The Public Burden of Liquid Candy:
The Costs of Sugared Beverages to San Francisco

HECG Health Economics Consulting Group LLC

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NEXUS STUDY

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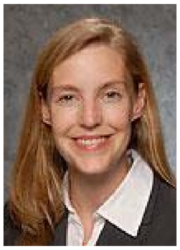

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EXECUTIVE SUMMARY

In the last 35 years, obesity has grown into a health problem of epidemic proportions. Nearly one third of all American adults are obese and another third are overweight. And at least 17% of children ages 2-19 years are now considered overweight or obese, with another 17% identifiably at risk of joining them. It has not always been this way. Just since the late 1970s, obesity in American adults has more than doubled, from 15% in 1976-1980 to 32% in 2001-2004. In the same time period, obesity rates have doubled among preschool children ages 2-5 years and adolescents aged 12-19 years, and more than tripled among children aged 6-11 years.

Calorically sweetened beverages, or "CSBs," have accelerated the obesity epidemic. CSBs are drinks containing sugar or any other caloric sweetener and include such beverages as non-diet soft drinks, fruit drinks, energy drinks and bottled coffee drinks. CSBs add substantial calories to the diet without providing significant (or often, any) levels of nutrients. When the added calories from CSBs are not offset by eating or drinking fewer calories elsewhere in the diet, CSBs lead to increased weight gain. An ever-heavier population creates a substantial cost to public entities like San Francisco. Economists estimate that the aggregate costs of obesity are as much as 7% of annual medical expenditures, adding an estimated $117 billion nationally to health care costs each year. In addition to direct medical care costs, obesity raises other costs associated with caring for the obese, such as workers' compensation benefits.

These steep medical costs drain public health resources just as much as private ones. San Francisco taxpayers must absorb the obesity-related medical expenses of the resident poor, who have no other source of support. Because CSBs impose a cost on its taxpayers, San Francisco may assess a regulatory fee to shift the public medical costs caused by CSBs back where they belong: onto the businesses that profit by selling them.

The purpose of this report is to explain the justification for a fee on CSBs and to calculate the proper amount of the fee. To do this, the study (1) describes how CSBs contribute to obesity; (2) quantifies the extent of the connection between CSBs and obesity; (3) calculates the dollar amount of obesity-related medical costs borne by the City and County of San Francisco (“City”); and (4) suggests how best to structure fees to take into account the differences between the types of CSB sellers in San Francisco. A more detailed explanation of these four steps follows.

■ CSBs Help Cause Obesity

The first section of this study draws on the epidemiological expertise of the City of San Francisco Department of Public Health (SFDPH). SFDPH experts reviewed in-depth the body of research on the relationship between CSB consumption and obesity with close attention to the merits of study methodologies and soundness of studies’ conclusions. The main conclusion of this section is that the biological mechanism, experimental evidence, and consistent effects among diverse study designs provide a compelling case for a causal effect of CSB consumption on weight gain, obesity and/or overweight. Overall, the stronger studies with better design features, analyses and interpretation consistently point to a causal effect of CSB consumption on obesity.

■ About 8.66% of Obesity is Attributable to CSB Consumption

Section 1 also describes the use of a statistical summary technique to calculate the magnitude of the role of CSBs in causing obesity in San Francisco. Based on the extensive review of the literature, we employed study aggregation techniques (referred to as “meta-analysis”) to aggregate the findings of the four most appropriate studies for this purpose. Through this calculation we found that 8.66% of the cases of obesity in San Francisco are due to consumption of CSBs (alternatively, that 8.66% of obesity would be prevented if the population stopped drinking CSBs).

■ About 6.8% of the City's Medical Expenditures are Attributable to Obesity

In Section 2, we develop estimates of the City’s expenditures that are attributable to obesity for the population whose medical expenditures fall to the City for payment. We used nationally representative medical expenditure data to estimate the percentage of annual medical payments that are attributable to obesity for those receiving health care services reimbursed by the City of San Francisco. We used a regression-based approach to estimate obesity-attributable payments, treating medical payments as a function of obesity status and several other individual-level characteristics likely to influence medical payments, including age, gender, race/ethnicity, education, income, marital status, insurance status, underweight and smoking status. We found that 6.8% of medical payments were attributable to obesity in this subset of the population.

■ The City is Justified in Imposing an Approximately $1.8 Million Fee

In Section 3, we calculate the City’s CSB-related direct medical care costs. We do this by multiplying the City’s total direct expenditures on medical care services by 6.8% (from Section 2), and then multiplying that number by 8.66%-- the proportion of obesity that is caused by CSBs (Section 1). The result is that $969,748 of the City’s annual general fund health care costs is attributable to CSB-attributable obesity costs. We add to this number the costs to the City of administering the regulatory fee ($285,356 per year) and maintaining an account to be used to fund programs aimed at reducing CSB consumption ($550,000 per year). Thus, we estimate that the costs to the City of San Francisco for caring for health problems related to obesity, including some of the costs of preventing a fraction of those cases in future years, is equal to $1,805,104 in FY2009-2010.

■ It is Fair to Divide the Fee According to the Type of CSB Seller

Section 3 describes the methods used to calculate regulatory fees by retail distribution channel. Using data from industry trade organizations and the U.S. Economic Census and industry, we develop “channel shares” for each type of retail organization selling CSBs in San Francisco. The recoverable amount ($1,805,104) is then allocated across those channel shares to derive aggregate fees by retail channel. These aggregate shares are then divided by establishment count data provided by the San Francisco Department of Public Health, resulting in proposals of per-establishment fees.

1. REVIEW OF THE LITERATURE[1]

The purpose of this section is to review the background, theory and evidence on the association between the consumption of calorically-sweetened beverages (CSBs) and weight gain, particularly weight gain that leads to overweight and obesity. CSBs are defined as beverages to which caloric sweeteners are added.[2] These include regular (non-diet) carbonated soft drinks, fruit drinks, energy drinks, sports drinks and ready-to-drink coffee beverages.[3] A relatively large number of studies have examined the relationship between CSB consumption, weight gain, and obesity. The wide range of methods used in those studies, and the broad range of results reported, has generated considerable debate over the role of CSBs in weight gain, overweight, and obesity.

In this section we review key studies on the relationship between CSBs and weight gain, overweight, and obesity to identify the studies that are most appropriate for our specific goal of combining results from the best studies to derive a single "attributable risk" of CSB consumption on obesity (described in detail in Section 1.7). Before undertaking our independent review, we first considered seven review articles published between 2006 and 2008.[4] These review articles helped us understand: (1) the state and scope of the literature on CSB consumption and energy consumption, weight, and obesity, (2) key methodological issues in that literature, and (3) represented a first pass at identifying observational epidemiologic studies for consideration. In our review, we identify the most reliable studies through a comprehensive evaluation of the methods employed.

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[1] This section was written by June M. Weintraub, Rajiv Bhatia, Michelle Kirian, and John Schneider.

[2] For the purposes of this study, we consider caloric sweeteners to include the processed caloric sweeteners, including: Confectioner's sugar (also known as powdered sugar, which is finely ground sucrose); corn sweeteners (sugars obtained from corn and used frequently in carbonated beverages, baked goods, and some canned products; it is a liquid that is a combination of maltose, glucose, and dextrose); dextrose (glucose combined with water); invert sugar (sugar that is made by dividing sucrose into its two parts: glucose and fructose); sucrose (raw sugar, granulated sugar, brown sugar, confectioner's sugar, turbinado sugar, and related compounds consisting of glucose and fructose and made by concentrating sugar beet juice and or sugar cane).

[3] CSBs include all carbonated sweetened beverages (such as Coca-Cola Classic, Sprite, Pepsi-Cola, Mountain Dew, Sierra Mist, etc.), all juices, teas and water wherein caloric sweeteners have been added (such as Tropicana Twister, Fuze, Hawaiian Punch, Snapple, Arizona, Sunny Delight, Lipton teas, Nestea, Gold Peak, Glaceau, SoBe Lifewater, etc.), sports drinks (such as Gatorade and Powerade), energy drinks (such as Red Bull, Rockstar, Jolt Cola) and ready-to-drink coffee beverages (such as Frappucino, Double Shot, Iced Coffee, Java Monster, Coke Caribou, etc.). CSBs do not include 100% fruit juices that contain no added sugar. The term also does not apply to alcoholic beverages. The definition of CSB used in this report conforms to this general definition.

[4] Refer to Section 1.5.1

1.1 Background

Nearly one third of all American adults are obese (BMI $\geq$ 30 kg/m^2) and 66% are either overweight or obese (BMI $\geq$ 25 kg/m^2).[5,6] Prevalence of obesity among adults doubled between the 1970s and early 2000s, from 15% in 1976-1980 to 32% in 2001-2004.[7] At least 17% of children 2-19 years of age are considered overweight in the United States (defined as a sex-adjusted BMI above 95th percentile for age) and an additional 17% are considered at risk of becoming overweight (BMI-for-age between the 85th and 95th percentiles).[8] Since the 1970s, the prevalence of obesity has doubled among preschool children aged 2-5 years and adolescents 12-19 years, and more than tripled among children aged 6-11 years.[9]

The prevalence of overweight or obesity in children and adults differs by race/ethnicity as well as by socioeconomic status.[10,11] According to the California Department of Health Services' California Children's Healthy Eating and Exercise Practices Survey, in 2005 40% of California children surveyed were overweight or at risk of being overweight. The proportion of African-American (45%) and Latino (48%) children who were overweight or at risk of being overweight was higher than that for white (32%) or Asian (33%) children.[12]

In San Francisco, more than 90,000 men, women and children are obese. According to the 2007 California Health Interview Survey (CHIS), in San Francisco obesity affects nearly 13% of adult men (45,000) and 11% of adult women (35,000).[13] For children and teens, the 2007 CHIS estimates for the nine-county bay area region are that about 15% of adolescents between 12 and 17 years of age are overweight or obese for their age (or approximately 4,000 in SF), and 8% of children under age 12 are considered overweight for their age (or approximately 7,000 in SF).[14]

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[5] BMI is body mass index calculated as weight in kilograms divided by height in meters squared. See section 1.4.

[6] Ogden et al. (2006)

[7] National Center for Health Statistics (NCHS) (2006)

[8] Ogden et al. (2006), op cit.

[9] Institute of Medicine (2004)

[10] In the 2003-2004 National Health and Nutrition Examination Survey, prevalence of overweight, defined as BMI for age 95th percentile or higher, was as follows: ages 12-19: Non-Hispanic black (21.8%); Mexican-American (16.3%); non-Hispanic white (17.3%). For ages 6-11: Mexican-American (22.5%); non-Hispanic black (22.0%); and non-Hispanic white children (17.7%) (Ogden et al., 2006, op cit).

[11] In 1997-98, women with incomes below the poverty level (28.7%) were more than twice as likely as women with the highest incomes (13.7%) to be obese. See Schoenborn, Adams, and Barns (2002)

[12] California Children's Healthy Eating and Exercise Practices Survey (CalCHEEPS) (2005)

[13] Defined in the California Health Interview Survey (CHIS) as BMI $\geq$ 30 kg/m^2. See http://www.chis.ucla.edu/main/default.asp for more information and interactive data generation capability using the latest (2007) version of CHIS.

[14] 2007 California Health Interview Survey defines overweight and obese teens 12 to 17 years as those having a BMI in the 95th percentile for age and gender. The underlying San Francisco population for the 2007 California Health Interview Survey was 29,000 teens and 87,000 children.

The burden of being overweight or obese manifests in premature death and disability, health care costs, and lost productivity. It is well established that obesity increases the risk of chronic conditions such as high cholesterol, high blood pressure, asthma, and type-2 diabetes.[15] Obese adults (BMI of 30 kg/m^2 or more) are approximately 1.5 to 2 times more likely to die prematurely compared to those with a BMI in the healthy range (20-25 kg/m^2). In the United States, approximately 300,000 deaths a year are associated with unhealthy dietary habits and sedentary behavior.[16]

The economic costs of obesity are substantial and increasing. It is estimated that the aggregate costs of obesity are as high as 7% of annual medical expenditures,[17] adding an estimated $117 billion to health care expenditures each year.[18] In addition to direct medical care costs, obesity-related costs include the costs of comorbid conditions, lower workplace productivity, higher workers' compensation claims and other indirect costs associated with caring for the obese.[19]

1.2 Role of CSBs in Obesity

The purpose of this section is to examine the relationship between CSB consumption and overweight/obesity. When a positive energy balance exists (energy intake exceeds energy expenditure), people gain weight, and when the energy balance is negative (energy expenditure exceeds energy intake), people lose weight. Obesity and being overweight are defined conceptually as "ranges of weights that are greater than what is generally considered healthy for a given height [and] that have been shown to increase the likelihood of certain diseases and other health problems."[20] Developing obesity and being overweight are simply and directly the results of a net positive energy balance over periods of time. While genetics may predispose some to energy imbalance, the genetic composition of the population is unlikely to change quickly and cannot be the cause of the increasing prevalence of obesity in the U.S for the short span of time researchers have been tracking these data.[21]

Following this underlying mechanism, increased obesity at the population level can result from changes in the quality and quantity of food and beverage consumption combined with sedentary lifestyle.[22] Evidence from population-level trends demonstrates substantial increases

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[15] Abenhaim et al. (2007); Field et al. (2001); Guh et al. (2009)

[16] U.S. Department of Health and Human Services (U.S. DHHS) (2001)

[17] Sturm (2004); Sturm (2007); Wolf (1998); Wolf and Colditz (1994); Wolf and Colditz (1998); Sturm (2002)

[18] Levi et al. (2008)

[19] Finkelstein, Fiebelkorn, and Wang (2004); Finkelstein, Ruhm, and Kosa (2005); Gates et al. (2008); Levi et al. (2008); McCormick and Stone (2007); Popkin et al. (2006); Runge (2007); Schmier, Jones, and Halpern (2006); Tucker et al. (2006)

[20] CDC (2008)

[21] Speakman (2004)

[22] Kaur et al. (2003); Kranz, Findeis, and Shrestha (2008); Nicklas et al. (2003); Proctor et al. (2003); Quatromoni et al. (2006)

in energy consumption. For example, dietary intake surveys show a 300 kcal/day intake increase among adult Americans between 1971-1975 and 1999-2000.[23] Growing evidence demonstrates that the increased consumption of high-calorie non-nutritious beverages—spurred by increasing availability, "super-sizing" and marketing—is likely to be a distinct contributor to the obesity epidemic.[24]

Although CSBs are considered "discretionary calories"[25] according to the U.S. Dietary Guidelines, consumers may not be treating them as special additions to daily food consumption.[26] Instead, consumption of CSBs adds to energy intake. In general, individuals gain weight when additional calories are not compensated for by additional energy expenditure. CSBs, in particular, add substantial calories to the diet without providing significant levels of nutrients themselves.[27] As a result, a person must meet nutritional requirements through other food or beverage sources, potentially contributing to energy imbalance. When CSB calorie intake is not offset by a proportional reduction in intake from other caloric sources, CSBs in the diet will cause an increase in weight. Currently, U.S. adults consume approximately 13% of their daily calories from CSBs.[28]

In addition to the clear biological mechanism identified above, parallel trends among consumption of CSBs, energy consumption, and obesity in the U.S. support the relationship between CSB consumption and the rise in obesity prevalence. As reported by Popkin et al. (2006), over the past 20 years, the average calorie intake for all Americans greater than two years of age increased between 150–300 kcal/day. Approximately 50% of this increase was attributed to the consumption of CSBs.[29] Increasing CSB consumption was also documented in a recent study by Bleich et al. (2009).[30] They analyzed 24-hour dietary recall data to estimate beverage consumption among adults aged 20 years or older who were participants in the third National Health and Nutrition Examination Survey (NHANES III, 1988-1994; n = 15,979) and NHANES 1999-2004 (n = 13,431). From 1988-1994 to 1999-2004, the percentage of adult CSB drinkers increased from 58% to 63% ($p < 0.001$), per capita consumption of CSBs increased by 46 kcal/day ($p = 0.001$), and daily CSB consumption among drinkers increased by 6 oz ($p < 0.001$).

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[23] Kant and Graubard (2006)

[24] Jacobson (2005); Young and Nestle (2002)

[25] Discretionary calories are from foods or beverages that an individual consumes after meeting all essential nutrient needs. When people consume nutrient dense foods they may meet their entire nutrient needs with fewer calories than their energy balance budget allows. As long as energy balance is maintained, the additional discretionary calories may then be nutrient poor without any nutrient deficiency or weight gain.

