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Original article

Estimating the effects of a calorie-based sugar-sweetened beverage tax on weight and obesity in New York City adults using dynamic loss models

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ABSTRACT

Purpose: Sugar-sweetened beverages (SSBs) contribute to weight gain and increase the risk of obesity. In this article, we determine the effects of an innovative SSB tax on weight and obesity in New York City adults.
Methods: Dynamic weight loss models were used to estimate the effects of an expected 5800-calorie reduction resulting from an SSB tax on weight and obesity. Baseline data were derived from the New York City Community Health Survey. One, five, and 10-year simulations of weight loss were performed.
Results: Calorie reductions resulted in a per-person weight loss of 0.46 kg in year 1 and 0.92 kg in year 10. A total of 5,531,059 kg was expected to be lost over 10 years when weighted to the full New York City adult population. Approximately 50% of overall bodyweight loss occurred within the first year, and 95% within 5 years. Results showed consistent but nonsignificant decreases in obesity prevalence.
Conclusions: SSB taxes may be viable strategies to reduce obesity when combined with other interventions to maximize effects in the population.

Introduction

Obesity poses a continued threat to the health of the American population, increasing risks for diabetes, stroke, and cardiovascular disease, [1] and with high levels of body mass index (BMI) increasing both all-cause and cause-specific mortality [2]. Sugar-sweetened beverage (SSB) consumption has been linked with weight gain [3–10] and poor diet [11–13], and increases in SSB consumption are associated with greater risks of obesity and overweight obesity [14–23]. SSBs are a substantial contributor to daily calorie intake, constituting more than 7% of the national per-capita energy consumption [24–26]. In New York City, more than 58% of the adult population is overweight or obese, and obesity has risen from 18% to 24% between 2002 and 2012 [27]. Adult SSB consumers in New York City derive 193 daily calories, or 10.6% of total energy intake, from SSBs [23].

As a food environment regulation, sugary drink taxes are frequently proposed strategies to improve nutrition and reduce obesity at the population level [24,28–30]. Previous simulations using econometrically estimated price elasticity of SSB demand showed that expected calorie reductions from a 20% targeted tax on SSBs, assumed to fully pass on to retail prices, may significantly reduce weight, obesity prevalence, and diabetes incidence [28,31,32]. However, quasi-experimental studies show that current soda taxes do not influence overall calorie intake and are ineffective in reducing population weight, but they may have larger effects in specific high-risk populations [33–36]. It should be noted that US soda taxes are generally small in magnitude, with a mean of roughly 5% and are not reflected in the shelf price in the case of sales tax [37]. Thus, it may not be surprising that existing taxes are ineffective in changing behavior because of their low visibility to consumers [38,39].

In a recent study, New York supermarket beverage sales data were used to predict the effectiveness of a hypothetical calorie-based SSB tax [24]. Using an innovative econometric demand model that formally accounted for substitutions among hundreds of beverage brands and assumed full tax pass-through to retail price, the authors demonstrated that a new .04-cent per kcal excise tax on SSBs would reduce energy consumption from SSBs from supermarket sources by 9.3%. Compared with a per-ounce tax that achieves the same level of beverage calorie reduction, the 0.04-cent per

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kcal SSB tax had a smaller adverse impact on consumer grocery budget, as the latter was more effective in nudging consumers to substitute low-calorie drinks for high-calorie ones. When applied to all market sources, where demand was assumed to respond to price changes similarly, total beverage energy was predicted to reduce by a national average of 5800 calories per person per year. Although this is one of the most sophisticated estimates of the effects of a calorie-based SSB tax on beverage demand to date, the impact of this reduction on population weight and obesity is still unknown.

