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Online Appendix

Table of Contents

1 Model overview

The model used in this study is a microsimulation model, which simulates food consumption and associated changes to the body mass index (BMI) and type 2 diabetes risk at the level of the individual. The model is stochastic rather than deterministic, meaning that the simulations sample from probability distributions of input parameters to generate a distribution of outcomes, which are reported in terms of the mean result and 95% confidence intervals around the mean. The model is run in discrete time daily time steps over the course of 10 years from 2015 to 2026, where the simulated policy changes are introduced at the start of year 2015. A model diagram is illustrated in Appendix Exhibit 1. Key parameters and data sources are summarized in Appendix Exhibit 2.

1.1 Demographic structure

Given prior literature reviews describing which key demographic variables are predictive of food consumption patterns in the United States (1–3), we classified individuals in this model by combinations of a few key demographic characteristics: age (5 to 11 years old, 12 to 18 years old, 18 to 44 years old, and 45 to 65 year old), sex (male or female), race/ethnicity (using NHANES categories of non-Hispanic White, non-Hispanic Black, Mexican American and Other), income (measured by 25% increments of the poverty income ratio, which corrects household income for the national poverty threshold for a given household size), and participation or non-participation in SNAP. 10,000 individuals were generated for each cohort defined by the combinations of these characteristics.

To account for individuals aging from a younger to an older cohort, we tracked the age of each simulated individual over the simulation period, and updated each individual's food consumption and health metrics to account for their age-specific consumption patterns and health risks. To account for demographic shifts over the 10 year period, we allowed individuals to enter the youngest cohort (5-18 years old) and leave all cohorts (mortality) at rates based on their age, sex and race/ethnicity; these rates of entry and exit were taken from standard life tables from the CDC (4). For the purposes of reporting results at the end of the simulation, we weighted each demographic group by its population size to arrive at overall population estimates of the outcome variables, as projected over the simulation period by the US Census (5); the proportion of the population participating in SNAP among each demographic group was assumed to remain stable at the average of annual levels reported by the USDA for fiscal years 2000 through 2011 (6).

To account for entry or exit from SNAP, we used annual probabilities of movement between SNAP and non-SNAP populations from the USDA median estimates of entry rates, duration of participation, and re-entry rates specific to age, sex, race/ethnicity, and income group, which are tabulated from the Survey of Income and Program Participation (SIPP) years 2004-2006 (7). Since rates of re-entry among prior SNAP participants are higher than rates of initial entry from the general population, an indicator variable of prior participation among simulated individuals was programmed into the model to account for higher re-entry rates among those with previous histories of SNAP participation.

1.2 Design steps

To estimate the impact of the various SNAP policy proposals, we designed the model to simulate food consumption from each of several representative food groups, then estimate the degree of change in consumption after a SNAP policy change such as an SSB ban or a fruit/vegetable subsidy. Three steps were taken to accomplish these tasks: (1) a simulation of food consumption before any intervention, by having simulated individuals sample from probability distributions describing their typical rates of consumption from the various food groups (establishing a baseline scenario); (2) an estimation of the degree to which changes in SNAP policy, in the form of price or benefit changes, would alter the probabilities of consumption for affected foods (estimation of own- and cross-price elasticities as well as the marginal propensity to consume); and (3) an estimation of how changes in food consumption would change key health metrics (BMI, type 2 diabetes risk). The subsequent sections of this Appendix describe this three-stage process in sequence.

2 Food consumption distributions

2.1 Data sources

Data from which to estimate probabilities of consumption for different foods among various demographic cohorts were assembled from NHANES, because the NHANES survey provides arguably the most detailed dietary data among available datasets for the US population, and provides detailed information on demographics and SNAP participation that is comparable over several years. NHANES is a continuous, multistage cross-sectional survey designed to be representative of the civilian, non-institutionalized US population.

NHANES years 1999-2010 were chosen for this analysis because these are the most recent available years of data at the current time (the 2011-2012 survey's dietary questionnaire has not been released at the time of this writing) and these survey years have comparable dietary files with reported consumption (kcals/person/day) from individual foods (8).

The dietary intake data files in NHANES provide estimates of the types and amounts of foods and beverages consumed during the 24-hour period prior to the interview (midnight to midnight). From 1999 to 2002, one 24-hour recall via in-person interview was performed; from 2003 to 2010, two recalls were performed, the first via in-person interview, and the second via telephone interview 3 to 10 days later (both surveys were completed by 93% of participants). The interviews were conducted using the USDA's dietary data collection instrument, the Automated Multiple Pass Method (AMPM), which includes a specialized child survey to assist younger children in reporting. The AMPM method was validated among 524 healthy weight-stable volunteers, among whom the AMPM was found to reasonably estimate energy intake (EI) to total energy expenditure (TEE) measured by the doubly labeled water technique (9). EI compared to TEE was under-reported by 11% overall, by less than 3% for normal weight subjects with body mass index (BMI) less than 25 kg/m^2, and 16% for overweight subjects with BMI greater than or equal to 25 kg/m^2. EI was not found to be significantly different from TEE for an independent sample of 20 females (10), and another assessment among 12 males (11). Following the dietary recall in NHANES, participants were asked questions on whether the person's overall intake on the previous day was much more than usual, usual or much less than usual. Macros described below were used to estimate "usual" intake from these 24-hour dietary recalls, incorporating sample weights to reflect unequal probabilities of sampling, missing data/non-response and non-coverage.

2.2 Estimation of usual intake

Foods and food groups were identified using the USDA Food and Nutrient Database for Dietary Studies (12). Grams and calories of consumption of foods were clustered into food groups using standard USDA food codes listed in the Database (see Appendix Exhibit 3). Foods were clustered into 20 groups to prevent model identifiability errors when estimating elasticities (see next section). Servings of fruits and vegetables per day were estimated by converting grams consumed to servings per day using USDA data relating consumption to servings for fruits and vegetables (13). Foods in the NHANES identified by USDA food codes have been disaggregated into component ingredients and equivalent food group servings. Before estimating the usual intake of foods for the studied populations, the significance of two-factor interaction terms between SNAP participation and survey wave over the period 1999-2010 were assessed for each of these food groups, which established the validity of combining data from the multiple survey years to estimate food intake distributions for SNAP participants and non-SNAP populations separately.

Distributions of "usual" intake for food groups were estimated for two populations—SNAP participants and non-SNAP populations—using a validated statistical method developed by the National Cancer Institute. The method preserves the NHANES weighting scheme while correcting for within-person variance in dietary intake. First, the MIXTRAN macro was used to estimate the probability of consumption from each food group (14). The macro uses a nonlinear mixed model that considers both a person-specific random effect and day of intake (correcting for day 1 versus day 2 of dietary recall and day of the week of intake, to account for differential intake between weekdays and weekends). Because the macro uses the 2-day dietary recalls from NHANES 2003-2010 for assessments of consumption variance, it assumes that usual dietary intake variations will remain relatively constant over the full study period. Second, the DISTRIB macro uses parameter estimates from MIXTRAN and estimates the distribution of usual intake on a transformed scale (14). Standard errors were estimated using the balanced repeated replication approach, which accounts for correlation among persons in the same sampling cluster while preserving NHANES sample weights (15). Third, estimates were made to determine how the usual intake distributions would be adjusted for each specific demographic cohort in the model (i.e., how usual intake is affected by age, sex, race/ethnicity, and income). The log-transformed dietary intake was regressed against age, sex, race/ethnicity and income, and the beta coefficients on these demographic variables were used to adjust the usual intake distributions for each demographic group (significance was defined as $p<0.05$). Results are provided in Appendix Exhibit 3. Details of SSB, fruit and vegetable consumption are further illustrated in Appendix Exhibit 4.

