Supplementary methods (S1 methods) to
“Regulating added sugars in sweetened beverages could curb the
obesity epidemic in Mexico: a modeling study”
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Notation

- **SSBs**, sugar sweetened beverages.
- **US**, United States.
- **UK**, United Kingdom.
- **TEI**, total energy intake. See $TEI_{init}$ for total energy intake at baseline.
- **ENSANUT**, National Health and Nutrition Survey.
- **INSP**, National Institute of Public Health.
- **BMI**, body mass index.
- **WHO**, World Health Organization.
- $TEI_{init}$, total energy intake at baseline.
- $SSB_{max}$, maximum consumption of kcals from SSB such that 10% added sugar is achieved.
- $\kappa_p$, percent added sugar desired.
- Others, consumption of other added sugars (kcal).
- $SSB_{init}$, current added sugar consumption from SSB (kcal).
- $\Delta c$, theoretical consumption change to achieve $\kappa_p \times 100\%$ consumption of added sugar.
- $i$ (superscript), $i$th individual in the sample. $TEI_{init}^{(i)}$ corresponds to total energy intake at baseline for individual $i$.
- prop, estimated average proportional change for SSBs consumers such that $\kappa_p \times 100\%$ added sugar is achieved.
- $y_1, y_2, \ldots, y_{10}$, year 1, year 2, year 10 (respectively).
- Reduction($y_k$), reduction of sugar % at year $k$.
- $\lambda$, proportion of added sugar reduction that one desires to achieve by year $\ell$.
- $\ell$, year at which a $\lambda \times 100\%$ added sugar reduction is achieved.
- $t$, variable for day.
- $BW$, body weight function (kg) as a function of time ($BW \equiv BW(t)$).
- $ECF$, extracellular fluid (kg) as a function of time ($ECF \equiv ECF(t)$)
- $G$, glycogen reservoir (kg) as a function of time ($G \equiv G(t)$).
- $F$, fat mass (kg) as function of time ($F \equiv F(t)$).
- $L$, lean mass (kg) as function of time ($L \equiv L(t)$).
- $EE$, energy expenditure as function of time ($EE \equiv EE(t)$).
- $AT$, adaptative thermogenesis as a function of time ($AT \equiv AT(t)$).
- $RMR_{init}$, resting metabolic rate at baseline.
- $F_{init}$, fat mass at baseline.
- $H_{init}$, height at baseline.
• $\Delta TEI$, change in energy intake as a function of time ($\Delta TEI \equiv \Delta TEI(t)$).
• $K$, constant for the initial energy balance condition (equilibrium).
• $p$, proportion of lean mass attributable to energy intake/expenditure difference.
• $PAL$, physical activity level.
• $TEF$, thermal effect of feeding.
1 Data collection

We used data from the National Health and Nutrition Survey (ENSANUT) from 2012 which is available in [1]. The final dataset called "Database Sugar regulation Mexico.dta" can be found at the Open Science Framework [2] with the DOI: 10.17605/OSF.IO/VFCM8 (web link osf.io/vfcm8). Table A details the variables in the dataset.

| Name     | Variable                                                                 |
|----------|--------------------------------------------------------------------------|
| intp     | Identifier for each individual in ENSANUT’s dataset.                     |
| agecat   | Age category. Levels: “20 to 40”, “40 to 60”, “Over 60”.                 |
| code_upm | Identifier of primary sampling unit.                                     |
|  
| est_var  | Complex survey weight.                                                   |
|  
| folio    | Strata for the estimation of variances accounting for survey design.    |
|  
| folio_c2 | Unique identifier for each household in ENSANUT’s dataset (to merge with anthropometric databases). |
|  
| sex      | Sex of the individual, coded as 1: “male”; 2: “female”.                 |
|  
| age      | Age (yrs).                                                               |
|  
| weight_baseline | Weight at baseline (kg).                                         |
|  
| height   | Height (cm).                                                             |
|  
| bmicategories | Categories of “normal” (1), “overweight” (2) and “obesity” (3) at baseline. |
|  
| ses      | Socioeconomic level, divided in tertiles, using the weighted sample.    |
|  
| sugar_ssb | Added sugar consumption at baseline from SSB (kcal).                    |
|  
| kcaltot  | Daily total caloric intake at baseline (kcal).                          |
|  
| finalweight | Weight after intervention (kg).                                        |
|  
| changekcal | Change in energy after intervention (kcal).                            |
|  
| changeweight | Change in weight after 12 years (kg).                                   |
|  
| bmfinal  | Body mass index after 12 years (kg/m²).                                 |
|  
| changebmi | Change in body mass index after 12 years (kg/m²).                       |
|  
| final_bmiPrevalences | Categories of “normal” (1), “overweight” (2) and “obesity” (3) after intervention. |
|  
| sugar_tot | Added sugar consumption from all sources before intervention (kcal).    |

