SUPPLEMENTAL MATERIAL

Cost-effectiveness of the U.S. FDA Added Sugar Labeling Policy for Improving Diet and Health.

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SUPPLEMENTAL TEXT 1. THE U.S. SUGAR POLICY MODEL

HIGH-LEVEL DESCRIPTION OF THE U.S. SUGAR POLICY MODEL

The U.S. Sugar Policy model* is a discrete time dynamic stochastic microsimulation model.[1,2] Within the U.S. Sugar Policy model each unit is a synthetic individual and is represented by a record containing a unique identifier and a set of associated attributes.

For this study, we considered age, sex, race/ethnicity†, education‡, income§, energy-adjusted added sugar intake, and body mass index (BMI). A set of stochastic rules is then applied to these individuals, such as the probability of developing coronary heart disease (CHD) or dying, as the simulation advances in discrete annual steps. The output is an estimate of the burden of CHD, stroke, and type 2 diabetes mellitus (T2DM) in the synthetic population including both total aggregate change and, more importantly, the distributional nature of the change.

The U.S. Sugar Policy model is a complex model that simulates the life course of synthetic individuals and consists of four modules: The 'population' module, the 'disease' module, the 'health economics' module, and the 'policy' module. We will fully describe the U.S. Sugar Policy model by describing the processes in each of the modules in the following chapters. The description is from an epidemiological rather than technical perspective. Main Figure 1 shows the modeled pathway through which the policy effect is translated into changes in disease burden, and Main Figure 2 depicts the model structure. Supplemental Table 1 and Supplemental Table 2 summarize the sources of the input parameters and the main assumptions and limitations, respectively.

Technical information

The US Sugar Policy model is being developed in R v3.4.0[3] and is currently deployed in a 40-core workstation with 192Gb of RAM running Ubuntu v16.4 server edition. The U.S. Sugar Policy model is built around the R package 'data.table',[4] which imports a new heavily optimized data structure in R. Most functions that operate on a data table have been coded in C to improve performance. Each iteration for each scenario is running independently in one of the CPU cores, and the R package 'foreach'[5] is responsible for the distribution of the jobs and collection of the results. To ensure the statistical independence of the pseudo-random number generators running in parallel, the R package 'doRNG'[6] was used to produce independent random streams of numbers, generated by L'Ecuyer's combined multiple-recursive generator.[7]

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* This is an extension of the U.S. IMPACT Food policy model. To avoid confusion with previous versions of the model, in this document we will refer to it as 'U.S. Sugar Policy' model.

† Hispanics / non-Hispanic whites / non-Hispanic blacks / other

‡ Less than 9th grade / 9-11th grade (Includes 12th grade with no diploma) / high school graduate/GED or equivalent / some college or AA degree / College graduate or above

§ Based on ratio of family income to poverty: <1.25 / 1.25 – 2 / 2 – 4 / 4+

POPULATION MODULE

Synthetic individuals enter the simulation in the initial year (2014 for this study). The number of synthetic individuals that enter the simulation is user-defined and for this study was set to 100,000. The algorithm ensures that the age, sex, and race/ethnicity distribution of the sample is as this of the U.S. population in mid-2014. The exposures to sugar and BMI are being calculated annually (in simulation time) for each synthetic individual until the simulation horizon is reached, or death occurs.

Estimating exposure to risk factors

The U.S. Sugar Policy model estimates the exposure of the synthetic individual to the modeled risk factors. It is essential the risk profile of each synthetic individual to be similar to the risk profiles that can be observed in the real U.S. population. For this, we first built a 'close to reality' synthetic population of U.S. from which we sampled the synthetic individuals. Then, we used generalized linear models (GLM) for added sugar intake and BMI, to simulate individualized risk factor trajectories for all synthetic individuals.

Generating the 'close to reality' synthetic population for the U.S. Sugar Policy model

The 'close to reality' synthetic population ensures that the sample of synthetic individuals for the simulation is drawn from a synthetic population similar to the real one regarding age, sex, race/ethnicity, and risk factors conditional distributions. In our implementation, we used the same statistical framework originally developed by Alfons *et al*.,[8] and we adapted it to make it compatible with epidemiological principles and frameworks.

In general, this method uses a nationally representative survey of the real population to generate a 'close to reality' synthetic population. Therefore, the method expands the, often small, sample of the survey into a significantly larger synthetic population, while preserves the statistical properties and important correlations of the original survey.

The main advantages over other approaches are: 1) it accounts for the hierarchical structure of the sample design of the original survey, and 2) it can generate trait combinations which were not present in the original survey but are likely to exist in the real population. The second is particularly important because it avoids bias from the excessive repetition of combinations of traits present in the original survey that results from multilevel stratification of a relatively small sample. For example, the original survey may have two 35-year-old man participants, one with BMI of 25 kg/m^2 and the other with a BMI of 30 kg/m2 and no other 35-year-old man participants with BMI between

these two values. Unlike other methodologies, the approach proposed by Alfons *et al.*[8] can produce 35-year-old man synthetic individuals with a BMI between 25 kg/m^2 and 30 kg/m^2. This is possible because the synthetic population is produced by drawing from conditional distributions that were estimated from multinomial models fitted in the original National Health and Nutrition Examination Survey (NHANES) data. The detailed statistical framework and justification can be found elsewhere.[9]

All the variables of the synthetic population for this study were informed by the National Health and Nutrition Examination Survey (NHANES) 2011–2014[10] and the appropriate weights[11] from the survey were used. The R language for statistical computing v3.4.0 and the R package 'simPop' v0.6.0 were used to implement the method.[3,12] For this study we first generated the demographic variables of the synthetic individuals (age, sex, race/ethnicity). Then, conditional on the demographic variables we generated the educational level variable. We generated income level conditional on the demographic and educational level variables. Finally, we generated added sugar intakes conditional on age, sex, race/ethnicity, and education, and BMI conditional on added sugar intake and the demographic variables.

The outcome of the method was to create a synthetic population of 50 million with similar characteristics to the non-institutionalized U.S. population in 2011–2014. We validated the synthetic population against the original NHANES 2011-2014 sample (internal validation). We present the validation results below, starting from page 28.

Estimating added sugar intakes

As mentioned above, added sugar intakes were estimated using nationally representative data from multiple NHANES cycles (2011-2014), accounting for complex survey design and sampling weights. Consistent with our prior work,[13,14] and to best approximate usual intake we used the average of two standardized 24-hour dietary recalls. Estimated intakes were then adjusted for energy intake using the residual method[15] to further minimize measurement error and account for potential non-dietary differences, such as body size, metabolic efficiency and physical activity. Additionally, we considered intakes from packaged foods only, e.g., excluding intakes from sources such as restaurants and sugar added by consumers using the 'source of food' variable in NHANES. In our microsimulation analysis we used the full exposure distribution rather than just the mean and standard deviation (SD) for the overall population or subpopulations. The population mean intake would be valid and unbiased, while the two tails of the distribution might be underestimated or overestimated.

In order to incorporate distinct trends in intakes and to apply different etiologic effects, we estimated added sugars from sugar-sweetened beverages (SSBs) and other foods separately. SSBs were defined as beverages containing at least 5 g of added sugar per 12 oz. (e.g., soft drinks, sports

and energy drinks, fruit drinks, and sweetened tea and coffee), consistent with certain local and state SSB tax bills that have been proposed or implemented in the U.S.[16] Milk, 100% juice, diet beverages, infant formula and alcoholic beverages were excluded. To estimate added sugar intake from non-SSB sources, we first calculated individuals' total added sugar intake by merging individual food files from NHANES 2011 – 2014 with the USDA Food Patterns Equivalents Database (FPED) 2011 - 2014.[17] FPED converts the foods and beverages in NHANES to major food groups, including intake of added sugar. We then calculated added sugar intake from non-SSB sources by deducting SSB intake from the total added sugar intake. Throughout the simulation these two exposures* were modeled separately.

Potential compensatory dietary behaviors

Because the evidence for changes in consumption comes from studies which largely assessed short- to medium-term changes in intakes, it is plausible that consumption elsewhere may change. Thus, the issue of dietary complements and substitutes was considered and discussed at length during our study design. Briefly, our estimated etiologic effects of how the changes in SSBs/added sugars influence BMI (and then subsequent risk) are not based simply on the observed caloric decrease, which would lead to a large estimated reduction in BMI. Rather, these etiologic effects are based on long-term observational studies where changes in SSBs over many years are related to changes in BMI over many years – such an analysis implicitly incorporates changes in dietary substitutes and complements over time. For example, these etiologic effects estimate that a decline in SSBs from 7 servings/week to 0 servings/week would lead to an average weight change of 0.45 kg over 4 years – a FAR smaller effect than the estimated direct caloric effect, which would lead to a predicted weight change of 3.78 kg over a year (based on the 3,500 kcal per pound simple weight loss rule, commonly used)[18] or 0.66 kg over one year (based on more recent modeled estimates).[19,20]

Implementation of individualized risk factor trajectories

The U.S. Sugar Policy model only applies the previous process for the initial year of the simulation (2014 for this study). As the simulation evolves, sugar intake and BMI are recalculated to take into account age and period effects. This feature justifies the classification of the U.S. Sugar Policy model as a dynamic microsimulation. It uses the continuous NHANES series to capture the time trends by age, sex, and race/ethnicity and project them into the future.

Demographic and socioeconomic variables

* For simplicity, throughout the supplement below we use the term 'sugars' to describe energy-adjusted added sugars from packaged products and we differentiate into SSB and non SSB sugars when necessary.

As the simulation progress in annual cycles, the age of the synthetic individuals in the model increase by one year in each loop. Their sex and socioeconomic variables remain stable. Therefore, social mobility is not simulated in the current version of the U.S. Sugar Policy model. Every simulated year, a new cohort of 30-year old synthetic individuals enter the simulation. The size of the cohort and the sex and race/ethnicity distribution of the synthetic individuals are informed by the published U.S. population projections.[21] The educational and income variables are directly standardized based on the initial 30-year old cohort and conditional on sex and race/ethnicity.

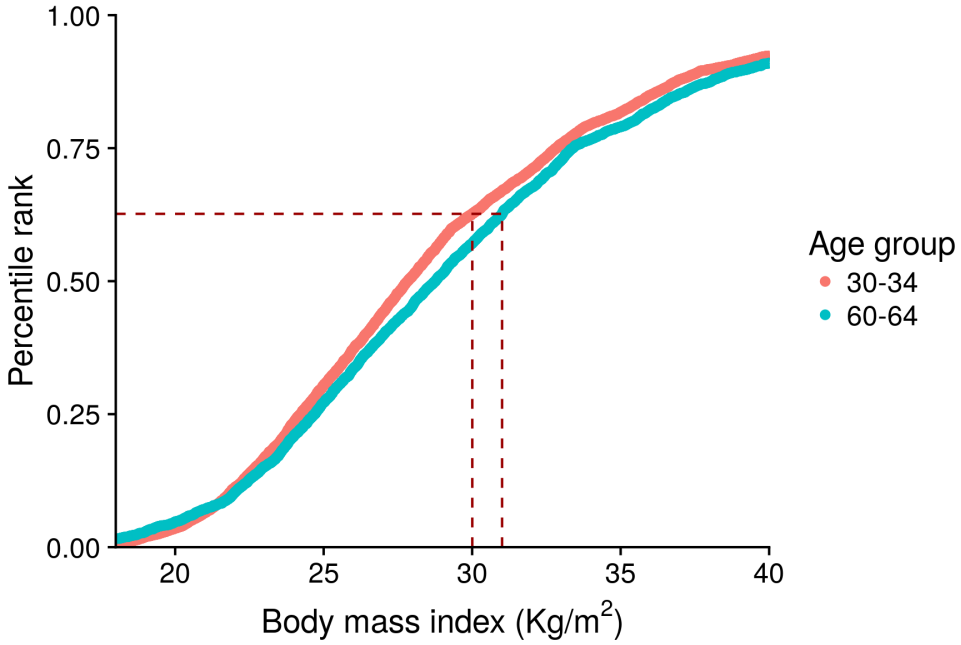
Continuous variables

In the U.S. Sugar Policy model, the value of each continuous risk factor (sugar, BMI) is calculated in a two-step process for each synthetic individual and each projected year. The first step simulates aging effects, while the second step simulates period effects. We follow this approach mainly for two reasons. Firstly, to simulate physiological mechanisms of aging. Secondly, because the variance of the risk factor distributions increases with age, and we wanted to model this. Below we describe the steps:

Step 1: Instead of tracking the actual continuous risk factor values for the synthetic individuals, we track the percentile ranks* of the values by age, sex and race/ethnicity. These percentile ranks remain fixed for each synthetic individual throughout the simulation. In each simulated year, the percentile ranks are converted back to actual risk factor values, by matching the percentile ranks of a sample of the initial synthetic population of same age group, sex, and race/ethnicity.

For example, in 2014 a 30-year-old non-Hispanic black man synthetic individual with BMI of 30 Kg/m^2 has a BMI percentile rank of 0.626. Thirty years later, the same synthetic individual has retained his percentile score for BMI. However, his BMI is now calculated to 31 Kg/m^2 to match the BMI of a 60-year old non-Hispanic black man in 2014 with the same percentile rank of 0.626. Supplemental Figure 1 illustrates the previous example. Although individuals retain their percentile for the respective risk factor throughout the simulation (vertical position in Supplemental Figure 1), this step remains stochastic because each time this step is implemented a different sample from the synthetic population is drawn. Finally, the distance from the mean for each risk factor is calculated stratified by 5-year age group, sex, and race/ethnicity. For instance, if a synthetic individual has BMI of 35 Kg/m^2 and the mean BMI in the respective group of same age group, sex and race/ethnicity is 30 Kg/m^2, the distance from the mean is 35 – 30 = 5 Kg/m^2.

* For the percentile rank the formula $R_{percentile} = (R-1)/(n-1)$ is used, where $R_{percentile}$ is the percentile rank and $R = (R_1, \dots, R_n)$ is the rank vector constructed from a random observation vector $(X_1, \dots, X_n)$. In this model specifically, vector X is constructed from the subset of the respective continuous risk factor values, by 5-year age group, sex and race/ethnicity, for each year of the simulation.



Supplemental Figure 1. Plot of the percentile rank against the body mass index of non-Hispanic black man synthetic individuals for age groups 30–34 and 60–64.

Step 2: We fitted regression models to the continuous NHANES data, for years 2004 to 2014 using the R package 'survey' that respects the complex sampling design of NHANES and adjust the variance of the regression models accordingly.[10,22,23] For sugar, we fitted separate GLM models for SSB and non-SSB sugars. The independent variables were year, age, sex, and race/ethnicity including significant quadratic and cubic terms and first order interactions based on Akaike's information criterion (AIC). For BMI, we followed a similar approach, with the addition of sugar intake in the independent variables. For all models, we used a logarithmic link function; therefore, we assumed logarithmic declining time trends for both sugar and BMI. These models are used to predict the mean of the relevant group. These predicted means are added then, to the distances calculated in the previous step. The result is the final value of the relevant risk factor that will be used for risk estimation.

Lag times

All the functions that have been described above for risk factor trajectories include time and age (in years) as one of the independent variables. Therefore, lag times can be potentially calculated on a per risk factor basis. When the 'disease' module of the U.S. Sugar Policy model, uses the exposure to

BMI to estimate the risk of a synthetic individual to develop CVD in a specific simulated year, the lag-timed exposure is used. Although changes in added sugar intake could influence BMI within weeks to months,[24,25] we assumed a median 1-year time lag from change in sugar intake to BMI and a median 1-year time lag from change in BMI to change in disease risk.

DISEASE MODULE

The risk (probability) for each synthetic individual aged 30–84, to develop each of the modeled diseases is estimated conditional on previous relevant exposures. For every simulated year, the model selects synthetic individuals to develop T2DM, CHD and stroke based on their risk. Finally, the risk of dying from CVD or any other cause is estimated and applied. Due to different data availability for T2DM and CVD, we model the two diseases differently.

Estimating the annual individualized disease risk and incidence of T2DM

To estimate the individualized annual probability of a synthetic individual to develop T2DM, the model first calculates the prevalence of T2DM conditional on age, sex, race/ethnicity, and BMI. Then, it estimates the incidence conditional on the same variables, considering the increased overall mortality of diabetics.

In detail, we first fitted a logistic regression model in NHANES data, for years 1999 to 2014[10] to predict T2DM prevalence (diagnosed and undiagnosed) from age, sex, race/ethnicity, and BMI.[*] The U.S. Sugar Policy model uses this, to estimate the future prevalence of T2DM taking into account population aging and BMI trends. Then, from T2DM prevalence it calculates annual T2DM incidence assuming it is an incurable disease while accounting for the increased mortality of diabetics. Hence, the model calculates for each non-diabetic individual in the synthetic population the probability of developing T2DM. Then it uses this probability in an independent Bernoulli trial to select those who finally develop the disease.

Finally, the model applies a similar approach to differentiate diagnosed from undiagnosed T2DM cases. For this, we fitted a logistic regression model to NHANES data to calculate the probability of a T2DM case to be diagnosed using age and sex as predictors. U.S. Sugar Policy model then uses an independent Bernoulli trial to select the diagnosed T2DM cases.

Estimating the annual individualized disease risk and incidence of CHD and stroke

To estimate the individualized annual probability of a synthetic individual to develop CHD or stroke conditional on his/her relevant risk exposures we follow a 3-step approach. Next, the implementation of the method is described in more detail using CHD as an example. The same process is used for both CHD and stroke.

[*] Due to the cross-sectional nature of the data the effect of BMI on T2DM prevalence may be underestimated, because of reverse causality bias. This is likely to underestimate the effect of the policy on T2DM incidence.

Step 1

The population attributable risk (PAF) is an epidemiological measure that estimates the proportion of the disease attributable to an associated risk factor.[26] It depends on the relative risk associated with the risk factor and the prevalence of the risk factor in the population. In a microsimulation context where exposure to risk factors are known to the individual level and assuming multiplicative risk factors PAF can be calculated with the formula:

$$PAF = 1 - \frac{n}{\sum_{i=1}^{n}(RR_1 * RR_2 * \ldots * RR_k)} \ ,$$

where n is the number of synthetic individuals in the population, and $RR_{1\ldots k}$ is the relative risks of the risk factors associated with CHD. We calculated PAF based on above formula stratified by age, sex, and race/ethnicity only in the initial year of the simulation. Consistent with findings from the respective meta-analyses that were used for the U.S. Sugar Policy model (Supplemental Table 1), BMI below 17 Kg/m^2, was assumed to have a relative risk of 1. All the relative risks were taken from published meta-analyses (Supplemental Table 3).

Step 2

The formula below can estimate the incidence of CHD not attributable to the modeled risk factors:

$$I_{Not\ attributable} = I_{Observed} * (1 - PAF)$$

Where $I_{Observed}$ is the CHD incidence and PAF is from Step 1. $I_{Not\ attributable}$ represents CHD incidence if all the modeled risk factors were at optimal levels. The not attributable incidence is calculated by year, age, sex, and race/ethnicity.

To account for future time trend in CHD incidence that is not attributable to the modeled risk factors (in this study BMI, T2DM, and SSB sugars[*]), the model updates $I_{Observed}$ every simulated year. For this we assume that half of the forecasted annual change in CHD mortality is attributed to changes in CHD incidence and the other half to changes in CHD case fatality. We based this assumption on observational evidence from England, and modeling studies in the England and the U.S.[27-30] Furthermore, we included this assumption in our probabilistic sensitivity analysis.

