2010. To assess whether the findings were robust to the analysis technique used, we repeated the primary analysis using a linear random-effects model using the same covariates (Supplementary Approaches). State random effects, instead of fixed effects, were used. This model also accounted for the longitudinal nature of the data. As an alternative falsification outcome, we refit the primary g-computation model with annual smoking prevalence, instead of diabetes, as the outcome to assess whether changes in the SNAP policy index tracked with secular trends in healthy behavior at the county level.

To handle missing data, we implemented multiple imputation by chained equations using five imputed data sets. All missing variables were imputed using predictive mean matching. Imputation models were fit using the same variables adjusted for in the g-computation model as well as with the proportion of county residents who are obese, physically inactive, and smoke.

Summary measures in the RESULTS section are presented as means with the SD or 95% CI or as medians with the interquartile range (IQR), as indicated. *P* values $<0.05$ were considered statistically significant. All analyses were performed using RStudio 1.1.463 software. The g-computation models were fit using a modification of the *gfoRmula* R package (21).

## RESULTS

The analysis included 3,135 of 3,143 U.S. counties. The mean SNAP policy index was 6.4 (SD 0.87) in 2004 and increased to 8.2 (SD 0.61) in 2014. The absolute change in the SNAP policy index from 2004 to 2014 ranged from −0.02 to 0.88 in the first quartile, 0.88 to 1.95 in the second quartile, 2.00 to 2.61 in the third quartile, and 2.68 to 4.22 in the fourth quartile (Fig. 1 and Supplementary Table 4). States in each of these quartiles are listed in Supplementary Table 5. Among counties in the bottom quartile, 61.4% were nonmetropolitan, 62.2% were nonmetropolitan in the second quartile,