3 Elasticity estimation

3.1 Data sources

Own- and cross-price elasticities among the food groups were estimated for both SNAP participants and non-SNAP populations by linking the NHANES data files to USDA Quarterly Food-at-Home Price Database supplemented by the Nielsen Homescan Panel Database (now known as the National Consumer Panel) organized into 35 retail market areas to account for regional price variations, providing longitudinal price distributions for each food group since 1999 (16). The price data provide household-level purchase prices of both Universal Product Code (UPC)-coded foods (such as packaged and canned foods) and random-weight (non-UPC) items (such as fresh fruits or vegetables) coded in dollars per 100 grams.

3.2 Demand system model

We made the elasticity calculations from these combined datasets using the Quadratic Almost Ideal Demand System, a standard microeconomic approach to elasticity estimation (17). We estimated a complete food demand system, rather than assuming separability of budgets between food items (i.e., budgets for beverages were not separated from budgets for solid foods; hence, money deferred from SSBs after a ban on these beverages could be used for any food purchase, not just the purchase of other beverages).

The equations specify that the share of expenditures for a given good i in an n-good system is:

$$(1) \qquad \omega_i = \left\{ \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln\left[\frac{x}{a(p)}\right] + \frac{\lambda_i}{b(p)}\left[\ln\left(\frac{x}{a(p)}\right)\right]^2 \right\} \Phi + \kappa_i \phi + \tau_i \quad \text{for } i=1,\ldots,k,$$

where ω_i is the share of expenditure associated with the ith food, α_i is is the constant coefficient to be estimated for the ith share equation, γ_i and κ_i are slope coefficients to be estimated for the jth good in the ith share equation, p_j is the price on the jth good, β_i is a parameter to be estimated that will enter into the elasticity estimate, x is the total expenditure on food, τ_i is the error term, and a, b, and λ are transformations of price specified below. Φ and ϕ are a univariate standard normal cumulative distribution function and a probability density function, respectively, estimated from equation 2 below. Equation 2 is a standard probit regression that we compute as a first stage to account for censoring and zero consumption; the equation estimates the probability that a person will consume good i:

$$(2) \qquad d_{ih} = \theta_0 + \sum_j \theta_{ij} \ln p_j + \theta_x \ln x_h + \sum_k \theta_{nk} n_{kh} + \mu_i,$$

where d_{ih} =1 if the hth person consumes the ith good and equals zero otherwise, and n are the demographic variables. We obtain probit estimates of θ_i using the binary outcome $d_i = 1$ and $d_i = 0$ for each i, then compute $\Phi(\theta_i)$ and $\phi(\theta_i)$ via maximum likelihood; Φ and ϕ are then entered into the estimation of equation 1 as instruments to correct for zero expenditures (18).

The price transformations include the transcendental logarithm function:

(3) $$\ln a(p) = \alpha_0 + \sum_{k=1}^{n} \alpha_k \ln p_k + \frac{1}{2}\sum_{k=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln p_k p_j$$

and a Cobb-Douglas price aggregator:

(4) $$b(p) = \prod_{k=1}^{n} p_{k=1}^{\beta_k}$$

and

(5) $$\lambda(p) = \sum_{i=1}^{k} \lambda_i \ln p_i$$

The demand system is constrained by the following restrictions on the parameters to ensure the parameters properly add up and follow homogeneity and Slutsky symmetry impositions:

(6) $$\sum_{i=1}^{k} \alpha_i = 1,$$

(7) $$\sum_{i=1}^{k} \beta_i = 0,$$

(8) $$\sum_{i=1}^{k} \lambda_i = 0$$

(9) $\sum_{i=1}^{k} \gamma_{ij} = 0$ for all *i* (homogeneity), and

(10) $\gamma_{ij} = \gamma_{ji}$ for all *i* and *j* (symmetry).

From this demand system, uncompensated price elasticities are estimated as:

(11) $$\varepsilon_{i,j} = \frac{1}{\omega_i}\left\{\gamma_{ij} - \left[\beta_i + \frac{2\lambda_i}{b(p)}(\ln x - \ln a(p))\right]\left(\alpha_j + \sum_{k=1}^{n} \gamma_{kj} \ln p_k\right) - \frac{\beta_i \lambda_i (\ln x - \ln a(p))^2}{b(p)}\right\} - \delta_{ij},$$

where δ_{ij} is the Kronecker delta function equal to 1 if $i=j$ (own-price elasticity) and equals zero (cross-elasticity) otherwise. The demand system was estimated in Stata version MP12.1 (StataCorp, College Station, Texas), and the resulting parameters are listed in Appendix Exhibit 5.

3.3 Validation

Own- and cross-price elasticities from the demand system were compared to published estimates from independent authors and data sources to assess the face validity of the estimates. In the case of fruits and vegetables, our estimates included an own-intake elasticity of -0.68 for fruit and -0.64 for vegetables. In a systematic review of published elasticity estimates for the general population, the mean for fruit was -0.70 (range -0.16 to –3.02) and for vegetables was -0.58 (-0.21 to -1.11) (19). Among assessments specific to low-income households, estimates have ranged from the low end of -0.34 for fruits and -0.32 for vegetables to high estimates of -0.98 for fruits and vegetables combined (20,21), with three other estimates of -0.66, -0.81 and -0.91 for fruits and -0.74, -0.72 and -0.91 for vegetables (22–24). Hence, the estimates in the current study were in the same range as prior estimates.

For SSBs, our estimate of own-price elasticity was -1.47; the systematic review of published estimates suggested a mean own-price elasticity of -0.79 (range -0.33 to -1.24) in the general population, while a USDA estimate among SNAP participants suggested an estimate of -1.3 (19,25) and two other estimates among low-income populations suggested -1.9 (24,26). The cross-elasticity estimates between SSBs and juices were significant in the current study, suggesting a 0.52% increase in fruit juice consumption for every 1% increase in SSB price. This is similar to independent estimates of a 0.56% rise in juice intake for a 1% SSB price increase (25).

3.4 Marginal propensity to consume

To perform simulations of the full set of interventions, it was also necessary to incorporate the marginal propensity to consume (MPC) food out of SNAP benefits and income. The MPC estimates the increase or decrease in overall food spending resulting from an effective increase or decrease in benefits (i.e., either real benefit changes, or restrictions in benefits such as an SSB ban). We calculated the MPC for both child and adult SNAP participants, using a double-log model of food expenditure; to apply this method, household food expenditure (M) per capita was regressed on total income (sum of SNAP benefits (B) and household income (Y)) per capita, ratio of SNAP benefits to income, and a vector containing the above-specified demographic variables (V), as shown in Equation (12):

$$(12) \qquad \log(M) = \alpha_1 V + \alpha_2 \log(B+Y) + \beta \frac{B}{B+Y},$$

where scalars α_2 and β and vector α_1 are parameters to be estimated. The MPC was derived by differentiating Equation 12 to give:

$$(13) \qquad MPC = \frac{\partial M}{\partial B} = \frac{M}{B+Y}\left(\alpha_2 + \beta \frac{Y}{B+Y}\right).$$

resulting in an MPC estimate of \$0.32 for children (95% CI: \$0.23-\$0.41) and \$0.35 for adults (95% CI: \$0.25-\$0.46). This is within the same range as a prior independent estimates ranging from \$0.17 to \$0.47 for overall SNAP participant households (23). The MPC result implies that for an effective benefit decrease of \$10 (e.g., from a restriction on purchasing such as an SSB ban, where a person prior to the ban would have spent \$10 in SNAP benefits on SSBs), the SNAP participant would reduce her expenditure by about \$2, not the full \$10 because disposable income is used to partially compensate for acquisitions no longer purchased through SNAP dollars.