Step 3

Assuming that $I_{Not\ attributable}$ is the baseline annual probability of a synthetic individual to develop CHD for a given age, sex, and race/ethnicity due to risk factors not included in the model, the

[*] SSB sugars was assumed to be a direct (e.g., not BMI-mediated) risk factor only for CHD and stroke, based on existing evidence (Supplemental Table 3).

individualized annual probability to develop CHD, $\mathbb{P}(\text{CHD} \mid \text{age, sex, race/ethnicity, exposures})$, given his/her risk factors were estimated by the formula:

$$\mathbb{P}(CHD \mid age, sex, \text{race/ethnicity}, exposures) = I_{Not\ attributable} * RR_1 * RR_2 * RR_3 * \ldots * RR_k$$

Where $RR_{1 \ldots k}$ the relative risks that are related to the specific risk exposures of the synthetic individual, same as in step 1.

Estimating CHD and stroke incidence at initial simulation year

It is evident that for the method above, disease incidence ($I_{Observed}$) in the population, need to be known, at least for the initial year of the simulation. However, the true incidence of CHD (and stroke) in the U.S., is largely unknown. Several estimates exist nonetheless all have limitations, and the same applies to incidence trends.[31,32] Therefore, for the estimation of CHD and stroke incidence by age, sex, and race/ethnicity we opted for a modeling solution to synthesize all the available nationally representative sources of information and to minimize bias. Specifically, we used CHD mortality (ICD10 I20–I25) for U.S. in 2014,[33] self-reported prevalence of CHD from NHANES 2013-2014,[10] and the 1-year risk of CHD for the NHANES 2013-2014 participants using the Framingham equation[34] to inform the WHO DisMod II model.[35] DisMod II is a multi-state life table model that can estimate the incidence, prevalence, mortality, case fatality and remission of a disease when information about at least three of these variables is available. A similar approach has been followed by the Global Burden of Disease team and others.[36,37] We considered CHD an incurable chronic disease (i.e. remission rate was set to 0); therefore, the derived DisMod II incidence refers to the first ever episode of CHD excluding any recurrent episodes. For the DisMod II calculations, we assumed that incidence and case-fatality rates had been declining by 2% (relative), over the last 20 years. We used the derived CHD incidence rates by age, sex, and race/ethnicity to inform the U.S. Sugar Policy model. We used the same approach for stroke.

Estimating CHD and stroke prevalence at initial simulation year

For the initial year of the simulation, some synthetic individuals need to be allocated as prevalent cases for each of the modeled diseases. We used DisMod II model estimates for prevalence of CHD and stroke by age, sex, and race/ethnicity. At the beginning of each simulation, the estimated number of prevalent cases are sampled independently from the synthetic individuals in the population with weights proportional to their exposures.

Simulating mortality

All synthetic individuals are exposed to the risk of dying from any of their acquired modeled diseases or any other non-modeled cause in a competing risk framework. The U.S. Sugar Policy model is calibrated to observed CHD, stroke, and any-other-cause mortality for years 2014–2015[30] and mortality forecasts for years 2016–2037. For years after 2015, coherent functional demographic models by sex and race/ethnicity were fitted to the reported CHD, stroke, and any-other-cause mortality rates from years 1999 to 2015,[33] and then were projected to the simulation horizon using the R package 'demography'.[38] Functional demographic models are generalizations of the Lee-Carter demographic model, influenced by ideas from functional data analysis and non-parametric smoothing.[39] The coherent approach ensures that subgroup forecasts do not diverge over time.[40] Finally, we used the observed and forecasted mortality rates to create life tables for each simulated year, by age, sex, race/ethnicity, and disease (CHD, stroke, any-other-cause). We applied the any-other-cause life tables to all synthetic individuals, and the CHD and stroke life tables to prevalent cases of CHD and stroke only, respectively. For the synthetic individual that died of more than one causes in a specific year, a cause was randomly selected to minimize bias.

Individuals with T2DM have a higher risk to die not only of CHD and stroke but from a spectrum of other diseases also.[41] Failure to model this would result in biased estimates in the health economics module because it would inflate the costs and disutility from T2DM, inappropriately. To account for this and minimize bias the U.S. Sugar Policy model inflates the any-other-cause mortality rates for synthetic individuals with T2DM in the model while it deflates it for non-diabetics. Hence, the algorithm ensures the total number of diabetics and non-diabetics synthetic individuals that die every year from any-other-cause is equal to the defined one in the life table. The algorithm is based on PAF approach, and the relative risk was derived from an individual level meta-analysis by Stringhini *et al*.[41]

HEALTH ECONOMICS MODULE

In the previous two modules, the U.S. Sugar Policy model creates synthetic individuals with traits similar to those observed in the U.S. population and tracks their future exposures to sugars and BMI, and important events (first manifestation of CHD / stroke / T2DM, death from CHD, stroke, or any other cause).

Health state utilities

We calculated the health state utility values (preference weights) using published censored least absolute deviations regression equations which used EQ-5D-3L data from the Medical Expenditure Panel Survey (MEPS) 2000-2002 for all major chronic conditions in the U.S., including CHD, stroke, and T2DM.[42] The equation uses the main condition, number of coexisting chronic conditions, age, sex, race, ethnicity, income, and education to estimate the health state utilities of the synthetic individuals every simulated year. We found that the most influential parameter in this equation was the number of coexisting chronic conditions, far exceeding its sampling error. Hence, we ignored the sampling error of this equation, and we calibrated the distribution of the number of coexisting chronic conditions in the synthetic population to the distribution reported by Sullivan *et al*.[35] We further modeled the number of coexisting chronic conditions to increase with age.

Disease costs

The U.S. Sugar Policy model applies CHD, stroke, and T2DM costs to cases of these diseases, during the simulation. These costs are mean estimates by age, sex, and race/ethnicity.

Disease costs per person-year were derived from a report of projections of CVD costs, prepared for the American Heart Association (AHA) by RTI International which was based on MEPS data.[43] The AHA report assumed that price increases and new technologies would produce a 2.45% increase in medical costs, above the impact of inflation, demographic change, and disease severity. We assumed an equal annual increase in medical costs. Medical costs per person-year for CHD and stroke were calculated by dividing total medical costs by the number of people with each condition in 2015 and disaggregated by the ratio of the point of service (physician, hospital, prescription, home health, nursing home, and other). The AHA paper included the ratio of medical costs at the point of service for each disease group; the point of service was grouped into physician, hospital, prescription, home health, nursing home, and other.

Productivity costs of morbidity and mortality for CHD and stroke (including workplace productivity and leisure time) were from the same analysis by RTI International and were converted to costs per person-year. For CHD and stroke, we applied morbidity costs to prevalent cases of CHD and stroke,

respectively; we applied mortality costs only to deaths from CHD and stroke. We assumed that productivity costs would increase by 1.29%, annually. Informal care costs for stroke were from a study by Joo *et al*.,[44] while informal care costs for CHD were based on the ratio of healthcare to informal care costs in Europe from a study by Leal *et al*.[45]

Diagnosed T2DM* costs (healthcare, morbidity) by age and sex were drawn from a paper by the American Diabetes Association (2013) which estimated diabetes costs by age and sex for the U.S. for 2012.[46] Costs for undiagnosed diabetes were drawn from Dall *et al.* which used the same methodology as the American Diabetes Association paper.[47] This paper only reported total non-medical costs; hence, we assumed that the ratio of morbidity to mortality related costs was the same in each age group for undiagnosed T2DM as for diagnosed T2DM. These costs were inflated to 2017 dollars using the Consumer Price Index (CPI).

Dieleman *et al.* estimated costs for many diseases in the U.S. for 2013.[48] The CVD costs in Dieleman *et al.* are generally similar to the AHA commissioned CVD costs estimates but the diabetes costs are much lower than the American Diabetes Association estimates despite only being one year apart ($176bn vs $101bn). The main difference is inpatient care ($9.6bn in Dieleman *et al.* vs $76bn American Diabetes Association). This may be due to how comorbidities like chronic kidney disease are attributed. We decided to use the American Diabetes Association estimates rather than Dieleman *et al.* for consistency, as the former included indirect costs as well as healthcare costs.

We assumed that any changes in diabetes outside of inflation were driven by changes in prevalence and age and gender structure of the population with diabetes. Dieleman *et al*. estimated the annual increase in diabetes costs in the U.S. from 1996-2013 was 6.1% above inflation (which means diabetes costs roughly double every ten years). This means that costs in 2013 were 2.58 times costs in 1996, however, diagnosed prevalence in 2013 was 2.92 times prevalence in 1996 so the cost increases are mainly driven by prevalence, and the model accounts for prevalence[49] and changes in the age structure of the diabetes population.

Informal care costs for age 70 and over were drawn from a study by Langa *et al* which found excess informal care costs of $1,700 p.a. in 1998 dollars (based on a person taking insulin compared to a person without diabetes).[50]

* The diabetes costs we have used are for type 1 and type 2 diabetes mellitus. The modeled policies will only prevent T2DM, but we do not have disaggregated costs, and only around 4% of diabetes cases in the U.S. are type 1.

Policy costs

The policy costs of FDA's added sugar labe include:

1. Government costs to administer and monitor the policy
2. Industry compliance cost
3. Industry reformulation cost (if companies choose to reformulate to lower sugar content in their products)

Government costs to administer and monitor the policy

To estimate the administrative costs for added sugar labeling, we reviewed FDA's budget reports and acquired cost data from a different FDA labeling policy. In 2012, the FDA requested $8,808,000 to administer the new restaurant menu and vending machine labeling regulation, including cost for outreach, education, review of regulatory issues, developing training for inspectors, etc.[51] Given that the scope of government activities for overseeing these two programs similar, we assumed that the rollout of the added sugar labeling policy would similarly cost $8,808,000 (inflated to $9,436,507 in 2017 dollars using CPI. We additionally assumed a $500,000 annual cost to monitor industry compliance, and evaluate the accuracy, usefulness and health impact of the new Nutrition Facts Labels. This amount was estimated based on the Nutrition Review Project report,[52] an internal FDA report that provided recommendations to improve FDA's nutrition activities and costs for such improvements. Given no range of uncertainty was provided in source materials, we assumed 20% uncertainty around these costs.

Industry compliance cost

The food manufacturing industry bears the cost to comply with the policy, such as cost to determine added sugar content in products and cost to redesign and reprint the labels. The best source to estimate industry compliance cost is FDA's Regulatory Impact Analysis (RIA),[53] which provides a breakdown of different types of costs. A challenge with using this source is that added sugar labeling is only one of many provisions in FDA's rule to update the Nutrition Facts label; other provisions included changes to daily values, adjustments to nutrients that are required or permitted to be labeled, and improvements to the visual design. The RIA additionally included industry cost to comply with FDA's new Serving Size rule, as manufacturers are likely to go through a one-time process to meet all the provisions in both of FDA's new rules on labeling. Since we are only modeling the health impact of the added sugar labeling provision, we have two options to use the industry cost provided in the RIA:

1. Attribute all or a high fraction of the industry cost to the added sugar labeling provision (suppose we think that mandating this provision is the key motivation for FDA to issue the new rules)
2. Attribute a low fraction (suppose that without the added sugar provision, FDA still could have issued the new rules, yet industry cost to comply would only be slightly lower)

Both approaches seem equally justifiable, so we attributed half of the total industry cost to the added sugar labeling provision, for the purpose of this manuscript. Using this method, we estimated that the one-time industry compliance costs for the added sugar labeling policy is $1,720,208,204 (UI: $786,395,724, $2,547,091,628), in 2017 USD. These costs were assumed to occur in year 1.

Industry costs to reformulate products

FDA's RIA assumed that 7.5 to 9% of the sugary product formulas would reformulate as a result of FDA's added sugar labeling policy and estimated the one-time costs of such reformulation.[53] Inflated to 2017 dollars, these costs equaled $683,100,180, (UI: $307,291,266, $1,267,576,474). We conservatively assumed the same costs would occur annually, while reformulation activities continued. As we assumed 1-year time lag between policy implementation and reformulation, and that reformulation would stop after year 5, we only included these costs in the model starting year 2, lasting 4 years until year 5.

FDA estimated industry reformulation costs using a reformulation cost model[54] developed by the Research Triangle Institute (RTI). RTI's reformulation model accounted for variations in product formula complexity, company size, reformulation type, compliance period and other factors, thereby producing a more accurate cost estimate compared to a standard per-product cost approach.

POLICY MODULE

So far, the description of the U.S. Sugar Policy model was for the base-case scenario. The policy module translates the policy scenarios to be modeled by the U.S. Sugar Policy model. Main Figure 2 depicts the logic of the model, and Main Figure 1 shows the modeled pathway through which the policy effect is translated into changes in disease burden. Then, the effect of a change in non SSB sugar intake is fully mediated through changes in BMI to changes in the risk for CHD, stroke, and T2DM. For SSB sugars we assumed an independent effect on CHD and T2DM risk, in addition to the effect mediated through BMI as with non SSB sugars. The model uses the updated disease risks to simulate new life courses for all synthetic individuals under the modeled policies. The structure of the causal pathway is based on current evidence.[14] When the simulation ends, the model compares all alternative life courses with the base-case scenario for each synthetic individual and calculates the outputs (page 25). Supplemental Figure 3 depicts the median added sugar intake under the baseline and the two policy scenarios. Supplemental Figure 4 depicts the CVD and T2DM cases and deaths prevented and postponed over 20 years for the two policy scenarios. Supplemental Table 3 summarizes the relative risks that we used.

Policy scenarios

In the *sugar* scenario, we assumed that added sugar intake would decrease by 6.8% (95% CI: 4.5-9.0%)[*] based on a recent meta-analysis of labeling interventions.[55] In the *sugar + reformulation* scenario, we additionally applied an 8.25% reduction in added sugar intake from the reformulation effect. The 8.25% reduction is calculated based on the following steps and assumptions:

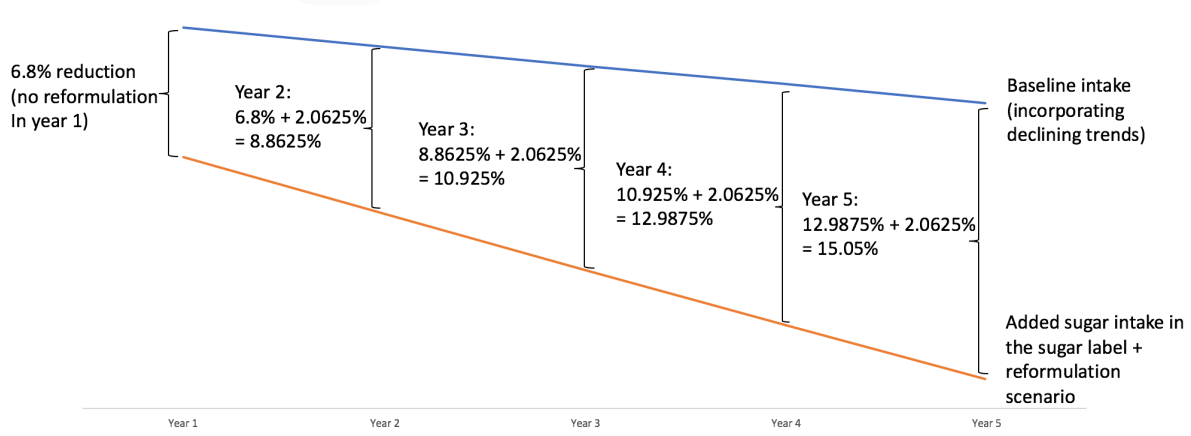
1) Based on FDA's own Regulatory Impact Analysis which reported that 7.5% to 9% of sugar-containing products would reformulate,[53] we assumed that an average of 8.25% (median based on 7.5% - 9%) of sugar-containing products would be reformulated as a result of FDA's labelling policy.
2) For these products, we assumed that they would achieve a 25% reduction in added sugar content each year as a result of the reformulation. Thus, in each year the reduction in added sugar among sugar-containing products would be 8.25% * 25% = 2.0625%. For a total of 4 years, the net reduction in added sugar content, and subsequently of intake, would be 2.0625%*4= 8.25%. This effect was applied to the model in addition to the 6.8% reduction in added sugar intake due to the FDA's labeling policy. The estimated total net reduction of 8.25% as a result of

[*] The estimate we used, 6.8% (95% CI: 4.5%-9.0%), was an earlier estimate based on 30 studies. The final published estimate, 6.6% (95% CI: 4.4%-8.8%), was based on 31 studies and is nearly identical to the one used.

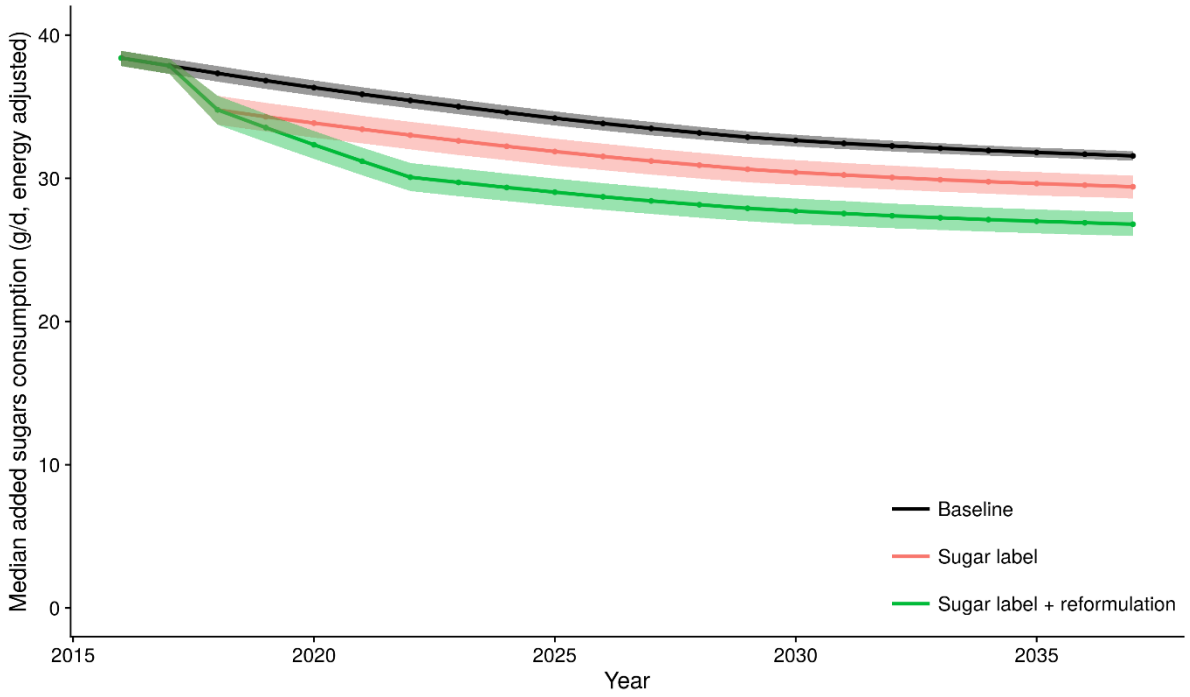
the industry reformulation is more conservative than the 5-year sugar reformulation plan in the UK.[56]

3) We modelled reformulation in years 2 – 5 of the intervention. We assumed a one year time lag between reformulation implementation and change in added sugar intake. We did not model reformulation after year 5, as we assumed that continued industry reaction to a one-time policy change would not last throughout the entire analytic period of 20 years. For example, a study that evaluated the reformulation effect of trans-fat labeling found that reduction in trans-fat significantly slowed after year 4 of the policy.[57]

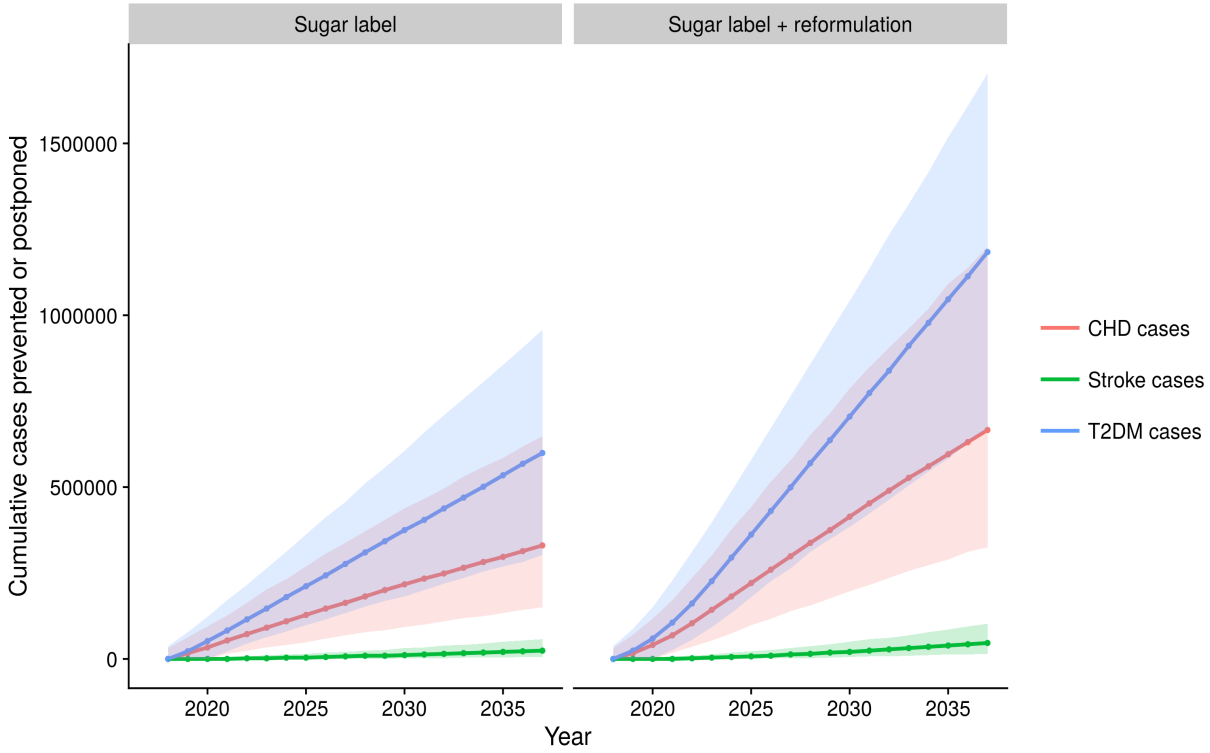
We demonstrate the above calculations in the figure below.