[26] O'Dea (1999)

[27] Cavadini, Siega-Riz, and Popkin (2000); Frary, Johnson, and Wang (2004); Harnack, Stang, and Story (1999); Whiting et al. (2001)

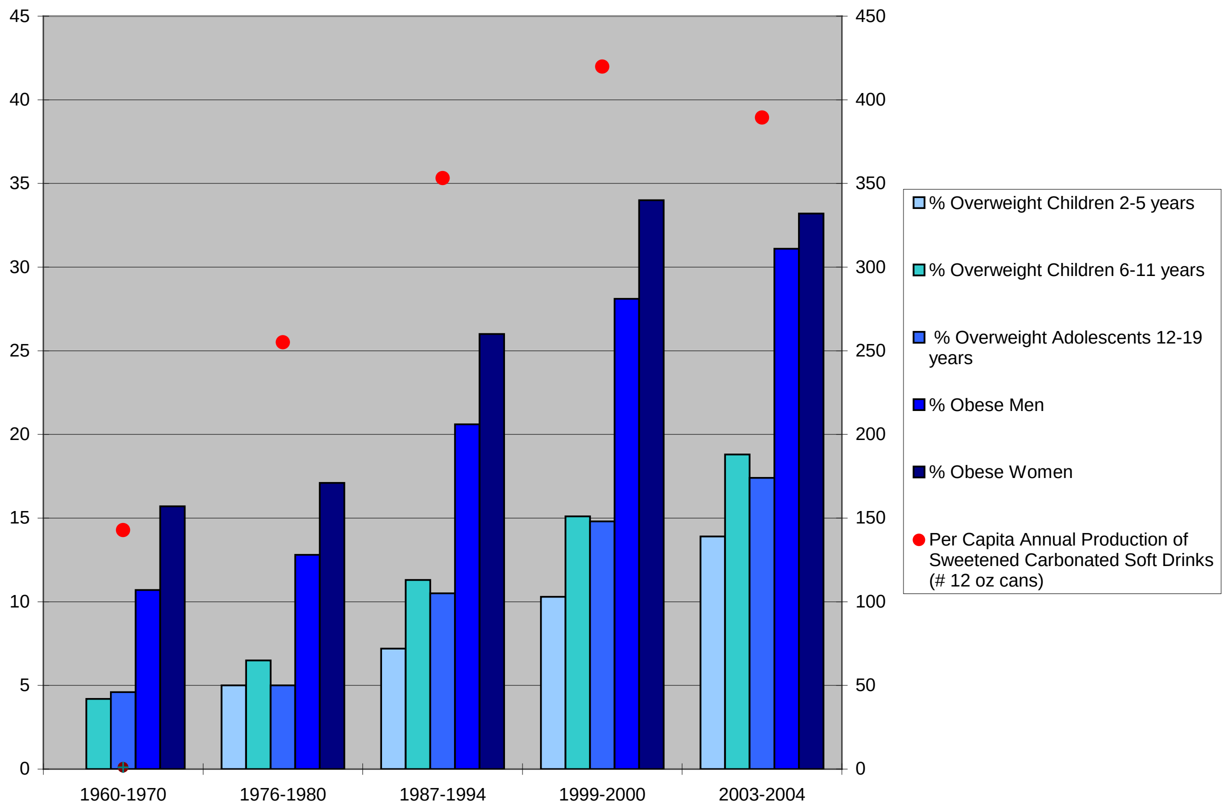
[28] 13% is estimated from the average daily caloric consumption of CSBs reported in NHANES [Table 5 of Bleich et al (2009)], divided by the average overall caloric consumption reported in NHANES (http://www.cdc.gov/mmwr/preview/mmwrhtml/mm5304a3.htm)

[29] Popkin et al. (2006)

[30] Bleich et al. (2009)

Figure 1-1 illustrates how the prevalence of obesity and the annual production of carbonated soft drinks more than doubled between 1960 and 2004 in the United States**.** As discussed below, observational and experimental studies in individuals support the hypothesis that increased CSB consumption is not just coincidental with the increase in obesity, but that CSB consumption is actually a contributing cause of obesity.

Figure 1-1
Prevalence of Overweight and Obesity and Annual Production of Carbonated Soft Drinks in the United States, 1960-2004



Sources: NCHS, 2006; Ogden et al., 2006; NCHS, 2007; USDA, 2007; USDA, 2004. Notes: Children's data (6-11 years) for period 1960-1970 from 1963-1965. Adolescent's data for period 1960-1970 from 1966-1970 and includes adolescents 12 to 17 years not 12 to 19 years. Data for adults, children and adolescents for period 1987-1994 are from 1988-1994. Adult data includes adults 20 to 74 years. Data for annual carbonated calorically sweetened beverage availability from the years 1965, 1978, 1990, 2000 and 2004. Carbonated CSB sales for years 1965 and 1978 are estimated by applying the proportion of available calorically sweetened beverages in 1984, the earliest data available to the total carbonated beverage availability for each year.

1.3 Types of Studies

A number of challenges face researchers using epidemiological methods to study the relationship between CSB consumption and obesity.[31] The contributing causes of positive and negative energy balance are numerous, largely behavioral and influenced by context and environment. In addition, to develop obesity individuals must have a net positive energy intake for a sufficient duration; the time period necessary for over consumption to result in clinically defined overweight or obesity differs depending on measurable characteristics such as gender, age and baseline weight. In addition, the way researchers measure and categorize obesity, consumption, and individual characteristics will influence the observable relationships.

There are a number of different ways to go about measuring the effect of CSB consumption on overweight/obesity. The most common epidemiologic approaches are (1) cross-sectional, (2) case-control, (3) longitudinal, and (4) experimental. Each study design is capable of illuminating some aspect of the CSB-overweight/obesity relationship, albeit in different ways and with important strengths and weaknesses associated with each type of study.

In *cross-sectional* studies, exposure to CSBs and weight status are assessed simultaneously, at one particular point in time, by surveying participants regarding their CSB consumption. In a cross-sectional study, we are assessing whether (at a point in time) an independent variable (e.g., CSB consumption) is associated with a dependent or "outcome" variable (e.g., weight or body mass index). While this type of study is useful for identifying the existence and magnitude of associations between independent and dependent variables, it is limited by its inability to establish a direction of causation. The main limitation with respect to studies of obesity is that the over-consumption / weight gain process is likely to take some amount of time to develop, and that an individual's current weight is a function of past consumption and health behaviors rather than present habits. If overweight participants have stopped drinking CSBs as part of a diet plan, and normal weight participants have not changed their CSB consumption, a cross-sectional study would fail to detect a relationship between CSB consumption and obesity. Studies that assess usual CSB consumption in the past years and that adjust for dieting behaviors may overcome the possibility of this type of bias.

In a *case control* study, researchers select participants based on the presence or absence of a disease or outcome of interest, and then assess the differences between the groups with respect to exposure. For a study of CSBs and obesity, cases would be selected as those who are overweight or obese, and controls would be those who are not. The consumption of CSBs among each group would then be assessed and the exposure of the obese cases compared to the exposure of the normal weight controls. Compared to longitudinal studies, case control studies are more efficient because researchers do not have to wait for outcomes to develop; in addition, the statistical techniques used to analyze case-control studies produce statistically significant results with fewer participants. However case control studies are particularly vulnerable to certain types of bias. For example, if obese cases under-report their historical exposure to CSBs or their

[31] Hu (2008)

physical activity but controls do not under-report, then the results of the study may understate the role of CSBs.

A marked improvement over "point in time" cross-sectional studies is to track individuals over time. These studies are referred to synonymously as *longitudinal, cohort, or prospective* studies. The main goal is to create a "dynamic" model of the relationship between the independent and dependent variables, where the interest is how the *changes or differences* in the independent variable affect *changes* in the dependent variable. Because such studies assess exposure and outcome over time, this study design is generally well-suited to measuring the effect of CSB consumption on weight gain. However, these studies require considerably more resources-- outcomes, health behaviors and consumption patterns need to be measured at multiple time periods, and steps need to be taken to minimize biases that could be introduced if study participants drop out of the study before its completion.

Experimental studies or controlled trials are considered the "gold standard" of observational epidemiologic studies because their design and analysis proffer a unique capacity to rule out alternative explanations for observed relationships. In experimental studies, the investigators randomly assign participants to one or more treatment groups and a comparison group, and compare the outcomes of participants assigned to different groups following the treatment. For example, to study the effect of CSB consumption on weight gain, researchers might select a group of people who normally consume CSBs. The researchers would then randomly assign half the participants to eliminate CSBs from their diet and drink only water, and the other half of participants, the comparison group, would be allowed to drink CSBs as they usually do. Participants would be weighed at the beginning of the study and then again after the intervention, and the weight change in each group could then be compared. Because the groups are assigned randomly, the intervention and comparison groups are similar with respect to variables such as exercise frequency, age, gender, or other diet types, and these characteristics do not need to be considered in the statistical analysis. Although these types of studies tend to be expensive to implement for a long enough period to observe measurable changes in weight, a well designed and faithfully conducted experimental study can provide reliable results.

1.4 Measurement and Methodological Issues

The measurement and definition of overweight and obesity varies. The gold standard for measuring obesity is a percent body fat measurement, which may be most accurately done using dual energy X-ray absorptiometry, densitometry or skinfold-measurements.[32] But these measurements require specific skills and equipment, and most researchers agree that the use of anthropometric measurements such as weight and height are a suitable proxy for body fat in the categorization of obesity. Researchers have developed numerous weight-height indices to assess body fat,[33] however Body Mass Index (BMI) measured as weight in kilograms divided by height in meters squared is most universally used in epidemiologic studies.

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[32] Hu (2008)

[33] Examples of weight-height indices include: W/H, W/H^2 (Body Mass Index), $W^{1/3}/H$ (ponderal index), $H/W^{1/3}$ (Sheldon's index), $cWt^2/H^{3.3}$ (Abdel-Malek's index, where $c = 4 \times 10^6$ for women and $c = 3 \times 10^6$

Studies that use BMI differ in how they define obesity. For adults, there is considerable agreement that individuals whose BMI is greater than or equal to 30 kg/m^2 are obese, and those with a BMI between 25 and 30 kg/m^2 are overweight. For children, the use of categorical cutoffs for BMI is problematic because children's growth and development patterns differ throughout childhood and adolescence. In the U.S., most epidemiologic studies compare BMI to standard curves for age and gender, categorizing individuals whose weight measure is greater than the 95th percentile of a reference population of the same gender and/or age (or in some cases, the 97th percentile) as overweight. Those between the 85th and 95th percentile for age and gender are considered at risk of becoming overweight.[34] Many studies conducted outside the U.S. use cutoffs defined by Cole et al.[35] which pooled data from six countries (Brazil, Great Britain, Hong Kong, Netherlands, Singapore and the United States) to derive BMI cut points for males and females between the ages of 2 and 18 that correspond to a BMI of 25 and 30 kg/m^2 at age 18.

As BMI depends on the accurate measurement of both height and weight, measurement error can introduce bias. Studies where clinicians take these measurements are more accurate than those that rely on self-reporting of height and weight. Studies that rely on measurements taken by study staff may have some error, but the error is unlikely to be systematically related to a causal factor under study. This type of error is known as non-differential measurement error,[36] and it biases the statistical analysis in such a way that could result in a failure to detect an association when one does exist. Studies that rely on self-reported measures could have differential measurement error that biases the measure of association in either direction. For example, there is some evidence that overweight or obese individuals underestimate their weight by a greater amount than normal weight individuals.[37] If such underreporting occurs more frequently only among those obese individuals who drink more CSBs, this could lead to bias that masks a true association between CSB consumption and obesity; conversely, if the underreporting occurs more frequently among obese individuals who do not drink CSBs, then the statistical relationship between CSBs and obesity would be inflated.

The measurement of CSB exposure (quantity, frequency and duration of consumption and characterization of what beverages are included) is subject to error and can lead to several forms of bias. The strengths and limitations of methods for diet characterization, such as dietary recall, food records, food frequency questionnaires and diet history, have been discussed elsewhere.[38] Typically the most accurate methods of short-term food consumption are detailed food records where study participants carefully weigh, measure and record each food they consume over a specified period of time. Food frequency questionnaires (FFQs) were developed to capture usual diet habits over a longer period. These questionnaires ask questions such as 'In the past month, how often did your child drink sodas, like Coca Cola or Sprite?' and give choices such as: never,

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for men, and H is in centimeters) and %DBW (percent desirable body weight—weight as a percentage of the mean weight for a given height and sex). See generally Smalley et al. (1990)

[34] National Center for Health Statistics (NCHS) (2000)

[35] Cole et al. (2000)

[36] See glossary for general definition

[37] Shields, Gorber, and Tremblay (2008)

[38] Willett (1998)

1 to 2 per week, 3 to 4 per week, 5 to 6 per week, 1 per day, 2 per day or 3 or more per day. Validation studies show that FFQs can accurately capture dietary habits.[39]

In all epidemiologic studies of the relationship between CSBs and obesity, researchers use statistical techniques to assess the relationships between the main exposure to CSBs and the weight outcome of interest. A variable such as exercise, which is known to be related to both CSB consumption as well as weight, is a potential confounder in the statistical relationship between CSB consumption and weight outcomes. Researchers typically use multivariate regression techniques to adjust these potential confounders. Unmeasured or inaccurately measured confounders may bias the study results. In addition, over-adjustment for confounding variables may lead to bias.

Studies may inappropriately treat variables intermediate on the pathway between CSB consumption and weight gain as potential confounders. For example, some studies adjust for total energy intake. But because CSB consumption is part of a person's total energy intake, including total energy intake independent of CSB consumption in a regression model can lead to an underestimate of a positive effect. This results because some of the effect of CSBs would be subsumed by the total energy intake variable.

Studies that are conducted in sub-populations and contexts may not be generalizable to other sub-populations or to a general population. There is no reason or evidence that the physiological response of CSBs on weight would differ by race, ethnicity, or geography. Therefore, the results of well-designed studies conducted in a limited geographic area or among a particular ethnic group should be generalizable to any other locale or ethnic or racial subgroup, or the general population. However, physiological effects of CSBs may differ based on age or current weight. For example, metabolism and satiety in children may be different than in adults. Similarly, studies limited to participants who are already overweight may not be generalizable to populations of normal weight, because the physiological response to CSB consumption may differ.

1.5 Review of the Evidence

1.5.1 Overall Approach

The main purpose of our literature review was to assess the current state of evidence on the relationship between CSB consumption, weight gain, and obesity. In selecting studies for review, we used a two-step process. First, we reviewed seven systematic review studies published between 2006 and 2008.[40] The purpose of the "review of reviews" was to identify key methodological issues across studies, and to gain a sense of what the field of nutrition and obesity epidemiology generally regards as the core studies on CSBs.

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[39] Hu et al. (1999)

[40] Bachman et al. (2008); Newby (2007); Pereira and Jacobs (2008); Vartanian, Schwartz, and Brownell (2007); Forshee, Anderson, and Storey (2008); Drewnowski and Bellisle (2007); Malik, Schulze, and Hu (2006)

Second, we conducted our own literature review, to apply our own search criteria to the body of literature and to identify new manuscripts that had been published in the intervening years. Our literature review allowed us to identify studies that we would be able to use to calculate a population-attributable risk (PAR)—a summary measure of the risk of obesity that is attributable to consumption of CSBs. The PAR calculation requires the computation of a weighted-average odds ratio or relative risk, and not all of the epidemiologic studies of the effects of CSBs report results in that form.

1.5.2 Search Criteria

We identified observational and experimental studies on the effect of CSB consumption on weight gain, overweight, and obesity using keyword and Medical Subject Heading searches in PubMed, and by consulting nutritional epidemiology experts to learn about studies that had not completed the publication process.[41] We searched with key words for calorically sweetened beverages and obesity, limiting to studies in humans, written in English and not categorized as reviews, letters, editorials or practice guidelines.[42] The search revealed a total of 319 manuscripts. Many were irrelevant due to alternative definitions of "pop" (e.g., studies of pelvic organ prolapse) or "soda" (e.g., studies of the "Soda" gene). Through abstract and title review we identified a total of 57 studies with data specific to the relationship between consumption of CSBs and weight gain and that met the following three study criteria: (1) explicitly defined CSBs; (2) included at least one outcome measure of obesity, overweight or weight gain;[43] and (3) included at least one measure of CSB "exposure."[44] Of the 57 studies meeting our criteria, 31 were cross-sectional, 17 were longitudinal, two were case-control studies, and seven were

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[41] PubMed is a service of the U.S. National Library of Medicine that includes over 18 million citations from medical, public health, and life science journals for biomedical articles back to 1948

[42] We performed our original in-depth search in September 2008, and supplemented the search with new citations added between September 2008 and May 2009. The URL for the PUBMED User Query that returned 319 results on May 5, 2009 was:
http://www.ncbi.nlm.nih.gov/sites/entrez?Db=pubmed&Cmd=DetailsSearch&Term=(sweetened[All+Fields]+AND+caloric[All+Fields]+AND+(%22beverages%22[MeSH+Terms]+OR+beverages[Text+Word])+OR+%22sugar-sweetened+beverages%22[All+Fields]+OR+%22sugar-sweetened+beverage%22[All+Fields]+OR+%22calorically+sweetened+beverages%22[All+Fields]+OR+%22sweetened+beverages%22[All+Fields]+OR+%22sugared+drinks%22[All+Fields]+OR+%22soft+drinks%22[All+Fields]+OR+pop[Text+Word]+OR+%22fruit+drinks%22[All+Fields]+OR+fruitades[All+Fields]+OR+%22sports+drinks%22[All+Fields]+OR+lemonade[All+Fields])+AND+((%22obesity%22[MeSH+Terms]+OR+obesity[Text+Word])+OR+(%22overweight%22[MeSH+Terms]+OR+overweight[Text+Word])+OR+((%22body+weight%22[TIAB]+NOT+Medline[SB])+OR+%22body+weight%22[MeSH+Terms]+OR+weight[Text+Word])+OR+%22weight+gain%22[All+Fields])+AND+%22humans%22[MeSH+Terms]+NOT+review[pt]+NOT+letter[pt]+NOT+practice+guideline[pt]+NOT+editorial[pt]+AND+english[la]+AND+(%221900%2F01%2F01%22[MHDA]+%3A+%222009%2F05%2F05%22[MHDA]).

[43] We included studies where weight and height was measured by study investigators and studies where these were self-reported.

[44] This included studies that assessed CSB consumption by the Food Frequency Questionnaire, the most accurate measure of longer term consumption, food diaries, 24 hour recalls or interviews with dieticians.

experimental. Most (43) were conducted among populations that included children or teens; only 14 studies were of adult populations. Forty of the 57 were included in at least one of the seven systematic reviews cited above; of these forty, 17 were cited in four or more of the seven review articles.[45] Below we summarize this literature in four sections: cross-sectional, case-control, longitudinal and experimental.

1.5.3 Cross-Sectional Studies

One of the more frequently cited cross-sectional studies is Giammattei et al. (2003).[46] This study focused on risk factors for Type 2 diabetes among 385 children age 11-14 years in Santa Barbara, California. The regression analysis used a less conservative definition of overweight (85th percentile of BMI for age and gender), finding that those who consumed three or more diet or regular soft drinks per day were 1.61 times more likely (95% CI: 1.14, 2.28) to be overweight compared to those who consumed fewer than three servings per day, after controlling for TV watching, age and sex. Ethnicity was a confounder in this study (Latino students were heavier and consumed more soft drinks per day than the non-Hispanic white or Asian students), and the relationship between CSB consumption and overweight was attenuated after adjusting for ethnicity as a confounder [OR: 1.46 (95% CI: 1.02, 2.10)]. This study was methodologically well designed in that it attempted to characterize "usual" soft drink consumption and also included a question about participants' perception of their own weight as a way of assessing presence of dieting to lose weight; however, the analysis did not appear to incorporate the perception variable. Moreover, combining diet with regular CSB consumption may have resulted in a biased effect estimate, which may have been further biased by the use of the less conservative definition of overweight in the regression analysis.