4 Policy simulation structure

Each policy intervention was assumed to begin with full coverage of the affected population by the policy at the start of year 2015, with the simulation proceeding 10 years from 2015 to 2026. For each policy simulation, a matrix of 10,000 simulated individuals was constructed for each demographic cohort, where each row was an individual person and each column defined a property of that person; the first set of columns defined demographic properties (age, sex, etc., as itemized above); the second set of columns defined usual dietary intake, where each column corresponded to a different food group; and the third set of columns defined values of the various health outcome metrics detailed in the next section. The second and third sets of columns were updated in discrete daily time steps over the simulated 10-year period. The second set of columns describing usual dietary intake was populated by Monte Carlo sampling from the food consumption probability distributions for each demographic cohort, as described above. The covariance matrix between the distributions was used to guide the sampling (using copulas (27)) to account for multivariate dependence in consumption (e.g., individuals who consume more high-fat dairy products may also consume more refined grains). The third set of columns was populated by a series of algorithms described in the next section of this Appendix.

To simulate each intervention, the food consumption probability distributions were shifted to the left or right (decreasing or increasing the probability of consumption of certain foods) based on the intervention-specific own- and cross-intake elasticity estimates, as well as the MPC estimate. To simulate a ban on purchasing SSBs with SNAP dollars, we simulated two effects: (i) SSB purchasing among SNAP recipients was lowered by the MPC multiplied by pre-policy SNAP expenditures on SSBs (because the SSB ban is an effective reduction in benefits); and (ii) the SNAP dollars no longer spent on SSBs were distributed among other food groups based on the statistically-significant (at the $p<0.05$ level) cross-elasticities between SSBs and the other foods (Appendix Exhibit 5). For example, suppose the MPC is \$0.3, and \$3 per day were spent on SSBs by an individual before the SSB ban. If the ratio of SNAP benefit to total food expenditure was 50% for that individual, then the SSB purchasing decrease would be \$0.3 * (\$3 * 0.5) = \$0.5 less expenditure on SSBs per day, incorporating both the reduction in SNAP dollars spent on SSBs due to the ban (\$3*0.5 = \$1.5), and the compensatory disposable income spent to maintain some consumption (in this example, \$1.5-\$0.5 = \$1). Note that the own-price elasticity of SSBs is the reduction in SSB consumption given an increase in SSB price. Therefore, since we have an estimate of the reduction in SSB consumption from the ban, the impact of the ban on SSB consumption can be translated into an effective price increase. Specifically, the net reduction in SSB consumption divided by the own-price elasticity of SSBs gives the effective price increase in SSBs that the ban is equivalent to. Hence, to estimate the increased consumption of any other product (such as increased juice consumption, as juices are substituted for SSBs), we multiply the cross-elasticity of the other product by the effective increase in SSB price, e.g., increased juice consumption = (cross elasticity of juice with SSBs) * (effective price increase in SSBs) = (cross elasticity of juice with SSBs) * (reduced SSB consumption / own-price elasticity of SSBs). In our simulations, the SSB ban included all sugar-sweetened beverages, such as sports drinks (not just carbonated sodas), but excluded 100% fruit juice, in line with current proposals (28,29). To simulate a thirty-cent-per-dollar subsidy on fruits and vegetables, we simulated two effects: (i) increased fruit and vegetable purchases as a result of the effectively lower price among the proportion of fruit/vegetable purchases that are made with SNAP dollars (own-price elasticity applied to the portion of fruit/vegetables purchased with SNAP benefits); and (ii) potential changes in consumption of other foods because of the effective purchasing power increase from the price change incentivizing fruit and vegetable purchases (see cross-elasticities in Appendix Exhibit 5). To match the USDA Healthy Incentives Pilot program, the subsidy was applied to all fruits and vegetables except for nuts, legumes, seeds, potatoes and juices (i.e., fruits and non-potato vegetables that are fresh, frozen, canned, or dried were eligible for the subsidy) (30).

5 Outcome metrics

Each policy simulation described above provides an estimate of the change in kilocalories of each food consumed following each intervention. These changes in consumption were translated, through the approach described below, into estimates of change in various health metrics.

5.1 BMI

A starting weight and height were given to each simulated individual by Monte Carlo sampling from their demographic cohort in NHANES (Appendix Exhibit 6), using the covariance matrix between these variables and the food consumption distributions to guide sampling. To estimate change in weight after each intervention, change in total calorie consumption was tabulated after each intervention.

For children, we employed a validated NIH model of body mass change among children aged 5 to 18 (31), which accounts for child growth trajectories. The net change in kilograms among children given a change in kilocalories per person per day is given by Equation 14 for males and Equation 15 for females:

(14) $\Delta kg = (\Delta\, kcal/person/day)/(68 - 2.5 \times age)$

(15) $\Delta kg = (\Delta\, kcal/person/day)/(62 - 2.2 \times age)$

The BMI was calculated in kilograms divided by height in meters squared. We measured child obesity by recording the proportion of children to exceeded standard international cut-points of body mass index, which are specific to age and sex (32).

For adults, we employed a validated NIH model of individual body weight *M(t)* change after a change in calorie consumption χ:

(16) $$\frac{dM(t)}{dt} = [\chi(t) - \kappa(t)(M(t) - M_0)]/\tau .$$

where M_0 is the initial body weight prior to the calorie consumption change, τ is the weight change associated with net energy consumption, and κ captures energy expenditure (33). The internal physiology of metabolism is captured by:

(17) $$\tau = \frac{\eta_f + \rho_f + c\eta_l + c\rho_l}{(1-d)(1+c)}$$ and

(18) $$\kappa(t) = \frac{1}{(1-d)}\left(\frac{\gamma_f + c\gamma_l}{(1+c)} + P(t)\right)$$

where Equation 17 captures the efficiency of fat and protein synthesis n_f and n_l, energy content per unit fat and lean tissue ρ_f and ρ_l , relative change in lean mass per change in fat mass *c*, and adaptive thermogenesis *d.* Equation 18 describes catabolic energy breakdown given resting metabolic rates of fat and lean tissue γ_f and γ_l and physical activity P. Parameters are tabulated in Refs. (33,34) and an online version of the model is available at http://www.niddk.nih.gov/research-funding/at-niddk/labs-branches/LBM/integrative-physiology-section/body-weight-simulator/Pages/body-weight-simulator.aspx.

5.4 Type 2 diabetes risk

A validated risk calculation algorithm (35,36) was employed to simulate change in type 2 diabetes risk attributable to a change in food consumption. The change in food consumption is believed to affect type 2 diabetes risk through a lagged dependent relationship between obesity status and between each type of food's ultimate glycemic load and contribution to insulin resistance; there is a dose-dependent relationship between glycemic load of different foods and subsequent type 2 diabetes risk (37). We used the relative risk estimates of type 2 diabetes of 7.28 (95% CI: 6.47-8.28) given new obesity (38), 1.45 (95% CI: 1.31-1.61) for each 100-gram increase in glycemic load among adults (37), and 1.07 (95% CI: 1.01-1.11) for each 100-gram increase in glycemic load among children (39–42), where the grams of glycemic load for each unit of food consumed was obtained from a prior national assessment (43).