Supplemental Figure 2. Illustration for modeling reduction in sugar content through industry reformulation. Net reduction between year 5 and year 1 is 8.25%.



Supplemental Figure 3. Projected median U.S. added sugar intakes (from packaged foods) among U.S. adults age 30 – 84 years under 'usual care' scenario and two modeled labeling policy scenarios. Intakes were adjusted for energy intake using the residual method to minimize measurement error and account for potential non-dietary differences, such as body size, metabolic efficiency and physical activity.



Supplemental Figure 4. Projected CVD and T2DM cases and deaths prevented and postponed from 2018 – 2037 for two modelled FDA added sugar labeling policy scenarios

UNCERTAINTY AND SENSITIVITY ANALYSIS

The U.S. Sugar Policy model implements a 2nd order Monte Carlo approach to estimate uncertainty intervals (UI) for each scenario.[58,59] Each simulation, which includes all policy scenarios, runs 2000 times. For each iteration, a different set of input parameters is used by sampling from the respective distributions* of input parameters, and a different sample of 100,000 synthetic individuals is drawn from the synthetic population of 50 million. Then, the life course† of every synthetic individual is simulated for the baseline, and all policy scenarios and the outcomes are collected and summarized for the population. For instance, if a synthetic individual developed CHD at the age of 50 in the base-case scenario and the age of 60 in a policy scenario, this is counted as a CHD case postponed, as a result of the policy. Therefore, all model outputs (cases and deaths prevented or postponed, net utility, net costs, etc. described on page 25) are separately estimated for each iteration, and conditional on the set of model inputs.

The framework allows stochastic uncertainty, parameter uncertainty, and individual heterogeneity to be reflected in the reported UI. The following example illustrates the different types of uncertainty that were considered in the U.S. Sugar Policy model. Let us assume that the annual risk of CHD is 5%. If we apply this risk to all individuals and randomly draw from a Bernoulli distribution with p = 5% to select those who will manifest CHD, we only consider stochastic uncertainty. If we allow the annual risk for CHD to be conditional on individual characteristics (i.e. age, sex, exposure to risk factors), then individual heterogeneity is considered. Finally, when the uncertainty of the relative risks due to sampling errors is considered in the estimation of the annual risk for CHD, the parameter uncertainty is considered. From these three types of uncertainty, only the parameter uncertainty can be reduced from better studies in the future.

The structure of the model is grounded on fundamental epidemiological ideas and well-established causal pathways; therefore, we considered this type of uncertainty relatively small and did not study it. However, the discrete-time nature of the model can potentially introduce bias in cases where the synthetic individual dies more than once within a year, and the model cannot identify which event happened first. As we describe on page 15, to minimize this type of bias we randomly select one of

* We assumed log-normal distributions for relative risks and hazard ratios, normal distributions for coefficients of regression equations, generalized beta of the second kind for costs, and PERT distributions for other parameters. The cost sources, except industry reformulation costs, did not include any measures of uncertainty like standard error so an estimate of +/-20% was used for uncertainty analyses, fitted to a generalized beta of the second kind distribution, which can account for the skewness of healthcare costs.[57]

† For this study, life course starts at the age of 30, as it is unlikely that CVD cases and deaths in younger ages can be prevented by sugar intake reduction.

the events to be considered as it happened before all others, whenever these cases arise during the simulation.

Input uncertainty

The sources of uncertainty we considered were:

1. *The sampling error of the baseline sugar intake.* When the model calculates individualized sugar intakes, it takes into account the sampling error of the regression models that were fitted in the NHANES (see page 10) and took into account the the effect of the complex sampling design.
2. *The sampling error of the baseline BMI*. Same as above.
3. *The sampling error of the baseline T2DM prevalence*. Same as above.
4. *The sampling error of all relative risks for exposures*. We used the reported relative risks and their confidence intervals to construct log-normal distributions.
5. *The uncertainty of lag times between exposure and outcome*. We assumed that the mean lag time between a change in sugar intake and change in BMI and disease risks is one year and we used a binomial to vary this between 0 and 3 years. We further assumed that the mean lag time between a change in BMI and change in CVD and T2DM risk is also one year and we varied this between 1 and 3 years.
6. *The uncertainty around the true incidence and prevalence rates of CHD and stroke*. We described on page 14 how we used DisMod II to estimate the incidence rate of CHD and stroke. We fitted beta distributions by age, sex, and race/ethnicity assuming the 0.025 percentile to be half of the central estimate, the median the central estimate, and the 0.975 percentile double the central estimate.
7. *The uncertainty of mortality forecasts*. We incorporated the predictive uncertainty of the mortality forecasts to the U.S. Sugar Policy model estimates.
8. *The uncertainty around the assumption that half of the forecasted annual change in CHD and stroke mortality is attributed to changes in CHD and stroke incidence, respectively.* We allowed this assumption to vary, independently for each disease, between 0% and 100% following a uniform distribution.
9. *The uncertainty around the policy effects.*
10. *The uncertainty around the quality of life decrements used to calculate QALY*. The most influential parameter of the equation was the number of coexisting chronic conditions (see page 16). Therefore, we allowed synthetic individuals to have a different number of coexisting chronic conditions in each Monte Carlo iteration.
11. *The uncertainty of all the costs.* The RTI model that was used to estimate the reformulation costs to the industry reported CI. We used these to fit generalized beta of the second kind distributions. For all other costs in the model, we fitted generalized beta of the second kind

distribution assuming the 0.2 percentile to be 80% of the central estimate, the median the central estimate, and the 0.8 percentile 120% of the central estimate.

Outputs

We summarized the output distributions of the U.S. Sugar Policy by reporting the medians and 95% UI. We also plotted the annual probability that a scenario was cost-effective or cost saving over the simulation period. Supplemental Table 12 presents model estimates for the base-case scenario.

Cases (Deaths) prevented or postponed, by comparing the life course of each specific individual in the base-case scenario with its life course in the policy scenario.

Net utility, by summing the quality-adjusted-life-years (QALY) through the life course of each specific individual in the base-case scenario and comparing it with the sum of QALY in the policy scenario life course.

Net disease costs, by summing the costs through the life course of each specific individual in the base-case scenario and comparing it with the sum of costs in the policy scenario life course.

Policy costs, by summing the administrative costs, monitoring and evaluation costs, and industry reformulation costs.

All outputs can be stratified by year, age, sex, race/ethnicity, and disease. Moreover, outputs are scaled to the U.S. population (from the 100,000 sample of synthetic individuals).

Costs were analyzed regarding incremental cost-effectiveness ratio (the difference in costs divided by the difference in QALY from the base-case scenario) and Net Monetary Benefit (NMB; incremental net costs plus the value of incremental QALY). For NMB, a central value of $100,000 per QALY gained was used based on Neumann *et al*.[61] which was varied from $50,000 to $150,000 in a sensitivity analysis. Costs were also presented in a disaggregated 'impact inventory' in line with 2nd U.S. panel recommendations.

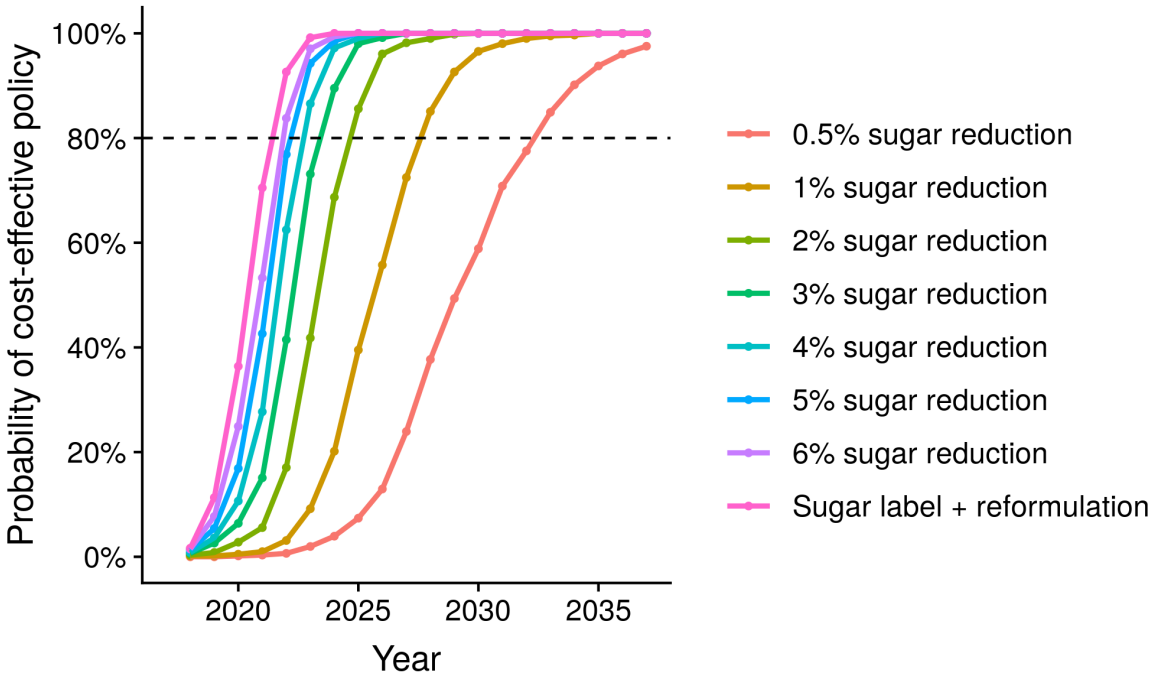
From our experience in communicating our results to policymakers and researchers, we realized that they tend to misinterpret 95% UIs as 95% confidence intervals (CI) and overlapping UIs as 'evidence against statistical significance.' This does not apply to our model outputs because the scenarios share common model inputs as explained above and should be treated as 'paired' from a statistical perspective.

One-way sensitivity analyses

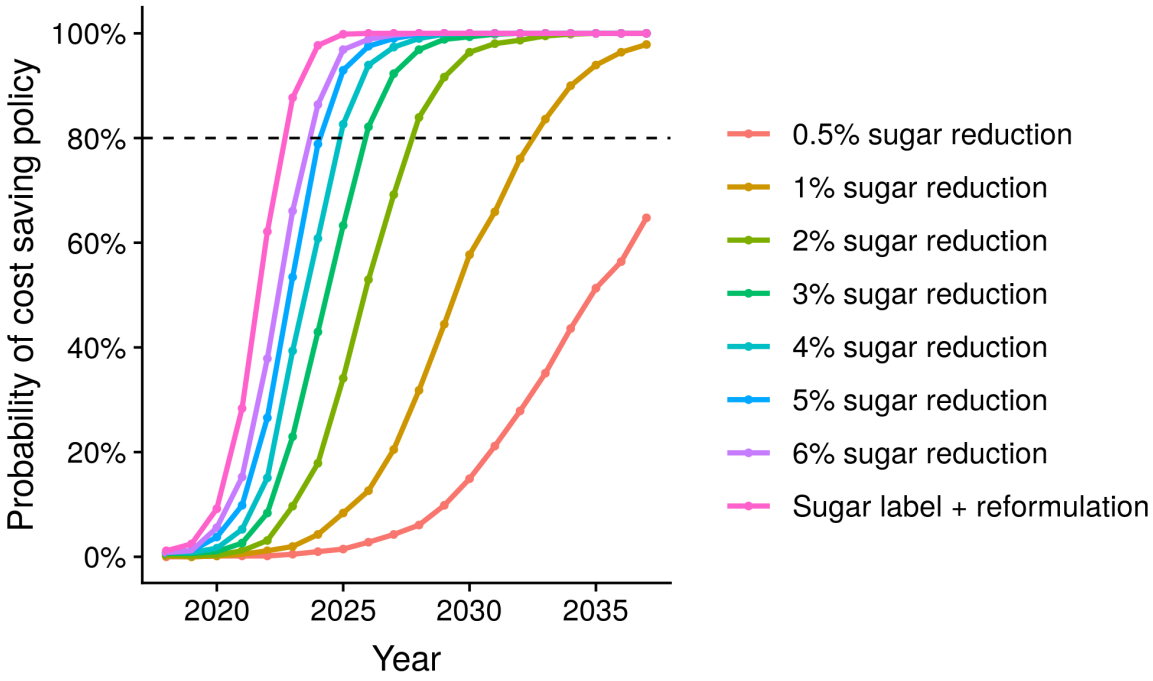
For our main analysis, we assumed 100,000 USD willingness to pay per QALY and 3% annual discount rate. We varied these assumptions in the one-way sensitivity analysis, and we present the results for incremental cost-effectiveness ratio and NMB in Supplemental Table 10 and Supplemental Table 11.

Overall, all policy scenarios remained cost-effective under all combinations of willingness to pay and discount rates.

We performed an additional one-way sensitivity analysis on the potential effect size of the *sugar label+reformulation* scenario. We allowed the effect size to vary in steps between 0.5-6% overall reduction in added sugars intake. Specifically, we modelled scenarios with 0.5%, 1%, 2%, 3%, 4%, 5%, and 6% overall reduction in added sugars intake and we plotted the probability of the scenarios to become cost-effective and cost saving over time. Apart from the effect size, other modelling assumptions were similar to the assumptions for the *sugar label+reformulation* including policy costs, the cost of reformulation to the industry, 100,000 USD willingness-to-pay per QALY, and 3% annual discount rate. For comparison, we plotted on the same graphs the results from our main analysis for the *sugar label+reformulation* scenario (Supplemental Figures 5 and 6).



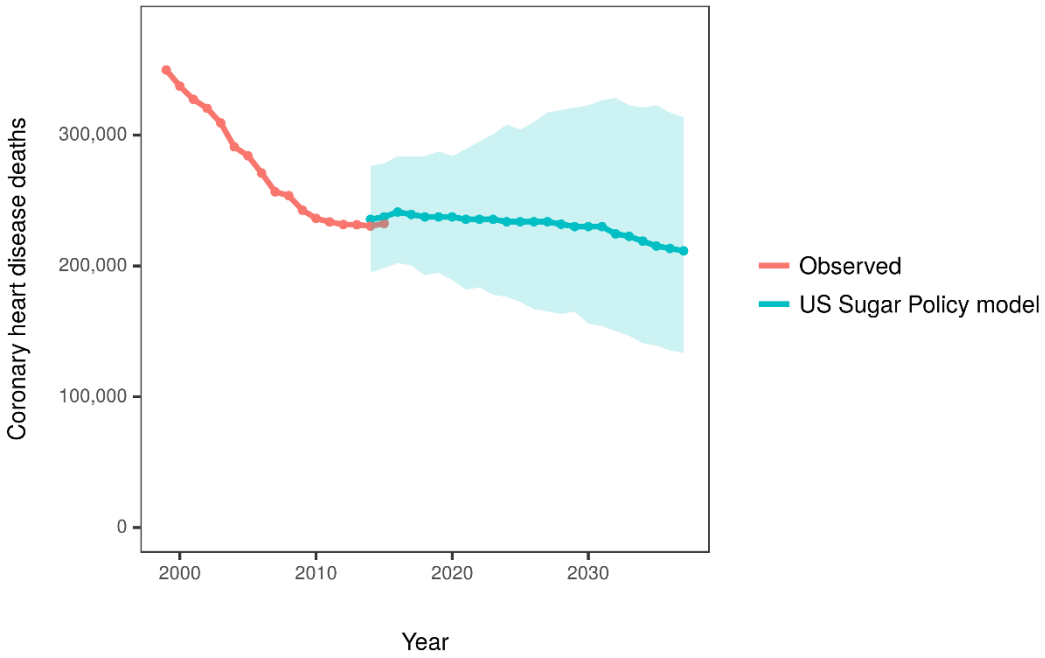
Supplemental Figure 5. One-way sensitivity analysis of the policy effect on the probability of cost-effective policy over time.