Another frequently cited study was conducted in Bogalusa Louisiana, among 1,562 children aged 10 years participating in the cross-sectional Bogalusa Heart Study. Compared to those who drank 14.1 ounces (399 g) of CSBs per day, children who consumed two times the average serving size (28.2 ounces) were 1.33 times more likely to be overweight (defined as BMI greater than the 95th percentile for age and gender) (95% CI: 1.12, 1.57).[47] Data stratified by race and gender found significant relationships between consumption and overweight among white boys and girls [boys: OR 1.68 (95% CI: 1.21, 2.33); girls: OR 1.53 (95% CI: 1.05, 2.22)], but null results for African Americans. This study used a 24-hour recall to assess beverage consumption. It also adjusted for total energy intake, which could have resulted in an underestimation of the effect of CSB consumption on obesity.

A subsequent study by Rajeshwari et al. (2005) examining the same population found mean BMI across seven survey years was 18.0 kg/m^2 in children who did not consume any sweetened beverages, compared to 18.6 kg/m^2 in children who consumed on average 770-868 grams/day of sweetened beverages (equivalent to about 26 to 29 ounces/day).[48]

[45] Two seminal studies-- Ludwig et al. (2001) and Berkey et al. (2004)-- were cited in all seven reviews.

[46] Giammattei et al. (2003)

[47] Nicklas et al. (2003)

[48] Rajeshwari et al. (2005)

The Center for the Health Assessment of Mothers and Children of Salinas study is an established cohort of women and their children who have been followed since birth. Warner and colleagues (2006) selected a point in time and conducted a cross-sectional analysis of the children at age 2, finding that after adjusting for fast food, breast feeding and maternal pre-pregnancy BMI, children who consumed more than one soda per day were at significantly greater risk of overweight (OR 3.39, 95% CI: 1.43, 8.07).[49] This study was well-designed, utilizing a Food Frequency Questionnaire for CSB exposure assessment, and height and weight measured by study staff. The analysis considered multiple potential confounders in addition to those used in the final model.

More recently, Linardakis et al. (2008) assessed the intake of CSBs in relation to BMI and waist circumference in 856 kindergarten children aged 4-7 years living in Crete, Greece as part of the baseline assessment in an intervention study.[50] Nutrient and food intake was assessed using 3-day food records; anthropometric measurements were made by study staff and obesity categorized using the international cutoffs developed by Cole et al[51]. Although only about one-third of eligible children participated in the baseline assessment, approximately 59.8% of the participants consumed sugar-added beverages on a daily basis. After adjusting for gender, age, energy intake and birth weight, children who consumed more than 250 grams of CSBs per day were more likely to be obese compared to children who did not consume any CSBs (OR: 2.35, p = 0.023).

In a similar cross-sectional study, Li et al. (2008) studied 1,804 adolescents aged 11 to 17 in Xi'an City, China.[52] After adjusting for age and gender, the authors identified several factors significantly associated with overweight and obesity, including the consumption of CSBs four or more times per week (OR: 1.6, 95% CI: 1.02, 2.5).

Several studies have been conducted using data from two large U.S. surveys—the U.S. Department of Agriculture's Continuing Survey of Food Intake by Individuals (USDA CSFII) and the National Health and Nutrition Examination Surveys.[53,54] The NHANES studies include measurement of weight by researchers; however, the USDA CSFII uses self-report for anthropometric measures. In general, these studies have not found strong or significant relationships between CSB consumption and overweight or obesity, however these studies

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[49] Warner et al. (2006)

[50] Linardakis et al. (2008)

[51] Cole et al. (2000). See also Section 1.4.

[52] Li et al. (2008)

[53] Forshee, Anderson, and Storey (2004); Forshee and Storey (2003); O'Connor, Yang, and Nicklas (2006); Troiano et al. (2000); Sun and Empie (2007)

[54] Bremer, Auinger, and Byrd (2009). Although this study focused on the relationship between physical activity and CSB consumption, a secondary analysis in this study used multivariate linear regression to evaluate the effect of CSB intake on BMI, finding a 0.90-percentile increase in BMI for age associated with each additional 8 oz serving of CSBs, after adjusting for differences in physical activity, age, sex, race, and energy intake.

measure exposure in the short term, and are not able to assess the relationship between past or "usual" CSB consumption and weight.

Several other studies met our inclusion criteria. Four studies conducted outside the U.S.,[55] and one among Mexican American Kindergarteners in Chicago[56] reported positive relationships between measures of CSB consumption and weight outcomes. Many of the international studies used the international definition of overweight developed by Cole et al. (2000).[57] All but Gibson and Neate (2007)[58] asked about CSB consumption using methods that characterized consumption over a longer time period, enhancing the likelihood that a true temporal relationship between CSB consumption and weight measures was assessed; these same four all used measurements, rather than self report.

Two studies with important methodological limitations did not find any significant associations. The study by Novotny et al. (2004) did not characterize children into overweight categories, only evaluating the linear relationship between CSB consumption and weight or skinfold measurement.[59] The study found that each gram/day of soda intake was associated with 0.0050 kg higher weight. Models were adjusted for several variables including height and energy intake. In this study, only 187 of 315 girls gave information on their soda intake; it is not clear if the non-respondents were missing or simply had no consumption. The inclusion of energy intake in the models may have biased the study results toward not finding significant effects; additionally, the use of weight as the outcome may not be sensible because it does not consider differences in development or stature. There were also important limitations to the study by Overby et al. (2004).[60] They calculated mean BMI for quartiles of added sugar consumption among girls and boys, finding a few differences in categories. However, there was no direct evaluation of CSB consumption, and overweight was not assessed.

Among adult populations, the study by Liebman et al. (2003) is a frequently cited cross-sectional analysis.[61] The researchers in this study of 1,817 men and women in rural Wyoming, Montana and Idaho found a significant association between the consumption of CSBs and overweight and obesity. They evaluated the gender specific probabilities of being obese in relation to CSB consumption among adults under and over the age of 50. Probabilities of obesity among adults who drank less than one drink per week were consistently lower than the probabilities for obesity among adults with higher consumption. For example, for women under age 50, the probability of obesity among those who drank CSBs less than once per week was 24.4%, and among those who drank CSBs once or more per week the probability was 31.5%.

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[55] Gibson and Neate (2007); Sanigorski, Bell, and Swinburn (2007); Serra-Majem et al. (2006); Utter et al. (2007)

[56] Ariza et al. (2004)

[57] Cole et al. (2000). Also refer to Section 1.4.

[58] Gibson and Neate (2007)

[59] Novotny et al. (2004)

[60] Overby et al. (2004)

[61] Liebman et al. (2003)

The Rancho Bernardo Study is one of the few cross-sectional studies in which researchers assessed longer-term consumption of beverages. Although this study did not specifically assess CSB consumption, they did find that women who had been drinking one or more servings of any carbonated beverage per day for one year or more had BMI 25.9 kg/m^2 compared to 24.5 kg/m^2 for others.[62] Similarly, the 2005 New York City Community Health Survey found that women who consumed one or more 12 ounce servings of sweetened beverages per day had mean BMI 0.7 kg/m^2 (by self-report) greater than those who consumed less than one CSB serving per day; men who consumed more than one serving per day had BMI 0.1 kg/m^2 lower than men who had less than one serving per day.[63]

Most of the other cross-sectional studies identified in our literature search found some relationship between various measures of CSB consumption and weight outcome,[64] although two did not.[65]

Summary. Cross-sectional studies were the most commonly identified study type in our search. Many of the cross-sectional studies we reviewed had different exposure and outcome measures, and differed with regard to the statistical effects reported, making comparison across study results difficult. The studies that revealed significant relationships tended to be those that had stronger methods. These stronger methods included the following three factors: (1) assessment of CSB consumption over longer periods; (2) reliance on measured rather than self-reported anthropometric measures and (3) use of an accepted standard definition for overweight or obesity. Of the studies that we identified as funded by parties with an interest in production or sale of CSBs, all were cross-sectional, and none found a significant relationship between CSB consumption and weight outcomes.[66] In general, consistent with the findings of other reviews, cross-sectional studies suggest that higher CSB intake is associated with higher energy intake and weight gain and possibly obesity, but these studies do not directly support a causal relationship.[67] In other words, we cannot distinguish whether overweight or obese individuals are more likely to drink CSBs or whether the consumption of CSBs is a determinant of overweight or obesity; in either case, cross-sectional findings show an association between CSB intake and weight gain/obesity.[68]

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[62] Kim, Morton, and Barrett-Connor (1997)

[63] Rehm et al. (2008)

[64] Bell et al. (2005); Daida et al. (2006); Stanton, Ahrens, and Douglass (1978); Wang et al. (2007)

[65] Andersen et al. (2005); Roseman, Yeung, and Nickelsen (2007)

[66] Forshee, Anderson, and Storey (2004); Forshee and Storey (2003); O'Connor, Yang, and Nicklas (2006); Sun and Empie (2007)

[67] See generally Pereira (2006); Malik, Schulze, and Hu (2006)

[68] In addition, it is important to note that of the studies that we identified as being funded by parties with an interest in production or sale of CSBs, all were cross-sectional, and none found a significant relationship between CSB consumption and weight outcomes. See generally Forshee, Anderson, and Storey (2004); Forshee and Storey (2003); Sun and Empie (2007).

1.5.4 Case Control Studies

We identified only two case-control studies in which researchers considered the relationship between CSB consumption and weight outcomes. Ochoa and colleagues (2007) conducted a case-control study in Spain of 185 obese cases and 185 controls ages 6 to 18.[69] After adjusting for total energy consumption, physical activity, TV watching and family obesity, for each additional serving of sweetened beverages per day, there was a 1.74 risk of obesity. (OR 1.74, 95% CI: 1.05, 2.89). This study characterized exposure over the past year; obesity was defined as children who were at or above the 97th percentile of weight for their age and gender, therefore the results may be more conservative compared to other studies. Using a similar study design, Gillis and Bar-Or (2003) analyzed data from 91 obese cases and 90 non-obese controls and compared characteristics of the two groups using t-tests.[70] The authors used stepwise multivariable regression to investigate the relation between body fat and diet consumption variables. They found that obese cases consumed seven servings per week of CSBs compared to five servings per week for non-obese controls.

1.5.5 Longitudinal Studies

Ludwig et al. (2001) is a strong study with careful design and analysis, for these reasons it is one of the most frequently cited epidemiologic studies of the relationship between CSBs and obesity. Researchers conducted this 19-month prospective epidemiologic study of 548 children ages 11 and 12 in metropolitan Boston between 1995 and 1997. This study estimated odds ratios for the incidence of obesity for both baseline consumption and change in consumption over the follow up period. Researchers controlled for baseline anthropometrics, age, sex, ethnicity, indicator variables for schools, percent energy from fat at baseline, energy-adjusted fruit juice intake at baseline, change in these variables from baseline to follow-up, physical activity, time spent watching television and videos and change in time spent watching television and videos. They found that for every 12 ounces of CSBs consumed per day (at baseline) study subjects increased the odds of developing obesity by 1.4 times (OR: 1.44, 95% CI: 1.22, 1.70).[71] This study used an obesity measure based on a composite measure which categorized as obese those participants for whom both BMI and triceps skinfold measurements were above the 85th percentile for age and sex. This atypical definition may have resulted in more children being characterized as obese than would have been if the authors had defined obesity by only BMI greater than the 95th percentile for age and gender.[72] But the authors cite reliable evidence that their definition of obesity is valid and that the use of triceps skinfold measurements ensures that the 85th percentile BMI cutoff is not overly inclusive.

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[69] Ochoa et al. (2007)

[70] Gillis and Bar-Or (2003)

[71] Ludwig, Peterson, and Gortmaker (2001)

[72] This definition could have inflated the effect estimate if children who would have otherwise been characterized as normal weight were also high consumers of CSBs.

Studies based on the Oslo Youth Study found odds ratios similar to those reported by Ludwig et al. Starting in 1979, 422 teens (ages 11 to 16 years) were followed for 10 years.[73] The Oslo study did not attempt to assess the effect of consumption of CSBs *per se*; rather, it looked at the effects of long term consumption (defined as more than three drinks per week in 1991 and 1999). For young men, long-term consumers had a higher odds of obesity (OR 1.33; 95% CI 0.35, 5.03) compared to long-term non-consumers. Among young women, the OR was 1.12, (95% CI 0.23, 5.50). This study was specifically investigating the stability of consumption over time. The researchers did not find a statistically significant association between obesity and long-term high consumption of carbonated CSBs. Because they stratified by gender and only compared groups that had stable consumption, the authors suggest that they may not have had the statistical power to detect a significant effect. The study did not look at the effect of changing consumption over time.

Two studies in much younger children also reached conclusions consistent with those of Ludwig et al. Welsh and colleagues found that preschool children who were overweight or at risk of overweight were about twice as likely to remain or become overweight if they consumed CSBs.[74] Similarly, the Longitudinal Study of Child Development in Quebec found that although total daily consumption of sweetened beverages among children aged 2-5 was not related to overweight, regular consumption between meals was associated with a 2.4 times higher risk of overweight after adjusting for birth weight, family income, and parental obesity; other models had similar results.[75] Also among younger children in North Dakota, a longitudinal study of 1,345 children aged 2 to 5 years whose families were low income participants in the federal Women Infants and Children (WIC) program found no significant results for associations between any beverages and weight gain or BMI; for example, weight change associated with each additional ounce of soda per day was 0.00 lb/year (-0.08 to 0.08).[76] The lack of significant results may be explained by the low consumption and low variability in consumption, possibly because the WIC program does not pay for soda. In addition, the mean follow-up time of 8.4 months may not have been long enough to observe significant changes in weight related to this low consumption.

In another frequently cited study, 11,755 boys and girls age 9 to 14 were followed for two one-year periods as part of the *U.S. Growing Up Today Study*. Berkey and colleagues found a dose-response trend with a statistically significant per-serving effect on weight gain. In linear models, for each serving of CSBs, the one-year change in BMI was 0.028 ± 0.014 kg/m^2 for boys and 0.021 ± 0.012 kg/m^2 for girls.[77] In models allowing for non-linear dose-response, girls who drank one serving per day of CSBs had BMI gains 0.07 kg/m^2 higher than girls drinking none; girls drinking two servings per day had BMI 0.09 kg/m^2 higher; and girls drinking three servings per day had BMI 0.08 kg/m^2 higher. Boys had similar effect sizes for the two and three servings per day categories, but lower effects were seen for boys consuming one serving per day (0.02 kg/m^2 higher). Results are adjusted for consumption of other beverages (including milk type),

[73] Kvaavik, Andersen, and Klepp (2005)

[74] Welsh et al. (2005)

[75] Dubois et al. (2007)

[76] Newby et al. (2004)

[77] Berkey et al. (2004)

Tanner stage,[78] race, menarche (girls), prior BMI, change in height, physical activity and inactivity. Results were not adjusted for overall energy intake. In addition to the prospective design and large study population, study strengths included a fine-grained exposure measure and adjustment for multiple potential confounders.[79]

Consistent with the findings of Berkey et al. and Ludwig et al., in the MIT Growth and Development Study, Phillips et al. (2004) followed 141 pre-menarchal girls aged 10 to 14 for four years, finding girls in the third and fourth quartiles of percentage calories from CSBs (equivalent to about 36 ounces/day) had BMI z-scores[80] that were 0.17 units higher on average than girls in the first quartile of exposure, after adjustments for fruit and vegetable intake, menarche, and parental weight status.[81] Similarly, a study by Mrdjenovic and Levitsky (2003) demonstrates that calories consumed in CSBs do not replace calories from other sources but instead result in additional energy intake.[82] In this 8-week study in New York, researchers found that children attending summer camp ingested an additional 244 calories per day when they consumed CSBs as compared to when they did not. Consequently, children who consumed more than 16 ounces per day of CSBs gained more weight (1.12 +/- 0.7 kg) than children who consumed between 6 and 16 ounces per day (0.32-0.48 +/- 0.4 kg).

A study of 682 children at age 5, 7 and 9 years in England looked at the relationship between Fat Mass Index (FMI)[83] and CSB consumption.[84] This study was a sub-sample from an established cohort-- the Avon Longitudinal Study of Parents and Children (ALSPAC)-- conducted between 1996 and 2001. The authors found no evidence of an association between CSB consumption and FMI, but this was likely due to low overall consumption among study participants.[85]

Blum et al. (2005), using a sub-sample from a larger cohort of elementary school children in grades 3 to 6, did not find an association between CSBs and weight gain. This study found a statistically significant relationship between increased diet soft drink consumption and BMI Z-score.[86]

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[78] The Tanner scale (or stage) is a scale of physical development in children, adolescents and adults. The scale defines physical measurements of development based on external primary and secondary sex characteristics, such as the size of the breasts, genitalia, and development of pubic hair.

[79] The authors acknowledged that although the study collected information by self-report, any reporting errors would be expected to occur randomly, which would bias any estimates of a true association toward the null.

[80] BMI z-scores are a measure of the deviation from the mean BMI for the population under study.

[81] Phillips et al. (2004)

[82] Mrdjenovic and Levitsky (2003)

[83] The "Fat Mass Index" is measured by dual x-ray absorptiometry ÷ height

[84] Johnson et al. (2007)

[85] Consumption ranged from 0-196 g/day, with averages of 57 g/day at age 5 and 67 g/day at age 7, or equivalent to about 2 oz/day.