Given the utility of economic modeling in predicting effects of potential public health interventions, it is critical to present estimated impacts in a form useful to both public health practitioners and the general public. Proper estimation of the health impact of proposed policies can lead to more informed interventions designed to reduce the burden of obesity and associated noncommunicable diseases. In New York City, a number of population-wide interventions have been proposed in efforts to reduce adult obesity prevalence but rarely produce appreciable effects that can be widely understood. In this study, we convert predicted per-capita calorie reductions described previously into expected immediate and long-term weight loss in the New York City adult population. In doing so, we assess the viability of an SSB tax as a standalone obesity intervention. The study is innovative in that it predicts the real-world impact of caloric reductions generated using a novel econometric demand model simulating a calorie-based SSB tax. First, self-reported data from the annual New York City Community Health Survey (CHS) were used to estimate individual body fat composition and resting metabolic rates. These were then combined with a 5800-calorie reduction and applied to a dynamic weight loss predictive model to estimate the effects of dietary change on population weight and obesity. Model simulations were performed over periods of 1, 5, and 10 years. Changes in obesity prevalence were tested for statistical significance. Results were compared using both BMI and percent-body fat estimates of obesity. We hypothesized that changes in dietary intake due to an SSB tax would significantly reduce obesity as measured by BMI and percent body fat over 10 years.

Methods

Data

Data providing baseline weight status for the New York City adult population were derived from the New York City CHS. Self-reported height, weight, age, and gender were used to estimate per-person resting metabolic rates and body fat mass. The CHS is a disproportionate, stratified, dual-sample (cellular and landline) clustered random survey conducted annually by the New York City Department of Health and Mental Hygiene and provides a representative sample of noninstitutionalized adult New Yorkers. The 2012 sample consisted of 8797 adults aged 18 years and older [27]. All data from the CHS are self-reported. Deidentified public use data sets of the CHS are available online through the New York City Department of Health and Mental Hygiene Web site. The most recently listed response rate was 40.0% in 2011, with a cooperation rate of 89.1%.

Simulated weight loss

Dynamic weight loss modeling was used to simulate the effects of anticipated calorie reductions from an SSB tax on population weight change. Dynamic models use initial body conditions and metabolic parameters to estimate the effects of dietary change on body composition, while adjusting for the physiological adaptations that occur in response to changes in diet or physical activity [28,40–43]. This process produces more reliable estimates of weight loss than traditional static models, which assume a fixed 3500-calorie requirement per pound of weight loss [40,44]. Although the advantages of dynamic weight loss models have been explained in detail elsewhere, a summary of benefits is as follows: weight loss is nonlinear and thus more appropriately modeled as a dynamic process; second, weight loss varies depending on the proportion of body fat relative to total body composition, so modeling initial body parameters is critical; and finally, bodyweight contributes to individual energy needs, so models should adjust for the diminishing returns to weight loss because energy requirements decrease when total overall bodyweight decreases [28,40,45,46]. Simulations using dynamic loss models can be conducted over multiple years, supporting their use in modeling the long-term effects of public health policies, and simulation results closely match those from experimental research [43]. For weight loss estimates, we assume that calorie reductions from an SSB tax are averaged across the New York City adult population. For comparison, we provide estimates of weight change for both dynamic and static loss models.

The Laboratory of Biological Modeling at the National Institute of Diabetes and Digestive and Kidney Diseases provided code for the dynamic weight loss model, which has been described in detail elsewhere [40]. Briefly, body fat and lean tissue change are modeled using a set of differential equations that use an overall energy expenditure function, consisting of parameters for resting metabolic rates for fat mass and lean tissue, thermogenesis, altered energy expenditure in response to changes in calorie intake, sodium intake, biochemical energies for protein and fat synthesis, and physical activity. These parameters are then combined with a user-supplied calorie reduction and used to model long-term weight loss.

Model parameters

Individual resting metabolic rates for CHS respondents were computed using the Mifflin-St. Jeor equations [47], per-person body fat mass was computed using the sex-specific equations derived from Jackson et al (2002), and initial lean mass was calculated by subtracting total bodyweight from estimated fat mass [28,48]. The proportion of bodyweight attributable to fat mass was used to determine percent body fat. Average sodium intake was specified as 3239 mg/day based on a previous study in New York City using 24-hour urinalysis [49]. Previous studies show that body fat predictive models account for a high proportion of variance in body fat and have a standard error of estimate of approximately 4% [50]. Urinalysis is considered the gold standard for measuring sodium intake [49]. Thermogenesis rates, biochemical energies for fat and protein synthesis, and average physical activity expenditure were provided by the National Institute of Diabetes and Digestive and Kidney Diseases.