To estimate the type 2 diabetes risk change from each intervention, we calculated an individual's risk of type 2 diabetes in each year of the simulation. The individual's relative hazard λ, the hazard of acquiring type 2 diabetes in relation to the typical hazard in that individual's cohort that year, is defined by:

$$\lambda = e^{\sum_i \beta_i x_i} \quad (19)$$

where β is the log relative risk of diabetes contributed by each risk factor i (overweight/obesity and glycemic load) and x is the average change in the value of each risk factor (change in overweight/obesity status and change in glycemic load). The exponent corrects for skew in the obesity and glycemic load distributions. The equation structure reflects current data suggesting the risk is additive rather than overlapping or multiplicative (44). The individual risk from diabetes for a particular year is then calculated from the population-level cohort- and year-specific diabetes incidence rate estimate ρ (45,46) (Appendix Exhibit 6), multiplied by the ratio of the individual's relative hazard λ and the mean relative hazard ψ in that individual's cohort that year:

$$\kappa = \rho \frac{\lambda}{\psi} \quad (20)$$

where κ is the type 2 diabetes incidence risk for the individual that year. When repeated over the time course of the simulation, this estimation procedure is equivalent to calculating the population impact fraction (PIF), which is an integrated metric of the change in incident diabetes that can be attributed to the change in a given risk factor (47).

5.3 Validation

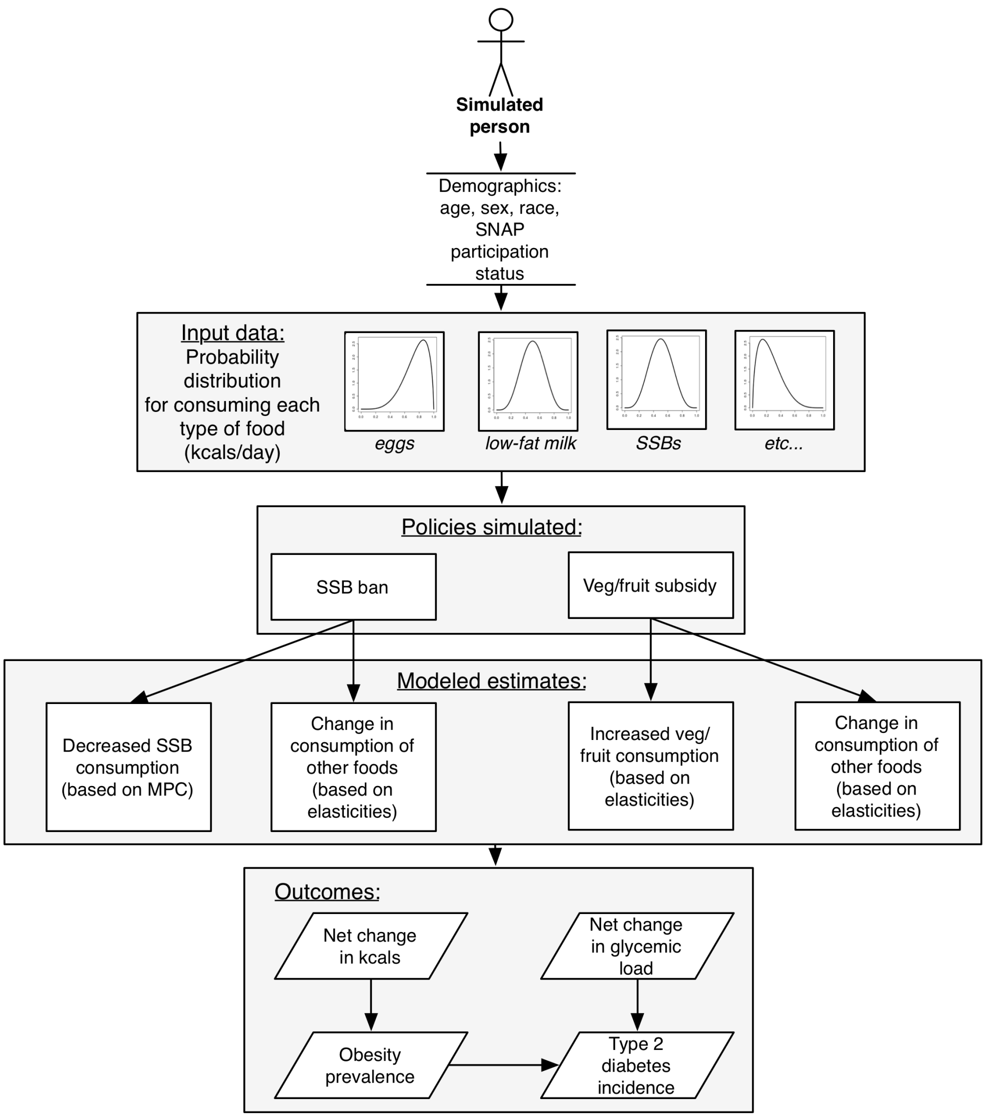
We compared estimated obesity and type 2 diabetes trajectories from this model against four independent analyses. First, we input 1999-2000 NHANES survey values and estimated secular trends in kcal/person/day consumption and ensured that predicted BMI trajectories were within statistical error of actual obesity prevalence trajectories for each subsequent year through 2010 for both children and adults. The model was found to be within the error range of such estimates, with no systematic biases across demographic groups or years (Appendix Exhibit 7). Second, we ensured that the estimated type 2 diabetes incidence rates matched estimates from the SEARCH for diabetes in youth study (48) and CDC estimates for incidence among adults (46); the model was again within the error range of the estimates with no systematic bias across demographic groups or years (Appendix Exhibit 7). Third, we ensured the modeled fruit and vegetable subsidy matched results of the recent USDA pilot study of the fruit and vegetable subsidy in Massachusetts. The USDA study revealed a 0.22 cup-equivalent increase in fruit and vegetable kilocalories per day, versus 0.24 in our model (95% CI: 0.20-0.28) (30).

5.4 Sensitivity and uncertainty analyses

Multivariate sensitivity and uncertainty analyses were performed by Monte Carlo sampling 10,000 times from the distributions of usual food intake, and from the probability distributions of each input parameter. It has been found that directly calculating partial rank correlation coefficients (PRCCs) to estimate the sensitivity of model outputs to each input variable provides a more comprehensive sensitivity analysis than standard univariate sensitivity analyses, because the PRCC approach incorporates the covariance among parameters and the realized range of a given parameter in a Monte Carlo simulation (49). PRCC estimates, describing the model outputs' sensitivities to key input parameters, are listed in Appendix Exhibit 8. Higher PRCC values indicate a greater correlation between changes in a parameter value and changes to the model output as compared to the baseline outcome, and vice versa. The results reveal sensitivity of model outcomes to intake elasticity estimates. Full results of the uncertainty analyses, disaggregated by demographic cohort, are provided in Appendix Exhibit 9.