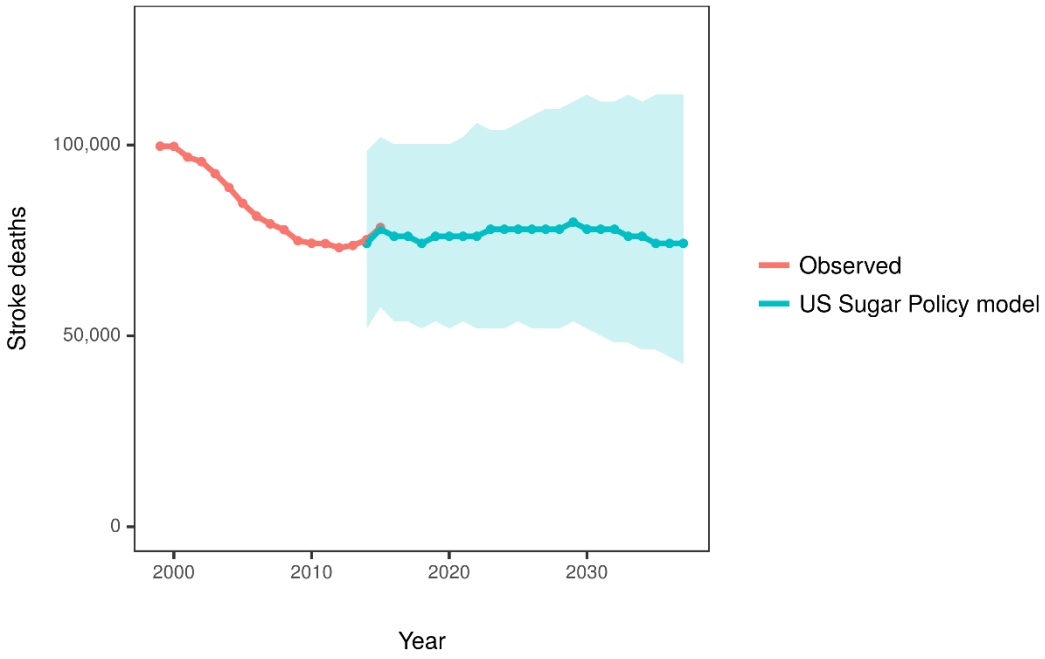
Supplemental Figure 6. One-way sensitivity analysis of the policy effect on the probability of cost-saving policy over time.

CALIBRATION AND VALIDATION

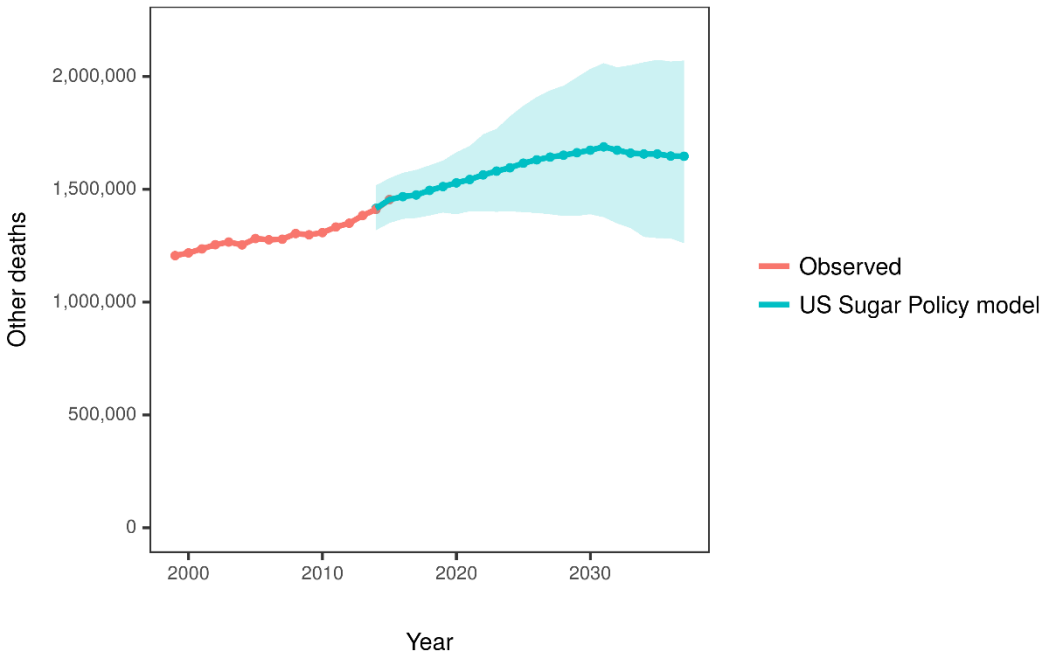
The U.S. Sugar Policy model is calibrated to forecasts of CHD, stroke, and any-other-cause mortality (previously described on page 17). Supplemental Figures 7-9 depict the observed and forecasted mortality that was used for the calibration. We included the uncertainty of the forecasts in our probabilistic uncertainty, and it is propagated in our model estimates.



Supplemental Figure 7. Observed and forecasted coronary heart disease mortality. U.S. population aged 30 to 84. Shaded areas represent 95% prediction intervals.



Supplemental Figure 8. Observed and forecasted stroke mortality. U.S. population age 30 to 84. Shaded areas represent 95% prediction intervals.



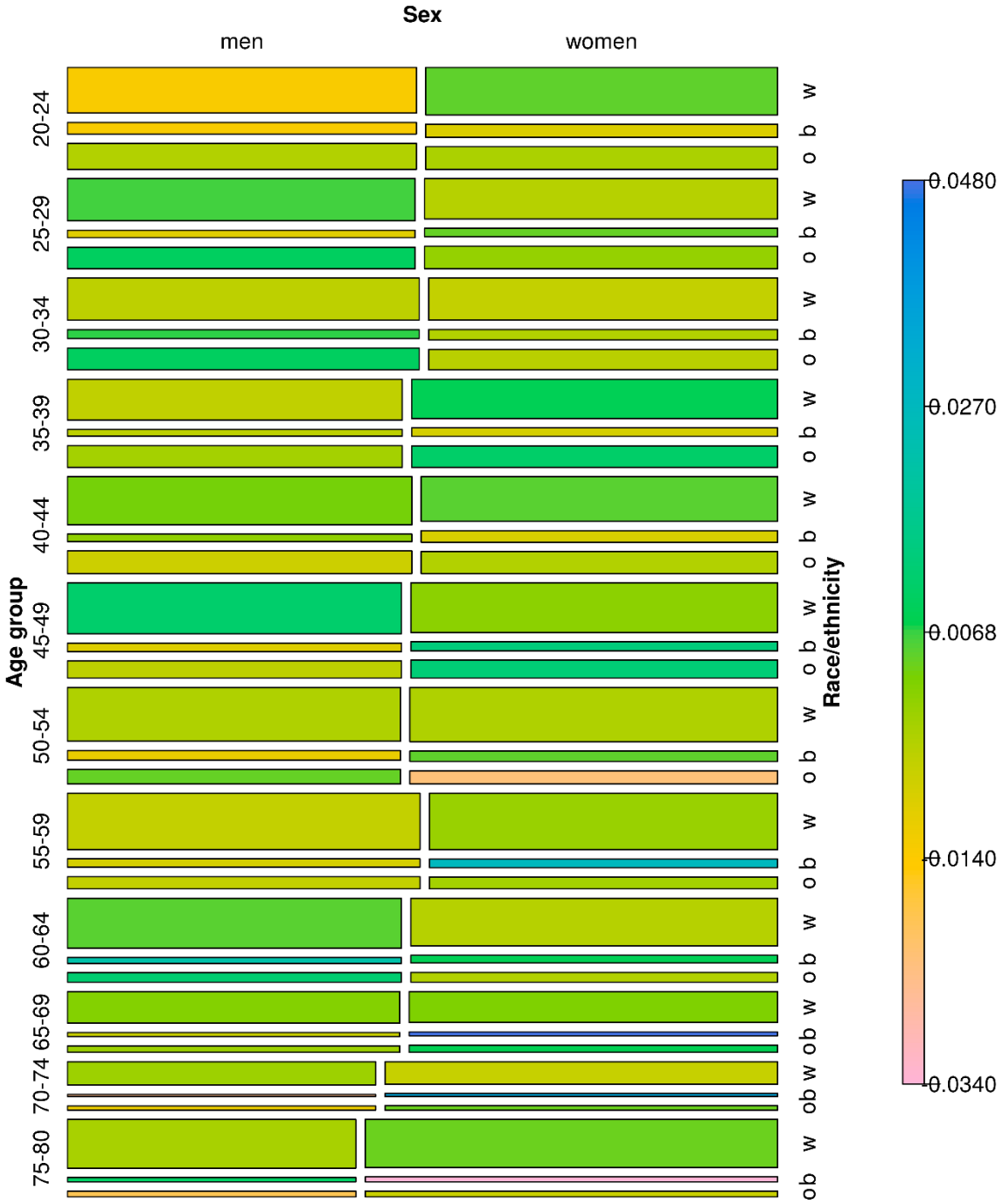
Supplemental Figure 9. Observed and forecasted mortality from any-other-cause (excluding coronary heart disease and strokes). U.S. population aged 30 to 84. Shaded areas represent 95% prediction intervals.

Synthetic population internal validation

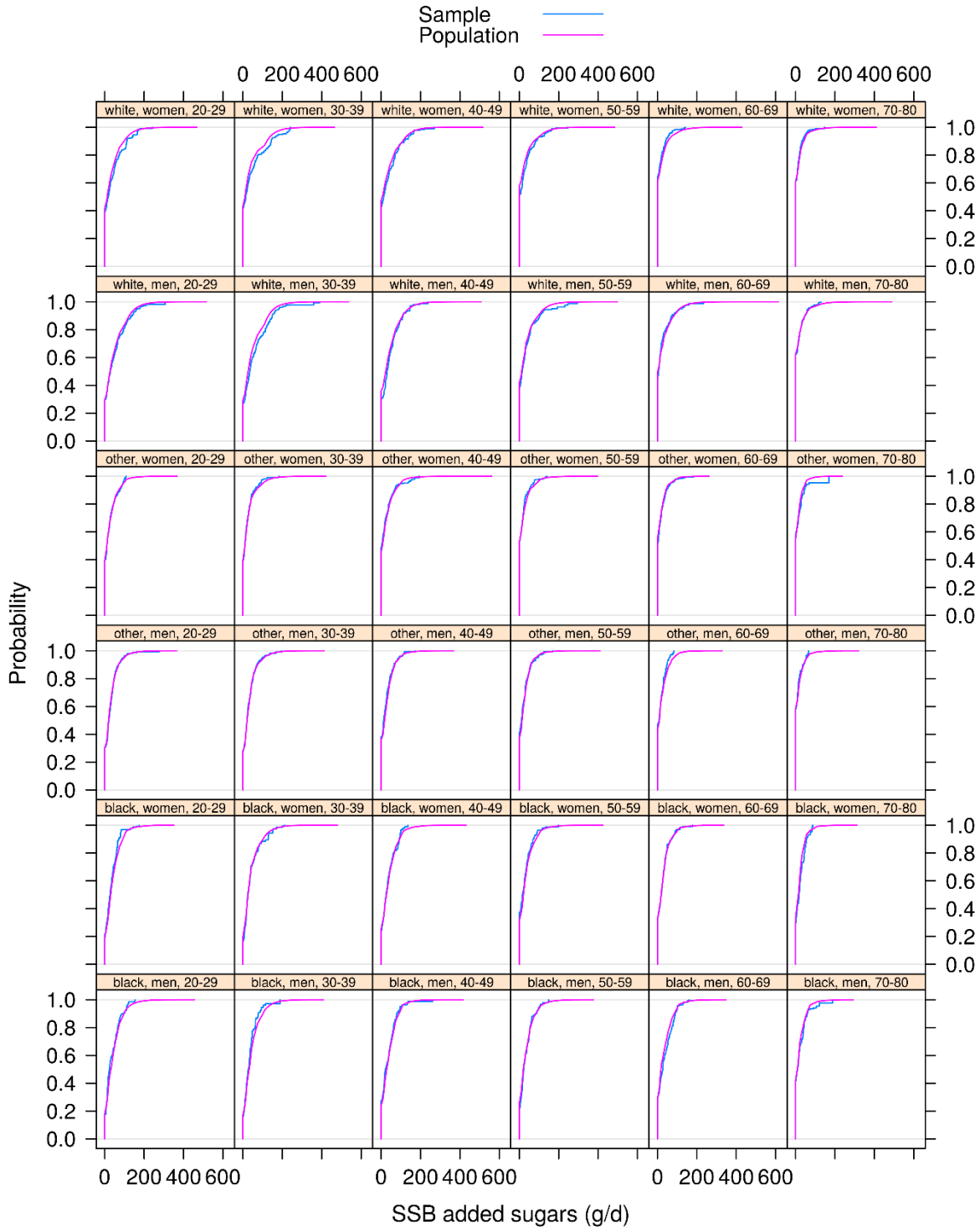
The following graphs compare a random sample of 1 million synthetic individuals from the synthetic population to the original sample of NHANES 2011-2014 (n = 10,907). Mosaic plots* were used for the categorical variables, and cumulative distribution plots were used for the continuous variables. The area of each tile of the mosaic plots is proportional to the proportion of each subgroup in the respective population. The color of each tile represents the relative difference between NHANES and the synthetic population.

The graphs support the argument that the final synthetic population is close to reality, at least as it was captured through the NHANES 2011-2014, and are useful for the internal validation of the method. Alfons *et al*. used a statistical simulation approach to evaluate the process and showed that this method produces synthetic populations very similar to the original survey.[8] Of course, the method cannot overcome any limitations of the original survey, such as selection bias, or misclassification.

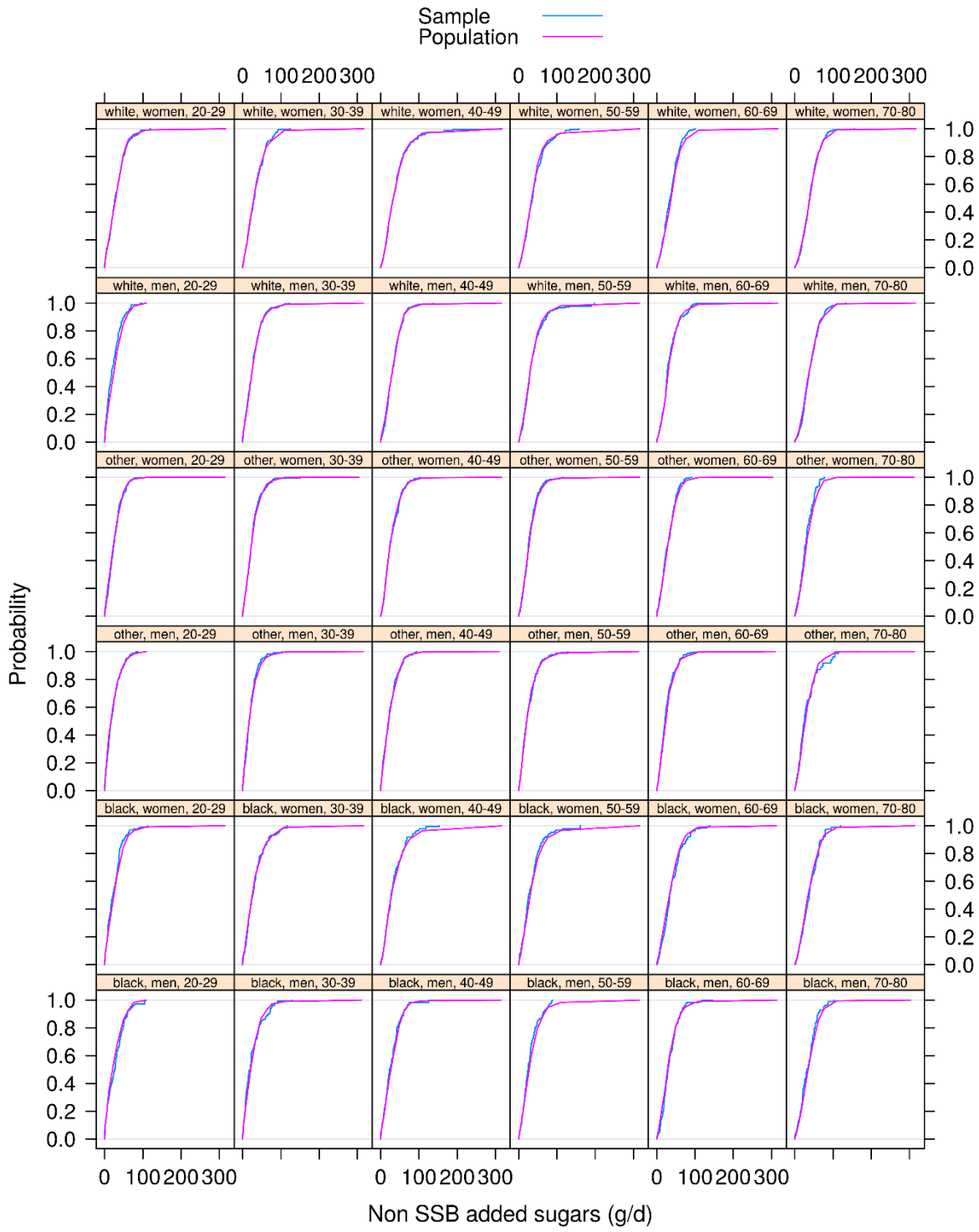
* Mosaic plots are graphical representations of a contingency table of two or more categorical variables, using tiles with areas proportional to the frequencies in each cell of the table.[59]



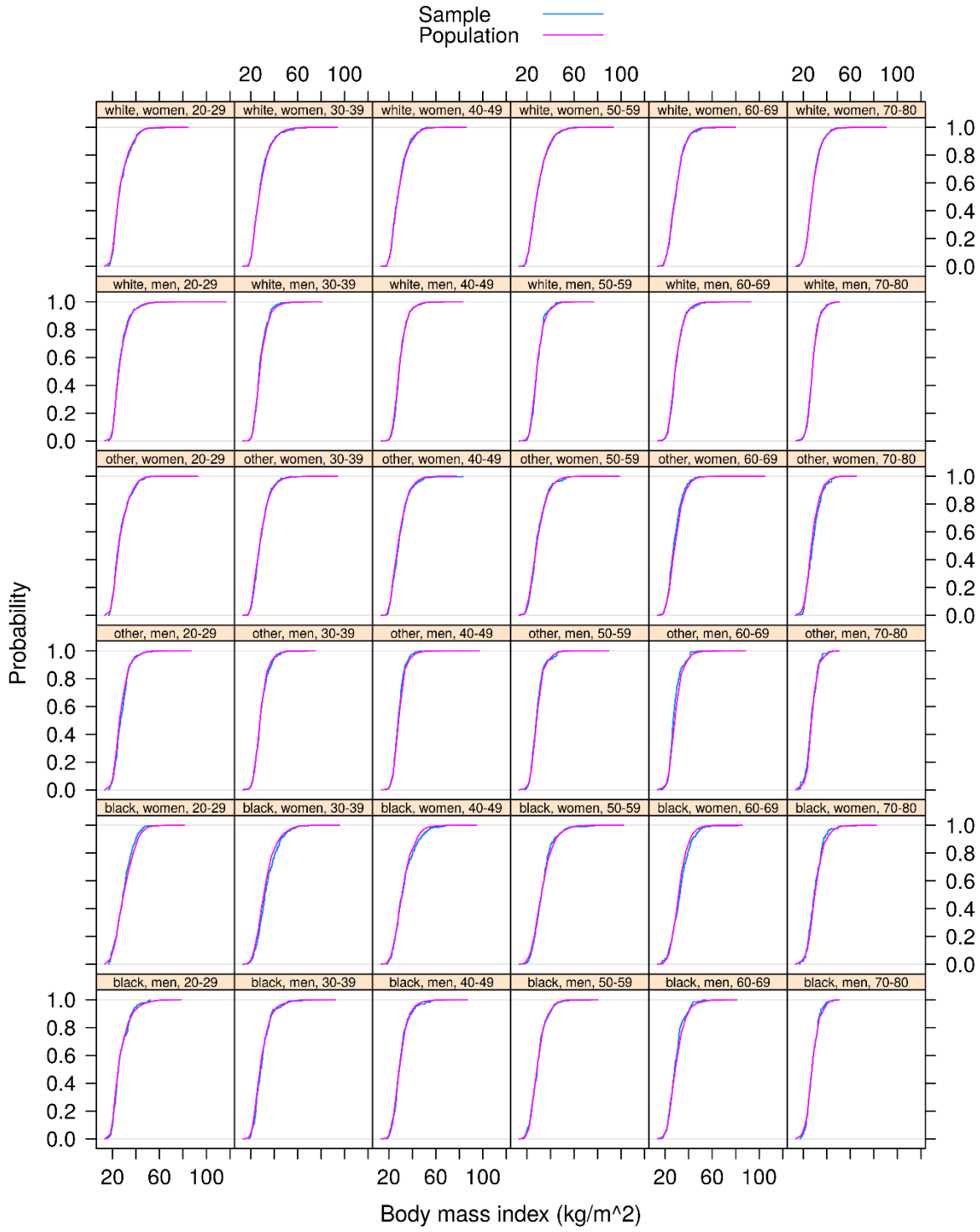
Supplemental Figure 10. Mosaic plot for comparison of age, sex, and race/ethnicity distribution between the synthetic population and the NHANES 2011-2014 sample. Green shades depict relative differences close to 0%, and all subgroups were within a ±5% difference compared to the NHANES sample. For race/ethnicity: b, non-Hispanic black; o, other; w, non-Hispanic white.