Calorie reductions

Calorie reductions used in analysis were based off previously published results from a new econometric model simulating a 0.04-cent per calorie SSB tax [24]. Based on New York sales data for 178 beverage brands accounting for 95% of all supermarket volume sales, an average of 3414 beverage ounces were consumed from supermarkets per capita for 2007 to 2011, resulting in a total energy purchase of 22,663 calories per person per year. Using a fully modified distance metric demand model, the authors estimated demand elasticities for SSBs in response to a hypothesized tax while adjusting for product-level substitution of alternative beverages and incorporating product heterogeneity into estimated cross-price effects. This method avoided overestimation of the net effect of beverage taxes on beverage calorie intake that has been encountered in previous analyses [28,44]. Key model assumptions included SSB taxes are passed one-for-one to retail price; and price elasticities of demand at other market sources are similar to those at supermarkets. Results indicated that a 0.04-cent per calorie SSB tax would reduce beverage energy from supermarket sources by 1976 calories per person per year (a 9.3% reduction). When extrapolated to include beverages from all market sources, the tax would result in a net reduction of 5800 calories per person per year based on National Health and Nutrition Examination Survey (NHANES) national estimates of per capita energy intake from SSBs. Full details on the specification and performance of the fully modified distance metric model are available online [24].

Obesity change

Following estimation of individual weight change, differences in population obesity as measured by BMI and percent body fat were analyzed. In doing so, the level of agreement of baseline obesity classification between BMI and percent body fat was assessed. Although BMI is considered the standard for classifying obesity, it may not be completely representative of body composition. Research has shown that while the variance of body fat is moderately attributable to BMI, it is also dependent on age and gender [48,50–54]. For example, BMI levels may not change with age despite a larger proportion of body composition being attributable to body fat, due to reductions in lean tissue and increases in adiposity. Given the utility of dynamic models in estimating changes in weight, it is worthwhile to consider multiple measures of obesity.

BMI was calculated using measured height and weight from the CHS. Obesity classification using BMI was determined using established cutoffs from the Centers for Disease Control and Prevention. Although there is no standard obesity classification by total body fat, obesity is typically qualified in the literature as 35% or more for women and 25% or more for men [48,55–58].

Computation

Analysis of changes in fat mass, obesity prevalence as determined by percent body fat and BMI, and shifts in the weight distribution pre-post the hypothetical tax scenario were conducted using SAS v9.2 (SAS Institute Inc., Cary, NC) and Stata v13 (StataCorp LP, College Station, TX) to adjust for the complex survey methodology of the CHS. Variance components were estimated using Taylor series linearization. Simulations of energy expenditure and weight loss over time were conducted using Berkeley Madonna dynamical systems software v8.3.18 (Macey & Oster, University of California, Berkeley, CA).

Results

Descriptive statistics

The sample size used in statistical analysis was 8341. The baseline BMI distribution from this sample is provided in Figure 1. Similarly, distributions of baseline body fat mass and lean mass are shown in Figures 2 and 3. The mean weight in kilograms for New York City adults was 75.4 kg (95% confidence interval [CI] = 74.8–76.0), with a mean estimated fat mass of 23.3 kg (95% CI = 22.9–23.7). Average resting metabolic rate was 1499.6 calories (95% CI = 1490.3–1508.9), average lean mass was 52.1 kg (95% CI = 51.8–52.5), and average BMI was 26.8 (95% CI = 26.6–27.0). Finally, the average estimated percent body fat in the sample was 24.6% (95% CI = 24.4–24.9).

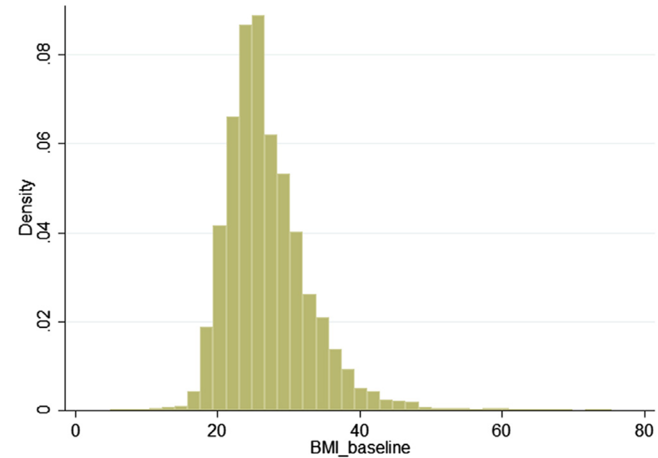

Fig. 1. Baseline BMI distribution, computed from the 2012 New York City CHS ($n = 8341$).