[86] Blum, Jacobsen, and Donnelly (2005)

Kral et al. (2008) prospectively assessed beverage consumption patterns and their relationship with weight status for three years in a small cohort of 49 children beginning at age three years.[87] Daily beverage consumption was evaluated annually by 3-day food records, and anthropometric measures were measured by study staff yearly. Although there was no significant association between BMI and change in intake from any of seven different categories of beverage type, children who increased their consumption of calories from soda had a statistically significant increase in waist circumference, while children who increased their calories from milk had a statistically significant decrease in waist circumference.

Similar longitudinal studies have been done on adult populations. Schulze et al. (2004) studied 51,603 women in the Nurse's Health Study II.[88] Weight gain over a four-year period was highest among women who increased their CSB consumption from one or fewer drinks per week to one or more drinks per day (multivariate-adjusted means, 4.69 kg for 1991 to 1995 and 4.20 kg for 1995 to 1999) and was smallest among women who decreased their intake (1.34 and 0.15 kg for the two periods, respectively). Study strengths included the large study population, and the reliable exposure and outcome reporting among the participants in the Nurses' Health Study II. In a cohort study of 7,194 university graduates who were followed up for two or more years in Spain, Bes-Rastrollo et al. (2006)[89] found increased risk of weight gain associated with higher CSB consumption in the participants who reported weight gain during the 5 years before baseline.[90] French and colleagues followed 3,552 adults in the Healthy Worker Project for a two-year study of smoking cessation intervention and weight control interventions.[91] In linear regression models, increases of one serving of non-diet soft drinks per week were not associated with body weight changes over the two-year period after adjusting for a number of dietary, anthropometric and socio-demographic variables. These null findings were likely due to over-adjustment for dietary variables and frequency of consumption of dairy and grain products, sweets, alcohol, meat, soda, eggs, French fries and fats) that, while appropriate for analysis of the relationship between smoking cessation and weight control interventions, would not have been considered in a study specific to the relationship between CSB consumption and weight gain.

Analyzing data from 810 adults who participated in an 18-month trial to assess the effects of behavioral interventions on blood pressure, Chen et al. (2009) found that a reduction in liquid calorie intake of 100 kcal/day was associated with a weight loss of 0.25 kg (95% CI: 0.11, 0.39; $p < 0.001$) at 6 months and of 0.24 kg (95% CI: 0.06, 0.41; $p = 0.008$) after 18 months, whereas reduction in solid calorie intake of 100 kcal/day was associated with much lower weight loss (0.06 kg at 6 months, and 0.09 kg at 18 months). Furthermore, participants who increased their CSB intake over the course of 18 months experienced much lower weight loss than the participants who decreased their CSB intake (those who increased intake by a median of 248.3 ml/day (approximately 8 ounces) lost an average of 1.5 kg, compared to an average of 5.2 kg lost by those who reduced their CSB intake by a median of 366.7 mL/d (approximately 12 ounces).

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[87] Kral et al. (2008)

[88] Schulze et al. (2004)

[89] Bes-Rastrollo et al. (2006)

[90] Odds ratio adjusted for age and sex for quintiles of consumption 1 to 5 were 1.00 (reference), 1.23, 1.09, 1.23 and 1.43, respectively; p for trend = 0.017

[91] French et al. (1994)

Three additional longitudinal studies in our literature search found some relationship between various measures of CSB consumption and weight outcome.[92] However, one did not report statistically significant results—Mundt et al. (2006) did not find a relationship between weight and beverage consumption. However, their analytic methods may not have been appropriate and may have obscured any significant finding.[93]

Summary. Although some studies did not always report statistically significant results the longitudinal studies consistently support a causal relationship between CSB consumption and BMI and other weight outcomes. Both Johnson et al. (2007)[94] and Newby (2004)[95] had extremely low consumption in their populations that may have made it difficult to detect a significant effect, or that may have been below a threshold whereby any effect would be seen. The study by French et al. (1994) was well designed, but over-adjustment for dietary variables in the linear regression models may have resulted in a finding of no effect.[96] The studies by Blum et al. (2005)[97] and Johnson et al. (2007) were sub-samples of larger cohorts, and their failure to find a relationship between CSB consumption and overweight may have been due to selection bias. Because longitudinal studies are able to assess consumption of CSBs before weight gain occurs, conclusions from these types of studies are better able to support causality compared to cross-sectional studies. This conclusion is consistent with the findings of most of the review articles that we considered. Only one review article (Forshee et al.[98]) concluded that the longitudinal evidence was inconclusive, but subsequent re-analyses of their data by Malik, Willett, and Hu (2009) "clearly suggest a positive association between [CSB] intake and BMI among children."[99]

1.5.6 Experimental Studies

Ebbeling et al. (2006) enrolled 103 adolescent residents of Boston, Massachusetts, age 13 to 18 years in a 25-week trial of the effect of non-caloric beverage replacements on weight gain.[100] The intervention group received weekly home deliveries of zero calorie beverages such as bottled water or diet soda for 25 weeks, while the comparison group was instructed to maintain their usual beverage consumption habits. The study showed that removing CSBs from the diet results in weight loss. Among adolescents with an initial BMI greater than 25.6 kg/m^2, those who received non-caloric beverage replacements for 25 weeks experienced significant reductions

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[92] Drapeau et al. (2004); Striegel-Moore et al. (2006); Tam et al. (2006)

[93] Mundt et al. (2006)

[94] Johnson et al. (2007)

[95] Newby et al. (2004)

[96] French et al. (1994)

[97] Blum, Jacobsen, and Donnelly (2005)

[98] Note that Forshee et al. (2008) was funded by the American Beverage Association.

[99] Malik, Willett, and Hu (2009). Note that the authors' use of the term "positive" is strictly in the statistical sense of the word, meaning that increases in CSB intake are associated with increases in BMI.

[100] Ebbeling et al. (2006)

in BMI (-0.63 kg/m^2) as compared to those who continued to consume CSBs (+0.12 kg/m^2).[101] This study was randomized but not blinded. At the start of the study, each group was similar to each other with regard to anthropometric variables, physical activity and dietary habits. Study participants who received the intervention reported that they did not drink CSBs outside of the home, and those in the comparison group reported continuing their usual beverage intake as instructed.

The Christchurch Obesity Prevention Project in Schools used a different intervention strategy. James et al. (2004) compared BMI z-scores[102] in relation to changes in sweetened beverage consumption after an educational intervention.[103] In this cluster randomized controlled trial of 644 children age 7 to 11 at six schools in England, children in the 15 intervention classes were instructed to reduce their consumption of all carbonated beverages and received information about the health benefits of reducing sugar intake and the benefits to dental health of avoiding diet and sweetened carbonated beverages.[104] Over the course of a year the children who received the intervention decreased their average consumption of carbonated sweetened beverages by 0.3 glasses per day. But this decrease was not statistically significant. There was no change in consumption of CSBs among the children who did not receive the intervention. The mean percentage of overweight and obese children (defined as BMI above the 91st percentile for age and gender) increased in the comparison clusters by 7.5%, compared with a decrease in the intervention clusters of 0.2%.

Two experimental studies looked at adult populations. One randomized, double-blind 10-week study of 41 overweight adults in Denmark found statistically significant ($p < 0.001$) greater weight gain over the ten week course of the study among those who were assigned to drink CSBs (weight gain 1.6 ± 0.4 kg, BMI change 0.5 ± 0.2 kg/m^2) compared to those who consumed diet drinks (weight change -1.0 ± 0.4 kg, BMI change -0.4 ± 0.2 kg/m^2). The authors suggested the difference in weight outcomes may have been due to the failure among the CSB group to compensate for the liquid calories by reducing intake of other foods and beverages.[105]

In an earlier study of similar design conducted among 30 Pennsylvania adults in 1987-1988, Tordoff and Alleva (1990) instructed men and women of mean BMI 25 kg/m^2 to drink soda containing high fructose corn syrup (HFCS), aspartame or nothing. The study lasted 9 weeks with each participant rotating through the drink options for three-week periods. The study found significantly increased calorie consumption and weight gain after the period of drinking HFCS drinks compared to aspartame or no soda. For women, weight change was -0.36, -0.11, 0.61 kg/three weeks for no soda, aspartame and HFCS groups respectively; for men 0.12, -0.25 and

[101] Ibid.

[102] “BMI z-scores” are a measure of the deviation from the mean BMI for the population under study. See glossary.

[103] James et al. (2004)

[104] The 14 control classes did not receive this information directly; however, because the classes were in the same schools, it is likely that some of the information given to the students in the intervention classes was received by the children in the control classes. This communication among the groups may have attenuated the observable intervention effect.

[105] Raben et al. (2002)

0.64 kg/three weeks. The differences between the HFCS weight gain and the no soda weight changes were statistically significant in both men and women ($p < 0.001$). Though the three-week period was brief compared to the 10-week Raben et al. study, the weight changes are comparable.[106]

Albala et al. (2008) conducted a randomized controlled trial to examine the effects on body composition of replacing CSBs with milk beverages in the homes of overweight and obese Chilean children.[107] They randomly assigned 98 children aged 8-10 years who regularly consumed CSBs to intervention and comparison groups. During a 16-week intervention, children were instructed to drink three servings per day (approximately 200 grams per serving) of the milk delivered to their homes and to not consume CSBs. Body composition was measured by dual-energy X-ray absorptiometry. For the intervention group, milk consumption increased by a mean of 452.5 +/- 37.7 grams per day ($p < 0.0001$), and consumption of CSBs decreased by -711.0 +/- 33.7 grams per day ($p < 0.0001$). For the comparison group, milk consumption did not change, and consumption of CSBs increased by 71.9 +/- 33.6 grams per day ($p = 0.04$). Changes in percentage body fat, the primary endpoint, did not differ between groups. Nevertheless, the mean accretion of lean body mass was greater ($p = 0.04$) in the intervention (0.92 +/- 0.10 kg) than in the comparison (0.62 +/- 0.11 kg) group.

A recent experimental study of the effect of an educational intervention on consumption of CSBs was conducted in Brazil by Sichieri et al. (2009).[108] The researchers randomized 1,140 fourth graders in 22 schools, with students in 11 of the schools receiving healthy lifestyle messages encouraging water consumption instead of CSB intake. At the beginning and end of the school year, CSB and juice intake were assessed through 24-hour recall, and height and weight were measured by study staff. Although BMI and weight increased among all students, CSB consumption decreased by 69 ml in the intervention group, compared with 13 ml among the students who did not receive the intervention. There was no significant difference in the change in BMI between the intervention and comparison groups; however, among students who were overweight at baseline, students who received the educational intervention reduced their BMI by 0.4 kg/m^2, compared to a reduction of 0.2 kg/m^2 among students who did not receive the intervention.

The following three experimental studies considered in one or more of the published reviews were included in our search results but were not applicable to our main objective due to specific design and measurement issues. Grandjean et al. (2000) was a hydration study focusing on caffeine which did not find any differences in weight among 18 men randomized to consume different combinations of water and caloric or non-caloric beverages with and without caffeine on a single day.[109] Van Wymelbeke et al. (2004) did not have a relevant weight change outcome.[110] DiMeglio and Matte (2000) compared the effect of liquid versus solid carbohydrate loads among 15 young adults, finding no significant change in body weight when participants

[106] Tordoff and Alleva (1990)

[107] Albala et al. (2008)

[108] Sichieri et al. (2009)

[109] Grandjean et al. (2000)

[110] Van Wymelbeke et al. (2004)

consumed the solid carbohydrate load for four weeks, but body weight was significantly higher after consuming liquid carbohydrates.[111]

Summary. Similar to the findings of cross-sectional, longitudinal, and case-control studies, experimental studies also suggest, on balance, a positive relationship between CSB consumption and weight gain. This conclusion is supported, even though the studies conducted by James et al. and Sichieri et al. did not find statistically significant results. However, both of these studies suffered from similar limitations. Principally, because these studies were aimed at analyzing the effect of an intervention on weight outcome, neither attempted to link change in CSB consumption directly to the weight outcome. Furthermore, in the James study, it is unclear why the prevalence of overweight *increased* in the comparison classrooms, despite no change in carbonated beverage intake. [112]

1.6 Causality

The preceding review suggests there is a relationship between CSB consumption and weight—a summary conclusion shared by others who have conducted similar literature reviews. Recent reviews lend additional support to the conclusion that there is a positive relationship between CSB consumption and development of obesity.[113] In an unpublished letter serving as a "review of reviews," French and Pereira (2008)[114] submit that while three reviews report mixed findings in the literature,[115] the authors note that two studies conclude that there is a "clear positive association between [CSB] and weight gain."[116]

In our review we observed that the studies designed to address the direction of causality suggest that higher CSB consumption is one of several factors *causing* weight gain or changes in BMI. To formally evaluate causality, we apply the criteria proposed by Bradford Hill in 1965, a recognized method for assessing the evidence for a causal association.[117] Bradford Hill's criteria are 1) the strength of the association between the causative agent and the outcome of interest, 2) the consistency of the findings in different environments and in different research methodologies, 3) specificity of the relationship between the causative agent and the outcome of interest, 4) temporality of the relationship, where the exposure precedes development of the outcome, 5) demonstration of a dose response, whereby exposure to more of the agent results in greater severity of the outcome of interest 6) biological plausibility, 7) coherence and consistency with what is already known, 8) experimental evidence and 9) evidence from

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[111] DiMeglio and Mattes (2000)

[112] For further discussion of the limitations of the James et al. study, see French, Hannan, and Story (2004)

[113] Harrington (2008); Malik, Willett, and Hu (2009)

[114] French and Pereira (2008)

[115] Bachman, Baranowski, and Nicklas (2006); Pereira (2006); Drewnowski and Bellisle (2007)

[116] Vartanian, Schwartz, and Brownell (2007); Malik, Schulze, and Hu (2006)

[117] Hill (1965)

analogous conditions. An assessment of the aforementioned evidence in the context of Hill's criteria suggests that CSB consumption is causally related to weight gain and obesity.

Strength of Effect. The strength of the association is fairly consistent throughout the studies. Although some studies failed to find a statistically significant relationship, effect measures in the stronger studies in general were between 1.5 and 2.5. In other words, many studies found that people who drink CSBs have 1.5 to 2.5 times greater risk for an adverse weight outcome such as overweight or obesity.

Consistency. Researchers consistently found positive point estimates of effects between CSB consumption and weight gain, and only one study suggested an inverse effect (the Blum et al. study found that among the 11 subjects who gained weight, CSB consumption had decreased over two years). These results were consistent regardless of whether the studies were conducted in children, teens, or adults, or in a U.S. population or elsewhere. Authors found positive relationships using differing methodologies and in studies with different definitions of obesity and weight. In addition, researchers found significant relationships using both broad and narrow definitions of CSB consumption.

Specificity. The specificity of the relationship is one of Hill's criteria and can not be met when studying risk factors for an outcome that has known multiple risk factors, such as obesity. But in studies that properly adjusted for potential confounders, authors consistently found an independent effect of CSB consumption on obesity.

Temporality. The most reliable evidence for this criterion comes from experimental and prospective cohort studies that assess CSB consumption before the development of obesity. In both longitudinal and experimental studies, study authors found consistent positive relationships between CSB consumption that subsequently resulted in either weight gain or obesity.

Dose Response. Dose response is revealed by studies that looked at whether increasing consumption led to increased weight. Several of the studies that had data sufficient to evaluate dose-response demonstrate that increased CSB consumption is associated with increased weight gain or increased obesity.[118]

Biological Plausibility / Coherence / Analogy. These three criteria are similar; they ask what is known about how CSB consumption could cause obesity, whether the proposed mechanisms are consistent with what is already known about obesity, and whether analogous causes are known. The clear physiological pathway between consumption of CSBs and weight gain was demonstrated in Section 1.2. This evidence is well summarized in Bachman et al. (2006),[119] which discussed several possible mechanisms by which CSBs cause weight gain: 1) CSBs contribute to an imbalance between energy expenditure and energy intake; 2) CSBs trigger a metabolic response that results in increased adiposity; 3) CSBs are less satiating and lead to increased consumption of calories; 4) CSBs displace milk, which inhibits the obesity-reducing

[118] Berkey et al. (2004); Bes-Rastrollo et al. (2006); Ludwig, Peterson, and Gortmaker (2001); Striegel-Moore et al. (2006); Welsh et al. (2005)

[119] Bachman, Baranowski, and Nicklas (2006)

role of calcium; 5) CSB consumption leads to increased energy intake by down-regulating the influence of insulin and leptin; or 6) certain individuals are more susceptible to weight gain from CSBs due to their specific genetic makeup. Although Bachman et al. concluded that more study is needed to confirm or refute any of the mechanisms, each of the proposed mechanisms is biologically plausible and the role of CSBs is coherent with each of the mechanisms.

Experimental Evidence. As discussed in Section 1.5., the experimental studies that have been reported in adults and children all support a relationship between CSB consumption and weight gain. The experimental studies we considered had strong designs and consistently showed an effect of CSB consumption on weight gain.

The evaluation of the body of evidence against the Hill criteria suggests that existing research does support a causal relationship. Considered collectively, the clear biological mechanism, experimental evidence, and consistent effects among diverse study designs provide a compelling case for a causal relationship. Overall, the stronger studies with better design, analyses and interpretation consistently point to a positive effect of CSB consumption on obesity.

1.7 Meta-Analysis

Strong evidence of a causal relationship does not translate *per se* into a precise estimate of the magnitude of effect. Diversity of study designs and results in the literature on CSB consumption and weight outcomes poses challenges for pooling a measure of effect. In this section, we describe a method of combining the results of the strongest studies to determine an "average" CSB effect on weight gain and obesity. This process of averaging study results across different studies is referred to as "meta-analysis."

Meta-analyses are quantitative syntheses of a number of study results, wherein "quantitative results of several studies are systematically combined to generate more precise estimates of the effects under investigation…"[120] Although there are many sophisticated methods of quantitatively combining study results to derive an "average" or overall effect, the most commonly used approach is to calculate an average of the study results, weighted by the inverse of the variances of each study result. Thus, studies with more precise estimates (i.e., small variances and standard errors) contribute more to the summary measure of effect.