6 Tables and figures

6.1 Appendix Exhibit 1: Model diagram



SSBs = sugar-sweetened beverages. MPC = marginal propensity to consume, an estimate of how much SNAP participants reduce their consumption given an effective reduction in SNAP purchasing power (as with an sugar-sweetened beverage ban)

Source: authors

6.2 Appendix Exhibit 2: Key parameters and data sources for the model.

Parameter	Source
SNAP population size, demographics and participation rates	US Department of Agriculture. Determinants of Supplemental Nutrition Assistance Program Entry and Exit in the Mid-2000s [Internet]. 2011. Available from: http://www.fns.usda.gov/ora/MENU/Published/snap/FILES/Participation/DeterminantsMid2000.pdf
Food consumption specific to demographic group and SNAP participation status	US Centers for Disease Control and Prevention. NHANES - National Health and Nutrition Examination Survey [Internet]. 2012 [cited 2012 Dec 29]. Available from: http://www.cdc.gov/nchs/nhanes.htm
Own- and cross-price elasticities (change in food consumption, and substitution between foods, given a change in price)	US Centers for Disease Control and Prevention. NHANES - National Health and Nutrition Examination Survey [Internet]. 2012 [cited 2012 Dec 29]. Available from: http://www.cdc.gov/nchs/nhanes.htm and US Department of Agriculture. USDA Economic Research Service - Quarterly Food-at-Home Price Database [Internet]. 2012 [cited 2012 Dec 18]. Available from: http://www.ers.usda.gov/data-products/quarterly-food-at-home-price-database.aspx#25638
Marginal propensity to consume out of SNAP benefits (change in food spending resulting from change in SNAP benefits)	Estimated from US Centers for Disease Control and Prevention. NHANES - National Health and Nutrition Examination Survey [Internet]. 2012 [cited 2012 Dec 29]. Available from: http://www.cdc.gov/nchs/nhanes.htm

Estimated change in body mass attributable to changes in calorie intake	Hall KD, Butte NF, Swinburn BA, Chow CC. Dynamics of childhood growth and obesity: development and validation of a quantitative mathematical model. Lancet Diabetes Endocrinol. 2013;epub ahead of print. and Hall KD, Sacks G, Chandramohan D, Chow CC, Wang YC, Gortmaker SL, et al. Quantification of the effect of energy imbalance on bodyweight. The Lancet. 2011;378(9793):826–37.
Change in type 2 diabetes risk given a change in food consumption	Basu S, Vellakkal S, Agrawal S, Stuckler D, Popkin B, Ebrahim S. Averting Obesity and Type 2 Diabetes in India through Sugar-Sweetened Beverage Taxation: An Economic-Epidemiologic Modeling Study. PLoS Med. 2014 Jan;11(1):e1001582

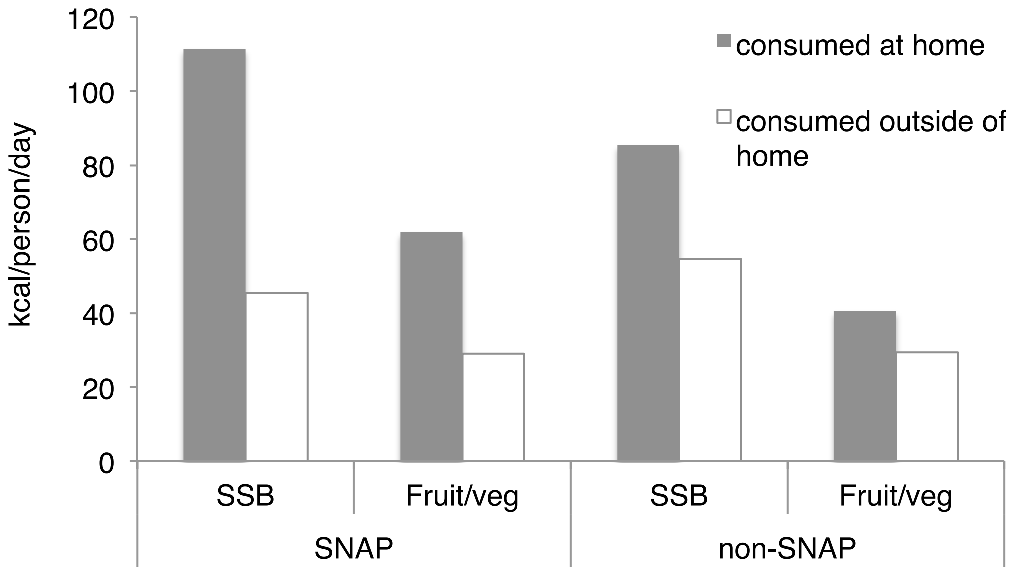
USDA=United States Department of Agriculture; NHANES=National Health and Nutrition Examination Survey

6.2 Appendix Exhibit 3: Consumption among SNAP participants

#	Food group	Ln (natural log) kcals/day	
		(Mean)	(SD)
1	Whole grains, nuts, legumes and seeds	4.71	0.91
2	Refined grains/potatoes	5.10	0.91
3	Vegetables excluding potatoes	2.36	1.37
4	100% Fruit juice	4.07	0.93
5	Fruit excluding juices	4.10	1.27
6	Whole milk	4.91	0.66
7	Skim milk	4.39	1.02
8	Low-fat milk	4.00	1.01
9	Low-fat non-milk dairy	4.79	0.64
10	High-fat non-milk dairy	5.16	0.76
11	Red meat	4.52	1.05
12	White meat	4.62	1.00
13	Fish and shellfish	4.88	1.02
14	Eggs	4.96	0.80
15	Fats and oils	3.76	1.04
16	Sweets	3.60	1.32
17	SSBs	4.46	1.41
18	Diet	4.17	1.49
19	Coffee/tea	2.11	1.41
20	Bottled water	N/A	N/A
	Total	7.62	0.44

SD: standard deviation
Source: NHANES (8)

6.3 Appendix Exhibit 4: SSB and fruit/veg consumption among SNAP participants versus matched non-participants



Source: authors calculations based on data from Ref. (8) using a matching approach detailed in Ref. (50)

6.4 Appendix Exhibit 5: Own-intake and cross-intake elasticities

Elasticities in table A, standard errors in table B. A 1% change in price of the food group in each row is associated with the listed change in consumption of the column food group. Groups numbers correspond to the numbers in Appendix Exhibit 3.