Table A: Variables in Database_Sugar_regulation_Mexico.dta

1.1 Included beverages in the regulation

Table [3] shows the beverages included not included in the sugar regulation. The beverages classification is the same as in Sanchéz-Pimienta, et al which states: [3]

“Regular soda” includes all brands of carbonated sodas with caloric sweeteners; “Fruit, flavored, sports, and energy drinks” include noncarbonated flavored water, industrialized juice, and energy and sport drinks; “sweetened coffee and tea” include coffee and tea with caloric sweeteners; “aguas frescas and homemade SSBs” include aguas frescas frescas, a traditional flavored water-based preparation, and fruit shakes without sugar or other caloric sweeteners, atoles without milk, and pozol (fermented corn beverage); and “sweetened milk and milk beverages” include milk, milk shakes, smoothies, coffee or tea made with milk (more than one-third of the preparation), and atoles with milk. [3]

1.2 Survey design

ENSANUT is a cross-sectional, multi-stage, probabilistic survey representative of the Mexican population survey whose methodology has been explained elsewhere [4]. To account for this design, we used the R [5] package survey [6] with the following design:

```r
svystr <- svydesign(id = "id", strata = "est_var", weights = "ponef.a", PSU = "code_upm,
                     data = Adults)

options(survey.lonely.psu = "adjust")
```

The same design in Stata [7], is achieved by:

```stata
svyset [w = ponef.a], psu(code_upm) strata(est_var) singleunit(centered)
```

All population-level estimations were done considering this design in either of the programmes.
| Sugar Regulation Beverages group | Description |
|--------------------------------|-------------|
| Included                       | *Industrialized carbonated beverages* | Regular soda. |
|                                | *Industrialized non-carbonated beverages* | Fruit, flavored, sports, and energy drinks. |
| Not Included                   | *Homemade sweetened beverages* | Sweetened coffee and tea, aguas frescas and homemade SSBs. |
|                                | *Dairy beverages* | Sweetened milk and milk beverages |

*Table B: Beverages included in the regulation.*

2 Estimation of the sugar reduction target for regulation

2.1 Formula derivation

To estimate the target for added sugar regulation in SSBs, we estimated the maximum added sugar intake from SSBs such that overall consumption of added sugar was under the WHO guidelines. These guidelines establish that at most, 10% of the total energy intake ($TEI_{init}$) should come from added sugars. To find the target, we considered only those individuals that reported a consumption > 0 and we calculated the amount of added sugar from SSBs and from other sources as well as the Total Energy Intake in kcals ($TTEI_{init}$). To estimate the individual level of maximum consumption of kcals from SSBs ($SSB_{max}$), such that a 10% added sugar is achieved, we set $\kappa_p = 0.1$ (10% of total energy intake coming from added sugar). This was specified in the following equation:

$$\kappa_p = \frac{SSB_{max} + Others}{TEI_{init} + (SSB_{max} - SSB_{init})} = 0.1,$$

where Others is the consumption of other added sugars (kcal), $TEI_{init}$ is the current total energy intake (kcal), and $SSB_{init}$ is the current added sugar consumption from SSBs (kcal). The maximum sugar consumption from SSBs ($SSB_{max}$) hence equals:

$$SSB_{max} = \frac{\kappa_p}{1 - \kappa_p} \cdot (TEI_{init} - SSB_{init}) - \frac{1}{(1 - \kappa_p)} \cdot Others. \quad (2)$$

Using the $SSB_{max}$, we obtained the theoretical consumption change, $\Delta_C$:

$$\Delta_C = \begin{cases} 
0, & \text{if } 0 \leq SSB_{init} \leq SSB_{max}, \\
-SSB_{init}, & \text{if } SSB_{max} \leq 0, \\
SSB_{max} - SSB_{init}, & \text{if } 0 < SSB_{max} < SSB_{init}.
\end{cases} \quad (3)$$

Intuitively, if current sugar consumption from SSBs ($SSB_{init}$) was lower than the maximum consumption from SSBs ($SSB_{max}$), we kept consumption at the current level ($\Delta_C = 0$). If sugar from additional sources was above the 10% threshold, we reduced all sugar from SSBs ($\Delta_C = -SSB_{init}$). Finally, if by reducing SSBs to the $SSB_{max}$ achieves the goal of 10% added sugars in overall energy intake, we reduced sugar consumption from SSBs to $\Delta_C = SSB_{max} - SSB_{init}$.