A very important strategy of meta-analysis is to assure that studies being combined are comparable. In other words, the differences across combined studies should mainly be limited to differences in the populations of individuals (or other units of observation) under study. For example, if one study uses simple linear regression to study the effects of education status on income in one geographic area, those results can be reasonably compared to another study that uses simple linear regression to study the effects of education status on income in a different geographic area, all else remaining more or less constant. Problems arise when combining studies that use different methodologies or define key variables differently. In the case of the

[120] Culyer (2005). For a more detailed discussion of meta-analytic techniques, see generally: Littell, Corcoran, and Pillai (2008); Pope, Mays, and Popay (2007); Sutton et al. (2000)

CSB effect on weight gain, the studies reviewed earlier in this section use somewhat different definitions of CSB exposure and weight change, somewhat different approaches and methodologies, and somewhat different study populations.

To address this, we limited our meta-analysis only to studies with longitudinal or case-control designs and that presented data as risk ratios that estimated the risk of obesity associated with consumption of approximately 12 ounces per day of CSB. Given the ultimate objective of estimating the causal effect of CSB consumption on weight gain, overweight, and obesity, we excluded cross-sectional studies from our meta-analysis because they are not an optimal method for assessing whether CSB exposure is a factor that occurs before development of overweight or obesity. Further, we limited studies for our meta-analysis to those among children, principally because the majority of studies that met our refined criteria were conducted among this group. Including the one study among adults that would have met the stronger criteria (i.e., Kvaavik et al. 2005) would have introduced excessive heterogeneity.

The final set of criteria concerned how data were calculated and reported in each study, and how key variables (CSB consumption and weight) were measured. We applied three additional screening criteria: (1) each study must state an explicit definition of obesity corresponding to the population under study;[121] (2) while allowing for some reasonable degree of heterogeneity in definition, each study must define explicitly the type of CSB exposure, including beverage type(s), time period and serving size (e.g., ounces per day or per week); and (3) each study must report data sufficient to calculate an odds ratio and a 95% confidence interval for the odds ratio for the effect of CSB consumption on obesity.

Only four studies satisfied all of these criteria: three longitudinal studies (Dubois et al. 2007; Ludwig et al. 2001 and Welsh et al. 2005) and one case-control study (Ochoa et al. 2007). We compiled the results of the studies into a Stata® database and then calculated a single odds ratio (and 95% CI) using a meta-analysis routine ("meta") included in Stata.[122] The inverse variance approach is the most straightforward of meta-analytic techniques.[123] Studies with greater precision (i.e., smaller confidence intervals) are weighted more heavily, and the contributions of studies with less precision are diminished. This simple technique is well-suited for a cross-design synthesis, where there is likely to be considerable heterogeneity in study precision.[124] The main findings of these studies and the results of the inverse-variance weighting are shown in Table 1-1.

Note that the odds ratio found by Ludwig et al. (2001) is associated with a relatively small standard error. Consequently, the inverse-variance weighting methodology assigned a large weight to the Ludwig et al. study, which in turn resulted in an overall weighted odds ratio of 1.49

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[121] For children, most studies use the standard U.S. definition which defines obesity as a BMI greater than or equal to the 95th percentile for age and sex.

[122] We used the latest version of Stata available at the time the research was conducted (version 10.0). This version of Stata is not preloaded with meta-analysis subroutines. However, users of Stata can download up to 14 different meta-analysis routines from the software website (www.stata.com).

[123] Littell, Corcoran, and Pillai (2008); Sutton et al. (2000)

[124] Pope, Mays, and Popay (2007)

(Table 1-1 row a; 95% CI 1.27, 1.72)—only slightly higher than the Ludwig et al. estimate. As a sensitivity analysis, we replicated the meta-analysis adding the most rigorous of the cross-sectional studies. Even with the added heterogeneity in study design, the result was a virtually identical mean OR (1.44).[125]

Table 1-1
Meta-Analysis of Selected CSB-Obesity Studies

Study	**No. of Study Subjects**	**Odds Ratio**	**Standard Error**	**95% CI***	
Dubois et al. 2007	1,944	2.36	0.38	1.11	5.05
Ludwig et al. 2001	398	1.44	0.08	1.22	1.70
Ochoa et al. 2007	370	1.74	0.26	1.05	2.89
Welsh et al. 2005	10,904	1.80	0.21	1.20	2.90
a) Inverse-Variance Weighted OR*		1.49		1.27	1.72
b) Weighted OR - 1		0.49		0.27	0.72
c) SF CSB Exposure Prevalence**		0.19		0.19	0.19
d) SF CSB Exposure Prevalence × (OR - 1)		0.09		0.05	0.14
e) SF CSB-Obesity Pop. Attributable Risk		**8.66%**		**4.95%**	**12.10%**

Notes: * CI = confidence interval; OR = odds ratio; **The CSB exposure estimate is based on the 2005 and 2007 California Health Interview Survey (www.chis.ucla.edu). CSB exposure is measured by a question asking whether "soda or other sugary drinks were consumed yesterday," with responses coded as either "two or more glasses" or "one glass or none at all." To reduce the variance and improve the stability of the estimate, we combined CHIS data from 2005 and 2007, and restricted to "Bay Area Counties" rather than just San Francisco County. The estimate in the table pertains to adolescents (aged 12-17), which is the age group most closely matching those of the studies included in the meta-analysis. We did not estimate a lower and upper confidence bound for the exposure prevalence.

The remaining rows of Table 1-1 (b – e) calculate the components necessary to convert the weighted odds ratio into a CSB-obesity population attributable risk (PAR). The term "attributable risk" refers to the additional risk of disease (obesity) due to exposure to a particular risk factor (CSB consumption). The PAR is the product of the attributable risk and the prevalence of exposure to the risk factor in the population; PAR is therefore a measure of the excess incidence of disease—the proportion that would be prevented if the exposure could be completely eliminated from a population. [126] The PAR for the effect of CSBs on obesity was calculated by using the following formula:

[125] The secondary meta-analysis included the following cross-sectional studies: Ariza et al. (2004); Gibson and Neate (2007); Nicklas et al. (2003); Serra-Majem et al. (2006); Warner et al. (2006)

[126] Fletcher and Fletcher (2005); Rothman (1986)

$$PAR = [CSB_e \times (OR_m - 1)] / [1 + CSB_e \times (OR_m - 1)] \qquad \textbf{(Equation 1-1)}$$

In Equation 1-1, CSB_e is the prevalence of CSB exposure, OR_m is the odds ratio calculated by the meta-analysis. The final PAR result is shown in row e) of Table 1-1. Based on the meta-analysis estimate of the Odds Ratio (OR_m; row *a*) and the CHIS-based estimate of CSB exposure (CSB_e; row *c*), we calculate a PAR of 8.66% (95% CI: 4.95%, 12.10%). The interpretation of this finding is that the "excess incidence" of obesity attributable to CSB consumption is 8.66%. Again, we submit that this PAR is substantially lower than extant estimates because of our conservative approach to its calculation. In our meta-analysis, we include only the most rigorously designed studies. We exclude studies that lack sufficient design features supporting direct tests of a causative link between CSBs and obesity. These criteria resulted in the exclusion of many studies showing a larger role of CSBs than those studies included in our analysis. Also, the effect of CSB on overweight and obesity is a cumulative process, and even the most rigorously designed longitudinal studies cannot perfectly measure CSB exposure over time, which in turn leads to an underestimation of the effects of CSBs on overweight and obesity.

2. OBESITY COSTS TO THE CITY[127]

The purpose of this section is to develop estimates that will allow San Francisco to estimate annual medical payments that are attributable to obesity for the population whose medical expenditures fall to the city for payment. We used nationally representative medical expenditure data to estimate the percentage of annual medical payments that are attributable to obesity for those likely to receive publicly-supported health care services in San Francisco.

We used a regression-based (RB) approach to estimate obesity-attributable payments. The RB approach was used to estimate medical payments as a function of obesity status and several other individual-level characteristics likely to influence medical payments, including age, gender, race/ethnicity, education, income, marital status, insurance status and smoking status. This study design is likely to *underestimate* obesity-attributable costs because more severe obesity has been associated with larger excess medical costs than moderate obesity and the method we used does not account for this difference.

Coefficient estimates from the regression models were used to calculate the fraction of total medical payments attributable to obesity. Data used for the study were drawn from the 2002–2005 Medical Expenditure Panel Survey (MEPS). MEPS is a nationally representative survey of the U.S. civilian, non-institutionalized population that includes data on demographics, self-reported medical conditions and detailed medical expenditure data reported by households. We limited our analysis to those with incomes at or below 400% of the federal poverty line and

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[127] This section is written by Eric Finkelstein, Amanda Honeycutt, and Joel Segel, RTI International, 3040 Cornwallis Road, Research Triangle Park, NC 27709.

performed a sensitivity analysis that used data for people at or below 200% of the federal poverty line to better represent the relevant population in San Francisco.

We found that 6.8% of medical payments (95% CI: 4.4%, 8.9%) were attributable to obesity in this population subset. Because this fraction is an increasing function of obesity prevalence and attributable medical costs per person with obesity, an increase in either component would lead to a higher estimated fraction of medical payments attributable to obesity. We analyzed the sensitivity of our findings to differences in the lower-income sample used, the inclusion or exclusion of specific model controls and the inclusion of the fraction of payments attributable to overweight. Our findings are robust to small changes in the analysis sample and control variables included in the model and are similar to published estimates for the United States of 5% to 7%. Therefore, we estimate that this same percentage of medical payments made by San Francisco to cover the medical expenses of uninsured patients treated in the city's hospitals and clinics is attributable to obesity, given current obesity prevalence estimates of approximately 28%.

2.1 Introduction

The goal of the work presented in this section is to provide estimates that will allow San Francisco to estimate annual medical payments that are attributable to obesity for the population for whom the City provides or contributes to health care services. We used nationally representative medical expenditure data to estimate separate shares of medical expenditures attributed to obesity for office-based, outpatient, inpatient and emergency department services. These shares represent the percentage of total annual medical payments in each of these settings that are attributable to obesity. Multiplying these fractions by corresponding actual payments in each of these settings will yield estimates of obesity-attributable medical payments. We also estimate the fraction of overall medical payments attributable to obesity.

In Section 2.2 of this report, we discuss alternative approaches for estimating the fraction of medical payments attributable to obesity and explain why the regression-based (RB) disease costing approach is preferred for this analysis. We then describe how we applied the RB approach to estimate the payments attributable to obesity for a national sample of individuals with incomes at or below 400% of the federal poverty line (FPL). In Section 2.3, we present estimates of the fraction of total medical spending attributable to obesity for the 400% FPL sample. We also provide estimates of obesity-attributable spending fractions for specific categories of medical spending, including office-based visits, outpatient, inpatient and emergency department services. For each obesity-attributable fraction, we provide a range of plausible values based on an estimated 95% confidence interval. In Section 2.4, we compare our estimates with obesity-attributable fractions from the published literature, and in Section 2.5, we discuss study limitations.

2.2 Methods

Alternative Approaches. We considered three possible approaches to estimate the fraction of medical payments attributable to obesity in San Francisco: accounting (claims-based), attributable fraction (AF) and RB. These three approaches have been widely used to estimate disease payments and the fraction of total medical payments attributable to a particular disease or risk factor. In this subsection, we summarize the advantages and disadvantages of each approach, particularly as they relate to estimating obesity-attributable medical payments for San Francisco.

An accounting, or claims-based, approach is frequently used to estimate disease payments. This approach uses health care claims to determine the cost to treat a condition, such as obesity, by linking all charges on a claim to the primary diagnosis. The charges are then summed across all claims with the primary diagnosis of interest—in this case, obesity. The accounting approach can also be used to include a portion of charges for obesity as a secondary condition. The main advantage of the accounting approach is that it is easy to apply. It is straightforward to add up payments for health care claims with a diagnosis of obesity. The main disadvantage of using an accounting approach to estimate obesity payments is that obesity is rarely selected as the primary or secondary diagnosis on health care claims. As a result, the accounting approach would severely underestimate the medical payments attributable to obesity, and we therefore would not recommend this approach even if claims data were readily available to estimate payments for San Francisco's uninsured patients.

Another approach commonly used to estimate disease payments is the AF approach. Using the AF approach to estimate obesity payments would involve first identifying all health conditions for which a link to obesity has been established (e.g., diabetes, heart disease) and then using epidemiologic formulas to estimate the portion of disease prevalence that is caused by obesity. For example, it would be necessary to estimate the fraction of diabetes prevalence that is due to obesity. These obesity-attributable fractions would then be multiplied by the total cost of each obesity-attributable condition to estimate obesity-attributable payments. For example, to estimate the diabetes payments that are attributable to obesity, it would be necessary to determine the total payments for diabetes and then multiply these payments by the obesity-attributable fraction for diabetes (e.g., the portion of diabetes prevalence that would be eliminated if obesity were eliminated). Total obesity payments would be calculated by summing the obesity-attributable payments across all conditions with an established causal link to obesity.

An advantage of the AF approach is that it does not require individual-level data with information on both obesity and medical payments. Rather, information on payments for obesity-attributable conditions, like diabetes, and on obesity-attributable fractions can be obtained from the literature or from multiple data sources. Another advantage of the AF approach is that it can be limited to include payments only for those conditions that clearly have been shown to be caused by obesity. For example, the AF approach allows researchers to limit obesity-attributable payments to include only those payments resulting from the development of diabetes or heart disease or both.

The AF approach also has several disadvantages that limit its usefulness for estimating obesity-attributable medical payments. First, naïve implementation of the AF approach can lead to confounding and effect modification, both of which lead to biased estimates. When implemented properly, the AF approach can be very time-consuming because the researcher needs to quantify disease prevalence, relative risks for the disease as a function of obesity status and corresponding disease costs for each obesity-attributable condition. In some cases, these data are available in the published medical literature; however, if estimates are not available for the obesity-attributable conditions of interest, then they must be estimated. Another challenge is that relative risks and disease cost estimates for each obesity-attributable condition should be estimated using the same approach to ensure that estimates are comparable across diseases. Different approaches can lead to different cost estimates for the same disease.[128]

Another disadvantage of the AF approach is the potential to miss some conditions and underestimate payments, especially given that the list of obesity-related conditions seems to be growing. We have also shown that the AF approach is unable to account for differences in payments related to differences in treatment intensity for people with obesity.[129] This would lead to underestimates of payments if, for example, people with obesity are responsible for 50% of the prevalence of diabetes but 80% of the medical expenditures. Another disadvantage of the AF approach is that the obesity-attributable fractions are not bounded between 0% and 100%. In other words, the AF approach can produce a fraction of medical spending attributable to obesity that exceeds 100%, which is clearly inaccurate and undesirable (e.g., suggesting that over 100% of the payments for diabetes are attributable to obesity).

The third approach that we considered for estimating obesity-attributable payments for San Francisco is an RB approach that uses individual-level data on actual medical spending, obesity status and several other characteristics likely to influence medical spending. Applying the RB approach involves estimating regression models of total medical spending on obesity and controlling for several other factors likely to affect medical payments, such as age, gender, race/ethnicity, education, income and other demographic variables. Coefficient estimates from these regression models are then used to predict obesity-attributable medical payments and the portion of total medical spending that is attributable to obesity.

An advantage of the RB approach is that it produces an estimate of obesity-attributable payments that is based on a comparison of the actual medical spending of people who are obese and those who are not obese. The approach also captures any payments associated with increased treatment intensity for obese individuals. For example, if obesity complicates the treatment of heart disease, then obese individuals may have longer hospital stays to treat and manage heart disease than non-obese individuals. The RB approach also allows researchers to control for a host of other factors that may affect medical payments, such as age, race/ethnicity, gender, education and income, better isolating the medical payments that are truly attributable to obesity. Another important advantage of the RB approach is that it produces estimates of the

[128] Ward et al. (2000)

[129] Honeycutt et al. (2009)

fraction of medical payments attributable to obesity that can be applied to other similar populations and their medical payments.[130]

A disadvantage of using the RB approach to estimate obesity payments is that it requires individual-level data on obesity status and medical spending. The approach also requires the use of econometric modeling techniques and statistical software programs for conducting regression analysis. In addition, the RB approach provides attributable payments for specific services (e.g., inpatient, emergency department), but it does not provide estimates of the underlying reasons for treatment (e.g., heart attack, stroke).

After carefully weighing the advantages and disadvantages of these three disease-costing approaches for estimating obesity-attributable payments, we chose to use the RB approach for this analysis. The RB approach is preferred when data on obesity, medical spending and other variables that affect medical payments are available in a single data source [as they are in the Medical Expenditure Panel Survey (MEPS) data].[131] The AF approach, on the other hand, is limited for this application because it is unlikely that all necessary estimates (e.g., obesity-attributable fractions and total payments for 30+ medical conditions) could be derived from a single data source. Estimating obesity-attributable fractions and payments for obesity-attributable conditions from multiple data sources could introduce a great deal of error in the calculation of both obesity-attributable fractions and total payments for obesity-attributable conditions. The accounting approach is limited in that it relies on the reporting of obesity on claims, a diagnosis that often goes unreported. Given the serious limitations of the accounting and AF approaches for estimating the fraction of medical spending attributable to obesity, the RB approach is likely to produce the most accurate and defensible estimates of the medical payments for obesity to San Francisco for the relevant population.

Data and Methods (RB Approach). We used the 2002–2005 MEPS data for all analyses. The MEPS is a nationally representative survey of the U.S. civilian, non-institutionalized population administered by the Agency for Healthcare Research and Quality.[132] The MEPS includes data on demographics, self-reported medical conditions and detailed medical expenditure data reported by households. The household data are augmented with data from medical providers and insurers. Professional coders convert verbatim self-reported narratives into fully specified *International Classification of Diseases, Ninth Revision, Clinical Modification* (ICD-9-CM) codes. The MEPS follows each respondent over 2 years using an overlapping panel design.