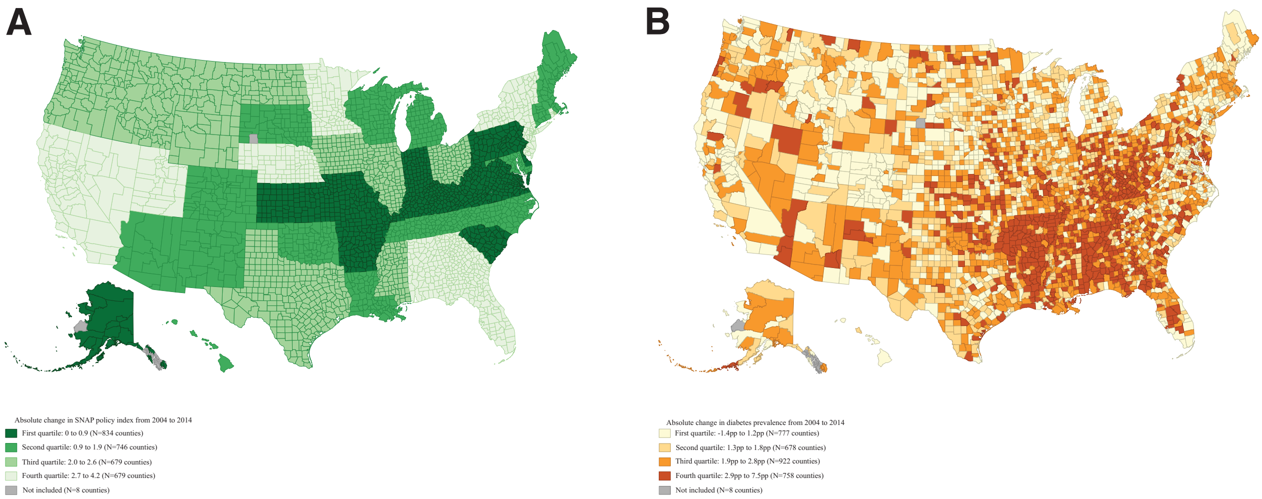


**Figure 1**—County-level maps for absolute change in the SNAP policy index and diabetes prevalence from 2004 to 2014. *A*) Absolute change in the SNAP policy index from 2004 to 2014. First quartile: 0 to 0.9 (*n* = 834 counties), second quartile: 0.9 to 1.9 (*n* = 746 counties), third quartile: 2.0 to 2.6 (*n* = 876 counties), and fourth quartile: 2.7 to 4.2 (*n* = 679 counties). *B*) Absolute change in adult diabetes prevalence from 2004 to 2014. First quartile: −1.4 pp to 1.2 pp (*n* = 777 counties), second quartile: 1.3 pp to 1.8 pp (*n* = 678 counties), third quartile: 1.9 pp to 2.8 pp (*n* = 922 counties), and fourth quartile: 2.9 pp to 7.5 pp (*n* = 758 counties). Eight counties were excluded due to lack of diabetes prevalence data.

70.7% were nonmetropolitan in the third quartile, and 55.1% were nonmetropolitan in the fourth quartile (Table 1). At baseline, the median proportion of county residents who were non-Hispanic Black was 6.9% (IQR 2.5–17.6) in the first quartile, 6.3% (IQR 2.1–18.8) in the second quartile, 4.9% (IQR 0.9–15.6) in the third quartile, and 8.7% (IQR 4.5–16.3) in the fourth quartile. The median proportion of county residents who were Hispanic (any race) was 2.5% (IQR 1.2–4.9) in the first quartile, 3.7% (IQR 2.0–7.9) in the second quartile, 4.4% (IQR 1.6–10.1) in the third quartile, and 16.8% (IQR 6.3–29.2) in the fourth quartile.

### Primary Analysis

Population-weighted mean diabetes prevalence increased from 7.3% (SD 1.3) in 2004 to 9.1% (SD 1.8) in 2014 (mean APC 2.5% [SD 1.2]) (Supplementary Table 6). Diabetes prevalence increased from 7.8% (SD 1.2) to 10.0% (SD 1.8) among counties in the bottom quartile for change in SNAP policy index (mean APC 2.6% [SD 1.3]), 7.47% (SD 1.4) to 9.41% (SD 1.73) in the second quartile (mean APC 2.5% [SD 1.2]), 7.09% (SD 1.3) to 8.69% (SD 1.86) in the third quartile (mean APC 2.4% [SD 1.0]), and 7.04% (SD 1.04) to 8.88% (SD 1.60) in the top quartile (mean APC 2.4% [SD 1.2]) (Fig. 2 and Supplementary Table 7). In the longitudinal g-computation model, which accounts for changes in the included demographic-, economic-, and health care-related variables and baseline SNAP policy index in 2004, a 1-point absolute increase in the SNAP policy index between 2004 to 2014 was associated with a 0.050 pp (95% CI 0.042–0.057) lower rate of diabetes prevalence per year (Table 2). From 2004 to 2014, a 1-point increase in SNAP policy index was therefore associated with a 0.50 pp (95% CI 0.42–0.57) lower diabetes prevalence by 2014.

The median change in the SNAP policy index from 2004 to 2014 across all states was 1.86, which over a 10-year period was associated with a 0.92 pp (95% CI 0.78–1.07) lower diabetes prevalence by 2014. If all states in the U.S. experienced this median change over the study period, with 236 million adults (≥20 years of age) in 2014, this would be associated with 2,181,427 (95% CI 1,839,586–2,523,267) fewer adults with diagnosed diabetes compared with if there was no change in the SNAP policy index.

### Subgroup and Stratified Analyses

A 1-point absolute increase in the SNAP policy index between 2004 and 2014 was associated with a 0.067 pp (95% CI 0.058–0.075) lower prevalence of diabetes for men and 0.039 pp (95% CI 0.030–0.047) lower prevalence for women (Table 2). When stratified by county metropolitan status, there was a significant association between change in the SNAP policy index and change in diabetes prevalence for nonmetropolitan (−0.045 pp [95% CI −0.052 to −0.037]) and metropolitan counties (−0.054 pp [95% CI −0.063 to −0.044]). There was also a significant association when stratified by U.S. Census regions: −0.036 pp (95% CI −0.052 to −0.019) in the Northeast region, −0.034 pp (95% CI −0.043 to −0.024) in the Midwest region, −0.090 pp (95% CI −0.10 to −0.078) in the South region, and −0.029 pp (95% CI −0.043 to −0.015) in the West region. States in each U.S. Census region are listed in Supplementary Table 8. When stratified by quartile of the baseline SNAP policy index, the association between change in the SNAP policy index and change in diabetes prevalence was significant for all quartiles: −0.066 pp (95% CI −0.088 to −0.044) for the quartile of counties with the lowest SNAP policy index at baseline, −0.068 pp (95% CI −0.089 to −0.048) for counties in the second quartile, −0.066 pp (95% CI −0.087 to −0.046) for counties in the third quartile, and −0.086 pp (95% CI −0.12 to −0.053) for counties in the highest quartile. States in each quartile for the baseline SNAP policy index are listed in Supplementary Table 9.