2.2 Individual estimation to obtain added-sugar percent reduction

For each individual, $i$, in the sample, we estimated their maximum amount of sugar from SSBs ($SSB_{max}^{(i)}$), such that the amount of added sugar in their total energy intake, $TEI_{init}^{(i)}$, is, at most, 10% for each individual. For that purpose, we used equation (2) and considered as inputs the individual’s current total energy intake.
\((\text{TEI}\textsubscript{\text{init}}^{(i)}),\) their SSBs caloric intake \((\text{SSB}\textsubscript{\text{init}}^{(i)}),\) and their caloric intake from other added sugars \((\text{Others}^{(i)}).\) The latter stand for \(\text{kcaltot}, \text{sugarssb},\) and \(\text{sugartot}\) variables in our database.

Using each individual’s SSB\textsubscript{\text{init}}\textsuperscript{(i)} and SSB\textsubscript{\text{max}}\textsuperscript{(i)} we obtained their theoretical consumption change \(\Delta C^{(i)}.\) The individual proportional change of sugar consumption from SSB was then calculated as \(\text{prop}^{(i)} = -\Delta C^{(i)}/\text{SSB}_{\text{init}}^{(i)}.\) We then estimated the average proportional change for consumers \(\text{prop} = 0.522,\) which is equivalent to a reduction of 52.2\% of sugar in SSB, which we rounded to 50\%.

### 2.3 Regulation scenarios

After obtaining the \(\lambda\%\) change of added sugar we then established different scenarios of regulation that would achieve said change. The decreasing scenario (section 2.3.1) was used for all analysis in the article (with \(k = 50\)) whilst the increasing (section 2.3.2) and constant (section 2.3.3) scenarios were used for the sensitivity analysis. As was shown in the sensitivity analysis; all scenarios converge after 12 years.

#### 2.3.1 Decreasing scenario

Let \(y_1, y_2, \ldots, y_{10}\) denote year 1, year 2 up to year 10 (respectively). The decreasing scenario assumes a yearly SSB-added-sugar reduction in which the yearly difference in added sugar\% decreases in time. This scenario was implemented in [8] and is given by:

\[
\text{Reduction}(y_k) = 1 - (1 - \text{Reduction}(y_{k-1}))^k, \tag{4}
\]

for \(k = 1, 2, \ldots, 10.\) The previous equation is equivalent to:

\[
\text{Reduction}(y_k) = 1 - (1 - \text{Reduction}(y_1))^k. \tag{5}
\]

To achieve a \(\lambda \times 100\%\) reduction by year \(y_\ell\) one would plug in the \(\lambda\) in \(\text{Reduction}(y_{\ell})\) \((\ref{eq:reduction})\) to obtain the first year reduction associated to \(\lambda:\)

\[
\text{Reduction}(y_1) = 1 - (1 - \lambda)^{\frac{1}{10}}, \tag{6}
\]

and then substitute in \((\ref{eq:reduction})\) to obtain an expression for the reduction in year \(k:\)

\[
\text{Reduction}(y_k) = 1 - (1 - \lambda)^{\frac{k}{10}}. \tag{7}
\]

In the specific case of a a reduction of \(\lambda = 0.5 (50\%)\) after 10 years, the \(k\)-th year formula is:

\[
\text{Reduction}(y_k) = 1 - (0.5)^{\frac{k}{10}}. \tag{8}
\]

The proportion reduced yearly from the original amount of sugar for a reduction of \(\lambda = 0.5\) after 10 years is shown in Table [C].

| Year | \(y_1\) | \(y_2\) | \(y_3\) | \(y_4\) | \(y_5\) | \(y_6\) | \(y_7\) | \(y_8\) | \(y_9\) | \(y_{10}\) |
|------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Reduction | 6.7% | 12.9% | 18.8% | 24.2% | 29.3% | 34.0% | 38.4% | 42.6% | 46.4% | 50.0% |
| Difference | 6.7% | 6.2% | 5.8% | 5.4% | 5.1% | 4.7% | 4.4% | 4.1% | 3.8% | 3.6% |

\(\text{Table C: Yearly proportion of sugar reduced from original amount of sugar for a reduction of } \lambda = 0.5 \text{ after 10 years and difference in reduction } \% \text{ with previous year (Difference}^{(y_k)} = \text{Reduction}(y_k) - \text{Reduction}(y_{k-1})}).\)