To obtain sufficient sample size for the obesity subgroup, we pooled 4 years of data in creating our sample. We excluded pregnant women and those with missing data, and all of our analyses focused on adults aged 18 and older. We also limited our analysis sample to exclude high income individuals to better represent the population covered by San Francisco. We limited our analysis sample to those with incomes at or below 400% FPL. We chose the higher cut point to increase the sample size and the precision of the estimates; however, in sensitivity analyses,

[130] Finkelstein, Fiebelkorn, and Wang (2004)

[131] Honeycutt et al. (2009)

[132] See generally http://www.meps.ahrq.gov/mepsweb/.

we also considered the impact of focusing on those with incomes at or below 200% of the FPL. Survey weighting variables were used throughout all analyses to generate estimates that are nationally representative for the civilian, non-institutionalized population in the relevant income range.

Obesity status was based on self-reported height and weight, which we used to calculate body mass index (BMI) for each individual in MEPS. BMI is equal to weight in kilograms divided by height in squared meters. Normal weight was defined as a BMI greater than or equal to 18.5 and less than 25, underweight was defined as a BMI less than 18.5, overweight was defined as a BMI greater than or equal to 25 and less than 30, and obese was defined as a BMI greater than or equal to 30. Our sample excludes pregnant women because we did not have information on their pre-pregnancy weight, which would be needed to calculate a pre-pregnancy BMI.

We estimated age-specific total annual medical payments for people with obesity using an RB approach. Because medical cost data are highly skewed, simple linear regressions often fit the data poorly.[133] Some early modelers of medical costs found that models of the natural logarithm of spending regressed on obesity and other individual-level characteristics provided a better fit, but such models may be misspecified, which could result in biased estimates of obesity-attributable payments.[134] Several approaches have been recommended recently for modeling health care payments. We used model selection criteria recommended by Manning and Mullahy (2001)[135] and Buntin and Zaslavsky (2004),[136] including tests for heteroscedasticity and kurtosis in the residuals from alternative functional forms, and found that the most appropriate model for our MEPS sample was a two-part generalized linear model (GLM) with a gamma distribution and a log link. We used a logit model to predict the probability of having any medical payments:

$$P(y_i > 0) = e^{x_i B_i} / (1 + e^{x_i B_i}) \qquad \text{(Equation 2-1)}$$

We then used a GLM model with a gamma distribution and a log link to estimate the level of payments, given positive spending:

$$E(y_i | x_i) = e^{x_i B_i} \qquad \text{(Equation 2-2)}$$

where y_i represents total medical spending in dollars for individual *i*, conditional on having positive payments. In both parts, x_i includes the continuous variables age and age squared and indicator variables for sex; race/ethnicity; education; marital status; rural status; health insurance status; current smoker; the presence of obesity, overweight or underweight; and the year of data.

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[133] Manning and Mullahy (2001)

[134] Mullahy (1998)

[135] Manning and Mullahy (2001), op cit.

[136] Buntin and Zaslavsky (2004)

We used the MEPS sampling weights to produce nationally representative estimates for the civilian, non-institutionalized population. We used the coefficient estimates from Equations 2-1 and 2-2 to predict total medical payments for the sub-sample with obesity. Using coefficient estimates from Equation 2-1, we estimated the predicted probability of positive medical payments for each person. We multiplied this predicted probability by an estimate from Equation 2-2 of the predicted medical payment level, given positive payments. These combined estimates yield annual expected payments for each obese individual in the sample. For this same obesity sub-sample, we again predicted medical spending, assuming each individual did not have obesity (i.e., *OBESE* = 0). To ensure that our estimates are not driven by smoking costs, we also treated the smoking variable as equal to zero in our predictions of obesity-attributable payments. Our estimates of obesity-attributable payments are means of the difference between the two predictions (i.e., predicted payments for each person with obesity minus predicted payments if the person did not have obesity, and assuming the individual is a nonsmoker).

We summed these obesity-attributable payments across all individuals with obesity and divided by total payments for the relevant MEPS sample (e.g., < 400% FPL) to estimate the fraction of medical spending attributable to obesity. We estimated bootstrapped 95% confidence intervals around this fraction using 1,000 iterations and accounting for the complex survey design. Analogous estimates were calculated for specific medical services, including office-based, outpatient, inpatient and emergency department services.

Because the estimated obesity-attributable medical payment shares are a function of both obesity prevalence and the per-person costs attributable to obesity, an increase in either component would lead to an increase in the estimated obesity-attributable medical payment shares, as shown in Equation 2-3 below:

$$OAMP = Obese * Cost_O / ((1 - Obese) + Obese * Cost_O) \qquad \text{(Equation 2-3)}$$

where *OAMP* denotes the fraction of medical payments attributable to obesity in a sample, *Obese* represents the prevalence of obesity in the sample, and $Cost_O$ denotes the per-person medical payments attributable to obesity for obese individuals in that sample. If obesity prevalence changes, but the medical payments attributable to obesity remain constant, the fraction of medical payments attributable to obesity will move in the same direction as obesity prevalence.

We considered the impact on results of varying the samples and control variables used in our analysis. First, we assessed the impact of using a lower-income sample from the MEPS—those with incomes at 200% of the FPL or less. Second, using our baseline income cutoff of 400% FPL, we ran alternative model specifications. One specification excluded indicator variables for the year of MEPS data and another included an indicator only for the uninsured, but not for specific types of health insurance (e.g., Medicare, Medicaid, private health insurance). We also evaluated the fraction of medical payments attributable to overweight, and not obesity, in San Francisco. These payments have been excluded from our baseline analysis in which we focus on estimating the fraction of medical payments attributable to obesity (BMI $\geq$ 30) but not to overweight. An additional analysis simply compares mean medical spending for obese individuals and normal weight individuals. This comparison of mean spending does not control for other factors that affect medical payments and is hypothesized to result in a higher estimate of the fraction of medical spending attributable to obesity.

2.3 Results

Table 2-1 shows sample statistics for the MEPS samples below 200% and 400% of the FPL and for the 2005 California Health Interview Survey (CHIS)–San Francisco County samples below 200% and 300% of the FPL. Because of data limitations, we could only identify individuals at 200% and 400% of the FPL in MEPS and 200% and 300% of the FPL in CHIS. An important difference between the MEPS sample and the general San Francisco populations is the BMI distribution. San Francisco has about two-thirds as many obese people and approximately three-fifths as many overweight people as the overall MEPS sample.

Yet, within the 300% FPL sample from San Francisco, obesity prevalence varies widely, as shown in **Table 2-2**. Table 2-2 shows obesity prevalence among the 300% FPL sample separately for individuals covered by MediCal (California's Medicaid program), for food stamp recipients and for the uninsured. As shown in this table, obesity prevalence for MediCal beneficiaries is 27.2%, almost identical to obesity prevalence of 27.6% in the 400% FPL MEPS sample. Obesity prevalence among food stamp recipients is even higher, almost 32%, while obesity prevalence among the uninsured is only 13%. Because the uninsured sub-sample appears to be much younger than the overall 300% FPL sub-sample of adults (53% of this sub-sample is 25 to 39 years), they may not be representative of the patients whose medical expenses fall to San Francisco for payment. In fact, the MediCal and food stamp recipient samples may better represent the relevant population whose medical expenses are paid by the City.

Because obesity prevalence in these sub-samples is similar to obesity prevalence in the 400% FPL MEPS sample used in our analysis, we treat results from our national sample as representing the fraction of medical payments in San Francisco that is attributable to obesity. All of our baseline regression models use the 400% FPL sample from MEPS because the larger sample size (as compared to the 200% FPL sample) produces more stable estimates.

Estimates of Obesity-Attributable Medical Spending and Fractions. **Table 2-3** shows the amount and fraction of medical payments by type of expenditure attributable to obesity. For the 400% FPL MEPS sample, we estimate per-person obesity-attributable medical payments of $1022 per year. Given that average annual medical payments for this sample are $4160 per person and obesity prevalence is 27.6%, our estimates imply that 6.8% of medical payments for this lower-income sample are attributable to obesity. In fact, using Equation 2-3, the fraction of medical payments attributable to obesity can easily be calculated using updated estimates of obesity prevalence, obesity-attributable payments, and average medical payments for the sample of interest. For example, if obesity prevalence increases to 30%, but average medical payments and obesity-attributable medical payments remain the same, the fraction of medical payments attributable to obesity would increase to 7.4%.

A 95% confidence interval around our 6.8% estimate indicates a plausible range of 4.4% to 8.9% for obesity-attributable medical payments in a low-income population with obesity prevalence of about 28%. For all of the specific medical services we analyzed, we estimated that 6% to 9% of medical payments are attributable to obesity. We found that the fractions of office-based and outpatient services costs for a lower-income population that are attributable to obesity are 6.3% to 6.9%. We found slightly higher fractions for inpatient (8.3%) and emergency department services (9.3%). However, for all of these services, 6.8% is within the plausible range.

Table 2-1

Statistics by Income Level for MEPS and CHIS–San Francisco County Samples

	2002-2005 MEPS		2005 CHIS–SF County	
Characteristic	< 200% FPL	< 400% FPL	< 200% FPL	< 300% FPL
Age				
18–24	15.6%	14.3%	13.1%	11.9%
25–39	27.4%	28.5%	28.8%	29.9%
40–64	34.5%	38.1%	32.9%	34.3%
65–79	15.4%	13.7%	17.7%	17.7%
80+	7.1%	5.4%	7.4%	6.2%
Female	55.5%	52.3%	61.1%	61.3%
Race/ethnicity				
Non-Hispanic white	56.4%	63.4%	22.8%	25.0%
Non-Hispanic black	17.4%	14.2%	7.0%	8.7%
Hispanic	20.0%	16.2%	18.8%	17.3%
Other race	6.2%	6.2%	51.4%	49.1%
Education				
Less than high school	34.5%	25.6%	29.0%	23.4%
High school equiv.	52.6%	54.9%	29.4%	29.0%
More than high school	12.9%	19.5%	41.6%	47.4%
Marital status				
Married	38.2%	46.7%	39.4%	37.9%
Not married	61.8%	53.3%	60.6%	62.1%
Rural	22.1%	21.1%	0.0%	0.0%
Insurance status				
Uninsured	26.8%	19.7%	22.5%	20.4%
Public	45.1%	32.8%	49.2%	44.0%
Private	28.1%	47.5%	28.3%	35.5%
BMI category				
Underweight	2.9%	2.3%	3.6%	4.1%
Normal weight	35.7%	35.9%	53.7%	54.6%
Overweight	33.0%	34.2%	21.8%	21.5%
Obese	28.4%	27.6%	20.8%	19.9%
Current smoker	27.5%	23.9%	16.7%	15.6%

Notes: MEPS = Medical Expenditure Panel Survey; CHIS = California Health Interview Survey; FPL = federal poverty line. Some categories may not sum to 100 due to rounding.

Table 2-2
Percentage Obese and Overweight by Subpopulation for the San Francisco Population < 300% of the FPL from 2005 CHIS

Population	% Obese	% Overweight
MediCal coverage	27.2%	17.6%
Receive food stamps	31.6%	28.1%
Uninsured	13.0%	23.3%

Source: 2005 California Health Interview Survey (CHIS). Notes: FPL = federal poverty line.

Table 2-3
Percentage of San Francisco Payments Attributable to Obesity

Expenditure Type	Per-Person Annual Payments Attributable to Obesity ($); < 400% FPL	Fraction of Payments Attributable to Obesity; < 400% FPL (% [95% CI])
Total	$1,022	6.8% [4.4, 8.9]
Office-based	$199	6.3% [4.6, 8.2]
Outpatient	$100	6.9% [3.1, 9.8]
Inpatient	$374	8.3% [4.7, 12.2]
Emergency department	$48	9.3% [6.0, 12.5]

Notes: FPL = federal poverty line

Sensitivity Analyses. Our estimates of the percentage of payments attributable to obesity appear to be quite robust. Table 2-4 presents our baseline estimates alongside estimates from several alternative model specifications and analyses. The column labeled with a (1) shows results from models that use the sample at 200% of the FPL instead of the baseline sample consisting of individuals with incomes at or below 400% of the FPL. For this sample, the estimated fraction of medical spending attributable to obesity is 6.2%, somewhat lower than our baseline estimate of 6.8%. Yet our baseline estimate of 6.8% still falls within the 95% confidence bounds for the 200% FPL sample (3.2, 8.7). The similarities between these and our baseline estimates suggest that our findings are robust to income level cutoff values.

Table 2-4
Results of Sensitivity Analyses: Estimated Fractions of Medical Payments Attributable to Obesity

Expenditure Type	(Baseline) < 400% FPL	[1] <200% FPL	[2] No Year Variables	[3] Uninsured Only	[4] Means Analysis
Total	6.8%	6.2%	6.7%	6.8%	9.6%
Office-based	6.3%	4.6%	6.3%	6.9%	8.6%
Outpatient	6.9%	6.9%	6.8%	7.4%	10.6%
Inpatient	8.3%	8.0%	8.3%	9.1%	10.1%
Emergency department	9.3%	8.5%	9.3%	9.7%	10.2%

Note: FPL = federal poverty line

Other model specifications excluded the year variables and included an indicator variable only for uninsured (and not for specific types of health insurance coverage). In the columns labeled (2) and (3) of Table 2-4, we show that results are similar to the baseline findings across different model specifications and analysis approaches. Our estimated fraction of total medical spending attributable to obesity for this lower-income population is consistently in the 6% to 7% range.

We also estimated the fraction of medical payments attributable to overweight for the 400% FPL sample (results not shown in Table 2-3). However, these estimates were not statistically different from zero for total medical payments or for any specific medical service other than outpatient services. We estimated that 0.1% of total medical payments were attributable to overweight, with 95% confidence bounds of –2.4% to 2.5%. These findings suggest that even if we had included overweight in our estimates of the fraction of payments attributable to excess weight in San Francisco's relevant population, we would still find an attributable cost fraction of 6.8%.

The final set of alternative analyses involved analyzing the unadjusted mean payments for each of the BMI categories and represents a naïve approach to estimating the fraction of payments attributable to obesity [column (4) of Table 2-4]. For this approach, we subtracted the mean payments for the normal weight population from the mean payments for the obese population and treated the difference as "obesity-attributable" payments. This approach gives a higher estimate than our baseline estimates because it does not account for any differences in the obese and normal weight populations that might affect payments but are not a result of obesity. For example, the obese population tends to be older than the normal weight population, which means their payments are likely to be higher. But we would not want to attribute the expenditure increase due to age to obesity. Therefore, the means analysis represents an overestimate of the obesity-attributable expenditure fractions.

2.4 Obesity-Attributable Estimates in the Scientific Literature

In this section, we briefly describe estimates of obesity-attributable medical payments and fractions of medical payments attributable to obesity from the published literature. We also discuss how these estimates compare with our estimates for San Francisco's 300% FPL population. Several studies used an AF approach to quantify obesity-attributable costs.[137] To reiterate, Thompson et al. (1998) found that total spending attributable to obesity accounts for approximately 5% of health insurance payments among businesses with employer-provided health insurance,[138] and Wolf and Colditz (1994, 1998) published several papers that suggest aggregate costs of obesity range from 5.5% to 7.0% of annual medical expenditures.[139] Similarly, Finkelstein et al. (2003 and 2004) produced cost estimates ranging from 5.3% to 5.7% of annual medical expenditures.[140] These papers provide evidence that the aggregate annual obesity-attributable medical payments in the United States are between 5% and 7% of annual health care expenditures. We estimate an obesity-attributable fraction of 6.8% for the 400% FPL MEPS sample. This estimate is at the upper end of published estimates, but it reflects the higher prevalence of obesity in a lower-income population in the United States.

2.5 Discussion and Summary

An important limitation of our analysis is that, due to small sample sizes in national surveys, we were unable to use data directly pertaining to obese and non-obese uninsured individuals in San Francisco to estimate the fraction of total medical spending for San Francisco's uninsured population that is attributable to obesity. Instead, we used national data for a population that excludes people with income above 400% FPL. We estimate that 6.8% of San Francisco's medical payments are attributable to obesity—within the range of published estimates of 5% to 7%. However, it is important to note that the estimated fraction of medical payments attributable to obesity is an increasing function of both obesity prevalence and obese individuals' excess medical payments, as shown in Equation 2-3. A change in the value of either of these components would produce a change in the estimated fraction of medical payments attributable to obesity. Excess medical payments for obese individuals are unlikely to change a great deal over time, as most estimates indicate that obesity is about one-third more expensive than normal weight,[141] but obesity prevalence has been trending upward, especially the prevalence of severe obesity.[142] Obesity prevalence above 27% or 28%—the prevalence in the MEPS 400% FPL sample—would lead to a larger estimate than our 6.8% estimate of the fraction of medical payments attributable to obesity. Moreover, the increase in severe obesity could also lead to

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[137] Some of this material was previously discussed in Section 1, sub-section 1.1

[138] Thompson et al. (1998)

[139] Wolf and Colditz (1994); Wolf and Colditz (1998)

[140] Finkelstein, Fiebelkorn, and Wang (2003); Finkelstein, Fiebelkorn, and Wang (2004)

[141] Sturm (2002)

[142] Sturm (2007)

higher estimates of per-person medical payments attributable to obesity as compared to our estimates from the MEPS 400% FPL of $1,022 per person per year.

Another limitation is that our analysis excluded pregnant women because their pre-pregnancy BMI measurements were not available. This means that when our estimated fraction of medical spending attributable to obesity is applied to pregnancy-related payments, we are assuming that 6.8% of those payments are attributable to obesity. Assuming the same fraction of payments attributable to obesity for pregnancy-related and non-pregnancy related medical payments may in fact be conservative. Several studies have shown that obesity in pregnancy raises costs by increasing the likelihood of complications, such as preeclampsia and eclampsia,[143] and raising the risk of cesarean delivery.[144] These complications tend to increase the length of hospital stays for deliveries in obese women.[145] One study showed that among cesarean deliveries, length of hospital stay was 7.3 days for obese women compared with 5.4 days for non-obese women.[146] It seems reasonable to assume that the fraction of medical payments attributable to obesity is likely to be at least as high for pregnancy-related payments as for non-pregnancy related payments.