Differences in obesity measurement

The obesity prevalence in the 2012 CHS sample as determined by BMI was 23.7% (95% CI = 22.3–25.1). Comparatively, obesity prevalence as determined by predicted body fat was 28.3% (95% CI = 26.9–30.0), significantly higher than BMI-based obesity. Data showing comparisons between BMI-measured and body fat–measured obesity are shown in Table 1, stratified by age and gender. Trends across age categories were similar between the two measures; however, obesity measured by percent body fat was significantly larger in the 45 to 64 and 65+ years age groups. No significant differences were found in 18 to 24 and 25 to 44 years age groups. Additionally, significantly more males were classified as obese using percent body fat cutoffs, whereas significantly fewer females were classified as obese. Differences are significant at the 0.05 level. Without exact measures of body composition, whether the BMI method underestimates population obesity or percent body fat overestimates it is unable to be determined.

Weight loss

Based on the static weight loss model, a reduction of 5800 calories per year would result in a total weight loss of −0.77 kg per person in year 1, −3.8 kg per person in year 5, and −7.7 kg in year 10.

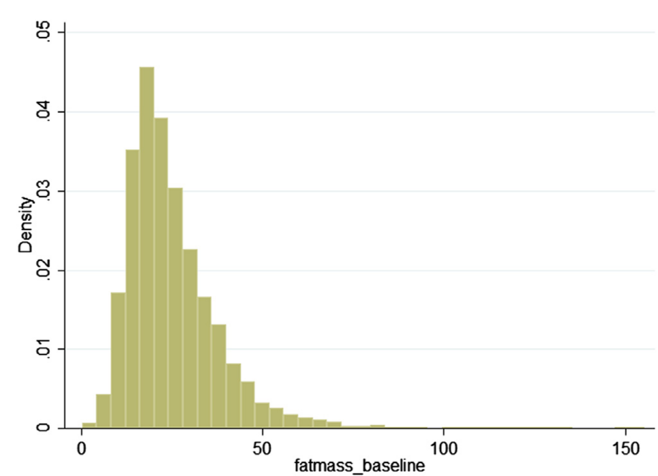

Fig. 2. Baseline distribution of body fat mass (kilogram), computed from 2012 New York City CHS ($n = 8341$).

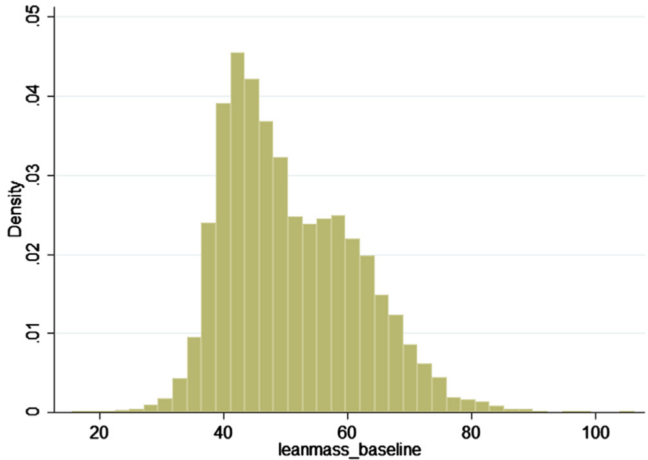

Fig. 3. Baseline distribution of lean body mass (kilogram), computed from 2012 New York City CHS ($n = 8341$).