### Sensitivity and Falsification Analyses

As a sensitivity analysis, annual prevalence of obesity and smoking were included as covariates in the g-computation model. The association between change in the SNAP policy index and change

**Table 1—County characteristics at baseline by quartile of absolute change in SNAP policy index***

| Quartile of change in SNAP policy index | First quartile | Second quartile | Third quartile | Fourth quartile |
|---|---|---|---|---|
| Absolute change in SNAP policy index from 2004 to 2014 (range) | 0 to 0.9 | 0.9 to 1.9 | 2.0 to 2.6 | 2.7 to 4.2 |
| Counties, *n*† | 834 | 746 | 876 | 679 |
| Nonmetropolitan counties, %‡ | 61.4 | 62.2 | 70.7 | 55.1 |
| Population (≥20 years of age), *n* | 17,254.5 (8,724, 35,614) | 23,732.5 (10,444, 58,292) | 14,261 (6,500.5, 35,115) | 21,985 (8,283, 71,812) |
| Demographic variables | | | | |
| Proportion of county residents (≥20 years of age) in following subgroups: | | | | |
| Women | 52.1 (51.4, 52.8) | 52.0 (51.0, 52.9) | 51.5 (50.9, 52.5) | 51.6 (51.0, 52.7) |
| Men | 47.9 (47.2, 48.6) | 48.0 (47.1, 49.0) | 48.5 (47.5, 49.1) | 48.4 (47.3, 49.0) |
| Non-Hispanic White | 85.6 (71.7, 93.4) | 77.3 (65.2, 88.7) | 74.5 (51.7, 88.6) | 60.7 (45.1, 80.4) |
| Non-Hispanic Black | 6.5 (2.4, 18.3) | 5.8 (2.1, 17.9) | 6.4 (1.6, 17.7) | 8.6 (4.3, 13.3) |
| Non-Hispanic other | 2.3 (1.3, 3.7) | 3.7 (2.2, 5.2) | 3.6 (1.8, 6.7) | 5.7 (3.0, 12.9) |
| Hispanic (any race) | 2.4 (1.2, 4.6) | 3.8 (2.3, 8.9) | 7.1 (2.6, 18.6) | 13.9 (5.1, 24.4) |
| Economic variables | | | | |
| Proportion of residents (≥18 years of age) with income below the poverty threshold | 10.3 (8.0, 12.9) | 11.0 (8.3, 13.3) | 11.6 (9.2, 13.7) | 10.0 (8.2, 13.4) |
| Median household income (U.S. dollars inflation adjusted to 2000) | 37,911.5 (32,226.7, 44,855.7) | 40,141.0 (35,205.2, 47,857.8) | 38,523.9 (35,298.9, 43,641.8) | 40,265.7 (36,080.6, 48,171.8) |
| Unemployment rate | 5.3 (4.5, 6.1) | 5.3 (4.4, 6.1) | 6.0 (5.2, 6.8) | 5.2 (4.5, 6.2) |
| Health-related variables | | | | |
| Proportion of adults who: | | | | |
| Are physically inactive§ | 26.4 (24.1, 29.2) | 23.1 (20.4, 28.7) | 25.1 (21.8, 26.9) | 23.6 (20.8, 26.8) |
| Are obese§ | 26.0 (24.3, 27.9) | 23.5 (19.9, 27.2) | 24.6 (22.3, 26.5) | 22.0 (20.0, 24.4) |
| Smoke cigarettes‖ | 27.0 (24.2, 29.2) | 24.0 (21.6, 27.6) | 24.3 (21.6, 26.6) | 21.9 (19.1, 24.9) |
| Primary care providers per 100,000 residents, *n*¶ | 68.8 (51.0, 88.8) | 75.4 (56.1, 92.2) | 65.9 (51.4, 90.2) | 72.3 (58.1, 89.5) |
| Proportion of 18- to 64-year-old residents without health insurance** | 16.2 (13.4, 19.1) | 16.2 (13.6, 21.7) | 19.8 (14.9, 26.5) | 21.0 (17.6, 26.1) |