Our analysis focused on the medical payments attributable to obesity and did not attempt to include payments attributable to overweight. However, when we did predict medical payments for the overweight sub-sample in our lower-income study sample, we found that medical payments attributable to overweight were close to zero. Only 0.1% of medical payments were found to be attributable to overweight, suggesting that our focus on obesity captures most of the fraction of medical payments attributable to both overweight and obesity.

Finally, our analysis does not account for the different levels of obesity, but treats all individuals with BMIs of 30 or higher as obese. However, because more severe obesity has been associated with larger excess medical costs than moderate obesity[147] and because the prevalence of severe obesity has increased considerably since 2000,[148] our estimated fraction of medical payments attributable to obesity may be conservative.

In sum, we used an RB approach to estimate the fraction of medical payments attributable to obesity for a nationally representative population with incomes at or below 400% of the FPL and with similar rates of obesity to San Francisco's population at 300% of the FPL. We found that 6.8% of medical payments (95% confidence range of 4.4% to 8.9%) were attributable to obesity, based on per-person estimated annual medical payments attributable to obesity of $1,022 per person and obesity prevalence of 27.6%. Assuming that obesity prevalence in San Francisco's relevant population is 27% to 28% and not accounting for the possible impact of severe obesity on raising per-person attributable costs, our findings suggest that approximately 6.8% of the medical payments borne by San Francisco for patients who do not pay their medical bills for services received in the city's hospitals and clinics are attributable to obesity.

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[143] Baeten, Bukusi, and Lambe (2001)

[144] Brost et al. (1997); Kaiser and Russell (2001)

[145] Bianco et al. (1998)

[146] Hood and Dewan (1993)

[147] Andreyeva, Sturm, and Ringel (2004)

[148] Sturm (2007)

3. REGULATORY FEE STRUCTURE[149]

This section describes the data and methodology used to estimate CSB sales for San Francisco-based food and beverage retail establishments. Estimates of sales shares by type of establishment ("channel" shares) are then used to calculate fee allocations by channel share. Section 3.1 applies the PAR (Section 1) and the obesity cost share (Section 2) to medical care costs incurred by the City of San Francisco. Section 3.2 describes the methods used to calculate the total sales of CSBs by channel share in the City of San Francisco. Section 3.3 describes the data and methods employed to convert channel shares to proportional fees. Section 3.4 describes the likely economic impact of the fees. Consistent with the definition put forth in Section 1, CSBs include all carbonated sweetened beverages (such as Coca-Cola Classic, Sprite, Pepsi-Cola, Mountain Dew, Sierra Mist, etc.), all juices, teas and water wherein sugar has been added (such as Tropicana Twister, Fuze, Hawaiian Punch, Snapple, Arizona, Sunny Delight, Lipton teas, Nestea, Gold Peak, Glaceau, SoBe Lifewater, etc.), sports drinks (such as Gatorade and Powerade) and ready-to-drink coffee beverages (such as Frappucino, Double Shot, Iced Coffee, Java Monster, Coke Caribou, etc.).

3.1 Costs to City of CSB Consumption

In this section we combine the PAR results of Section 1 with the obesity cost share results of Section 2. We take fiscal year 2009-2010 to be the index year, implying that all data and estimates are based on obesity-related costs to the City anticipated and budgeted for FY2009-2010. These costs include direct medical care costs, regulatory administrative costs, and the costs of the establishing a fund to support CSB consumption reduction programs (See Appendix B). These data are shown on **Table 3-1**. The total direct City medical costs of $164.6 million[150] are adjusted by 6.8% to derive obesity-related direct costs. The result is $11.2 million. This amount is then adjusted to reflect the CSB-attributable obesity incidence (8.66%). This results in a "CSB-obesity" attributable cost of $969,748. We then add to that the administrative costs ($285,356) and the costs of the CSB consumption reduction program ($550,000) in FY2009-2010 (the latter outlined in Appendix B). The resulting total is $1,805,104 for FY2009-2010.

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[149] This section was compiled by John Schneider (HECG), Christopher Decker (HECG and University of Nebraska-Omaha), and Janet Benton (HECG).

[150] Based on data provided by the City for FY2009-2010 budgets (released July 27, 2009). Includes all funds used to fund health care expenses *not* reimbursed by other payers (such as Medi-Cal, Medicare, private payers, etc.).

Table 3-1

Estimate of Total CSB-Obesity-Attributable Costs to City of San Francisco, 2009-10

	Mean Estimate (f)	**Low Estimate** (f)	**High Estimate** (f)
Direct health care costs	$164,617,324	$164,617,324	$164,617,324
Share of direct costs attributable to obesity (a)	6.80%	6.80%	6.80%
Direct health care costs attributable to obesity	$11,193,978	$11,193,978	$11,193,978
Share of obesity costs attributable to CSBs (b)	8.66%	4.95%	12.10%
Direct health care costs attributable to CSBs	**$969,748**	**$553,638**	**$1,354,537**
Regulatory administrative costs (Collections) (c)	$120,918	$120,918	$120,918
Regulatory administrative costs (SFDPH) (d)	$164,438	$164,438	$164,438
Total regulatory administrative costs	$285,356	$285,356	$285,356
Cost of program to reduce CSB consumption (e)	$550,000	$550,000	$550,000
TOTAL	**$1,805,104**	**$1,388,994**	**$2,189,893**

Notes: CSB = calorically sweetened beverage; PAR = population attributable risk (of CSBs on obesity; refer to Section 1); (a) for more information on how this was derived, refer to Section 2; (b) for more information on how this was derived, refer to Section 1.7; (c) based on first-year (2009-10) cost estimates from City Office of the Tax Collector; (d) based on administrative costs incurred by the SFDPH; (e) refer to Appendix B for program description; (f) column multiplication and addition is performed on spreadsheets making use of detail (for some data) to 0.0001; thus, performing calculations based only on data shown in the table will not necessarily result in the exact same totals.

3.2 CSB Channel Shares

We refer to the amount of CSB sold by type of seller as "CSB channel shares." Examples of channels are supermarkets, "big box" supercenters, restaurants, convenience stores and so on. There are a number of ways to impute channel shares for a given geographic area. The method we employ is to assume that the channel shares in the geographic area are essentially the same as channel shares nationally; for example, the proportion of CSBs sold in San Francisco supermarkets reflects the proportion of CSBs sold in supermarkets nationwide.

First, we obtained national channel share data from the seven distribution channels reported in the annual *Beverage Digest Fact Book* (2008).[151] The *Beverage Digest* data are based on all-channel data, franchisor reports, syndicated data, interviews and other reports; the *Fact Book* is regarded as the industry standard in terms of accuracy and compiles data from multiple sources to improve accuracy.[152] These national channel shares are shown in column 1 of **Table 3-2**.

[151] Sicher (2008)

[152] Personal communication with John Sicher, editor of the *Beverage Digest Fact Book*.

The second step was to calculate weights based on San Francisco firms' share of total revenue within each channel share using data from the U.S. Census Bureau's Economic Census. The US Census Bureau conducts an Economic Census every five years profiling American business from the national to the local level. In 2002, the latest year for which complete data are available, there were nearly 25 million business establishments in the U.S. and 7 million of these had paid employees. This accounted for about 97% of business receipts. These are the businesses that are included in most Economic Census reports. The Census results in a substantial amount of information at both the industrial sector and geographic level of detail, including industry-level information (categorized by NAICS, or North American Industrial Classification System, code) on number of establishments, employment, revenues generated and payroll expenses. It also provides detailed data at the national, state, MSA and county level.[153]

While the industry information provided in the Economic Census is detailed, it does not provide enough detail to obtain direct estimates of calorically-sweetened beverage (CSB) consumption. Thus, to generate estimates of CSB sales in San Francisco County, we employ the national and county data (for San Francisco County) as a means to weight the *Beverage Digest* market share data. To do so, we identified seven NAICS code sectors from the U.S. Census data that matched reasonably well with the market segments reported by *Beverage Digest*. For these sectors, at the national and San Francisco County level we compiled the Census estimates of total sales (dollar value of revenues generated) for each sector in 2002-- the most recent year for which detailed data is available. We then calculated each sector's sales share of the total (that is, the total sales for these seven sectors), for both the nation and San Francisco County.

To generate San Francisco County estimates for sale shares of CSBs, we adjusted the *Beverage Digest* data in the following fashion. We start with the assumption that the ratio of the share of CSB markets to the share of each sector is constant for each market (i) across all regions within the United States. That is:

$$\frac{CSB_{share\_US,i}}{Sector_{share\_US,i}} = \frac{CSB_{share\_SF,i}}{Sector_{share\_SF,i}} \qquad \text{(Equation 3-1)}$$

where CSB_{share_US} is data from *Beverage Digest* measuring market share for CSB groups at the national level, $Sector_{share\_US}$ and $Sector_{share\_SF}$ are data from the US Census measuring sector sales shares for the seven identified sectors for both the nation and San Francisco County, and CSB_{share_SF} is the (unknown) measure of market share for the CSB channels for San Francisco County. To construct CSB_{share_SF}, we simply adjust CSB_{share_US} by the following factor:

[153] Further details on the 2002 Economic Census and NAICS classification schemes can be found at the following web site: http://www.census.gov/econ/census02/.

$$\mathrm{CSB}_{\mathrm{share\_SF,i}} = \mathrm{CSB}_{\mathrm{share\_US,i}} \frac{\mathrm{Sector}_{\mathrm{share\_SF,i}}}{\mathrm{Sector}_{\mathrm{share\_US,i}}} \qquad \text{(Equation 3-2)}$$

Table 3-2

CSB Retail Channel Shares and Fee Per Seller

Distribution Channel (a)	[1] **Adjusted National CSB share** (b,f)	[2] **Pro-rated Weighted SF Share** (c,f)	[3] **Number of SF CSB sellers** (d)	[4] **Aggregate CSB Fee Allocation** (f)	[5] **Approx. annual fee per seller** (f)
Supermarkets/"big box"	44.3%	40.7%	32	$735,410	$22,982
Restaurants	23.3%	38.7%	4,109	$698,011	$170
Vending machines	13.0%	3.0%	3,741	$54,572	$15
Grocery/convenience	15.2%	11.7%	393	$211,725	$539
Drug chains	2.1%	2.3%	65	$42,074	$647
Other N.E.C. (e)	2.1%	3.5%	297	$63,312	$213
TOTAL	100.0%	100.0%	8,637	$1,805,104	

Notes and Sources: (a) category descriptions are provided in Appendix C; (b) Sicher (2008) based on Table 23 of Sicher, J. *Beverage Digest Fact Book 2008*. Bedford Hills, NY: Beverage Digest, 2008; personal communication with John Sicher of *Beverage Digest*; and other sources (see text); (c) see text for description of weighting methodology; also note that "restaurants" is adjusted for sales of CSBs combined with alcohol; (d) based on 2008-09 establishment counts from the San Francisco Department of Public Health (except vending machine counts, which are based on personal communication with soft drink industry expert Stan Chavarria); (e) N.E.C. is "not elsewhere classified;" (f) column multiplication and addition is performed on spreadsheets making use of detail (for some data) to 0.0001; thus, performing calculations based only on data shown in the table will not necessarily result in the exact same totals.

We make one final adjustment to the shares. Many restaurants and most bars sell a proportion of their total CSB sales in the form of "mixed" drinks (i.e., CSBs or other "mixers" combined with one or more distilled spirit beverages). According to data from the 2002 Economic Census, sales of distilled spirits (product code 20131) by restaurants and bars (NAICS codes 72211 and 72241, respectively) are about 11.6% of revenue. Using a conservative assumption that 75% of all distilled spirits sold at restaurants and bars are mixed with CSBs, we estimate that CSB-based mixed drinks comprise, on average, approximately 8.7% of sales for this channel. In order to remove the sales of CSBs mixed with alcohol, we then use this weight to adjust the restaurant/bar intermediate weights used to calculate the final pro-weighted channel shares. These final shares are also normalized to ensure summation to 100%.

The resulting final weights are used to make adjustments to column 2 of Table 3-2. The supermarket channel is the largest (40.7%) and includes 32 supermarkets located within City limits. San Francisco has a disproportionately high density of small to mid-sized restaurants, bars and taverns, resulting in a disproportionately high channel share (38.7%) compared to national channel shares. The drug store category refers to *chain* drug stores, which typically devote cooler space to CSBs. The "other" category is a residual "not elsewhere classified" category and represents the volume of sales in venues such as stadium concessions, pushcarts, retail food vehicles, special events, and small lodgings equipped to dispense CSBs (e.g., bed and breakfasts and similar small lodgings). Detailed descriptions of retail channels are provided in Appendix C.

We evaluated the accuracy of the retail channel share methodology using three sources: (1) expert opinion; (2) supermarket retail sales data for the Northern California region from Information Resources, Inc. (IRI) and Nielsen; and (3) a small survey (n = 100)[154] of a stratified random sample of San Francisco sellers.[155] The first step was to assure that resulting channel shares were reasonable based on the opinion of experts. This process was largely confirmatory, although expert opinion suggested that our estimate for the supermarket channel is somewhat low, and may be as high as 45%.[156] Table 3-3 shows the results of the data verification. The channel share method compares very favorably to the retail sales from supermarkets and the survey data for the categories of "restaurants" (including bars and cafes) and "grocery/convenience."

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[154] San Francisco County has more than 4,800 beverage sellers (according to the San Francisco Department of Public Health). Consequently, a comprehensive survey of the population of beverage sellers would have been time-consuming and costly, and would likely have resulted in low response rates for some distribution channels, particularly those for which owners and managers responsible for inventory are typically difficult to reach (e.g., small groceries, convenience stores, and supermarkets).

[155] The survey research firm (Pacific Crest Research) indicated that respondents' verbatim comments suggested that respondents faced considerable difficulty in reporting CSB sales, mainly because of difficulties disaggregating calorically-sweetened beverages from other beverages, including non-sweetened beverages, diet carbonated beverages, bottled water, and alcoholic beverages.

[156] Professional opinion from a Stan Chavarria, a former Coca-Cola executive with more than 20 years of experience with the northern California market.

Table 3-3
Comparisons of Channel Share Method to
Alternative Data Sources

Distribution Channel (a)	[1] **Prorated Weighted SF Share** (e)	[2] **Approx. CSB Revenue Shares** (b,e)	[3] **Alternative Data Sources** (c)
Supermarkets/"big box"	40.7%	$72,489,746	$73,492,239
Restaurants	38.7%	$68,803,285	$86,157,512
Vending machines	3.0%	$5,379,224	NA
Grocery/convenience	11.7%	$20,869,885	$16,974,849
Drug chains	2.3%	$4,147,269	NA
Other N.E.C.(d)	3.5%	$6,240,652	NA
TOTAL	100.0%	$177,930,060	

Notes and Sources: (a) category descriptions are provided in Appendix C; (b) applies revenue shares calculated in Table 3-2A to total CSB sales calculated from Sicher, J. *Beverage Digest Fact Book 2008*. Bedford Hills, NY: Beverage Digest, 2008 and Datamonitor. "Soft Drinks in the United States: Industry Profile 2007." New York, NY: Datamonitor USA, 2008 (weighted to San Francisco population and adjusted for non-CSBs); (c) supermarket data is from Information Resources, Inc. (IRI) and Nielsen; other data from HECG 2008 survey of CSB sellers; (d) N.E.C. is "not elsewhere classified;" (e) column multiplication and addition is performed on spreadsheets making use of detail (for some data) to 0.0001; thus, performing calculations based only on data shown in the table will not necessarily result in the exact same totals.

3.3 Proportional Fees

Aggregate and per-establishment fee calculations are shown in columns 4 and 5 of Table 3-2. The fee distribution is based solely on the PAR-based cost estimate ($1,805,104; Table 3-1) allocated by the prorated weighted channel shares (column 2). Column 4 of Table 3-2 shows establishment counts based on data from the San Francisco Department of Public Health, which was verified using establishment count data from the U.S. Bureau of Labor Statistics and website inspection.[157] The resulting per-establishment fees range from a high of $22,982 for supermarkets and "big-box" sellers to a low of $15 per vending machine. For comparison purposes, estimated total CSB revenue per seller is shown on **Table 3-4**.

It is important to emphasize that the derivation of these fees is based on an approach that has been conservative throughout. As we noted in the Executive Summary, there are three ways in

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[157] San Francisco vending machine counts are based on data from Coca Cola, Pepsi, and other vending machine owners. Note that the establishment counts consider an individual vending machine as one establishment, thus the grand total establishment count does not correspond to other establishment counts for the City and County of San Francisco (vending machine counts were provided by Stan Chavarria, a former Coca-Cola executive with more than 20 years of experience with the northern California market).

which our estimates are likely to understate the true health care costs of CSBs to the City. First, when we combine the results of studies, we include only the most rigorously designed studies. Second, by focusing on obesity, we are most likely underestimating attributable cost. Over-consumption of CSBs may cause other conditions in normal weight individuals such as diabetes and hypertension that result in additional attributable costs. Finally, the regression-based methodology put forth in Section 2 is likely to understate true attributable costs due to the type of data available and the methods used. Our choice of methods, throughout the study, was designed to take into account the limits of existing research and to establish a solid "floor" for all critical data elements.

Table 3-4
Estimated Total CSB Revenue Shares and
Estimated CSB Revenue Per Seller

Distribution Channel (a)	**Approx CSB Revenue Shares** (b,d)	**Number of SF CSB sellers** (d)	**Estimated CSB Revenue Per Seller**
Supermarkets/centers	$72,489,746	32	$2,265,305
Restaurants/bars/cafes	$68,803,285	4,109	$16,745
Vending machines	$5,379,224	3,741	$1,438
Grocery/convenience	$20,869,885	393	$53,104
Drug chains	$4,147,269	65	$63,804
Other N.E.C. (c)	$6,240,652	297	$21,012
TOTAL	$177,930,060	8,637	

Notes and Sources: (a) category descriptions are provided in Appendix C; (b) applies revenue shares calculated in Table 3-2A to total CSB sales calculated from Sicher, J. *Beverage Digest Fact Book 2008*. Bedford Hills, NY: Beverage Digest, 2008 and Datamonitor. "Soft Drinks in the United States: Industry Profile 2007." New York, NY: Datamonitor USA, 2008 (weighted to San Francisco population and adjusted for non-CSBs); (c) N.E.C. is "not elsewhere classified;" (d) column multiplication and addition is performed on spreadsheets making use of detail (for some data) to 0.0001; thus, performing calculations based only on data shown in the table will not necessarily result in the exact same totals.