Supplemental Figure 11. Empirical cumulative distributions of SSB sugar intake in NHANES 2011-2014 (sample) and the synthetic population (population), by age group, sex, and race/ethnicity.



Supplemental Figure 12. Empirical cumulative distributions of non SSB sugar intake in NHANES 2011-2014 (sample) and the synthetic population (population), by age group, sex, and race/ethnicity.



Supplemental Figure 13. Empirical cumulative distributions of BMI in NHANES 2011-2014 (sample) and the synthetic population (population), by age group, sex, and race/ethnicity.

Supplemental Table 1. The U.S. Sugar Policy model data sources.

Parameter	Outcome	Details	Comments	Source (Author, Year)
Population size estimates	Population	July 1 U.S. resident population from the Vintage 2014 postcensal series, the revised 2000-2009 intercensal series, and the 1990-1999 intercensal series	Stratified by year, age, sex, bridged-race, and Hispanic origin	United States Department of Health and Human Services (US DHHS), Centers for Disease Control and Prevention (CDC), National Center for Health Statistics (NCHS), 2016.[63]
Population projections	Population	2014–2060 U.S. population projections produced by the Census Bureau in 2014	Stratified by year, age, sex, race, and ethnicity	U.S. Census Bureau. National population projections: United States by age, gender, ethnicity and race for years 2014–2060, released by the U.S. Census Bureau on December 10, 2014.[21]
Mortality	Deaths from CHD, stroke, and any other non-modeled causes	Underlying cause of death 1999–2015	Stratified by year, age, sex, race, ethnicity, and cause of death	United States Department of Health and Human Services (US DHHS), Centers for Disease Control and Prevention (CDC), National Center for Health Statistics (NCHS), 2016.[33]
Added sugars	Exposure of individuals	National Health and Nutrition Examination Survey (NHANES)	Anonymized, individual-level data sets. Years 2003–2014.	Centers for Disease Control and Prevention (CDC), National Center for Health Statistics (NCHS). National Health and Nutrition Examination Survey data. Hyattsville, MD: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, 1999–2014.[10]
Body mass index	Exposure of individuals	National Health and Nutrition Examination Survey (NHANES)	Anonymized, individual-level data sets. Years 2003–2014.	Centers for Disease Control and Prevention (CDC), National Center for Health Statistics (NCHS). National Health and Nutrition Examination Survey data. Hyattsville, MD: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, 1999–2014.[10]

Supplemental Table 1. The U.S. Sugar Policy model data sources (continued)

Parameter	Outcome	Details	Comments	Source (Author, Year)
Type 2 diabetes mellitus	Prevalence (diagnosed / undiagnosed)	National Health and Nutrition Examination Survey (NHANES)	Anonymized, individual-level data sets. Years 2003–2014.	Centers for Disease Control and Prevention (CDC), National Center for Health Statistics (NCHS). National Health and Nutrition Examination Survey data. Hyattsville, MD: US Department of Health and Human Services, Centers for Disease Control and Prevention, 1999–2014.[10]
Effect of labelling policy on sugar intake	Change in added sugar intake	Meta-analysis of 31 interventional studies	The estimate we used 6.8% (95% CI: 4.5%-9.0%) was an earlier estimate based on 30 studies. The final estimate published in the paper is based on 31 studies and is nearly identical to the one we used.	Shangguan *et al*, 2019. [55]
Effect of change in sugar intake on body mass index	Body mass index change	Meta-analysis of 3 cohort studies	Differential effect per body mass index. The studies measured exposure to SSB. We assumed 20g of sugar per 8oz of SSB serving based on NHANES. We also assume same effect for non SSB sugars	Micha *et al*.[14]
Relative risk for SSB sugars	CHD	Meta-analysis of 4 cohort studies	Body mass index adjusted. We assumed 20g of sugar per 8oz of SSB serving based on NHANES	Micha *et al*.[14]
	T2DM	Meta-analysis of 17 cohort studies	Body mass index adjusted. We assumed 20g of sugar per 8oz of SSB serving based on NHANES	Micha *et al*.[14]

Supplemental Table 1. The U.S. Sugar Policy model data sources (continued)

Parameter	Outcome	Details	Comments	Source (Author, Year)
Relative risk for body mass index	CHD and stroke	Meta-analysis of 97 cohort studies	Glucose adjusted (as a proxy for diabetes adjustment). The authors reported that more cohorts had data for glucose instead of diabetes, and in sensitivity analysis the authors found no significant difference between diabetes adjusted model and glucose adjusted model.	The Global Burden of Metabolic Risk Factors for Chronic Diseases Collaboration (BMI Mediated Effects), 2014.[64]
	T2DM	Pooled analysis of APCSC, PSC, and ERFC international pooling projects	CHD and stroke adjusted	Micha *et al*.[14]
Relative risk for T2DM	CHD and stroke	Meta-analysis of 102 prospective studies.	Stratified by age. Adjusted for sex, smoking status, BMI, and SBP. For stroke, we used the relative risks for ischemic stroke	The Emerging Risk Factors Collaboration, 2010.[65]
	Non-CVD mortality	Individual-level data from 48 independent prospective cohort studies	Minimally adjusted (age, sex, race or ethnicity). The relative risk for all-cause mortality was used.	Stringhini *et al*, 2017.[41]
Health state utility values	For CHD, stroke, T2DM, and their combinations	Uses EQ-5D-3L data from the Medical Expenditure Panel Survey (MEPS) 2000-2002	We used the published regression coefficients to estimate utility values by age, sex, race, ethnicity, income, education, and the number of chronic conditions	Sullivan PW, Ghushchyan V, 2006.[42]

Supplemental Table 1. The U.S. Sugar Policy model data sources (continued)

Parameter	Outcome	Details	Comments	Source (Author, Year)
Disease costs	Medical, mortality, and morbidity costs for CHD and stroke	Based on the Medical Expenditure Panel Survey (MEPS)	Stratified by age, sex, and race, adjusted for comorbidities	Khavjou O, Phelps D, Leib A, 2016.[43]
	Informal care costs for CHD		Costs were extrapolated for U.S. settings	Leal *et al*, 2006.[45]
	Informal care costs for stroke	Difference-in-differences technique to propensity score-matched populations		Joo *et al*, 2014.[44]
	Medical, mortality, and morbidity costs for diagnosed T2DM			American Diabetes Association, 2013.[46]
	Medical, mortality, and morbidity costs for undiagnosed T2DM		We assumed that the ratio of morbidity to mortality related costs was the same in each age group for undiagnosed T2DM as for diagnosed T2DM	Dall *et al*, 2014.[47]

Supplemental Table 1. The U.S. Sugar Policy model data sources (continued)

Parameter	Outcome	Details	Comments	Source (Author, Year)
	Informal care costs for T2DM		Only for ages 70+	Langa *et al*, 2002.[50]
Government costs to administer and monitor the policy		Assumed to be similar to the new restaurant menu and vending machine labeling regulation		Food and Drug Administration (FDA), Department of Health and Human Services (DHHS). Food and Drug Administration justification of estimates for appropriations committees, 2012.[51] The Nutrition Review Project, 2014.[52]
Industry compliance cost		Attributed half of the total industry costs to implement all proposed changes to the Nutrition Facts label to the added sugar provision		Food and Drug Administration (FDA), 2014.[53]
Industry costs to reformulate products		Spreadsheet model	The model accounted for variations in product formula complexity, company size, reformulation type, compliance period and other factors	RTI International, 2015.[54]

Abbreviations: BMI, body mass index; CHD, coronary heart disease; T2DM, type 2 diabetes mellitus; SSB, sugar-sweetened beverage.

Supplemental Table 2. Key modeling assumptions and limitations.

Population module
We assumed no migration after the age of 30.
We assumed NHANES to be representative of the U.S. population.
Disease module
We assumed log-linear exposure-response relationship for continuous exposures with 1-year mean lag time.
We only modeled first ever event of CHD and stroke because we focused on primary prevention.
For CHD and stroke initial incidence rates (year 2014), we used modeled estimates derived from mortality and NHANES prevalence and CVD risk data.
We assumed the non-attributable to the modeled risk factors incidence rate trends for CHD and stroke, to be 50% of the forecasted mortality rates trends.
We assumed that the modeled risk factors are not modifying CHD, stroke, and T2DM survival.
We assumed that changes in sugar intake have an immediate effect on SBP and changes in SBP have a median 5-year time lag to impact the risk of CVD.
Policy module
We assumed that the recently observed trends in sugar intake, BMI, and disease-specific mortality would continue in the future (base-case scenario).
We estimated the policy effect on the energy-adjusted sugar intake and we assumed equal effectiveness irrespective of age, sex, race/ethnicity, or education.
We calculated from NHANES that an 8oz of SSB contain 20g of sugar on average.
We assumed that FDA's added sugar labeling policy would not affect added sugar intake from other sources, e.g., restaurants, sugar added by consumers at home.
We assumed that individuals would not change other sugar consumption behavior because of the reformulation (labeling + reformulation scenario).
Policy micro-costing
We assumed that government monitoring costs would be the same in each year.
We assumed that industry reformulation costs would be the same in each year.
We assumed that industry reformulation as a response to FDA's policy would occur in year 2 - 4, with no reformulation and reformulation costs thereafter.

Abbreviations: CHD, coronary heart disease; T2DM, type 2 diabetes mellitus; BMI, body mass index; SSB, sugar-sweetened beverage.

Supplemental Table 3. Estimates of etiologic effects of added sugar and risk of cardiometabolic disease.

Cardiometabolic Outcome	Source	Unit of relative risk (RR)	RR by age*					
			25-34 y	35-44 y	45-54 y	55-64 y	65-74 y	75+ y
SSB → BMI (Baseline BMI < 25)[†]	Micha *et al*, 2017[14]	kg/m^2 per 8-oz servings/d	0.1	0.1	0.1	0.1	0.1	0.1
			(0.05. 0.15)	(0.05. 0.15)	(0.05. 0.15)	(0.05. 0.15)	(0.05. 0.15)	(0.05. 0.15)
SSB → BMI (Baseline BMI ≥25)	Micha *et al*, 2017[14]	kg/m^2 per 8-oz servings/d	0.23	0.23	0.23	0.23	0.23	0.23
			(0.14, 0.32)	(0.14, 0.32)	(0.14, 0.32)	(0.14, 0.32)	(0.14, 0.32)	(0.14, 0.32)
SSB → CHD	Micha *et al*, 2017[14]	Per 8-oz servings/d	1.33	1.31	1.26	1.21	1.17	1.09
			(1.19, 1.47)	(1.18, 1.45)	(1.15, 1.37)	(1.13, 1.3)	(1.10, 1.24)	(1.06, 1.13)
SSB → Diabetes	Micha *et al*, 2017[14]	Per 8-oz servings/d	1.35	1.33	1.27	1.22	1.18	1.1
			(1.14, 1.59)	(1.13, 1.56)	(1.11 1.46)	(1.09, 1.36)	(1.07, 1.29)	(1.05, 1.15)
Non-SSB added sugar[‡] → BMI (Baseline BMI<25)[†]	Micha *et al*, 2017[14]	kg/m^2 per gram of sugar	0.005	0.005	0.005	0.005	0.005	0.005
			(0.0025, 0.0075)	(0.0025, 0.0075)	(0.0025, 0.0075)	(0.0025, 0.0075)	(0.0025, 0.0075)	(0.0025, 0.0075)
Non-SSB added sugar[‡] → BMI (Baseline BMI≥25)	Micha *et al*, 2017[14]	kg/m^2 per gram of sugar	0.0115	0.0115	0.0115	0.0115	0.0115	0.0115
			(0.007, 0.016)	(0.007, 0.016)	(0.007, 0.016)	(0.007, 0.016)	(0.007, 0.016)	(0.007, 0.016)
BMI-Mediated CHD (Independent of diabetes[||])	Lu *et al*, 2014[64]	Per 5 kg/m^2 increase in BMI	1.45	1.42	1.35	1.28	1.23	1.13
			(1.36, 1.53)	(1.35, 1.51)	(1.29, 1.41)	(1.23, 1.33)	(1.19, 1.27)	(1.11, 1.14)
BMI-Mediated Stroke (Independent of diabetes[||])	Lu *et al*, 2014[64]	Per 5 kg/m^2 increase in BMI	1.24	1.23	1.19	1.16	1.13	1.07
			(1.16, 1.33)	(1.15, 1.32)	(1.13, 1.26)	(1.10, 1.21)	(1.09, 1.17)	(1.05, 1.09)
BMI-Mediated Diabetes	Micha *et al*, 2017[14]	Per 5 kg/m^2 increase in BMI	3.55	3.07	2.66	2.32	2.03	1.52
			(2.41, 5.23)	(2.28, 4.15)	(2.15, 3.30)	(2.04, 2.63)	(1.95, 2.11)	(1.40, 1.65)

Supplemental Table 3. Estimates of etiologic effects of added sugar and risk of cardiometabolic disease (continued)

Cardiometabolic Outcome	Source	Unit of relative risk (RR)	RR by age*		
			30 – 59 y	**60 – 69 y**	**70+ y**
T2DM → CHD	Sarwar *et al*, 2010.[65]		2.51	2.01	1.78
			(2.25, 2.80)	(1.80, 2.26)	(1.54, 2.05)
T2DM → stroke	Sarwar *et al*, 2010.[65]		3.74	2·06	1.80
			(3.06, 4.58)	(1.64, 2.58)	(1.42, 2.27)
			30+ y		
T2DM → Non-CVD mortality	Stringhini *et al*, 2017[41]		1.87		
			(1.72, 2.03)		

Abbreviations: SSB, sugar-sweetened beverage; BMI, body mass index; CHD, coronary heart disease; T2DM, type 2 diabetes mellitus.

* Age patterns were incorporated in relative risks because proportional effects decline with age.[66]
† We did not model BMI <17 kg/m^2.
‡ For non-SSB added sugar, we utilized data on BMI-mediated effects of SSBs,[14] which were more conservative than effect sizes reported in a meta-analysis of added sugar and body weight.[67] We assumed no additional effects of non-SSB added sugars on CHD, stroke, or diabetes beyond those mediated by changes in BMI.
|| These relative risks were glucose-adjusted in because more cohorts had data for glucose instead of diabetes. However, authors reported that in sensitivity analysis, there was no significant difference between diabetes adjusted model and glucose adjusted model.

Supplemental Table 4. Health-related costs per prevalent case for 2017.

Disease	Type	Age group	Sex	Race / ethnicity	Cost (95% UI)	Annual Increase
CHD	medical	30-44	men	black	$1,241 ($911 to $1,681)	2.45%
				Hispanic	$972 ($703 to $1,302)	2.45%
				other	$1,041 ($763 to $1,408)	2.45%
				white	$1,131 ($818 to $1,515)	2.45%
			women	black	$1,623 ($1,200 to $2,211)	2.45%
				Hispanic	$1,269 ($929 to $1,717)	2.45%
				other	$1,363 ($1,000 to $1,845)	2.45%
				white	$1,482 ($1,072 to $1,984)	2.45%
		45-64	men	black	$3,830 ($2,770 to $5,131)	2.45%
				Hispanic	$2,972 ($2,199 to $4,052)	2.45%
				other	$3,192 ($2,363 to $4,354)	2.45%
				white	$3,459 ($2,560 to $4,717)	2.45%
			women	black	$5,018 ($3,631 to $6,720)	2.45%
				Hispanic	$3,914 ($2,831 to $5,244)	2.45%
				other	$4,182 ($3,093 to $5,701)	2.45%
				white	$4,530 ($3,356 to $6,183)	2.45%
		65-79	men	black	$6,196 ($4,482 to $8,299)	2.45%
				Hispanic	$4,834 ($3,498 to $6,473)	2.45%
				other	$5,161 ($3,828 to $7,050)	2.45%
				white	$5,626 ($4,070 to $7,537)	2.45%
			women	black	$8,116 ($5,872 to $10,871)	2.45%
				Hispanic	$6,333 ($4,584 to $8,478)	2.45%
				other	$6,802 ($4,920 to $9,112)	2.45%
				white	$7,370 ($5,331 to $9,873)	2.45%
		80-84	men	black	$7,837 ($5,669 to $10,500)	2.45%
				Hispanic	$6,077 ($4,509 to $8,304)	2.45%
				other	$6,568 ($4,751 to $8,799)	2.45%

Supplemental Table 4. Health-related costs per prevalent case for 2017 (continued)

Disease	Type	Age group	Sex	Race / ethnicity	Cost (95% UI)	Annual Increase
				white	$7,117 ($5,148 to $9,534)	2.45%
			women	black	$10,267 ($7,426 to $13,754)	2.45%
				Hispanic	$8,010 ($5,794 to $10,730)	2.45%
				other	$8,605 ($6,228 to $11,522)	2.45%
				white	$9,323 ($6,746 to $12,486)	2.45%
	morbidity	30-64	all	all	$2,211 ($1,636 to $3,015)	1.29%
	mortality	30-44	men	Hispanic	$1,114,784 ($806,448 to $1,493,521)	1.29%
				white	$1,177,832 ($852,053 to $1,577,984)	1.29%
				black	$1,371,047 ($992,312 to $1,836,222)	1.29%
				other	$1,565,271 ($1,132,567 to $2,097,396)	1.29%
			women	Hispanic	$758,792 ($548,891 to $1,016,544)	1.29%
				white	$801,703 ($579,939 to $1,074,042)	1.29%
				black	$933,184 ($675,060 to $1,250,201)	1.29%
				other	$1,065,464 ($770,764 to $1,427,438)	1.29%
		45-64	men	Hispanic	$663,783 ($480,152 to $889,245)	1.29%
				white	$701,321 ($507,314 to $939,544)	1.29%
				black	$816,335 ($590,532 to $1,093,656)	1.29%
				other	$932,049 ($674,257 to $1,248,706)	1.29%
			women	Hispanic	$451,802 ($326,786 to $605,314)	1.29%
				white	$477,358 ($345,302 to $639,500)	1.29%
				black	$555,647 ($401,938 to $744,388)	1.29%
				other	$634,412 ($458,916 to $849,911)	1.29%
		65-79	men	Hispanic	$260,170 ($188,201 to $348,548)	1.29%
				white	$274,886 ($198,841 to $368,255)	1.29%
				black	$319,969 ($231,453 to $428,651)	1.29%
				other	$365,341 ($264,373 to $489,268)	1.29%
			women	Hispanic	$177,088 ($128,095 to $237,234)	1.29%
				white	$187,102 ($135,341 to $250,653)	1.29%
				black	$217,789 ($157,537 to $291,760)	1.29%