Values are shown as percentages and are listed as medians and IQR except as otherwise indicated. *All baseline values are for 2004, except as otherwise indicated for variables where data from 2004 were not available. †Eight counties were excluded due to lack of diabetes prevalence data. ‡Based on the 2013 National Center for Health Statistics Urban-Rural Classification Scheme. §Estimates obtained from the CDC's U.S. Diabetes Surveillance System derived from the BRFSS. ‖Prevalence of any cigarette use (daily or nondaily) obtained from estimates by Dwyer-Lindgren et al. (16) using data from the BRFSS. ¶Estimates listed are from 2010. **Estimates listed are from 2005.

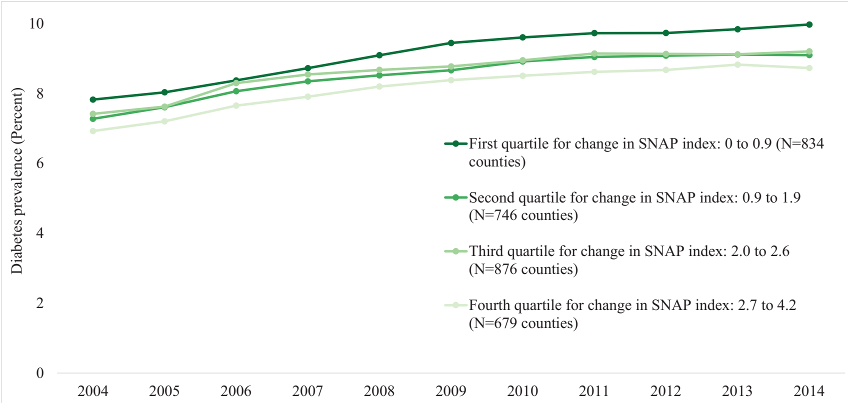


**Figure 2**—Mean adult diabetes prevalence by quartile of absolute change in the SNAP policy index from 2004 to 2014. The age-adjusted prevalence of diagnosed diabetes for all adults ≥20 years of age obtained from the CDC's U.S. Diabetes Surveillance System derived from the BRFSS.

in diabetes prevalence in this model was statistically significant (−0.046 pp [95% CI −0.053 to −0.038]). In the sensitivity analysis fitting the primary g-computation model with data from 2004 to 2010, the association between change in the SNAP policy index and change in diabetes prevalence was also statistically significant (−0.037 pp [95% CI −0.047 to −0.027]). As an additional sensitivity analysis, a random-effects model with the same covariates as those included in the main g-computation model was fit. In the random-effects model, a 1-point increase in the SNAP policy index between 2004 and 2014 was associated with a 0.061 pp (95% CI 0.058–0.064) lower annual diabetes prevalence (Supplementary Table 10).

To test the association between SNAP policies and other health-related trends, we used smoking prevalence as an alternative falsification outcome with the same covariates as the main g-computation model. In this alternative model, a 1-point increase in the SNAP policy index between 2004 and 2014 was associated with a 0.027 pp (95% CI 0.014–0.040) higher smoking prevalence per year (Table 2).