In contrast, results for the dynamic loss models show an average weight loss of −0.46 kg in year 1 (1.01 lbs), −0.87 kg in year 5 (1.92 lbs), and −0.92 kg in year 10 (2.03 lbs). This results in an average bodyweight of 74.9 kg (95% CI = 74.3–75.5) in year 1 and 74.5 kg (95% CI = 73.9–75.1) in years 5 and 10, respectively. Means, linearized standard errors, and 95% CIs from simulation results are displayed in Table 2. Approximately 50% of overall bodyweight loss occurred within the first year, and 95% within 5 years. After 5 years of simulation, weight loss begins to plateau with only miniscule changes in subsequent years, demonstrating a diminishing return to reduced calorie intake as metabolic adaptation reduces calorie needs over time.

Obesity change

Estimated weight losses were applied to average BMI and percent body fat, resulting in new predicted prevalence of overweight and obesity as shown in Table 3. When averaged over a period of 10 years, a 5800-calorie reduction due to a per-calorie beverage tax would result in a total reduction of 5,531,059 kg when weighted to the full New York City adult population. Compared with baseline BMI, average BMI was 26.7 (95% CI = 26.5–26.9) in year 1 and 26.5 (95% CI = 26.3–26.7) in years 5 and 10. Using adjusted BMI to estimate the prevalence of obesity yielded an expected obesity prevalence of 23.0% (95% CI = 21.7–24.4) in year 1 and 22.0% (95% CI = 20.7–23.4) in years 5 and 10. No significant differences were found in the prevalence of BMI-measured obesity in year 10 compared with baseline. Obesity measured by percent body fat was also not significantly different from baseline, with an obesity prevalence of 26.9% (95% CI = 25.5–28.3) at year 10. Comparisons of the distributions of overall bodyweight, lean tissue, and fat mass before and after simulations show differences in estimated densities. These are shown in Figures 4–6 and can be compared with Figures 1–3.

Table 1
BMI-measured and percent body fat-measured obesity in the New York City adult population ($n = 8341$)

Variable	BMI obese		Body fat % obese	
	%	95% CI	%	95% CI
Overall	23.7	22.3–25.1	28.3	26.9–30.0
Age (y)				
18–24	15.2	11.6–19.6	10.2	7.2–14.3
25–44	21.0	18.9–23.3	21.4	19.2–23.7
45–64	29.5	27.1–31.9	37.3	34.8–40.0
65+	26.7	23.9–29.8	43.9	40.7–47.2
Gender				
Male	20.7	18.8–22.6	44.4	42.0–46.9
Female	27.2	25.3–29.1	13.6	12.2–15.1

Table 2
Mean bodyweights (kilogram) and cumulative change in weight loss from dynamic loss models

Weight	Mean	SE	95% CI
Year 1 BW	74.92343	0.307439	74.32077 to 75.52609
ΔBW	−0.4563794	0.0027989	−0.461865 to −0.450892
Year 5 BW	74.50748	0.3078564	73.90401 to 75.11096
ΔBW	−0.8723259	0.0209801	−0.913452 to −0.831199
Year 10 BW	74.45552	0.3089883	73.84983 to 75.06122
ΔBW	−0.9242853	0.0315591	−0.986148 to −0.862421

SE = standard error; BW = body weight.

Additional simulations

Separate from primary analyses, we conducted an additional simulation to quantify possible differences in model estimates resulting from underreporting in height and weight. It has been shown that the level of error in self-reported height and weight compared with measured data results in biased estimation of BMI [59–62]. Present in both men and women, the extent of bias is particularly high for obese individuals. Based on recent data from NHANES, BMI was underestimated by 1.05 in obese men and 1.58 in obese women. This was due to discrepancies in self-reported height and weight, where obese men were found to underreport their weight by 1.32 kg and obese women by 2.99 kg [59]. As a result, true weight is a function of reported weight and error, and effects of an SSB tax on these specific subgroups may not reflect change in the true weight in the population. Because dynamic weight loss models use baseline bodyweight as an initial parameter, predictions of weight change in the population may be biased. If it can be assumed that underreporting in NHANES is similar in the New York City adult population, it is possible to approximate the extent of bias in weight loss. We adjusted self-reported height and weight for men and women in the CHS by introducing an error term representing the mean difference between self-reported and measured height and weight. Within each BMI category for males and females, we generated a normally distributed random variable with mean and SD equivalent to the extent of bias found in NHANES. Adjusted height and weight were then used in an additional 10-year simulation of weight loss. Results show that weight loss was approximately 5,409,501 kg after 10 years when weighted to the New York City adult population. As before, no differences were found in obesity prevalence after simulations.