Supplemental Table 4. Health-related costs per prevalent case for 2017 (continued)

Disease	Type	Age group	Sex	Race / ethnicity	Cost (95% UI)	Annual Increase
				other	$248,662 ($179,870 to $333,120)	1.29%
		80-84	men	Hispanic	$30,464 ($22,036 to $40,810)	1.29%
				white	$32,187 ($23,283 to $43,117)	1.29%
				black	$37,465 ($27,100 to $50,190)	1.29%
				other	$42,776 ($30,942 to $57,305)	1.29%
			women	Hispanic	$20,735 ($14,999 to $27,778)	1.29%
				white	$21,908 ($15,847 to $29,349)	1.29%
				black	$25,501 ($18,446 to $34,162)	1.29%
				other	$29,116 ($21,061 to $39,005)	1.29%
	Informal care	30-84	all	all	$1,610 ($1,165 to $2,156)	0%
stroke	medical	30-44	men	Hispanic	$1,077 ($790 to $1,458)	2.45%
				white	$741 ($536 to $992)	2.45%
				black	$1,271 ($931 to $1,720)	2.45%
				other	$852 ($616 to $1,141)	2.45%
			women	Hispanic	$1,139 ($835 to $1,542)	2.45%
				white	$783 ($567 to $1,049)	2.45%
				black	$1,349 ($976 to $1,806)	2.45%
				other	$901 ($652 to $1,207)	2.45%
		45-64	men	Hispanic	$4,044 ($2,995 to $5,519)	2.45%
				white	$2,774 ($2,048 to $3,775)	2.45%
				black	$4,800 ($3,475 to $6,425)	2.45%
				other	$3,188 ($2,360 to $4,348)	2.45%
			women	Hispanic	$4,277 ($3,168 to $5,837)	2.45%
				white	$2,948 ($2,133 to $3,949)	2.45%
				black	$5,075 ($3,671 to $6,798)	2.45%
				other	$3,391 ($2,454 to $4,539)	2.45%
		65-79	men	Hispanic	$7,635 ($5,522 to $10,228)	2.45%
				white	$5,233 ($3,786 to $7,008)	2.45%

Supplemental Table 4. Health-related costs per prevalent case for 2017 (continued)

Disease	Type	Age group	Sex	Race / ethnicity	Cost (95% UI)	Annual Increase
				black	$9,008 ($6,516 to $12,066)	2.45%
				other	$6,017 ($4,352 to $8,061)	2.45%
			women	Hispanic	$8,074 ($5,840 to $10,816)	2.45%
				white	$5,533 ($4,003 to $7,413)	2.45%
				black	$9,526 ($6,891 to $12,761)	2.45%
				other	$6,363 ($4,603 to $8,524)	2.45%
		80-84	men	Hispanic	$9,065 ($6,557 to $12,144)	2.45%
				white	$6,213 ($4,494 to $8,323)	2.45%
				black	$10,696 ($7,741 to $14,321)	2.45%
				other	$7,144 ($5,168 to $9,571)	2.45%
			women	Hispanic	$9,586 ($6,934 to $12,842)	2.45%
				white	$6,570 ($4,752 to $8,801)	2.45%
				black	$11,310 ($8,181 to $15,151)	2.45%
				other	$7,555 ($5,465 to $10,121)	2.45%
	morbidity	30-64	all	all	$2,203 ($1,594 to $2,952)	1.29%
	mortality	30-44	men	Hispanic	$1,199,307 ($867,585 to $1,606,749)	1.29%
				white	$1,050,321 ($760,209 to $1,406,471)	1.29%
				black	$1,337,832 ($967,830 to $1,792,387)	1.29%
				other	$1,645,853 ($1,190,621 to $2,205,004)	1.29%
			women	Hispanic	$789,754 ($571,656 to $1,057,469)	1.29%
				white	$691,557 ($500,278 to $926,503)	1.29%
				black	$880,985 ($637,739 to $1,179,568)	1.29%
				other	$1,083,726 ($783,998 to $1,451,938)	1.29%
		45-64	men	Hispanic	$668,195 ($483,357 to $895,174)	1.29%
				white	$585,148 ($423,299 to $783,940)	1.29%
				black	$745,382 ($539,189 to $998,576)	1.29%
				other	$916,992 ($663,322 to $1,228,471)	1.29%
			women	Hispanic	$439,987 ($318,263 to $589,426)	1.29%

Supplemental Table 4. Health-related costs per prevalent case for 2017 (continued)

Disease	Type	Age group	Sex	Race / ethnicity	Cost (95% UI)	Annual Increase
				white	$385,303 ($278,715 to $516,181)	1.29%
				black	$490,807 ($355,035 to $657,524)	1.29%
				other	$603,831 ($437,009 to $808,621)	1.29%
		65-79	men	Hispanic	$327,354 ($236,806 to $438,561)	1.29%
				white	$286,676 ($207,365 to $384,042)	1.29%
				black	$365,173 ($264,149 to $489,206)	1.29%
				other	$449,246 ($324,965 to $601,837)	1.29%
			women	Hispanic	$215,554 ($155,921 to $288,767)	1.29%
				white	$188,766 ($136,542 to $252,878)	1.29%
				black	$240,454 ($173,931 to $322,122)	1.29%
				other	$295,813 ($213,974 to $396,283)	1.29%
		80-84	men	Hispanic	$38,442 ($27,805 to $51,499)	1.29%
				white	$33,666 ($24,362 to $45,084)	1.29%
				black	$42,882 ($31,018 to $57,447)	1.29%
				other	$52,755 ($38,160 to $70,672)	1.29%
			women	Hispanic	$25,312 ($18,309 to $33,909)	1.29%
				white	$22,167 ($16,034 to $29,695)	1.29%
				black	$28,236 ($20,424 to $37,826)	1.29%
				other	$34,737 ($25,127 to $46,535)	1.29%
	Informal care	30-84	all	all	$4,735 ($2,255 to $8,601)	0%
T2DM (diagnosed)	medical	30-34	all	all	$4,375 ($3,165 to $5,861)	0%
		35-44	all	all	$4,821 ($3,490 to $6,456)	0%
		45-54	all	all	$5,490 ($3,972 to $7,355)	0%
		55-59	all	all	$5,882 ($4,258 to $7,879)	0%
		60-64	all	all	$6,636 ($4,802 to $8,892)	0%
		65-84	all	all	$12,451 ($9,311 to $17,112)	0%
	morbidity	30-34	men	all	$4,837 ($3,499 to $6,480)	0%
			women	all	$3,023 ($2,189 to $4,047)	0%

Supplemental Table 4. Health-related costs per prevalent case for 2017 (continued)

Disease	Type	Age group	Sex	Race / ethnicity	Cost (95% UI)	Annual Increase
		35-44	men	all	$6,837 ($5,110 to $9,393)	0%
			women	all	$4,567 ($3,304 to $6,119)	0%
		45-54	men	all	$7,211 ($5,390 to $9,906)	0%
			women	all	$4,483 ($3,243 to $6,006)	0%
		55-59	men	all	$5,467 ($3,955 to $7,325)	0%
			women	all	$3,613 ($2,615 to $4,838)	0%
		60-64	men	all	$4,041 ($2,923 to $5,414)	0%
			women	all	$2,542 ($1,840 to $3,406)	0%
		65-69	men	all	$1,692 ($1,224 to $2,267)	0%
			women	all	$902 ($652 to $1,208)	0%
		70-84	men	all	$931 ($673 to $1,247)	0%
			women	all	$687 ($497 to $920)	0%
	Informal care	70-84	all	all	$2,532 ($1,832 to $3,393)	0%
T2DM (undiagnosed)	medical	30-34	all	all	$3,791 ($2,744 to $5,078)	0%
		35-44	all	all	$1,465 ($1,060 to $1,963)	0%
		45-54	all	all	$2,188 ($1,584 to $2,929)	0%
		55-59	all	all	$1,965 ($1,422 to $2,630)	0%
		60-64	all	all	$1,656 ($1,197 to $2,220)	0%
		65-84	all	all	$4,449 ($3,219 to $5,961)	0%
	morbidity	30-34	all	all	$971 ($703 to $1,301)	0%
		35-44	all	all	$694 ($502 to $930)	0%
		45-54	all	all	$2,775 ($2,008 to $3,718)	0%
		55-59	all	all	$1,962 ($1,420 to $2,628)	0%
		60-64	all	all	$1,140 ($825 to $1,527)	0%
		65-84	all	all	$377 ($272 to $505)	0%

Abbreviations: CHD, coronary heart disease. T2DM, type 2 diabetes mellitus.

Supplemental Table 5. Estimated added sugar intake, health gains, costs, and cost-effectiveness of the U.S. FDA added sugar labeling policy over the 20-year simulation period from 2018 to 2037, for U.S. adults aged 30 to 84 years stratified by sex.[*]

	Sex	Sugar label	Label + reformulation
Population (million)	Men	107.9 (106.21 to 109.34)	107,93 (106.22 to 109.36)
	Women	111.5 (110.18 to 112.59)	111.51 (110.19 to 112.59)
Added sugar Intake[†] (g/d)			
Median intake from SSBs in 2037	Men	7.5 (7 to 7.9)	6.8 (6.4 to 7.2)
	Women	2.4 (2.3 to 2.6)	2.2 (2.1 to 2.4)
Median intake from non-SSBs in 2037	Men	23.2 (22.6 to 23.9)	21.2 (20.5 to 21.9)
	Women	27 (26.3 to 27.7)	24.6 (23.8 to 25.4)
Mean intake from SSBs in 2037	Men	23.3 (22.5 to 24.1)	21.3 (20.5 to 22)
	Women	18.89 (18.1 to 19.4)	17.1 (16.4 to 17.7)
Mean intake from non-SSBs in 2037	Men	28 (27.1 to 28.9)	25.5 (24.6 to 26.4)
	Women	32.2 (31.1 to 33.1)	29.3 (28.3 to 30.3)
Health outcomes			
BMI in 2022 (kg/m^2)	Men	28.4 (28.3 to 28.5)	28.4 (28.3 to 28.5)
	Women	28.8 (28.7 to 28.9)	28.7 (28.6 to 28.8)
CVD cases prevented/postponed	Men	211,500 (98,340 to 410,100)	426,800 (218,900 to 747,700)
	Women	141,000 (64,940 to 272,800)	283,900 (144,700 to 506,600)
CVD deaths prevented/postponed	Men	18,550 (5,566 to 38,960)	35,250 (14,840 to 63,090)
	Women	7,422 (0 to 18,550)	14,840 (3,711 to 29,690)
T2DM cases prevented/postponed	Men	328,400 (166,900 to 527,000)	653,100 (365,200 to 946,400)
	Women	269,000 (137,300 to 437,900)	532,500 (304,200 to 777,400)
T2DM-related deaths prevented/postponed	Men	11,130 (0 to 25,980)	20,410 (3,711 to 40,820)
	Women	5,566 (0 to 18,550)	12,990 (1,855 to 27,830)
Life-years gained	Men	76,070 (14,840 to 181,800)	137,300 (48,240 to 267,200)
	Women	202,200 (74,220 to 384,100)	365,500 (178,000 to 607,000)
QALYs gained	Men	425,100 (232,500 to 674,800)	779,400 (496,000 to 1,129,000)
	Women	302,000 (160,800 to 482,300)	554,900 (345,500 to 807,900)
Change in health-related costs[‡] ($ billion)	Men	-38.15 (-64.39 to -20.27)	-70.78 (-107.7 to -43.63)
	Women	-25.39 (-42.39 to -13.14)	-46.38 (-72.97 to -27.7)
CHD medical costs	Men	-6.2 (-13.34 to -2.36)	-11.8 (-23.36 to -4.99)
	Women	-5.51 (-12.14 to -2.04)	-10.4 (-21.11 to -4.37)
CHD mortality productivity costs	Men	-8.83 (-20.88 to -2.23)	-16.83 (-34.58 to -5.92)
	Women	-1.99 (-6.13 to 0)	-3.8 (-9.41 to -0.68)
CHD morbidity productivity costs	Men	-2.33 (-5.52 to -0.88)	-4.41 (-9.41 to -1.89)
	Women	-1.6 (-3.89 to -0.56)	-3.03 (-6.68 to -1.2)
CHD informal care costs[‖]	Men	-1.86 (-4.18 to -0.76)	-3.459 (-7.44 to -1.55)
	Women	-1.27 (-2.95 to -0.49)	-2.37 (-5.06 to -0.99)
Stroke medical costs	Men	-0.33 (-1.06 to 0.03)	-0.63 (-1.67 to -0.05)
	Women	-0.29 (-0.95 to 0.02)	-0.54 (-1.55 to -0.08)
Stroke mortality productivity costs	Men	0 (-2 to 0.42)	0 (-2.7 to 0.55)
	Women	0 (-1.13 to 0.03)	0 (-1.51 to 0.23)
Stroke morbidity productivity costs	Men	-0.1 (-0.31 to -0.0006)	-0.19 (-0.5 to -0.02)
	Women	-0.08 (-0.27 to 0)	-0.14 (-0.42 to -0.02)

Supplemental Table 5. Estimated added sugar intake, health gains, costs, and cost-effectiveness of the U.S. FDA added sugar labeling policy over the 20-year simulation period from 2018 to 2037, for U.S. adults aged 30 to 84 years stratified by sex (continued)

	Sex	Sugar label	Label + reformulation
Stroke informal care costs[||]	Men	-0.24 (-0.84 to 0)	-0.44 (-1.34 to -0.06)
	Women	-0.19 (-0.7 to 0)	-0.36 (-1.16 to -0.05)
T2DM medical costs	Men	-9.57 (-17.53 to -4.158)	-17.35 (-29.41 to -8.57)
	Women	-8.5 (-15.91 to -3.89)	-15.54 (-26.89 to -7.78)
T2DM productivity costs	Men	-7.12 (-13.03 to -3.16)	-13.03 (-22.01 to -6.33)
	Women	-4.57 (-8.44 to -2.13)	-8.42 (-14.24 to -4.3)
T2DM informal care costs[||]	Men	-0.19 (-0.43 to -0.04)	-0.32 (-0.69 to -0.1)
	Women	-0.17 (-0.38 to -0.04)	-0.3 (-0.58 to -0.11)
Change in policy costs[‡] ($ billion)	Men	0.82 (0.32 to 1.84)	2.1 (1.1 to 3.7)
	Women	0.86 (0.34 to 1.94)	2.22 (1.16 to 3.9)
Government administrative costs	Men	0.008 (0.006 to 0.01)	0.008 (0.006 to 0.01)
	Women	d0.008 (0.006 to 0.01)	0.008 (0.006 to 0.01)
Industry compliance costs	Men	0.81 (0.31 to 1.83)	0.81 (0.31 to 1.83)
	Women	0.86 (0.33 to 1.94)	0.86 (0.33 to 1.94)
Industry reformulation costs	Men	0 (0 to 0)	1.2 (0.45 to 2.6)
	Women	0 (0 to 0)	1.27 (0.48 to 2.75)
Total net cost from healthcare perspective[#] ($ billion)	Men	-16.39 (-28.88 to -8.32)	-30.27 (-49.28 to -16.71)
	Women	-14.63 (-26.29 to -7.15)	-27 (-43.89 to -14.49)
Total net cost from societal perspective[#] ($ billion)	Men	-37.24 (-63.35 to -19.45)	-68.56 (-105.5 to -41.37)
	Women	-24.51 (-41.83 to -12.09)	-44.23 (-71.07 to -25.5)
Net monetary benefit[**] ($ billion, valuing QALYs at $100,000)	Men	79.99 (43.7 to 130.1)	146.5 (92.96 to 217.4)
	Women	54.66 (28.96 to 89.3)	99.55 (60.88 to 148.8)
Incremental cost-effectiveness ratio[††] (2017 USD per QALY)	Men	-88,270 (-113,100 to -68,950) dominant	-88,000 (-110,300 to -70,010) dominant
	Women	-80,990 (-104,600 to -59,730) dominant	-79,920 (-101,400 to -60,730) dominant

Abbreviations: SSB, sugar-sweetened beverages; BMI, body mass index; CHD, coronary heart disease; T2DM, type 2 diabetes mellitus; QALY, quality-adjusted life years.

[*] Values are median estimates from 2,000 Monte Carlo iterations (95% uncertainty intervals). Costs and QALYs were discounted at 3% annually.

[†] We evaluated only the subset of added sugar in NHANES from packaged products that would carry a Nutrition Facts label, i.e. sugars from supermarkets, convenience stores, vending machines. We excluded added sugar consumed from other sources, e.g., in restaurants and as sugar added by consumers. Intakes were adjusted for energy intake using the residual method[15] to minimize measurement error and account for potential non-dietary differences, such as body size, metabolic efficiency and physical activity.

[‡] Costs are median from 2,000 Monte Carlo iterations so may not add up to totals. Negative costs represent savings. Costs are inflated to 2017 USD using the Consumer Price Index.

[||] Informal care costs refer to unpaid caregiving costs. We conservatively excluded other informal healthcare costs such as transportation costs and patient time costs.

[#] Net costs were calculated as policy costs minus health-related costs from reduced cardiometabolic diseases. Healthcare perspective included policy costs and medical costs; societal perspective further incorporated informal healthcare costs and productivity costs.

[**] Net monetary benefit was calculated by summing net savings and QALYs gained multiplied by a $100,000 willingness-to-pay threshold per QALY.

[††] Incremental cost-effectiveness ratios were calculated as the net change in costs divided by the net change in QALYs. Dominant = cost-saving and more effective than the base-case scenario.