(A) Elasticities

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	-0.369	-0.192	-0.143	0.010	-0.088	-0.007	-0.007	-0.007	-0.042	-0.042	-0.205	-0.069	-0.123	-0.125	-0.065	0.057	0.017	0.011	-0.034	0.011
2	-0.204	-0.368	-0.109	-0.021	-0.091	-0.005	-0.005	-0.005	-0.051	-0.051	-0.112	-0.057	-0.060	-0.050	-0.031	0.099	-0.150	-0.096	-0.029	-0.096
3	-0.130	-0.041	-0.644	0.053	-0.305	-0.037	-0.037	-0.037	-0.021	-0.021	-0.156	-0.079	-0.034	-0.070	-0.023	0.103	-0.054	0.074	0.020	0.074
4	-0.031	-0.018	0.029	-1.046	-0.002	-0.054	-0.033	-0.071	0.015	0.015	-0.046	0.021	-0.043	0.027	0.045	0.053	0.180	-0.257	-0.009	-0.430
5	-0.103	0.008	-0.327	0.035	-0.682	-0.079	-0.079	-0.079	-0.049	-0.049	-0.152	-0.071	-0.138	-0.067	-0.014	0.103	-0.059	0.069	0.014	0.069
6	-0.002	-0.049	-0.004	-0.071	0.027	-1.063	-0.850	-0.662	-0.248	-0.248	-0.016	0.018	0.005	0.034	0.012	0.116	0.272	0.029	-0.004	0.096
7	-0.002	-0.049	-0.004	-0.073	0.027	-0.841	-1.071	-0.937	-0.248	0.020	0.007	0.083	0.018	0.055	0.020	0.116	0.120	0.109	0.032	-0.051
8	-0.002	-0.049	-0.004	-0.077	0.027	-0.644	-0.934	-1.198	-0.248	0.020	0.007	0.083	0.018	0.055	0.020	0.116	0.229	0.142	0.102	-0.130
9	-0.059	-0.099	-0.049	0.002	-0.043	-0.275	-0.275	-0.275	-0.725	-0.725	0.005	-0.018	-0.005	-0.003	0.001	0.000	-0.075	-0.036	-0.055	-0.036
10	-0.059	-0.099	-0.049	0.003	-0.032	-0.275	-0.275	-0.275	-0.725	-0.577	0.005	-0.018	-0.005	-0.003	0.001	0.000	-0.075	-0.036	-0.055	-0.036
11	-0.101	-0.075	-0.086	-0.049	-0.044	-0.061	-0.061	-0.061	-0.006	-0.006	-0.522	-0.124	-0.126	-0.116	0.036	-0.044	-0.151	-0.047	-0.022	-0.047
12	-0.021	-0.052	-0.059	-0.016	-0.016	-0.064	-0.064	-0.064	-0.051	-0.034	-0.173	-0.459	-0.109	-0.108	-0.044	-0.044	-0.145	-0.041	-0.016	-0.041

13	-0.086	-0.086	0.035	-0.091	-0.099	-0.089	-0.089	-0.089	-0.046	-0.046	-0.171	-0.099	-0.530	-0.122	-0.065	-0.044	-0.167	-0.063	-0.038	-0.063
14	-0.092	-0.144	-0.064	-0.021	-0.024	-0.049	-0.049	-0.049	-0.066	-0.066	-0.094	-0.157	-0.113	-0.321	-0.072	-0.044	-0.161	-0.057	-0.032	-0.057
15	-0.049	-0.063	-0.015	0.011	0.037	-0.045	-0.045	-0.045	-0.010	-0.010	-0.007	-0.025	-0.082	-0.041	-0.580	0.003	0.007	-0.005	0.002	-0.005
16	-0.168	-0.090	-0.063	-0.008	-0.063	-0.056	-0.056	-0.056	-0.012	-0.012	-0.217	-0.217	-0.217	-0.217	-0.050	-0.509	0.223	-0.008	-0.048	-0.008
17	0.004	0.081	0.136	0.524	0.136	0.197	0.047	0.128	0.050	0.050	0.051	0.051	0.051	0.051	0.052	-0.007	-1.467	-0.169	0.126	0.130
18	0.004	-0.008	0.032	-0.373	0.032	0.068	0.030	0.091	0.123	0.055	0.062	0.062	0.062	0.062	0.043	0.053	-0.394	-1.059	0.008	0.039
19	-0.004	-0.009	-0.015	-0.133	-0.015	-0.142	-0.071	0.091	-0.011	-0.011	-0.008	-0.008	-0.008	-0.008	0.023	0.000	0.184	-0.032	-0.368	0.043
20	0.004	-0.008	0.032	-0.795	0.032	0.073	-0.133	-0.361	0.055	0.055	0.062	0.062	0.062	0.062	0.043	0.053	0.483	-0.288	-0.023	-0.836

Source: (8,16)

(B) Standard errors

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.026	0.019	0.023	0.020	0.021	0.019	0.019	0.019	0.018	0.018	0.029	0.028	0.025	0.011	0.014	0.008	0.019	0.015	0.015	0.015
2	0.022	0.048	0.025	0.021	0.023	0.021	0.021	0.021	0.020	0.020	0.033	0.033	0.027	0.010	0.014	0.005	0.012	0.009	0.009	0.009
3	0.129	0.015	0.039	0.017	0.017	0.016	0.016	0.016	0.015	0.015	0.023	0.022	0.020	0.008	0.011	0.006	0.007	0.012	0.011	0.012
4	0.034	0.032	0.039	0.073	0.045	0.034	0.029	0.038	0.028	0.028	0.051	0.053	0.044	0.016	0.026	0.004	0.054	0.041	0.018	0.031
5	0.026	0.025	0.030	0.026	0.075	0.024	0.024	0.024	0.023	0.023	0.040	0.037	0.033	0.012	0.019	0.006	0.007	0.012	0.011	0.012
6	0.012	0.013	0.015	0.047	0.013	0.094	0.056	0.089	0.017	0.017	0.019	0.016	0.015	0.007	0.008	0.006	0.071	0.061	0.028	0.046
7	0.012	0.013	0.015	0.037	0.013	0.061	0.074	0.075	0.017	0.017	0.019	0.016	0.015	0.007	0.008	0.006	0.056	0.045	0.023	0.036
8	0.012	0.013	0.015	0.030	0.013	0.047	0.037	0.067	0.017	0.017	0.019	0.016	0.015	0.007	0.008	0.006	0.052	0.038	0.019	0.030
9	0.012	0.013	0.015	0.014	0.013	0.017	0.017	0.017	0.044	0.017	0.019	0.016	0.015	0.007	0.008	0.006	0.015	0.012	0.011	0.012
10	0.012	0.013	0.015	0.014	0.013	0.017	0.017	0.017	0.017	0.057	0.019	0.016	0.015	0.007	0.008	0.006	0.015	0.012	0.011	0.012
11	0.024	0.021	0.010	0.022	0.024	0.022	0.022	0.022	0.021	0.021	0.043	0.032	0.028	0.011	0.015	0.007	0.017	0.013	0.012	0.013
12	0.036	0.034	0.041	0.033	0.039	0.034	0.034	0.034	0.034	0.034	0.056	0.065	0.046	0.014	0.023	0.007	0.017	0.013	0.012	0.013
13	0.007	0.010	0.010	0.013	0.010	0.121	0.121	0.121	0.008	0.008	0.206	0.208	0.138	0.052	0.083	0.007	0.017	0.013	0.012	0.013
14	0.029	0.033	0.036	0.037	0.037	0.025	0.025	0.025	0.024	0.024	0.046	0.049	0.043	0.068	0.034	0.007	0.017	0.013	0.012	0.013
15	0.028	0.026	0.032	0.030	0.031	0.022	0.022	0.022	0.022	0.022	0.041	0.040	0.036	0.017	0.055	0.003	0.007	0.007	0.005	0.007
16	0.008	0.011	0.011	0.014	0.011	0.011	0.011	0.011	0.008	0.008	0.011	0.011	0.011	0.011	0.009	0.055	0.019	0.014	0.014	0.014
17	0.005	0.007	0.007	0.029	0.007	0.016	0.012	0.022	0.005	0.005	0.006	0.006	0.006	0.006	0.006	0.005	0.112	0.030	0.014	0.024
18	0.004	0.006	0.006	0.041	0.006	0.024	0.016	0.029	0.004	0.004	0.006	0.006	0.006	0.006	0.005	0.004	0.058	0.058	0.020	0.034
19	0.004	0.005	0.005	0.098	0.005	0.060	0.040	0.073	0.004	0.004	0.006	0.006	0.006	0.006	0.004	0.004	0.137	0.108	0.066	0.082
20	0.004	0.006	0.006	0.073	0.054	0.043	0.030	0.054	0.004	0.004	0.006	0.006	0.006	0.006	0.005	0.004	0.105	0.082	0.035	0.084