\(^1\text{In accordance with the survey design established on section 1.2}\)
2.3.2 Increasing scenario

This implementation scenario was done for sensitivity analysis. Instead of implementing a decrease in reduction of added sugar; we created a scenario in which the yearly difference in % reduction increases over time. In this case, the equation for the $k$-th year is given by:

$$\text{Reduction}(y_k) = \lambda \cdot (1 - \lambda)^{\frac{k}{\ell}};$$

where $\lambda \times 100\%$ is the desired reduction by year $\ell$. In the case of a 50% ($\lambda = 0.5$) SSB-added-sugar reduction by year 10 the specific equation for the $k$-th year is given by:

$$\text{Reduction}(y_k) = \left(0.5\right)^{\frac{10-k}{10}},$$

which yields the values in Table D.

| Year | $y_1$ | $y_2$ | $y_3$ | $y_4$ | $y_5$ | $y_6$ | $y_7$ | $y_8$ | $y_9$ | $y_{10}$ |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----------|
| Reduction | 3.6% | 7.4% | 11.6% | 16.0% | 20.7% | 25.8% | 31.2% | 37.1% | 43.3% | 50.0% |
| Difference | 3.6% | 3.8% | 4.1% | 4.4% | 4.7% | 5.1% | 5.4% | 5.8% | 6.2% | 6.7% |

Table D: Yearly proportion of sugar reduced using incremental scheme with a 50% reduction ($\lambda = 0.5$) after $\ell = 10$ years and difference in reduction % with previous year (Difference$(y_k) = \text{Reduction}(y_k) - \text{Reduction}(y_{k-1})$).

These reduction values are the ones implemented in the paper’s sensitivity analysis (see section below).

2.3.3 Constant scenario

This implementation scenario was done for sensitivity analysis (see section 4). In this scenario we implemented a constant % reduction such that if a $\lambda\%$ reduction is implemented over $\ell$ years then each year a $\lambda\%/\ell$ is reduced such that by year $\ell$, $\lambda\%$ is achieved. For the specific case of $\lambda = 0.5$ (50% reduction) for $\ell = 10$ years the percent reduction is presented in Table E. The general formula for the $k$-th year in this case is given by:

$$\text{Reduction}(y_k) = k \cdot \frac{\lambda}{\ell},$$

where $\lambda$ denotes the expected reduction at year $\ell$. In the particular case of a 50% reduction in 10 years (the one implemented in the paper’s sensitivity analysis) the formula is:

$$\text{Reduction}(y_k) = k \cdot \frac{0.5}{10}.$$  

Table E: Yearly proportion of sugar reduced using the constant $50\%$ reduction and difference in reduction % with previous year (Difference$(y_k) = \text{Reduction}(y_k) - \text{Reduction}(y_{k-1})$).

| Year | $y_1$ | $y_2$ | $y_3$ | $y_4$ | $y_5$ | $y_6$ | $y_7$ | $y_8$ | $y_9$ | $y_{10}$ |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----------|
| Reduction | 5% | 10% | 15% | 20% | 25% | 30% | 35% | 40% | 45% | 50.0% |
| Difference | 5% | 5% | 5% | 5% | 5% | 5% | 5% | 5% | 5% | 5% |

2.4 Individual modelling of energy intake for reduction scenarios

The caloric reduction scenarios were designed globally. However, the reductions were conducted individually. Thus for each individual $i$ we model their energy intake change at day $t$ with a function $\Delta \text{TEI}^{(i)}(t)$ given by:

$$\Delta \text{TEI}^{(i)}(t) = \text{TEI}_\text{init}^{(i)} - \text{Reduction}(y_{\left\lceil t/365 \right\rceil}) \cdot SSB_{\text{init}}^{(i)};$$

with $\left\lceil \cdot \right\rceil$ the ceiling function where $\left\lceil x \right\rceil$ stands for the smallest integer larger or equal to $x$. In the previous equation, $\text{TEI}_\text{init}^{(i)}$ stands for the total energy intake (kcal) of the $i$-th individual and $SSB_{\text{init}}^{(i)}$ their initial SSB consumption (kcal).
3 Weight change model

The weight change model [9] defines individual weight (kg) as the sum of fat $F$ and lean mass $L$, extracellular fluid $ECF$ and glycogen $G$:

$$BW = ECF + 3.7G + F + L.$$  \hspace{1cm} (14)