**Table 2—G-computation estimates for change in diabetes prevalence associated with absolute change in SNAP policy index***

| | Estimate (95% CI)† | *P* value |
|---|---|---|
| Primary analysis | | |
| All counties | −0.050 (−0.057, −0.042) | <0.001 |
| Secondary analyses | | |
| Stratified by sex | | |
| Men | −0.067 (−0.075, −0.058) | <0.001 |
| Women | −0.039 (−0.047, −0.030) | <0.001 |
| Stratified by county metropolitan status‡ | | |
| Nonmetropolitan counties | −0.045 (−0.052, −0.037) | <0.001 |
| Metropolitan counties | −0.054 (−0.063, −0.044) | <0.001 |
| Stratified by U.S. Census Region§ | | |
| Northeast | −0.036 (−0.052, −0.019) | <0.001 |
| Midwest | −0.034 (−0.043, −0.024) | <0.001 |
| South | −0.090 (−0.10, −0.078) | <0.001 |
| West | −0.029 (−0.043, −0.015) | <0.001 |
| Stratified by quartile of baseline (2004) SNAP policy index‖ | | |
| First quartile | −0.066 (−0.088, −0.044) | <0.001 |
| Second quartile | −0.068 (−0.089, −0.048) | <0.001 |
| Third quartile | −0.066 (−0.087, −0.046) | <0.001 |
| Fourth quartile | −0.086 (−0.12, −0.053) | <0.001 |
| Alternative outcome | | |
| Smoking (all counties)¶ | 0.027 (0.014, 0.040) | <0.001 |

*Age-adjusted prevalence of diagnosed diabetes for all adults ≥20 years of age obtained from the CDC's U.S. Diabetes Surveillance System derived from the BRFSS. †Additional change in diabetes prevalence per year in pp associated with 1-unit greater absolute increase in SNAP policy index from 2004 to 2014. Estimate for interaction between year and absolute change in SNAP policy index. ‡Based on the 2013 National Center for Health Statistics Urban-Rural Classification Scheme. §States in each U.S. Census Region listed in Supplementary Table 8. ‖Quartiles of counties based on value of SNAP policy index in 2004. First quartile: 3.8 to 5.8, second quartile: 5.8 to 6.4, third quartile 6.4 to 6.9, and fourth quartile: 7.0 to 8.1. States in each quartile are listed in Supplementary Table 9. ¶Prevalence of any cigarette use (daily or nondaily) obtained from estimates by Dwyer-Lindgren et al. (16) using data from the BRFSS.

## CONCLUSIONS

In the years 2004 to 2014, a greater increase in the adoption of state-level policies that increased SNAP participation was associated with a lower annual increase in the county-level diabetes prevalence among U.S. adults. In subgroup analyses, this association was noted for diabetes prevalence among both men and women and was significant across census regions and for both metropolitan and nonmetropolitan counties. In contrast, a greater increase in the SNAP policy index was associated with a greater annual increase in the alternative falsification outcome of smoking prevalence, suggesting that this association was not mediated by secular trends in healthy behaviors.

The persistent global increase in diabetes and obesity seen has been labeled as an epidemic due to its pervasiveness and impact on numerous important health outcomes, including premature death (22–24). The prevalence of diabetes is concentrated among individuals with a low socioeconomic status, who are also most vulnerable to food insecurity. Food insecurity has been associated with diabetes prevalence in multiple prior studies (4,25–27). One possible mechanism linking food insecurity and diabetes is the lack of access to healthy options and lower quality of dietary options available to households that are food insecure

(28). Additionally, greater psychosocial stress is associated with increased insulin resistance and diabetes in both animal and human studies (29,30). The evidence for whether addressing food insecurity reduces the risk of developing diabetes or improves glycemic control among those with diabetes is sparse. A small randomized trial of providing medically tailored meal delivery to patients with diabetes with food insecurity demonstrated an improvement in diet quality (31). Other pre-post studies of food assistance for food insecure patients with diabetes have shown improvements in food insecurity, diabetes management, and glycemic control (32,33).