Supplemental Table 6. Estimated added sugar intake, health gains, costs, and cost-effectiveness of the U.S. FDA added sugar labeling policy over the 20-year simulation period from 2018 to 2037, for U.S. adults aged 30 to 84 years stratified by age.[*]

	Age group	Sugar label	Sugar Label + reformulation
Population (million)	30-49	94.21 (93.88 to 94.47)	94.21 (93.88 to 94.47)
	50-69	77.05 (76.08 to 77.82)	77.06 (76.08 to 77.84)
	70-84	48.14 (46.41 to 49.65)	48.15 (46.42 to 49.66)
Added sugar Intake[†] (g/d)			
Median intake from SSBs in 2037	30-49	7.4 (6.9 to 7.8)	6.7 (6.2 to 7.2)
	50-69	2.4 (2.1 to 2.9)	2.2 (1.9 to 2.6)
	70-84	3.7 (3.5 to 3.9)	3.4 (3.2 to 3.5)
Median intake from non-SSBs in 2037	30-49	20.4 (19.8 to 21)	18.6 (18 to 19.2)
	50-69	25.7 (25 to 26.4)	23.4 (22.7 to 24.2)
	70-84	33.2 (32.2 to 34.2)	30.2 (29.2 to 31.3)
Mean intake from SSBs in 2037	30-49	25.4 (24.5 to 26.2)	23.1 (22.3 to 24)
	50-69	19.5 (18.7 to 20.3)	17.8 (17 to 18.5)
	70-84	14.8 (14 to 15.7)	13.5 (12.8 to 14.3)
Mean intake from non-SSBs in 2037	30-49	26 (25.1 to 26.9)	23.7 (22.8 to 24.6)
	50-69	31 (30 to 32.1)	28.2 (27.2 to 29.4)
	70-84	36.6 (35.5 to 37.9)	33.4 (32.3 to 34.7)
Health outcomes			
BMI in 2022 (kg/m^2)	30-49	28.7 (28.6 to 28.8)	28.7 (28.6 to 28.8)
	50-69	29 (28.9 to 29.1)	29 (28.9 to 29.1)
	70-84	27.8 (27.7 to 27.9)	27.7 (27.6 to 27.8)
CVD cases prevented/postponed	30-49	167,000 (66,800 to 356,200)	330,300 (148,400 to 666,100)
	50-69	152,100 (72,360 to 274,600)	300,600 (165,100 to 499,300)
	70-84	35,250 (14,840 to 66,800)	76,070 (40,820 to 122,600)
CVD deaths prevented/postponed	30-49	5,566 (0 to 12,990)	9,277 (1,855 to 24,120)
	50-69	12,990 (3,711 to 27,830)	24,120 (9,277 to 44,530)
	70-84	7,422 (0 to 20,410)	14,840 (3,711 to 31,540)
T2DM cases prevented/postponed	30-49	328,400 (163,300 to 525,100)	643,800 (352,400 to 939,000)
	50-69	256,100 (126,200 to 411,900)	512,100 (285,600 to 740,500)
	70-84	12,990 (3,711 to 27,830)	27,830 (12,990 to 50,100)
T2DM-related deaths prevented/postponed	30-49	1,855 (0 to 7,422)	3,711 (0 to 12,990)
	50-69	11,130 (1,855 to 24,120)	20,410 (5,566 to 40,820)
	70-84	3,711 (0 to 12,990)	7,422 (0 to 20,410)
Life-years gained	30-49	126,200 (38,960 to 254,200)	224,500 (98,340 to 393,400)
	50-69	94,630 (29,690 to 198,500)	165,100 (66,800 to 295,000)
	70-84	33,400 (0 to 96,530)	66,800 (14,840 to 146,600)
QALYs gained	30-49	265,300 (140,800 to 428,600)	492,300 (303,700 to 733,200)
	50-69	361,200 (195,300 to 570,900)	660,600 (415,000 to 947,700)
	70-84	102,800 (50,100 to 176,100)	182,600 (106,300 to 278,000)
Change in health-related costs[‡] ($ billion)	30-49	-21.38 (-36.9 to -10.78)	-40.46 (-63.65 to -23.65)
	50-69	-33.61 (-55.39 to -17.83)	-61.6 (-93.69 to -37.04)
	70-84	-8.49 (-14.69 to -4.24)	-15.42 (-24.79 to -8.47)
CHD medical costs	30-49	-2.45 (-5.87 to -0.84)	-4.67 (-10.36 to -1.82)
	50-69	-6.16 (-13.06 to -2.43)	-11.55 (-22.92 to -4.97)
	70-84	-3.12 (-6.47 to -1.17)	-5.95 (-11.42 to -2.47)

Supplemental Table 6. Estimated added sugar intake, health gains, costs, and cost-effectiveness of the U.S. FDA added sugar labeling policy over the 20-year simulation period from 2018 to 2037, for U.S. adults aged 30 to 84 years stratified by age (continued)

	Age group	Sugar label	Sugar Label + reformulation
CHD mortality productivity costs	30-49	-3.86 (-11.81 to 0)	-7.84 (-19.1 to -1.45)
	50-69	-5.51 (-13.7 to -1.04)	-10.43 (-22.01 to -3.62)
	70-84	-1.2 (-3.35 to 0)	-2.27 (-5.27 to -0.4)
CHD morbidity productivity costs	30-49	-1.96 (-5.05 to -0.7)	-3.8 (-8.7 to -1.52)
	50-69	-1.95 (-4.33 to -0.76)	-3.62 (-7.54 to -1.64)
	70-84	0 (0 to 0)	0 (0 to 0)
CHD informal care costs[||]	30-49	-1.16 (-3.04 to -0.42)	-2.22 (-5.28 to -0.88)
	50-69	-1.46 (-3.22 to -0.61)	-2.69 (-5.52 to -1.24)
	70-84	-0.49 (-1.03 to -0.19)	-0.91 (-1.82 to -0.41)
Stroke medical costs	30-49	-0.07 (-0.26 to 0)	-0.14 (-0.44 to -0.01)
	50-69	-0.38 (-1.12 to -0.036)	-0.69 (-1.83 to -0.14)
	70-84	-0.16 (-0.71 to 0.11)	-0.32 (-1.07 to 0.08)
Stroke mortality productivity costs	30-49	0 (-1.67 to 0)	0 (-1.93 to 0)
	50-69	0 (-1.6 to 0)	0 (-2.1 to 0.41)
	70-84	0 (-0.6 to 0.33)	0 (-0.84 to 0.41)
Stroke morbidity productivity costs	30-49	-0.05 (-0.21 to 0)	-0.11 (-0.35 to -0.01)
	50-69	-0.12 (-0.35 to -0.01)	-0.22 (-0.57 to -0.05)
	70-84	0 (0 to 0)	0 (0 to 0)
Stroke informal care costs[||]	30-49	-0.1 (-0.39 to 0)	-0.18 (-0.64 to -0.01)
	50-69	-0.26 (-0.89 to -0.02)	-0.47 (-1.43 to -0.09)
	70-84	-0.07 (-0.33 to 0.05)	-0.14 (-0.53 to 0.03)
T2DM medical costs	30-49	-5.3 (-9.79 to -2.47)	-9.91 (-16.79 to -4.99)
	50-69	-10.22 (-18.91 to -4.68)	-18.68 (-31.79 to -9.36)
	70-84	-2.49 (-5.06 to -0.95)	-4.37 (-8.11 to -2)
T2DM productivity costs	30-49	-5.43 (-9.95 to -2.53)	-10.1 (-16.9 to -5.08)
	50-69	-6.07 (-10.9 to -2.77)	-11.06 (-18.54 to -5.39)
	70-84	-0.18 (-0.34 to -0.07)	-0.31 (-0.55 to -0.15)
T2DM informal care costs[||]	30-49	0 (0 to 0)	0 (0 to 0)
	50-69	0 (0 to 0)	0 (0 to 0)
	70-84	-0.36 (-0.74 to -0.12)	-0.62 (-1.17 to -0.26)
Change in policy costs[‡] ($ billion)	30-49	0.73 (0.29 to 1.64)	1.87 (0.97 to 3.28)
	50-69	0.7 (0.28 to 1.58)	1.79 (0.94 to 3.14)
	70-84	0.25 (0.1 to 0.57)	0.66 (0.35 to 1.18)
Government administrative costs	30-49	0.007 (0.005 to 0.009)	0.007 (0.005 to 0.009)
	50-69	0.006 (0.005 to 0.009)	0.007 (0.005 to 0.009)
	70-84	0.003 (0.002 to 0.004)	0.003 (0.002 to 0.004)
Industry compliance costs	30-49	0.72 (0.28 to 1.64)	0.72 (0.28 to 1.64)
	50-69	0.69 (0.27 to 1.58)	0.69 (0.27 to 1.57)
	70-84	0.25 (0.1 to 0.57)	0.25 (0.1 to 0.57)
Industry reformulation costs	30-49	0 (0 to 0)	1.06 (0.4 to 2.30)
	50-69	0 (0 to 0)	1.02 (0.38 to 2.21)
	70-84	0 (0 to 0)	0.39 (0.14 to 0.84)
Total net cost from healthcare perspective[#] ($ billion)	30-49	-7.99 (-14.48 to -3.93)	-15.05 (-24.68 to -8.21)
	50-69	-17.14 (-30.16 to -8.4)	-31.47 (-51.05 to -17.01)
	70-84	-5.92 (-10.7 to -2.75)	-10.8 (-18.29 to -5.64)

Supplemental Table 6. Estimated added sugar intake, health gains, costs, and cost-effectiveness of the U.S. FDA added sugar labeling policy over the 20-year simulation period from 2018 to 2037, for U.S. adults aged 30 to 84 years stratified by age (continued)

	Age group	Sugar label	Sugar Label + reformulation
Total net cost from societal perspective[#] ($ billion)	30-49	-20.56 (-36.22 to -10.03)	-38.63 (-61.47 to -21.63)
	50-69	-32.92 (-54.54 to -17.1)	-59.74 (-91.89 to -35.53)
	70-84	-8.2 (-14.45 to -3.97)	-14.74 (-24.1 to -7.82)
Net monetary benefit[**] ($ billion, valuing QALYs at $100,000)	30-49	47.06 (24.67 to 77.81)	87.55 (52.63 to 134.6)
	50-69	69.04 (37.72 to 110.5)	125.6 (78.46 to 184.2)
	70-84	18.53 (9.4 to 30.8)	33.18 (19.25 to 50.53)
Incremental cost-effectiveness ratio[††] (2017 USD per QALY)	30-49	-79,020 (-102,400 to -58,850) dominant	-78,100 (-98,750 to -60,520) dominant
	50-69	-91,030 (-117,000 to -69,890) dominant	-90,470 (-114,100 to -70,230) dominant
	70-84	-80,200 (-123,400 to -49,920) dominant	-80,850 (-116,600 to -54,270) dominant

Abbreviations: SSB, sugar-sweetened beverages; BMI, body mass index; CHD, coronary heart disease; T2DM, type 2 diabetes mellitus; QALY, quality-adjusted life years.

[*] Values are median estimates from 2,000 Monte Carlo iterations (95% uncertainty intervals). Costs and QALYs were discounted at 3% annually.

[†] We evaluated only the subset of added sugar in NHANES from packaged products that would carry a Nutrition Facts label, i.e. sugars from supermarkets, convenience stores, vending machines. We excluded added sugar consumed from other sources, e.g., in restaurants and as sugar added by consumers. Intakes were adjusted for energy intake using the residual method[15] to minimize measurement error and account for potential non-dietary differences, such as body size, metabolic efficiency and physical activity.

[‡] Costs are median from 2,000 Monte Carlo iterations so may not add up to totals. Negative costs represent savings. Costs are inflated to 2017 USD using the Consumer Price Index.

[||] Informal care costs refer to unpaid caregiving costs. We conservatively excluded other informal healthcare costs such as transportation costs and patient time costs.

[#] Net costs were calculated as policy costs minus health-related costs from reduced cardiometabolic diseases. Healthcare perspective included policy costs and medical costs; societal perspective further incorporated informal healthcare costs and productivity costs.

[**] Net monetary benefit was calculated by summing net savings and QALYs gained multiplied by a $100,000 willingness-to-pay threshold per QALY.

[††] Incremental cost-effectiveness ratios were calculated as the net change in costs divided by the net change in QALYs. Dominant = cost-saving and more effective than the base-case scenario.

Supplemental Table 7. Estimated added sugar intake, health gains, costs, and cost-effectiveness of the U.S. FDA added sugar labeling policy over the 20-year simulation period from 2018 to 2037, for U.S. adults aged 30 to 84 years stratified by race/ethnicity.[*]

	Race	Sugar label	Sugar Label + reformulation
Population (million)	White	125.12 (123.09 to 126.88)	125.14 (123.1 to 126.9)
	Black	27.36 (26.84 to 27.76)	27.36 (26.86 to 27.77)
	Other	66.92 (66.45 to 67.34)	66.93 (66.45 to 67.33)
Added sugar Intake[†] (g/d)			
Median intake from SSBs in 2037	White	2.9 (2.7 to 3.1)	2.6 (2.5 to 2.8)
	Black	13.4 (12.5 to 14.2)	12.2 (11.4 to 13)
	Other	5.9 (5.5 to 6.4)	5.4 (5 to 5.8)
Median intake from non-SSBs in 2037	White	28.9 (27.6 to 29.2)	25.9 (25.1 to 26.7)
	Black	24.4 (23.6 to 25.3)	22.3 (21.4 to 23.1)
	Other	19.6 (19 to 20.2)	17.9 (17.2 to 18.5)
Mean intake from SSBs in 2037	White	22.3 (21.6 to 23.1)	20.3 (19.6 to 21.1)
	Black	25 (24 to 26)	22.8 (21.8 to 23.8)
	Other	16.9 (16.2 to 17.5)	15.4 (14.8 to 16)
Mean intake from non-SSBs in 2037	White	33.3 (32.2 to 34.3)	30.3 (29.3 to 31.3)
	Black	30.3 (29.2 to 31.5)	27.6 (26.6 to 28.8)
	Other	24.1 (23.3 to 24.9)	21.9 (21.2 to 22.7)
Health outcomes			
BMI in 2022 (kg/m^2)	White	28.3 (28.2 to 28.4)	28.3 (28.2 to 28.4)
	Black	29.9 (29.6 to 30)	29.8 (29.6 to 30)
	Other	28.5 (28.4 to 28.6)	28.4 (28.3 to 28.5)
CVD cases prevented/postponed	White	174,400 (76,070 to 356,200)	345,100 (168,800 to 653,200)
	Black	102,000 (48,240 to 183,700)	206,000 (109,500 to 335,800)
	Other	77,930 (33,400 to 150,300)	157,700 (77,840 to 280,300)
CVD deaths prevented/postponed	White	18,550 (5,566 to 37,110)	33,400 (14,840 to 61,320)
	Black	5,566 (0 to 12,990)	9,277 (1,855 to 22,270)
	Other	3,711 (0 to 11,130)	7,422 (0 to 16,700)
T2DM cases prevented/postponed	White	283,900 (141,000 to 458,300)	552,900 (313,500 to 805,400)
	Black	115,000 (53,810 to 193,000)	230,100 (122,400 to 341,400)
	Other	196,700 (98,290 to 321,000)	398,900 (218,900 to 579,000)
T2DM-related deaths prevented/postponed	White	9,277 (0 to 24,120)	16,700 (1,855 to 37,110)
	Black	3,711 (0 to 11,130)	7,422 (0 to 18,550)
	Other	3,711 (0 to 11,130)	7,422 (0 to 16,700)
Life-years gained	White	51,950 (5,566 to 133,600)	96,480 (25,980 to 202,200)
	Black	44,530 (1,855 to 115,100)	81,640 (22,270 to 176,400)
	Other	157,700 (55,660 to 319,200)	282,000 (128,000 to 488,100)
QALYs gained	White	373,200 (200,400 to 595,300)	677,500 (425,900 to 987,800)
	Black	106,000 (82,600 to 267,300)	297,700 (179,600 to 444,500)
	Other	191,200 (99,140 to 310,000)	360,500 (216,600 to 529,100)
Change in health-related costs[‡] ($ billion)	White	-32.64 (-55.43 to -17.01)	-59.73 (-93.11 to -36.49)
	Black	-15.05 (-26.69 to -7.33)	-27.75 (-44.65 to -15.75)
	Other	-15.99 (-26.72 to -8.2)	-29.71 (-45.42 to -17.45)
CHD medical costs	White	-5.76 (-13.38 to -2.17)	-11.01 (-23.4 to -4.48)
	Black	-3.74 (-7.68 to -1.39)	-7.05 (-13.55 to -2.97)
	Other	-2.12 (-4.67 to -0.73)	-4.06 (-8.18 to -1.69)
CHD mortality productivity costs	White	-7.02 (-17 to -1.79)	-13.5 (-28.3 to -4.85)
	Black	-2.06 (-7.52 to 0)	-4.13 (-11.53 to -0.43)

Supplemental Table 7. Estimated added sugar intake, health gains, costs, and cost-effectiveness of the U.S. FDA added sugar labeling policy over the 20-year simulation period from 2018 to 2037, for U.S. adults aged 30 to 84 years stratified by race/ethnicity (continued)

	Race	Sugar label	Sugar Label + reformulation
	Other	-1.33 (-5.26 to 0)	-2.7 (-7.83 to 0)
CHD morbidity productivity costs	White	-1.71 (-4.46 to -0.58)	-3.21 (-7.8 to -1.29)
	Black	-1.36 (-2.96 to -0.48)	-2.48 (-5.01 to -1.01)
	Other	-0.88 (-2.09 to -0.3)	-1.69 (-3.68 to -0.69)
CHD informal care costs[‖]	White	-1.48 (-3.69 to -0.57)	-2.75 (-6.46 to -1.15)
	Black	-0.97 (-2.16 to -0.38)	-1.81 (-3.77 to -0.8)
	Other	-0.67 (-1.56 to -0.25)	-1.25 (-2.69 to -0.54)
Stroke medical costs	White	-0.23 (-0.77 to 0.03)	-0.43 (-1.21 to -0.03)
	Black	-0.21 (-0.85 to 0.11)	-0.41 (-1.3 to 0.06)
	Other	-0.16 (-0.61 to 0.001)	-0.31 (-0.93 to -0.01)
Stroke mortality productivity costs	White	0 (-1.28 to 0.27)	0 (-1.75 to 0.4)
	Black	0 (-1.41 to 0.04)	0 (-1.87 to 0.37)
	Other	0 (-1.36 to 0)	0 (-1.7 to 0)
Stroke morbidity productivity costs	White	-0.07 (-0.25 to 0)	-0.12 (-0.39 to -0.01)
	Black	-0.05 (-0.21 to 0.002)	-0.1 (-0.32 to -0.002)
	Other	-0.05 (-0.19 to 0)	-0.09 (-0.28 to 0)
Stroke informal care costs[‖]	White	-0.19 (-0.73 to 0.005)	-0.35 (-1.2 to -0.04)
	Black	-0.12 (-0.5 to 0.03)	-0.23 (-0.77 to 0)
	Other	-0.11 (-0.44 to 0)	-0.2 (-0.67 to -0.02)
T2DM medical costs	White	-8.85 (-16.62 to -4.13)	-16.01 (-27.69 to -8.07)
	Black	-3.4 (-6.67 to -1.43)	-6.26 (-11.04 to -2.96)
	Other	-5.73 (-10.73 to -2.53)	-10.69 (-18.3 to -5.23)
T2DM productivity costs	White	-5.42 (-9.96 to -2.45)	-9.88 (-16.87 to -5.02)
	Black	-2.21 (-4.23 to -0.95)	-4.1 (-7.19 to -2.04)
	Other	-4.03 (-7.34 to -1.74)	-7.51 (-12.59 to -3.66)
T2DM informal care costs[‖]	White	-0.21 (-0.45 to -0.05)	-0.35 (-0.71 to -0.12)
	Black	-0.06 (-0.17 to 0.01)	-0.11 (-0.25 to -0.01)
	Other	-0.09 (-0.24 to -0.01)	-0.16 (-0.35 to -0.04)
Change in policy costs[‡] ($ billion)	White	1.1 (0.43 to 2.49)	2.82 (1.48 to 4.96)
	Black	0.2 (0.08 to 0.44)	0.5 (0.26 to 0.89)
	Other	0.38 (0.15 to 0.86)	0.99 (0.52 to 1.75)
Government administrative costs	White	0.01 (0.008 to 0.01)	0.01 (0.008 to 0.01)
	Black	0.002 (0.001 to 0.003)	0.002 (0.001 to 0.003)
	Other	0.004 (0.003 to 0.005)	0.004 (0.003 to 0.005)
Industry compliance costs	White	1.09 (0.42 to 2.48)	1.09 (0.42 to 2.48)
	Black	0.19 (0.07 to 0.44)	0.19 (0.07 to 0.44)
	Other	0.38 (0.15 to 0.86)	0.38 (0.15 to 0.86)
Industry reformulation costs	White	0 (0 to 0)	1.61 (0.6 to 3.49)
	Black	0 (0 to 0)	0.29 (0.11 to 0.63)
	Other	0 (0 to 0)	0.57 (0.21 to 1.24)
Total net cost from healthcare perspective[#] ($ billion)	White	-15.22 (-27.22 to -7.51)	-28.21 (-46.61 to -15.39)
	Black	-7.49 (-13.61 to -3.49)	-13.89 (-22.92 to -7.41)
	Other	-8.23 (-14.56 to -3.96)	-15.22 (-24.94 to -8.01)
Total net cost from societal perspective[#] ($ billion)	White	-31.46 (-54.21 to -15.92)	-56.7 (-90.3 to -33.43)
	Black	-14.86 (-26.36 to -7.1)	-27.24 (-44.07 to -15.24)

Supplemental Table 7. Estimated added sugar intake, health gains, costs, and cost-effectiveness of the U.S. FDA added sugar labeling policy over the 20-year simulation period from 2018 to 2037, for U.S. adults aged 30 to 84 years stratified by race/ethnicity (continued)

	Race	Sugar label	Sugar Label + reformulation
	Other	-15.56 (-26.44 to -7.77)	-28.71 (-44.6 to -16.13)
Net monetary benefit[**] ($ billion, valuing QALYs at $100,000)	White	68.77 (36.64 to 112.8)	124.5 (77.74 to 188.7)
	Black	30.98 (15.77 to 52.64)	57.14 (34.01 to 87.21)
	Other	34.74 (18 to 57.15)	65 (38.52 to 96.48)
Incremental cost-effectiveness ratio[††] (2017 USD per QALY)	White	-84,400 (-108,500 to -63,940) dominant	-84,020 (-105,300 to -65,100) dominant
	Black	-92,300 (-123,400 to -66,160) dominant	-92,190 (-118,800 to -70,440) dominant
	Other	-81,030 (-105,300 to -60,460) dominant	-79,660 (-101,300 to -61,080) dominant

Abbreviations: SSB, sugar-sweetened beverages; BMI, body mass index; CHD, coronary heart disease; T2DM, type 2 diabetes mellitus; QALY, quality-adjusted life years.