Discussion

This study presents new estimates of the effects of SSB taxes on weight and obesity in New York City adults. We applied expected energy reductions from a calorie-based SSB tax to a dynamic weight loss model to predict changes in body composition over time. This provided a more realistic expectation of the effectiveness of sugary drink taxes as one strategy to improve nutrition and reduce obesity across the population of New York City. SSB taxes have been shown, using simulation, to significantly reduce obesity and other noncommunicable diseases, but these findings have not been replicated in applied quasi-experimental research [28,30,32]. In addition to potential direct health impacts, taxes can raise revenue for other government programs, such as educational

Table 3
Estimated change in average BMI and percent body fat, obesity, and overweight prevalence over time

Time	BMI						% Body fat			
	Average		Overweight		Obesity		Average		Obesity	
	Mean	95% CI	%	95% CI	%	95% CI	Mean	95% CI	%	95% CI
Baseline	26.8	26.6–27.0	32.9	31.3–34.4	23.7	22.3–25.1	24.6	24.4–24.9	28.3	26.9–29.8
Year 1	26.7	26.5–26.9	30.9	29.4–32.4	23.0	21.7–24.4	24.4	24.1–24.7	27.4	26.0–28.9
Year 5	26.5	26.3–26.7	30.9	29.4–32.4	22.0	20.7–23.4	24.2	23.9–24.5	26.9	25.5–28.4
Year 10	26.5	26.3–26.7	30.9	29.4–32.4	22.0	20.7–23.4	24.1	23.8–25.5	26.9	25.5–28.3

campaigns on the dangers of poor nutrition or sponsored physical activity programs [63].

In comparing measures of obesity, we found that baseline obesity estimated by percent body fat was significantly larger than obesity measured by BMI, which may underestimate obesity in older adults and in males. This is intuitive due to the expectation that weight may be similar as the population ages, but body composition gradually skews toward higher body fat and reduced lean tissue mass. Similar results were observed in the literature, where obesity in older populations was underestimated by BMI due to changing distributions in body composition [50–54]. Obesity measured by percent body fat may be suitable as an alternative surveillance measure of obesity for these subpopulations. However, as estimates were produced using predictive models, we recommend caution in their use. Comparisons of predicted results to a cross-sectional study of the New York City adult population using more precise laboratory-based measures of body fat are encouraged.

Results from weight loss simulations showed that static loss models overestimated the change in body composition over time. In our analysis, the static approach predicted an average weight loss of 7.7 kg per person over a period of 10 years. Comparatively, the dynamic loss model predicted an average weight loss of 0.92 kg per person over the same period. Similar results were found by Lin et al, where a total beverage energy reduction of 38 calories/day resulted in a static model prediction of a linear weight reduction of 1.6 kg in year 1 and 8 kg in year 5. In contrast, the dynamic model predicted a 1-year weight reduction of 0.97 kg and a 5-year reduction of 1.8 kg, after which weight reduction plateaus [28]. Other research, such as that from Finkelstein et al [44], rely solely on static loss estimates and therefore greatly overestimates the effects of taxes on weight loss.

Although reductions in obesity prevalence were not significant after simulation, inspection of BMI and weight distributions show shifts across weight in the population. Additionally, the prevalence of overweight adults as measured by BMI was shown to reduce by 2%, although this difference was within the bounds of sampling error. Similar results were found with average percent body fat and obesity prevalence measured by percent body fat, with a downward sloping trend in both BMI and obesity measures. Modest reductions in daily calorie intake result in changes in the distribution of weight but have little impact on average BMI or obesity measured by BMI or percent body fat. These results are in contrast to previous estimates of the effectiveness of SSB taxes, which showed more significant effects on obesity, diabetes, and coronary heart disease [28,31,32,44,64]. These differences may be due to the more modest expectations of calorie change that were used in our models.