However, it is unlikely that small-scale interventions will lead to population-level changes in diabetes prevalence. As the largest government program providing food assistance to low-income individuals, SNAP is one of the primary mechanisms of addressing food insecurity in the U.S. Several studies have noted that SNAP participation is associated with reductions in food insecurity (34–36). Whether SNAP participation leads to changes in diabetes prevalence in an area has not, however, been previously studied. In this analysis, we found that an index of state policies associated with increased participation in SNAP were associated with diabetes prevalence such that states that had the greatest absolute increase in these policies experienced a slower increase in diabetes prevalence, after accounting for baseline levels of SNAP policies and changes in other important demographic-, economic-, and health care-related variables during the study period. Because there were significant differences in important county-level factors among states that differed in the SNAP policy index at baseline, by accounting for baseline SNAP policy index levels, comparisons of change in SNAP policies were made between states with a similar level of SNAP policy generosity at baseline.

Given the nature of this analysis, it is not possible to determine the specific mechanisms by which SNAP participation may have been associated with changes in diabetes prevalence. Although SNAP includes a nutritional education component (37) and restrictions to discourage purchasing processed foods (38), the evidence that SNAP participation is associated with improvements in diet quality is mixed (39,40). Obesity may be an important mediator between food insecurity and diabetes on an individual level; however, in this county-level analysis, inclusion of obesity prevalence in the multivariable model did not substantially change the association between change in the SNAP policy index and diabetes prevalence, suggesting the presence of other factors mediating the association. There is significant evidence that SNAP participation is associated with improved economic well-being and poverty alleviation (41,42). Given the association between psychosocial stress and insulin resistance, poverty reduction may play a role in slowing the growth in population level diabetes prevalence. Another possibility is that states that had the greatest increase in the SNAP policy index had populations that were engaged in a healthier lifestyle independent of changes in SNAP policies.

There is evidence that dietary quality among adults in the U.S. may have improved during the study period of this analysis, although to a lesser degree among SNAP participants (43); however, it is unlikely that the association between the SNAP policy index and diabetes is being primarily driven by this secular trend given the association was noted across all U.S. regions as well as for both metropolitan and nonmetropolitan counties. Additionally, a similar negative longitudinal association was not noted between the SNAP policy index and cigarette smoking, suggesting against an association between the SNAP policy index and secular trends in healthy behaviors in the U.S. population driving the relationship with diabetes prevalence. Although the prevalence of diagnosed diabetes increased throughout most of the study period of this analysis, followed by a plateauing, it has been noted that the incidence of diagnosed diabetes in the U.S. may be declining starting around the year 2007 (44). By focusing on the annual change in diabetes prevalence, this analysis is able to account for yearly change in the level of diabetes prevalence in the study period. However, how a continued decline in the incidence of diabetes influences the association between adoption of more generous SNAP policies and diabetes prevalence is unclear. Additionally, how other policies, such as more widespread availability of the Diabetes Prevention Program (45), will influence the relationship between SNAP policies and diabetes prevalence remains to be seen.

### Limitations

This study has several limitations. Because this is a retrospective, observational, area-level analysis, causal inferences, particularly at the individual level, cannot be made. However, by examining the association of state-level policies on county-level trends in diabetes prevalence, this analysis incorporates the substantial heterogeneity that exists in important demographic and economic factors at a substate level that could influence diabetes prevalence. Although the g-computation method improves upon traditional regression methods by being able to account for time-varying confounding, like other regression based methods, unmeasured confounding is still possible. The primary outcome, prevalence of diagnosed diabetes, is based on self-reported diabetes from the BRFSS. Therefore, it is not possible to extrapolate the results of this analysis to undiagnosed diabetes. However, the association between SNAP policy and diagnosed diabetes likely is not explained by trends in health care access alone because the multivariable models account for some time-varying markers of health care access: health insurance coverage and availability of primary care providers in an area.

### Conclusion

County-level diabetes prevalence among U.S. adults increased at a slower rate in states that adopted policies that are correlated with greater SNAP participation between 2004 and 2014. Several studies have linked food insecurity and diabetes in the past; however, this analysis suggest that programs, such as SNAP that are known to improve food insecurity, may play a role in the population level diabetes trends in the U.S. States that have yet to implement some of these strategies to increase SNAP participation, should consider their impact on population level health markers such as diabetes when making policy decisions.

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