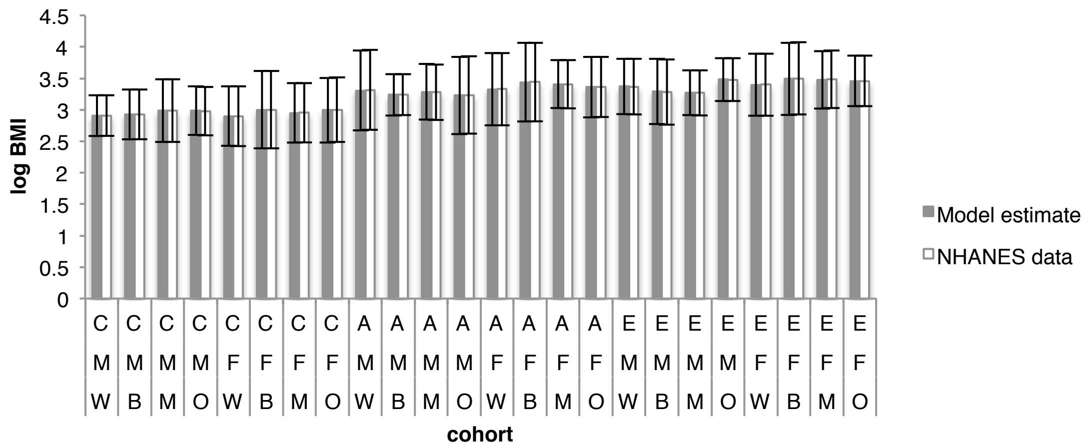
Source: (8,16)

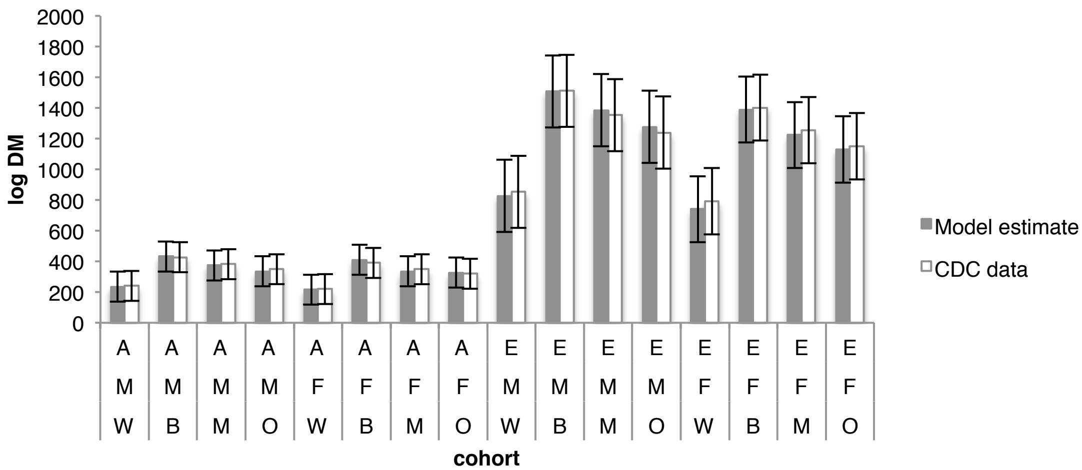
6.5 Appendix Exhibit 6: Body mass index and diabetes incidence rate estimates

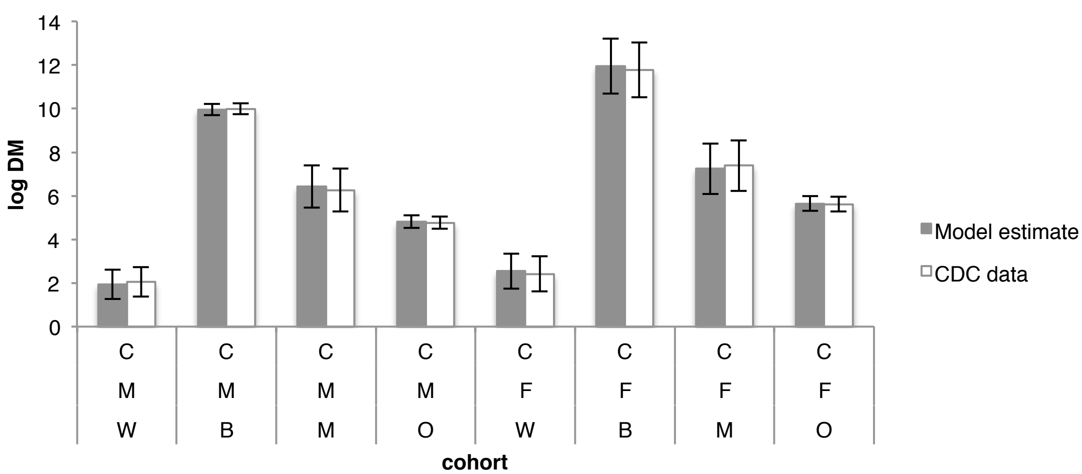
Demographic cohort			Ln BMI (kg/m^2)		Diabetes (/100,000/yr)	
Age	Gender	Race	(Mean)	(SD)	(Mean)	(SD)
5 to <18	M	White	2.91	0.16	2.05	0.35
5 to <18	M	Black	2.93	0.20	9.99	3.50
5 to <18	M	Mexican	2.99	0.26	6.26	15.73
5 to <18	M	Other	2.98	0.20	4.77	2.89
5 to <18	F	White	2.90	0.24	2.42	0.41
5 to <18	F	Black	3.00	0.31	11.78	1.71
5 to <18	F	Mexican	2.95	0.24	7.38	1.57
5 to <18	F	Other	3.00	0.26	5.62	0.46
18 to <45	M	White	3.31	0.32	240.98	50.00
18 to <45	M	Black	3.24	0.17	426.89	50.00
18 to <45	M	Mexican	3.28	0.23	382.13	50.00
18 to <45	M	Other	3.24	0.31	350.00	50.00
18 to <45	F	White	3.33	0.29	220.33	50.00
18 to <45	F	Black	3.44	0.32	390.30	50.00
18 to <45	F	Mexican	3.40	0.19	349.38	50.00
18 to <45	F	Other	3.37	0.25	320.00	50.00
45 to 65	M	White	3.37	0.23	853.77	120.00
45 to 65	M	Black	3.28	0.26	1512.39	120.00
45 to 65	M	Mexican	3.27	0.18	1353.84	120.00
45 to 65	M	Other	3.48	0.18	1240.00	120.00
45 to 65	F	White	3.40	0.25	791.80	110.00
45 to 65	F	Black	3.50	0.29	1402.62	110.00
45 to 65	F	Mexican	3.49	0.23	1255.57	110.00
45 to 65	F	Other	3.46	0.21	1150.00	110.00

Source: (8,46,48). SD: standard deviation

6.6 Appendix Exhibit 7: External validation







Cohort labels: First letter: 5-18 (C); 18-45 (A); or 45-65 year olds (E) Second letter: Male (M) or Female (F). Third letter: White (W), Black (B), Mexican-American (M), or Other (O). Source: (8,48)

6.7 Appendix Exhibit 8: Sensitivity to key parameters

Mean partial rank correlation coefficient (PRCC) indicating degree of sensitivity of kcal/person/day consumption change to variation in key parameters across their uncertainty ranges.