An important assumption of this analysis is that the predicted calorie reductions from an SSB tax are experienced equally across all members of the New York City adult population. As found by Lin et al [28], energy intake from SSBs varied by income level. By extension, any SSB tax would have a differential impact on overall calorie intake and weight loss. Although these differences were restricted to variations in income, it is possible that an SSB tax may affect energy intake to varying degrees in those adults with higher BMI should they be associated with greater energy intake from SSBs. Indeed, based on 2012 data from the New York City CHS, those who self-reported as obese reported consuming significantly more sugary drinks per day than those who were under or normal weight. Although these data were based off of the total number of sugary drinks consumed per day and not actual calorie intake from a dietary recall, it suggests that an assumption of equal reduction across the population may be incorrect. It is therefore possible that an SSB tax could significantly reduce weight in the obese population should the effects of a tax be more readily apparent in that subgroup. Unfortunately, as our previous estimates of daily SSB intake were derived from scanner data, we are unable to differentiate intake by income, weight, or other potential variables of

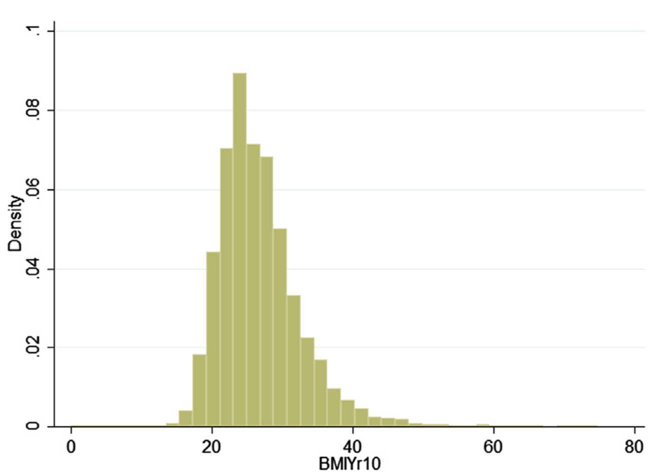

Fig. 4. Year-ten BMI distribution after an expected calorie reduction of 5800 calories/year ($n = 8341$).

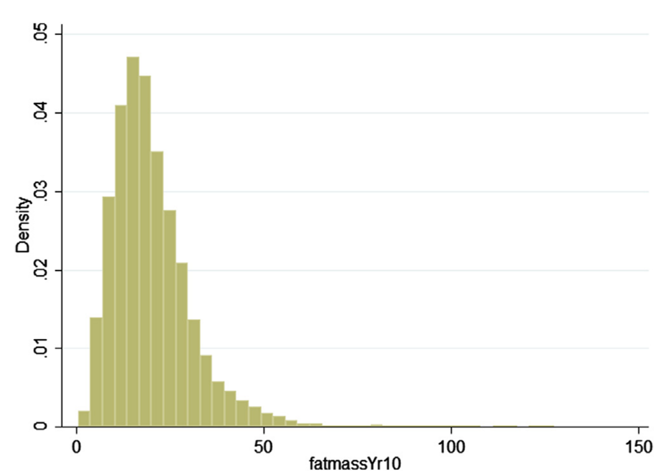

Fig. 5. Year-ten distribution of body fat mass (kilogram) after an expected calorie reduction of 5800 calories/year ($n = 8341$).

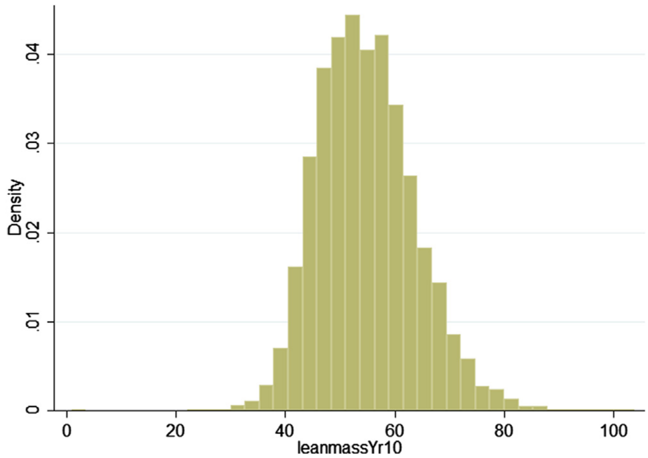

Fig. 6. Year-ten distribution of lean body mass (kilogram) after an expected calorie reduction of 5800 calories/year ($n = 8341$).

interest and cannot produce stratum-specific demand elasticities that may support estimation of calorie reductions by weight, income, or other variables. It was therefore necessary to assume an average reduction across the population.