[*] Values are median estimates from 2,000 Monte Carlo iterations (95% uncertainty intervals). Costs and QALYs were discounted at 3% annually.

[†] We evaluated only the subset of added sugar in NHANES from packaged products that would carry a Nutrition Facts label, i.e. sugars from supermarkets, convenience stores, vending machines. We excluded added sugar consumed from other sources, e.g., in restaurants and as sugar added by consumers. Intakes were adjusted for energy intake using the residual method[15] to minimize measurement error and account for potential non-dietary differences, such as body size, metabolic efficiency and physical activity.

[‡] Costs are median from 2,000 Monte Carlo iterations so may not add up to totals. Negative costs represent savings. Costs are inflated to 2017 USD using the Consumer Price Index.

[||] Informal care costs refer to unpaid caregiving costs. We conservatively excluded other informal healthcare costs such as transportation costs and patient time costs.

Net costs were calculated as policy costs minus health-related costs from reduced cardiometabolic diseases. Healthcare perspective included policy costs and medical costs; societal perspective further incorporated informal healthcare costs and productivity costs.

[**] Net monetary benefit was calculated by summing net savings and QALYs gained multiplied by a $100,000 willingness-to-pay threshold per QALY.

[††] Incremental cost-effectiveness ratios were calculated as the net change in costs divided by the net change in QALYs. Dominant = cost-saving and more effective than the base-case scenario.

Supplemental Table 8. Estimated health gains, costs, and cost-effectiveness of the U.S. FDA added sugar labeling policy over the 5-year simulation period, for U.S. adults aged 30 to 84 years.[*]

	Sugar label	Sugar label + reformulation
Population (million)	200.68 (200.27 to 201.07)	200.68 (200.27 to 201.07)
Health outcomes		
BMI in 2022 (kg/m^2)	28.29 (28.212 to 28.35)	28.25 (28.17 to 28.32)
CVD cases prevented/postponed	74,220 (25,980 to 167,000)	105,800 (35,250 to 239,400)
CVD deaths prevented/postponed	1,855 (0 to 7,422)	1,855 (0 to 9,277)
T2DM cases prevented/postponed	115,000 (44,530 to 215,300)	161,400 (55,660 to 311,700)
T2DM-related deaths prevented/postponed	0 (0 to 3,711)	0 (0 to 3,711)
Life-years gained	1,855 (0 to 11,130)	1,855 (0 to 12,990)
QALYs gained	43,730 (13,390 to 94,150)	56,260 (15,480 to 123,100)
Change in health-related costs[†] ($ billion)	-3.67 (-9.63 to -0.93)	-4.76 (-12.16 to -1.10)
CHD medical costs	-0.64 (-1.74 to -0.15)	-0.84 (-2.3 to -0.20)
CHD mortality productivity costs	-0.5 (-4.69 to 0)	-1.03 (-5.55 to 0)
CHD morbidity productivity costs	-0.3 (-0.85 to -0.08)	-0.39 (-1.11 to -0.10)
CHD informal care costs[‡]	-0.24 (-0.69 to -0.07)	-0.31 (-0.89 to -0.08)
Stroke medical costs	-0.007 (-0.084 to 0.004)	-0.010 (-0.098 to 0.005)
Stroke mortality productivity costs	0 (0 to 0)	0 (0 to 0)
Stroke morbidity productivity costs	0 (-0.029 to 0)	-0.004 (-0.03 to 0)
Stroke informal care costs[‡]	-0.008 (-0.079 to 0.002)	-0.011 (-0.097 to 0.003)
T2DM medical costs	-0.82 (-2.07 to -0.20)	-1.04 (-2.65 to -0.24)
T2DM productivity costs	-0.62 (-1.56 to -0.15)	-0.78 (-2.00 to -0.18)
T2DM informal care costs[‡]	0 (-0.02 to 0.004)	0 (-0.02 to 0.004)
Change in policy costs[†] ($ billion)	1.68 (0.66 to 3.79)	4.31 (2.25 to 7.59)
Government administrative costs	0.01 (0.01 to 0.02)	0.01 (0.01 to 0.02)
Industry compliance costs	1.66 (0.64 to 3.77)	1.66 (0.64 to 3.77)
Industry reformulation costs	0 (0 to 0)	2.46 (0.93 to 5.35)
Total net cost from healthcare perspective[||] ($ billion)	-1.53 (-3.5 to -0.45)	-1.95 (-4.56 to -0.53)
Total net cost from societal perspective[||] ($ billion)	-1.9 (-7.94 to 1.56)	-0.33 (-8.15 to 4.61)
Net monetary benefit[#] ($ billion, valuing QALYs at $100,000)	6.31 (0.31 to 16.8)	5.89 (-2.25 to 19.52)
Incremental cost-effectiveness ratio[**] (2017 USD per QALY)	-41,390 (-122,600 to 80,110); dominant	-6,155 (-83,840 to 231,900); dominant

Abbreviations: SSB, sugar-sweetened beverages; BMI, body mass index; CHD, coronary heart disease; T2DM, type 2 diabetes mellitus; QALY, quality-adjusted life years.

[*] Values are median estimates from 2,000 Monte Carlo iterations (95% uncertainty intervals). Costs and QALYs were discounted at 3% annually.

[†] Costs are median from 2,000 Monte Carlo iterations so may not add up to totals. Negative costs represent savings. Costs are inflated to 2017 USD using the Consumer Price Index.

[‡] Informal care costs refer to unpaid caregiving costs. We conservatively excluded other informal healthcare costs such as transportation costs and patient time costs.

[||] Net costs were calculated as policy costs minus health-related costs from reduced cardiometabolic diseases. Healthcare perspective included policy costs and medical costs; societal perspective further incorporated informal healthcare costs and productivity costs.

[#] Net monetary benefit was calculated by summing net savings and QALYs gained multiplied by a $100,000 willingness-to-pay threshold per QALY.

[**] Incremental cost-effectiveness ratios were calculated as the net change in costs divided by the net change in QALYs. Dominant = cost-saving and more effective than the base-case scenario.

Supplemental Table 9. Estimated health gains, costs, and cost-effectiveness of the U.S. FDA added sugar labeling policy over the 10-year simulation period, for U.S. adults aged 30 to 84 years.[*]

	Sugar label	Sugar label + reformulation
Population (million)	209.04 (207.88 to 210.03)	209.05 (207.89 to 210.03)
Health outcomes		
BMI in 2022 (kg/m^2)	28.4 (28.3 to 28.5)	28.3 (28.3 to 28.4)
CVD cases prevented/postponed	170,700 (74,220 to 348,900)	311,700 (150,300 to 599,300)
CVD deaths prevented/postponed	7,422 (0 to 18,550)	11,130 (1,855 to 25,980)
T2DM cases prevented/postponed	276,500 (133,600 to 456,600)	499,100 (263,500 to 764,400)
T2DM-related deaths prevented/postponed	3,711 (0 to 11,130)	5,566 (0 to 14,840)
Life-years gained	25,980 (1,855 to 72,360)	38,960 (7,422 to 94,630)
QALYs gained	195,800 (96,830 to 332,7000)	314,700 (170,000 to 510,900)
Change in health-related costs[†] ($ billion)	-17.03 (-31.37 to -8.03)	-27.4 (-47.27 to -14.24)
CHD medical costs	-2.94 (-6.61 to -1.05)	-4.86 (-10.38 to -1.83)
CHD mortality productivity costs	-3.42 (-10.42 to 0)	-5.89 (-14.84 to -0.87)
CHD morbidity productivity costs	-1.22 (-2.98 to -0.45)	-2.01 (-4.61 to -0.77)
CHD informal care costs[‡]	-0.97 (-2.35 to -0.37)	-1.59 (-3.60 to -0.65)
Stroke medical costs	-0.09 (-0.39 to 0.02)	-0.15 (-0.55 to 0)
Stroke mortality productivity costs	0 (-1.19 to 0)	0 (-1.43 to 0)
Stroke morbidity productivity costs	-0.03 (-0.13 to 0)	-0.05 (-0.18 to 0)
Stroke informal care costs[‡]	-0.08 (-0.36 to 0)	-0.13 (-0.5 to -0.01)
T2DM medical costs	-4.21 (-8.46 to -1.73)	-6.70 (-12.84 to -2.9)
T2DM productivity costs	-3.09 (-6.11 to -1.27)	-4.88 (-9.16 to -2.08)
T2DM informal care costs[‡]	-0.02 (-0.09 to 0.01)	-0.04 (-0.12 to 0)
Change in policy costs[†] ($ billion)	1.67 (0.66 to 3.79)	4.31 (2.26 to 7.59)
Government administrative costs	0.01 (0.01 to 0.02)	0.01 (0.01 to 0.02)
Industry compliance costs	1.66 (0.64 to 3.77)	1.66 (0.64 to 3.77)
Industry reformulation costs	0 (0 to 0)	2.46 (0.93 to 5.35)
Total net cost from healthcare perspective[||] ($ billion)	-7.45 (-13.75 to -3.36)	-11.92 (-21.23 to -5.73)
Total net cost from societal perspective[||] ($ billion)	-15.27 (-29.92 to -5.77)	-23.08 (-42.98 to -9.26)
Net monetary benefit[#] ($ billion, valuing QALYs at $100,000)	34.95 (16.26 to 62.25)	54.46 (27.1 to 93.43)
Incremental cost-effectiveness ratio[**] (2017 USD per QALY)	-77,590 (-107,800 to -49,250); dominant	-73,110 (-99,820 to -46,210); dominant

Abbreviations: SSB, sugar-sweetened beverages; BMI, body mass index; CHD, coronary heart disease; T2DM, type 2 diabetes mellitus; QALY, quality-adjusted life years.

[*] Values are median estimates from 2,000 Monte Carlo iterations (95% uncertainty intervals). Costs and QALYs were discounted at 3% annually.

[†] Costs are median from 2,000 Monte Carlo iterations so may not add up to totals. Negative costs represent savings. Costs are inflated to 2017 USD using the Consumer Price Index.

[‡] Informal care costs refer to unpaid caregiving costs. We conservatively excluded other informal healthcare costs such as transportation costs and patient time costs.

[||] Net costs were calculated as policy costs minus health-related costs from reduced cardiometabolic diseases. Healthcare perspective included policy costs and medical costs; societal perspective further incorporated informal healthcare costs and productivity costs.

[#] Net monetary benefit was calculated by summing net savings and QALYs gained multiplied by a $100,000 willingness-to-pay threshold per QALY.

[**] Incremental cost-effectiveness ratios were calculated as the net change in costs divided by the net change in QALYs. Dominant = cost-saving and more effective than the base-case scenario.

Supplemental Table 10. One-way sensitivity analysis by alternative discount rates and willingness to pay per QALY: incremental cost-effectiveness ratio (2017 USD per QALY) of the U.S. FDA added sugar labeling policy over the 20-year simulation period from 2018 to 2037 for U.S. adults aged 30 to 84 years.*

Willingness to pay	Discount	Sugar label	Sugar label + reformulation
$50,000	0%	-86,290 (-106,900 to -67,650)	-85,530 (-106,300 to -68,300)
	3%	-85,400 (-106,400 to -67,020)	-84,600 (-104,600 to -67,200)
	6%	-84,200 (-105,100 to -65,340)	-83,050 (-102,800 to -65,410)
	9%	-82,480 (-103,900 to -62,330)	-81,030 (-100,700 to -62,590)
$100,000	0%	-86,290 (-106,900 to -67,650)	-85,530 (-106,300 to -68,300)
	3%	-85,400 (-106,400 to -67,020)	-84,600 (-104,600 to -67,200)
	6%	-84,200 (-105,100 to -65,340)	-83,050 (-102,800 to -65,410)
	9%	-82,480 (-103,900 to -62,330)	-81,030 (-100,700 to -62,590)
$150,000	0%	-86,290 (-106,900 to -67,650)	-85,530 (-106,300 to -68,300)
	3%	-85,400 (-106,400 to -67,020)	-84,600 (-104,600 to -67,200)
	6%	-84,200 (-105,100 to -65,340)	-83,050 (-102,800 to -65,410)
	9%	-82,480 (-103,900 to -62,330)	-81,030 (-100,700 to -62,590)

Abbreviations: QALY: quality-adjusted life year.
* Values are the median estimate (95% UI).

Supplemental Table 11. One-way sensitivity analysis by alternative discount rates and willingness to pay per QALY: net monetary benefits ($ billion in 2017 USD) of the U.S. FDA added sugar labeling policy over the 20-year simulation period from 2018 to 2037 for U.S. adults aged 30 to 84 years.*

Willingness to pay	Discount	Sugar label	Sugar label + reformulation
$50,000	0%	151.1 (84.99 to 242.8)	279.6 (177 to 415.1)
	3%	98.5 (54.91 to 159.6)	180.1 (112.9 to 270.8)
	6%	64.47 (35 to 105.4)	115.8 (71.31 to 174.5)
	9%	42.6 (22.32 to 71.04)	74.9 (44.76 to 115.7)
$100,000	0%	207 (115.3 to 330.4)	382.6 (244.2 to 558.1)
	3%	134.8 (74.96 to 217.3)	247 (156 to 363.9)
	6%	88.75 (48.33 to 143.3)	159.1 (99.62 to 238.5)
	9%	58.61 (31.6 to 95.57)	103.2 (62.48 to 157)
$150,000	0%	263 (146.5 to 418.4)	485.9 (312.1 to 701)
	3%	171.5 (95.24 to 274)	313.1 (197.9 to 457.3)
	6%	112.5 (61.75 to 181.2)	202.6 (126.6 to 301.8)
	9%	74.57 (40.28 to 120.9)	131.7 (80.78 to 198.8)

Abbreviations: QALY: quality-adjusted life year.
* Values are the median estimate (95% UI).

Supplemental Table 12. Added sugar intake, CVD and T2DM cases, prevalence, deaths and costs for the usual care' base-case scenario over the 20-year simulation period from 2018 to 2037, for U.S. adults aged 30 to 84 years.*

Model outputs	Base-case scenario
Person-years (30 to 84 years, in billions)	4.17 (4.14 to 4.19)
Median SSB added sugar intake† in 2037 (g/d)	4.7 (4.47 to 4.92)
Median non SSB added sugar intake† in 2037 (g/d)	26.9 (26.6 to 27.1)
Mean SSB added sugar intake† in 2037 (g/d)	22.5 (22.1 to 22.9)
Mean non SSB added sugar intake† in 2037 (g/d)	32.3 (31.9 to 32.8)
Median BMI in 2037 (Kg/m^2)	28.6 (28.6 to 28.7)
New CHD cases (first ever episode, cumulative)	22.3m (11.9m to 34.5m)
New stroke cases (first ever episode, cumulative)	11.0m (5.52m to 19.1m)
New CVD cases (first ever episode, cumulative)	33.2m (21.5m to 48.2m)
New T2DM cases (diagnosed + undiagnosed, cumulative)	24.1m (23.8m to 24.4m)
CHD prevalence in 2037	19.9m (9.25m to 33.6m)
Stroke prevalence in 2037	8.33m (3.81m to 15.4m)
CVD prevalence in 2037	26.5m (16.0m to 40.2m)
T2DM prevalence in 2037	33.8m (33.0m to 34.6m)
CVD or T2DM prevalence in 2037	50.5m (43.4m to 60.1m)
CHD deaths (cumulative)	4.6m (3.61m to 5.85m)
Stroke deaths (cumulative)	1.55m (1.26m to 1.89m)
Deaths from other causes (cumulative)	32.3m (28.2m to 37.0m)
CHD medical costs (cumulative)	2,590bn (1,120bn to 4,920bn)
CHD mortality costs (cumulative)	402bn (186bn to 763bn)
CHD morbidity costs (cumulative)	1,690bn (1,160bn to 2,460bn)
CHD informal care costs (cumulative)	557bn (250bn to 1,040bn)
Stroke medical costs (cumulative)	1,130bn (482bn to 2,190bn)
Stroke mortality costs (cumulative)	135bn (56.8bn to 279bn)
Stroke morbidity costs (cumulative)	478bn (328bn to 695bn)
Stroke informal care costs (cumulative)	679bn (239bn to 1,620bn)
Diagnosed T2DM medical costs (cumulative)	4,350bn (3,160bn to 5,920bn)
Diagnosed T2DM productivity costs (cumulative)	1,450bn (1,070bn to 1,940bn)
Diagnosed T2DM informal care costs (cumulative)	390bn (285bn to 520bn)
Undiagnosed T2DM medical costs (cumulative)	354bn (253bn to 477bn)
Undiagnosed T2DM productivity costs (cumulative)	143bn (104bn to 189bn)
Undiagnosed T2DM informal care costs (cumulative)	0 (0 to 0)
QALYs (cumulative)	3.53bn (3.5bn to 3.56bn)
QALYs lost due to CHD (cumulative)	250m (116m to 424m)

Supplemental Table 12. Added sugar intake, CVD and T2DM cases, prevalence, deaths and costs for the usual care' base-case scenario over the 20-year simulation period from 2018 to 2037, for U.S. adults aged 30 to 84 years* (continued)

Model outputs	Base-case scenario
QALYs lost due to stroke (cumulative)	103m (47.3m to 188m)
QALYs lost due to CVD (cumulative)	336m (203m to 510m)
QALYs lost due to T2DM (cumulative)	442m (436m to 448m)
QALYs lost due to CVD or T2DM (cumulative)	662m (572m to 786m)

Abbreviations: SSB, sugar-sweetened beverages; BMI, body mass index; CHD, coronary heart disease; CVD, cardiovascular disease (the sum of CHD and stroke cases, avoiding double counting of cases with coexisting CHD and stroke); QALY, quality adjusted life years; SBP, systolic blood pressure; SSB, sugar sweetened beverages; T2DM, type 2 diabetes mellitus; UI, uncertainty intervals.

* Values are the median estimate (95% UI). Results are rounded to the third significant digit. Costs are presented in discounted (3%) 2017 USD.

† Intake from packaged products only.

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