Parameter	PRCC
SNAP participation rate	0.063
Own-intake elasticity for intervened food item	0.114
Cross-intake elasticity between intervened food item and others	0.036
Marginal propensity to consume	0.045
Estimated change in weight attributable to changes in total calorie intake	-0.001
Change in diabetes risk given a change in consumption	0.010

Source: authors

6.8 Appendix Exhibit 9: Detailed outcomes by demographic cohort for each simulated policy

(A) SSB ban

Demographic cohort			Change in kcal/person/day		Change in glycemic load (g/person/day)		Reduction in obesity prevalence (%)		Reduction in type 2 diabetes incidence (%)	
Age	Gender	Race	(Mean)	(SD)	(Mean)	(SD)	(Mean)	(SD)	(Mean)	(SD)
5 to <18	M	White	-8.72	1.17	-2.09	0.14	0.01%	0.07%	0.14%	1.41%
5 to <18	M	Black	-7.79	1.20	-1.87	0.14	0.54%	0.08%	0.17%	0.01%
5 to <18	M	Mexican	-8.68	1.45	-2.08	0.18	0.56%	0.07%	0.96%	0.04%
5 to <18	M	Other	-8.01	1.12	-1.92	0.13	0.29%	0.08%	0.34%	0.07%
5 to <18	F	White	-10.23	1.38	-2.45	0.16	0.61%	0.06%	1.21%	0.04%
5 to <18	F	Black	-7.00	1.06	-1.68	0.13	0.62%	0.07%	0.57%	0.02%
5 to <18	F	Mexican	-6.04	1.23	-1.45	0.16	0.04%	0.07%	0.15%	0.23%
5 to <18	F	Other	-7.93	1.22	-1.90	0.15	0.60%	0.09%	0.49%	0.04%
18 to <45	M	White	-13.58	1.72	-3.26	0.20	0.18%	0.13%	1.62%	1.03%
18 to <45	M	Black	-12.84	1.70	-3.08	0.20	0.22%	0.11%	1.21%	0.50%
18 to <45	M	Mexican	-17.34	1.72	-4.16	0.18	0.45%	0.37%	2.20%	1.72%
18 to <45	M	Other	-15.83	2.10	-3.80	0.24	2.34%	0.23%	4.37%	0.15%
18 to <45	F	White	-13.87	1.77	-3.32	0.20	0.57%	0.10%	2.19%	0.25%
18 to <45	F	Black	-11.34	1.52	-2.72	0.18	2.35%	1.19%	2.44%	1.07%
18 to <45	F	Mexican	-13.08	1.47	-3.14	0.16	1.66%	0.15%	2.72%	0.11%
18 to <45	F	Other	-12.12	1.40	-2.91	0.16	1.62%	0.44%	2.62%	0.57%
45 to 65	M	White	-14.54	1.62	-3.49	0.18	3.24%	0.16%	3.60%	-0.01%
45 to 65	M	Black	-14.90	1.60	-3.57	0.17	0.35%	0.14%	1.97%	0.70%
45 to 65	M	Mexican	-16.55	1.65	-3.97	0.17	0.08%	0.17%	1.46%	2.94%
45 to 65	M	Other	-12.84	1.36	-3.08	0.15	1.85%	0.24%	3.15%	0.26%
45 to 65	F	White	-10.93	1.67	-2.62	0.20	0.75%	0.83%	1.39%	1.43%
45 to 65	F	Black	-10.08	1.58	-2.42	0.19	0.55%	0.38%	1.34%	0.84%
45 to 65	F	Mexican	-11.88	1.20	-2.85	0.13	0.99%	0.30%	2.19%	0.58%
45 to 65	F	Other	-10.08	1.28	-2.42	0.15	0.76%	0.33%	1.54%	0.57%

Source: authors

(B) Fruit/vegetable subsidy. No significant change in type 2 diabetes incidence was observed.

Demographic cohort			Change in kcal/person/day		Change in glycemic load (g/person/day)		Reduction in obesity prevalence (%)		Reduction in type 2 diabetes incidence (%)	
Age	Gender	Race	(Mean)	(SD)	(Mean)	(SD)	(Mean)	(SD)	(Mean)	(SD)
5 to <18	M	White	4.57	1.50	0.19	0.04	0.00%	0.03%	0.00%	0.00%
5 to <18	M	Black	1.18	1.55	-0.28	0.05	-0.08%	0.09%	0.02%	0.02%
5 to <18	M	Mexican	-3.59	1.63	-0.79	0.05	0.23%	0.03%	0.46%	0.09%
5 to <18	M	Other	4.08	1.49	0.14	0.04	-0.15%	0.05%	0.00%	0.00%
5 to <18	F	White	2.84	1.70	0.10	0.06	-0.17%	0.05%	0.00%	0.00%
5 to <18	F	Black	-0.93	1.58	-0.41	0.05	0.08%	0.03%	0.03%	0.01%
5 to <18	F	Mexican	1.26	1.63	-0.08	0.05	-0.01%	0.05%	0.01%	0.03%
5 to <18	F	Other	1.76	1.71	-0.14	0.06	-0.13%	0.19%	0.01%	0.02%
18 to <45	M	White	3.39	1.94	0.04	0.07	-0.05%	0.05%	0.00%	0.00%
18 to <45	M	Black	9.38	1.45	0.41	0.04	-0.16%	0.06%	0.00%	0.00%
18 to <45	M	Mexican	-0.55	1.57	-0.27	0.05	0.01%	0.10%	0.10%	0.74%
18 to <45	M	Other	4.29	1.53	0.34	0.05	-0.64%	0.06%	0.00%	0.00%
18 to <45	F	White	4.92	1.99	0.23	0.08	-0.20%	0.10%	0.00%	0.00%
18 to <45	F	Black	0.98	1.87	-0.21	0.07	-0.20%	0.06%	0.08%	0.05%
18 to <45	F	Mexican	-3.43	1.83	-0.55	0.06	0.43%	0.10%	0.64%	0.22%
18 to <45	F	Other	-0.56	2.29	-0.18	0.09	0.07%	0.14%	0.07%	0.16%
45 to 65	M	White	1.61	1.78	-0.06	0.06	-0.36%	0.11%	0.02%	0.03%
45 to 65	M	Black	-2.23	1.50	-0.35	0.04	0.05%	0.09%	0.16%	0.30%
45 to 65	M	Mexican	10.18	1.61	0.55	0.05	-0.05%	0.14%	0.00%	0.00%
45 to 65	M	Other	-1.26	1.61	-0.62	0.05	0.18%	0.13%	0.52%	0.42%
45 to 65	F	White	4.24	1.63	0.19	0.05	-0.29%	0.06%	0.00%	0.00%
45 to 65	F	Black	2.51	1.77	-0.01	0.06	-0.14%	0.09%	0.00%	0.03%
45 to 65	F	Mexican	-0.21	1.44	-0.21	0.04	0.02%	0.07%	0.08%	0.34%
45 to 65	F	Other	-0.31	1.57	-0.41	0.05	0.02%	0.13%	0.30%	1.67%

Note: negative reductions in obesity and type 2 diabetes specify a net increase (perversity), but are non-significant at the $p<0.05$ level as discussed in the main text, given the standard deviations displayed.
Source: authors

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