As noted by Hall et al, responses in bodyweight change due to shifts in energy intake are generally slow, with approximate half times of 1 year. In other words, 50% of the maximum weight loss due to a reduction in energy intake is expected to be achieved within the first year of the intake change, and 95% of the maximum in 5 years due to metabolic adaptation [40]. We observed similar results in our analysis, where shifts in calorie intake in response to an SSB tax were quickly offset by reduced energy needs. The reductions in overall weight across the population observed in this study, although substantial, are tempered by more modest shifts in obesity prevalence, reinforcing the difficult problem of reducing obesity across the population [40]. As such, a combination of interventions designed to increase physical activity and improve diet can result in greater impacts on weight loss and obesity. For example, research indicates that equivalent changes in physical activity results in predicted weight loss that is faster and larger than conventional calorie reductions [40], and economic policies form only one possible lever to be used to address the environmental determinants of obesity [65]. SSB taxes in particular are useful as part of a multidimensional approach to obesity prevention [65]. Recently, the New York City Department of Health and Mental Hygiene conducted a city-wide dietary recall, although estimates of calorie intake were imprecise due to small sample sizes and possible selection bias. In the future, it may be possible to use multi-year dietary recall data from New York City and produce both specific beverage and food elasticities that can be used to test a number of hypotheses related to the combined impact of economic interventions on population weight.

In 2012, a multi-agency collaboration was formed in New York City to develop a long-term strategic plan to prevent and control obesity [66]. This Obesity Task Force focused on reducing obesity, addressing community disparities, reducing preventable health conditions, and lowering health care spending. Major initiatives were planned in the domains of the food environment, physical activity and physical design, and city practices. In their report, *Reversing the Epidemic*, obesity is classified as an environmental disease where nonnutritious foods are ubiquitous and the urban built environment reduces the utility of physical activity. Although SSB taxes are not listed in the recommended initiatives to encourage healthy eating, they may be viable strategies to meet the task force goals of reducing obesity and reducing the consumption of SSBs. Research shows that taxes can be more effective when tax revenue is reinvested in other public health programs, and when the connection between SSB consumption, obesity, and diabetes is clear to consumers [67]. As such, taxes may form part of an effective strategy to reduce the burden of obesity. Although no individual program may be the answer to the obesity crisis, synergistic efforts to improve nutrition and increase physical activity can have substantial effects on population weight.

Limitations

Study limitations largely stem from three sources: known deficiencies of dynamic loss models, parameters used in the computational model, and the economic assumptions made in the derivation of calorie reductions. As discussed by Hall et al, uncertainty due to measurement error in initial energy requirements results in individual variability in weight loss; however, these errors are minimized when conducting population average studies. Additionally, shifts in the obesity distribution assume perfect adherence to calorie reductions in diet while holding all other energy intake and physical activity constant, which is unlikely to occur. Second, the use of predicted body fat equations, although based on nationally representative samples, is not as valid or reliable as laboratory-measured obesity such as hydrostatic weighting or dual-energy x-ray absorptiometry. As such, the starting distribution of body fat mass in the New York City adult population may be biased. Finally, the estimates derived from Zhen et al were produced from a demand model that did not include food data. When prices of SSB increase, demand for other foods may or may not change, which can affect alternative food substitution and offset part of the original calorie reduction. As simulations of the SSB-weight relationship use these estimates, predicted weight loss may be biased. There is mixed evidence regarding the effects of SSB taxes on purchases of other untaxed beverages and foods. On one hand, some experimental research has shown SSB taxes are likely to decrease SSB consumption without significantly increasing consumption of other unhealthy foods and beverages [63,68]. On the other hand, other field experiment and observational studies suggest SSB taxes may encourage purchases of less healthful beverages and foods [69,70]. Despite these limitations, population interventions such as SSB taxes may also help prevent future weight gain. In the long term, the impact of prevention may be greater than weight loss in the population. As the dynamic model only considers weight loss resulting from a reduction in calorie intake, true effects across the population may be more substantial.

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