Extracellular fluid $ECF \equiv ECF(t)$ is the solution to the ordinary differential equation system:

$$\left\{ \begin{array}{l}
\frac{dECF}{dt} = \frac{1}{Na}(\Delta Na_{diet} + \xi Na(ECF - ECF_{init}) - \xi CI(1 - CI/CIb)), \\
ECF_{init} = 0.
\end{array} \right.$$  \hspace{1cm} (15)

where $Na = 3.22 \text{ mg/ml, } \xi Na = 3000 \text{ mg/L/d, and } \xi CI = 4000 \text{ mg/d, are physiological constants [9].} \Delta Na_{diet}$ represents the change in sodium (mg/d) for the individual [9]. $CIb$ is the carbohydrate intake at baseline (assumed to be 1/2 of energy intake estimated in (3)) and $CI \equiv CI(t)$ is the carbohydrate intake after the consumption reduction (assumed to be half the energy intake after reduction, $CI \equiv \Delta TEI(t)/2$).

Glycogen mass $G \equiv G(t)$ is described by the ordinary differential equation:

$$\frac{dG}{dt} = \frac{1}{\rho_G}(CI - k_G \cdot G^2),$$  \hspace{1cm} (16)

where $\rho_G = 4206.501 \text{kcals/kg (17.6 MJ/kg), and } k_G = CIb/G_{init}^2$ is a constant with $G_{init} = 0.5 \text{ kg the initial glycogen mass.}$

Fat and lean mass, $F \equiv F(t)$ and $L \equiv L(t)$, represent the solutions to the following system of nonlinear ordinary differential equations:

$$\frac{dF}{dt} = \frac{(1 - p)}{\rho_F}(TEI_{init} - EE - \rho_G \frac{dG}{dt}),$$

$$\frac{dL}{dt} = \frac{p}{\rho_L}(TEI_{init} - EE - \rho_G \frac{dG}{dt}),$$  \hspace{1cm} (17)

with $\rho_F = 9440.727 \text{ kcals/kg (39.5 MJ/kg), } \rho_L = 1816.444 \text{ kcals/kg (7.6 MJ/kg) are constants, and } p \equiv C/(C + F) \text{ a function of fat mass with } C = 10.4 \cdot \rho_L \rho_F^{-1}$. Total energy expenditure $EE$ is given by:

$$EE = K + \gamma_F F + \gamma_L L + \delta BW + TEF + AT + \eta_L \frac{dL}{dt} + \eta_F \frac{dF}{dt},$$  \hspace{1cm} (18)

with $\gamma_F = 3.107075 \text{kcals/kg/d (13 kJ/kg/d), } \gamma_L = 21.98853 \text{kcals/kg/d (92 kJ/kg/d), } \eta_F = 179.2543 \text{kcals/kg (750 kJ/d), } \eta_L = 229.4455 \text{kcals/kg (960 kJ/kg) are physiological constants.}$ $K$ is determined by the initial energy balance condition:

$$K = RMR_{init} \cdot PAL - \gamma L L_{init} - \gamma F F_{init} - \delta BW_{init}$$  \hspace{1cm} (19)

with $RMR_{init}$ the initial resting metabolic rate (as estimated by (21)), $PAL$ the physical activity level (assumed $PAL = 1.5$), $L_{init}, F_{init}, BW_{init}$ the initial lean, fat and body weight masses. The constant $\delta$ is determined defined as $\delta = RMR_{init} (1 - \beta_{TEF} \cdot PAL - 1)/BW_{init}$ with $\beta_{TEF} = 0.1$. Furthermore, the thermal effect of feeding is defined as $TEF \equiv \beta_{TEF} \Delta TEI(t)$ with $\Delta TEI(t)$ as specified in (13). Finally, adaptive thermogenesis is given by the solution to the ODE system:

$$\left\{ \begin{array}{l}
\frac{dAT}{dt} = \beta_{AT} \Delta TEI - AT, \\
AT_{init} = \beta_{AT} \cdot PAL \cdot RMR_{init}.
\end{array} \right.$$  \hspace{1cm} (20)

We remark that for each individual, the initial resting metabolic rate $RMR_{init}$ is described by the equations [10]:

$$RMR_{init} = \begin{cases} 
9.99 \cdot BW_{init} + 625 \cdot H_{init} - 4.92 \cdot AGE_{init} + 5 & \text{if Sex = Male,} \\
9.99 \cdot BW_{init} + 625 \cdot H_{init} - 4.92 \cdot AGE_{init} - 161 & \text{if Sex = Female.}
\end{cases}$$  \hspace{1cm} (21)
with $H_{init}$, $AGE_{init}$ initial height and age respectively. Initial fat mass was obtained via the function:

\[
F_{init} = \begin{cases} 
  (1/100) \cdot BW_{init} \cdot \left(0.14 \cdot AGE_{init} + 37.31 \times \ln(BW_{init}/H_{init}^2) - 103.94\right) & \text{if Sex = Male,} \\
  (1/100) \cdot BW_{init} \cdot \left(0.14 \cdot AGE_{init} + 39.96 \times \ln(BW_{init}/H_{init}^2) - 102.01\right) & \text{if Sex = Female.}
\end{cases}
\]  

Additional information on the model can be found in [9, 11, 12, 13].

### 3.1 Individual implementation

For each individual $i$ in the ENSANUT sample we estimated their energy intake change $\Delta T E I_{init}^{(i)}$ as a function of time from their individual diet and their reported total energy intake $T E I_{init}^{(i)}$ (kcalot). We used this quantity to obtain their carbohydrate intake change $C I_{init}^{(i)}(t) = \Delta T E I_{init}^{(i)}(t)/2$ and their carbohydrate intake at baseline $C I_{init}^{(i)} = T E I_{init}^{(i)}/2$.

The individual’s resting metabolic rate $R M R_{init}^{(i)}$ was estimated from their initial body weight in kilograms $B W_{init}^{(i)}$ (weight baseline in database), height in centimeters $H_{init}^{(i)}$ (height in database), age in years $AGE_{init}^{(i)}$ (age in database), and sex, $S e x_{init}^{(i)}$ (sex in database) following (12). Their initial fat mass $F_{init}^{(i)}$ was also estimated from $B W_{init}^{(i)}$, $H_{init}^{(i)}$, $AGE_{init}^{(i)}$, $S e x_{init}^{(i)}$ in accordance to (22). The individual’s initial lean mass was obtained by setting $L_{init}^{(i)} = B W_{init}^{(i)} - \left(F_{init}^{(i)} + 3.7 \cdot G_{init}^{(i)} + E C F_{init}^{(i)}\right)$, with $G_{init} = 0.5$ and $E C F_{init} = 0$. Finally each individual’s energy balance constant was estimated as $K^{(i)} = R M R_{init}^{(i)} \cdot P A L^{(i)} - \gamma L_{init}^{(i)} - \gamma F L_{init}^{(i)} - \delta L_{init}^{(i)} B W_{init}^{(i)}$ where $\delta L^{(i)} = R M R_{init}^{(i)} \left(1 - \beta_{T E F}\right) \cdot P A L^{(i)} - 1 \cdot B W_{init}^{(i)}$. For all individuals we set a physical activity level of 1.5 ($P A L^{(i)} = 1.5$) which corresponds to “sedentarism” in accordance to [9].

For each individual, we estimated lean and fat masses, glycogen and extracellular fluid from the system of equations given by (15–20) using the parameters described above and setting $\Delta N a_{diet}^{(i)} = 0$.

To solve this system of differential equations, we used a 4th order Runge-Kutta algorithm (RK4) with a stepsize $\Delta t = 1$. RK4 was programmed in C++ for speed and connected to R via the Rcpp package.

The RK4 algorithm throws numerical estimates for each time $t$ of each individual’s extracellular fluid $E C F^{(i)}(t)$, glycogen $G^{(i)}(t)$, fat and lean masses $F^{(i)}(t), L^{(i)}(t)$. We estimated body weight for each individual adult in the ENSANUT sample as:

\[
B W^{(i)}(t) = E C F^{(i)}(t) + 3.7 \cdot G^{(i)}(t) + F^{(i)}(t) + L^{(i)}(t)
\]

where $t$ stands for the number of days since the intervention. Each individual’s BMI was estimated as:

\[
B M I_{init}^{(i)}(t) = B W^{(i)}(t)/(H_{init}^{(i)})^2
\]

The previous model is completely programmed in the bw package in R. Finally, we used the survey package to create summary statistics of $B W^{(i)}(t)$ and $B M I^{(i)}(t)$ (both in the overall adult population and in specific subpopulations by sex, SES, and age). For these estimates we accounted for the survey design as established in section 1.2.

This model has been written in pseudocode and is presented in Algorithm [1].

The different scenarios described in section 2.3 were implemented following the same algorithm by changing the formula for the reduction by year $k$ in [13] and thus obtaining a different $\Delta T E I(t)$. 

---

2 Albeit we assumed no change in sodium intake $\Delta N a_{diet} = 0$, reducing sugar in SSB can have an effect on the recipe resulting in sodium intake changes.
Algorithm 1 Individual level weight change model

1: procedure Weight change model
2: Input:
3: \( n \) \hspace{1cm} \triangleright \text{Number of individuals in sample}
4: \( \text{Years} \) \hspace{1cm} \triangleright \text{Number of years to run the model for}
5: \( w_k \) \hspace{1cm} \triangleright \text{Survey weight for } k\text{-th individual (} k = 1, 2, \ldots, n \text{)}
6: \( TEI^{(k)}_{\text{init}} \) \hspace{1cm} \triangleright \text{ } k\text{-th individual’s reported total energy intake (} k = 1, 2, \ldots, n \text{)}
7: \( SSB^{(k)}_{\text{init}} \) \hspace{1cm} \triangleright \text{ } k\text{-th individual’s reported SSB consumption (} k = 1, 2, \ldots, n \text{)}
8: \( BW^{(k)}_{\text{init}} \) \hspace{1cm} \triangleright \text{ } k\text{-th individual’s reported body weight (} k = 1, 2, \ldots, n \text{)}
9: \( H^{(k)}_{\text{init}} \) \hspace{1cm} \triangleright \text{ } k\text{-th individual’s reported height (} k = 1, 2, \ldots, n \text{)}
10: \( \text{AGE}^{(k)}_{\text{init}} \) \hspace{1cm} \triangleright \text{ } k\text{-th individual’s reported age (} k = 1, 2, \ldots, n \text{)}
11: \( \text{Sex}^{(k)} \) \hspace{1cm} \triangleright \text{ } k\text{-th individual’s sex (} k = 1, 2, \ldots, n \text{)}
12: \( \text{PAL}^{(k)} \) \hspace{1cm} \triangleright \text{ } k\text{-th individual’s physical activity level (} k = 1, 2, \ldots, n \text{)}
13: \( \Delta N_{\text{NA}}^{(k)}_{\text{init}} \) \hspace{1cm} \triangleright \text{ } k\text{-th individual’s change in sodium intake (} k = 1, 2, \ldots, n \text{)}
14: for \( i \) in 1 to \( n \) do
15: \( \Delta TEI^{(i)}(t) \leftarrow TEI^{(i)}_{\text{init}} - \text{Reduction}(y_{(t/365)}) \cdot SSB^{(i)}_{\text{init}} \)
16: \( CI^{(i)}(t) \leftarrow \Delta TEI^{(i)}(t)/2 \)
17: \( CI_b^{(i)} \leftarrow TEI^{(i)}_{\text{init}}/2 \)
18: Calculate \( RMR^{(i)}_{\text{init}} \) from \( BW^{(i)}_{\text{init}}, H^{(i)}_{\text{init}}, \text{AGE}^{(i)}_{\text{init}}, \text{Sex}^{(i)} \) using \eqref{eq:21}.
19: Calculate \( F^{(i)}_{\text{init}} \) from \( BW^{(i)}_{\text{init}}, H^{(i)}_{\text{init}}, \text{AGE}^{(i)}_{\text{init}}, \text{Sex}^{(i)} \) using \eqref{eq:22}.
20: \( L^{(i)}_{\text{init}} \leftarrow BW^{(i)}_{\text{init}} - (F^{(i)}_{\text{init}} + 3.7 \cdot G_{\text{init}} + ECF_{\text{init}}) \)
21: \( K^{(i)} \leftarrow RMR^{(i)}_{\text{init}} \cdot \text{PAL}^{(i)} - \gamma L_{\text{init}}^{(i)} - \gamma F_{\text{init}}^{(i)} - \delta BW_{\text{init}}^{(i)} \) as in \eqref{eq:19}.
22: \( \delta^{(i)} \leftarrow RMR^{(i)}_{\text{init}} \left(1 - \beta_{TEF}\right) \cdot \text{PAL}^{(i)} - 1) / BW_{\text{init}}^{(i)} \)
23: Runge Kutta 4 do
24: Calculate \( AT^{(i)} \) from \eqref{eq:20} using \( RMR_{\text{init}}, \Delta TEI^{(i)} \) and \( \text{PAL}^{(i)} \).
25: Calculate \( ECF^{(i)} \) from \eqref{eq:15} using \( CI^{(i)}, CI_b^{(i)} \) and \( \Delta N_{\text{NA}}^{(i)} \).
26: Calculate \( G^{(i)} \) using \( CI^{(i)}, CI_b^{(i)} \) as in \eqref{eq:16}.
27: Calculate \( F^{(i)} \) and \( L^{(i)} \) as in \eqref{eq:17} using \( AT^{(i)}, K^{(i)}, TEI^{(i)}, G^{(i)}, \text{PAL}^{(i)}, \Delta TEI^{(i)} \).
28: end Runge Kutta 4
29: \( BW^{(i)}(t) \leftarrow ECF^{(i)}(t) + 3.7 \cdot G^{(i)}(t) + F^{(i)}(t) + L^{(i)}(t) \)
30: \( BW_{F}^{(i)} \leftarrow BW_{F}^{(i)}(365 \cdot \text{Years}) \)
31: \( BM_{I}^{(i)} \leftarrow BW_{F}^{(i)} / (H_{\text{init}}^{(i)})^2 \)
32: \( \Delta BW^{(i)} \leftarrow BW^{(i)}_{\text{init}} - BW_{F}^{(i)} \)
33: end for
34: \( \Delta BW_{\text{Overall}} = \sum_{i=1}^{n} w_i \cdot \Delta BW^{(i)} \)
35: for \( \text{cat} \) in \{Males, Females, SES low, SES middle, SES high, Age 20-39, Age 40-59, Age 60+ \} do
36: \( \Delta BW_{\text{cat}} = \sum_{i=1}^{n} w_i \cdot \Delta BW^{(i)} \cdot I_{\text{cat}} \)
37: end for
38: end procedure
4 Sensitivity analysis

4.1 Different scenarios

The increasing and constant percent change scenarios from sections 2.3.2 and 2.3.3 were implemented as a sensitivity analysis. These resulted in different functional forms for $\Delta TEI(t)$ as different formulas for the reduction were used in (13); the remaining part of the estimation process (section 3) was the same.

4.2 Model under compensation assumptions

As different combinations of compensation and regulations result in different values of energy reduction ($\lambda \times 100\%$, following the notation of section 2.3) at year 10, we created a consumption-percent change matrix $\Lambda$ whose entries correspond to the overall reduction associated to both, the % compensation and the % added sugar reduction (Table F). The rows of the matrix stand for % added sugar reduction whilst the columns for % compensation (both in multiples of 10). Hence for a reduction of 10% ($1 \times 10\%$) and compensation of 30% ($3 \times 10\%$) the entry $\Lambda_{1+1,3+1}$ of the matrix equals $1 \times (10 - 3)\% = 7\%$. In general, each entry of the matrix corresponds to a $\lambda \times 100\%$ reduction es given by $\Lambda_{i+1,j+1} = i \times (10 - j)\%$. Table F shows the reductions $\Lambda_{i+1,j+1} \times 100\%$ modelled for the sensitivity analysis.

| % Compensation |
|----------------|
| 0 10 20 30 40 50 60 70 80 90 100 |
| 0 0 0 0 0 0 0 0 0 0 0 |
| 10 10 9 8 7 6 5 4 3 2 1 0 |
| 20 20 18 16 14 12 10 8 6 4 2 0 |
| 30 30 27 24 21 18 15 12 9 6 3 0 |
| 40 40 36 32 28 24 20 16 12 8 4 0 |
| 50 50 45 40 35 30 25 20 15 10 5 0 |
| 60 60 54 48 42 36 30 24 18 12 6 0 |
| 70 70 63 56 49 42 35 28 21 14 7 0 |
| 80 80 72 64 56 48 40 32 24 16 8 0 |
| 90 90 81 72 63 54 45 36 27 18 9 0 |
| 100 100 90 80 70 60 50 40 30 20 10 0 |

Table F: Matrix $\Lambda$ with percent reductions. For $i \times 10\%$ added sugar reduction and $j \times 10\%$ compensation the entry $\Lambda_{i+1,j+1}$ ($i+1$-th row, $j+1$-th column) denotes the corresponding % added sugar diminishment.

Each entry $\lambda = \Lambda_{i,j}$ of the matrix was applied to the main scenario (7) to obtain the $k$-th year reduction. The reductions resulting from (7) were then plugged into (13) and the weight change model (section 3) was applied. There results were associated to a weight reduction matrix $W$ whose entries $W_{i+1,j+1}$ correspond to weight (kg) reduced after added sugar reduction to $i \times 10\%$ accounting for $j \times 10\%$ compensation. We represented the matrix graphically with the ggplot2 package [20] using cell-shading as seen in figure 1 in the main article.
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