3.4 Anticipated Effects

There are two anticipated effects of proposed regulatory fee assessment: (1) strategic behavior *ex ante* on the part of establishments; and (2) the overall economic impact of a $1.6 million aggregate fee levied on the San Francisco beverage industry. The first of these is expected in the implementation of virtually any new regulatory mechanism.[158] These fee allocations are obviously very sensitive to the number of establishments counted in each category (Table 3-2, column 3). Typical of any regulatory program wherein distinctions are

[158] See generally Peltzman (1976); Owen and Braeutigam (1978)

made between industry establishments,[159] the implementation of a fee may encourage establishments to make cases for classifications into lower-fee categories. Two other *ex ante* scenarios are anticipated. First, if the regulation provides a "zero volume" clause—that is, the provision for establishments to argue that they do not sell CSBs—there will likely be a large number of applications requiring some level of verification. Second, some establishments may argue that they are not an appropriate fit in any of the categories and will request reclassification to the residual "other" category or the creation of a new category. As reclassification rules evolve, in order to assure the collection of the annual CSB-related costs ($1,755,104 in FY2009-2010), aggregate fees will have to be reapportioned by channel share and the fee schedule recalculated.

The second broad category of effects is the overall economic impact of taking $1.76 million from the retail food and beverage industry and "moving" those expenditures to health care. A redistribution of funds from the private retail industry to the public medical care industry would only have a meaningful impact if a dollar spent in the "receiving" industry had different multiplicative effects than a dollar spent in the "giving" industry. We used data from Minnesota IMPLAN[160] and the input-output data form of the Bureau of Economic Analysis to calculate the difference in sector multipliers. In San Francisco, the retail food and beverage multiplier is approximately 1.47 (i.e., a $1 reduction in revenues results in an additional 47 cents of lost economic value). However, the San Francisco multiplier for medical care services ("hospitals and physicians' offices") is a slightly higher 1.52, meaning that a $1 increase in revenues results in an additional 52 cents of economic value. Thus, the redistributive impact is likely to be very small, or even positive, given the similarity in sector multipliers.

[159] See generally Breyer (1982)

[160] To create a detailed input-output matrix and multiplier model of the San Francisco economy, two Minnesota IMPLAN Group (MIG) products are required: (1) IMPLAN Professional® 2.0 software and (2) the IMPLAN® data file(s) relating to the geographic area being analyzed. IMPLAN Professional® 2.0 is used to create a detailed input-output matrix for the indicated geographic area, and is also used to calculate the specific multipliers. IMPLAN Professional® 2.0 also provides an environment for managing information about your specific project and calculating the economic impacts your project may have on the Study Area. Impact results show how attributes such as employment and income of more than 500 different types of industries in a Study Area are affected.

APPENDIX A

Model Output Detail (Section 2)

Table A-1

Regression Coefficients—Logistic Model <400% FPL from 2002-2005 MEPS

Variable	β	S.E.	z	p-value	Lower 95% CI	Upper 95% CI
Age	-0.019	0.006	-3.29	0.001	-0.030	-0.008
Age squared	0.001	0.000	8.03	<0.001	0.000	0.001
Obese	0.385	0.040	9.59	<0.001	0.306	0.464
Overweight	0.142	0.041	3.50	0.001	0.062	0.222
Underweight	-0.075	0.107	-0.70	0.483	-0.287	0.136
Female	0.941	0.030	31.30	<0.001	0.882	1.001
Black non-Hispanic	-0.697	0.048	-14.49	<0.001	-0.792	-0.602
Hispanic	-0.805	0.045	-18.08	<0.001	-0.893	-0.718
Other race	-0.564	0.069	-8.12	<0.001	-0.700	-0.427
< High school	-0.254	0.040	-6.41	<0.001	-0.333	-0.176
> High school	0.467	0.050	9.28	<0.001	0.368	0.567
Married	-0.043	0.034	-1.26	0.209	-0.110	0.024
Rural	0.084	0.052	1.63	0.104	-0.017	0.186
Smoker	-0.132	0.033	-3.97	<0.001	-0.197	-0.066
Smoker missing	-0.232	0.050	-4.61	<0.001	-0.331	-0.133
Uninsured	-1.166	0.039	-30.14	<0.001	-1.242	-1.090
Public insurance	0.370	0.050	7.41	<0.001	0.271	0.468
2002 indicator	0.043	0.043	0.99	0.323	-0.042	0.128
2003 indicator	0.078	0.043	1.82	0.070	-0.006	0.163
2004 indicator	-0.043	0.038	-1.13	0.259	-0.117	0.032
Constant	1.207	0.114	10.60	<0.001	0.982	1.431

Note: FPL = federal poverty line; CI = confidence interval

Table A-2

Regression Coefficients—GLM Model <400% FPL from 2002-2005 MEPS

Variable	β	S.E.	z	p-value	Lower 95% CI	Upper 95% CI
Age	0.074	0.007	11.11	<0.001	0.060	0.087
Age squared	-0.001	0.000	-7.86	<0.001	-0.001	0.000
Obese	0.191	0.047	4.06	<0.001	0.098	0.284
Overweight	-0.012	0.049	-0.24	0.813	-0.108	0.085
Underweight	0.002	0.079	0.03	0.980	-0.153	0.157
Female	0.031	0.032	0.97	0.331	-0.031	0.093
Black non-Hispanic	-0.159	0.054	-2.93	0.004	-0.265	-0.052
Hispanic	-0.299	0.063	-4.74	<0.001	-0.424	-0.175
Other race	-0.300	0.061	-4.90	<0.001	-0.420	-0.179
< High school	0.032	0.043	0.75	0.456	-0.053	0.118
> High school	-0.089	0.040	-2.23	0.027	-0.167	-0.010
Married	-0.142	0.038	-3.78	<0.001	-0.216	-0.068
Rural	0.032	0.038	0.85	0.398	-0.042	0.106
Smoker	0.083	0.046	1.79	0.074	-0.008	0.174
Smoker missing	-0.018	0.057	-0.31	0.758	-0.131	0.095
Uninsured	-0.580	0.046	-12.74	<0.001	-0.670	-0.490
Public insurance	0.676	0.063	10.66	<0.001	0.551	0.800
2002 indicator	-0.101	0.036	-2.80	0.005	-0.172	-0.030
2003 indicator	-0.066	0.049	-1.34	0.181	-0.162	0.031
2004 indicator	-0.051	0.037	-1.39	0.167	-0.124	0.022
Constant	6.146	0.124	49.64	<0.001	5.902	6.390

Note: FPL = federal poverty line; CI = confidence interval

APPENDIX B

Description of CSB Consumption Reduction Program

Background

There is limited specific evaluation evidence for any public health interventions to reduce CSB consumption. In general, educational campaigns to change behavioral factors linked to poor health have little track record of success when implemented alone and in the absence of environmental change. In contrast, public health interventions aimed at structural or environmental change have higher likelihood of success especially when combined with educational interventions.

There is substantial evidence on the influence of media on consumption behavior, most significantly with regards to tobacco consumption. For example, a recent study in the Journal of Law and Economics, demonstrated that a ban on fast food advertisements or eliminating the fee deductibility associated with television advertising could reduce the number of overweight children by as much as 18%, through reductions in fast food consumption.

A CSB consumption reduction program would need to change cultural norms around beverage consumption through environmental interventions that support alternatives to CSB consumption in public spaces. Environmental strategies to changing norms and behaviors that reduce CSB consumption may take the form of restricting availability of CSBs and making healthy beverage choices available. For example, San Francisco has already adopted restrictions on CSB sales in public schools. Establishing drinking water stations and/or the replacement and improvement of poorly functioning fountains in public schools and recreation centers and other public venues could be another complementary environmental intervention to increase access to the healthiest beverage choice. This strategy could be coupled with social marketing campaigns aimed at promoting the use of these drinking water resources and eliminating soda from the diet. The social marketing campaigns could include both a community and a media component and will be focused both on school aged children as well as the larger community.

Although there have been very few studies specifically focused on eliminating soda consumption, one study from the United Kingdom[161] focused on promotion of water in schools. This study demonstrated that when provided with cooled, filtered water and promotion of drinking water, students increase the amount of water they consume at school.

We found no published evaluations of social marketing efforts focused on reducing CSB consumption. The proposed social marketing campaign for decreasing or eliminating CSB consumption in San Francisco builds on an existing campaign piloted in Alameda County in 2007 by the Alameda Public Health Department. The campaign consisted of educational curricula, community trainings and an interactive brochure for participants to document days without soda. Internal evaluation of the campaign showed that 65% reported that the campaign

[161] Loughridge and Barratt (2005)

materials helped them to reduce or eliminate soda consumption; 27% increased water consumption, and 43% reported consuming less soda and other sweetened beverages than three months prior.

Proposed CSB Consumption Reduction Program

Allocation of Funds to Reducing Excessive Consumption of CSBs

Approximately 50% of funds collected annually through a CSB regulatory fee shall be used to support public programs and infrastructure projects aimed at reducing excessive consumption of CSBs. Programs and projects funded shall be selected through a competitive application process open to public agencies in the City and County of San Francisco. Annually, the San Francisco Department of Public Health (SFDPH) will issue a Request for Proposals (RFP) consistent with city rules and subject to the funding guidelines below. SFDPH, with the support of a technical review committee, shall select and fund the most effective programs and projects subject to fund availability.

Funding Guidelines and Procedures

In general, educational campaigns to change behavioral factors linked to poor health have little track record of success when implemented alone and in the absence of environmental change. In contrast, public health interventions aimed at structural or environmental change have higher likelihood of success, especially when combined with educational interventions. Projects and programs funded through the CSB consumption reduction fund shall aim to change beverage consumption behaviors and cultural norms in San Francisco to be more consistent with available health-based beverage consumption guidelines. Consistent with the current understanding of effective public health practice, interventions shall combine environmental or structural change with education and social marketing. For example, a program might establish or improve drinking water fountains in a City recreational center while providing re-usable water bottles and promoting the consumption of public water. The RFP will provide information to potential applicants including:

- Introduction and Schedule
- Scope of Work
- Submission Requirements
- Evaluation and Selection Criteria
- Bidder’s Conference and Contract Award
- Terms and Conditions for Receipt of Proposals
- City Contract Requirements
- Protest Procedures

This RFP will be available to public agencies, who may partner with community organizations. The RFP process will follow a standard schedule of activities including a bidders' conference and period for responding to questions from potential applicants. SFDPH will assemble a Technical Review Panel to review and rate proposals according to standard evaluation and selection criteria.

APPENDIX C

CSB Retail Channel Descriptions

1. **Supermarkets/"big box" stores.** Establishments generally known as supermarkets and grocery stores primarily engaged in retailing a general line of food, such as canned and frozen foods, fresh fruits and vegetables, and fresh and prepared meats, fish, and poultry. Included in this industry are delicatessen-type establishments primarily engaged in retailing a general line of food (NAICS 44511). Also includes establishments known as warehouse clubs, "big box" stores, superstores or supercenters primarily engaged in retailing a general line of groceries in combination with general lines of new merchandise, such as apparel, furniture, and appliances (NAICS 45291).

2. **Restaurants/bars/cafes.** Establishments primarily engaged in providing food services to patrons who order and are served while seated (i.e. waiter/waitress service) and pay after eating. These establishments may provide this type of food service to patrons in combination with selling alcoholic beverages, providing carry out services, or presenting live non-theatrical entertainment (NAICS 72221). Also includes "limited service" establishments primarily engaged in providing food services where patrons generally order or select items and pay before eating (NAICS 72211). Food and drink may be consumed on premises, taken out, or delivered to the customer's location. Some establishments in this industry may provide these food services in combination with selling alcoholic beverages. We also include cafes, bars, taverns, and lounges in this category (NAICS 72241).

3. **Vending machines/operators.** Establishments primarily engaged in retailing merchandise through vending machines that they own, stock, and/or service (NAICS 45421). Given that volume of services depends mainly on the number of vending machines managed by the operator, the fee is calculated on a "per machine" basis.

4. **Grocery/convenience.** Establishments known as convenience stores, food marts (with and without fuel pumps), and grocery stores (excluding supermarkets and supercenters) primarily engaged in retailing a limited line of goods that generally includes milk, bread, produce, cereal, beverages, and snacks (NAICS 44711; 44511; 44512; 4452X; 4453X). These establishments can either be in the form of a small grocery market, convenience store (or food mart) or a combination convenience/gasoline station setting (which in some cases also provide automotive repair services).

5. **Drug chains.** Establishments known as pharmacies and drug stores engaged in retailing prescription or nonprescription drugs and medicines and a limited array of food (including some of the same staples generally sold by convenience stores), health and beauty products, house wares, etc. (NAICS 44611). Drug chains are distinguished from

pharmacies in that pharmacies typically focus mainly on retailing prescription or nonprescription drugs and medicines.

6. **Other, not elsewhere classified.** A variety of establishments that retail food and beverages in venues not elsewhere classified. Includes food service contractors (NAICS 72231) primarily engaged in providing food services at institutional locations of others via contractual arrangements; bakeries/confectionary/nut stores and other specialty food stores (NAICS 44529); caterers and mobile food services (NAICS 72232; 72233); bed and breakfasts (NAICS 72119); RV parks and campgrounds (NAICS 72121); and rooming and boarding houses (NAICS 72131).

GLOSSARY OF TERMS	
Term	Definition
Aggregate	An amount summed to form a total amount and put together or combined into a whole
Anthropometric Variables	Human body measurements
Aspartame	A crystalline compound that is used as a low-calorie sweetener in substitute of sugar
Attenuate	To weaken, diminish, or lessen the intensity of
Bias	A predisposition towards a certain outcome due to a methodical or sampling error *or* an instance when the expected value of a statistical estimate differs from the true value of the parameter being estimated
Blinded Study	A controlled experiment in which participants and/or researchers are unaware as to the particular treatment that individuals are assigned to, thereby mitigating any placebo effect
BMI formula	Weight in kilograms divided by height in squared meters
BMI Z-Score	The number of standard deviations that an individual's BMI is from the mean for a particular age group and gender.
Case	A participant in an epidemiologic study who has the disease or outcome under study.
Case-control study	A type of epidemiologic study where study participants are those with a given disease ("cases") and individuals without the disease ("controls"). The cases and controls are then compared with respect to an exposure of interest.
Cohort Study	A study in which groups of individuals who differ with respect to a characteristic of interest (such as CSB consumption), are observed over time and compared in terms of a specific outcome (such as obesity). Synonymous with longitudinal study.
Comorbid Conditions	Two or more diseases or disorders coexisting in the same individual
Confidence Interval	An estimated range of values that accounts for uncertainty in a statistical estimate, and is likely to include the true value of the parameter being estimated.
Confounder	A factor that is related to both an exposure and outcome of interest in an epidemiologic study. Researchers typically use multivariate regression techniques to adjust for potential confounders in a statistical analysis and eliminate bias that may result from their presence.
Control	A participant in a case control study who does not have the disease or outcome under study.
Cross-Sectional Study	A study which measures the relationship between exposure and outcomes simultaneously by observing participants at a single point in time
Discretionary Calories	The remainder of an individual's daily caloric intake allowance after basic nutritional needs have been met
Double-Blind	A characteristic of certain epidemiologic studies where both researchers and participants are unaware as to which treatment or exposure the study participants are assigned, thereby mitigating any effects that could result from such knowledge and reducing the potential for bias
Dual X-Ray Absorptiometry	An imaging test that measures bone density by passing x-rays with two

	different energy levels through the bone
Eclampsia	A hypertensive disorder characterized by convulsions and coma during pregnancy
Econometric Modeling Techniques	Statistical models that specify the statistical relationship that is believed to hold between two or more economic quantities pertaining to a particular economic subject under study
Effect Measures	Measures that show the strength of the relationship between two variables.
Empirical	Based on observation or experimental data
Epidemic	A rapidly spreading disease or disorder that affects a population at a higher rate than would be expected under normal conditions
Epidemiology	The branch of medicine that deals with the study of the causes, distribution, and control of disease in populations and serves as a logic of interventions made in the interest of public health
Experimental Study Design	Using predetermined protocols to study relationships between dependent and independent variables
Extrapolate	To estimate an unknown value, or infer unknown knowledge from the extension or expansion of known information
Gamma Distribution	A continuous probability function that compares the density function (frequency of occurrence) and the distribution function (time of occurrences)
Heterogeneity	Variability or non-uniformity
Heteroscedasticity	A characteristic used to describe a sequence of random variables that do not have constant variance
Hypothesis	The prediction of a certain relationship between independent and dependent variables which is shown true or false through regression analysis and experimentation
Intervention Effect	The impact of a given intervention on an observed state of health
Inverse Association	Negative relationship, where the increase of one variable is parallel to the decrease of another
Kurtosis	A statistical measure of how peaked or flat a distribution is when centered about its mean.
Linear Regression	A statistical technique for fitting the best line through a series of data points
Longitudinal Study	A study in which groups of individuals who differ with respect to a characteristic of interest (such as CSB consumption), are observed over time and compared in terms of a specific outcome (such as obesity). Synonymous with cohort study.
Menarche	The first menstrual period in a young woman's life
Meta-Analysis	A statistical analysis of data pooled from a collection of similar studies
Non-Differential Measurement Error	A type of error or bias that is equivalent for all study groups. Non-differential error typically reduces any measurable difference between groups.
Null	No effect or an effect that does not achieve statistical significance.
Obese	BMI $\geq$ 30kg/m^2
Odd Ratios	Measures of the effect size that describes the strength of the association between two data values. It is the ratio of the odds of an event occurring in one group to the odds of it occurring in another group
Overweight	BMI $\geq$ 25kg/m^2 and less than 30 kg/m^2

Pathophysiology	Alteration in or deviation from normal bodily functions as a result of disease or a medical disorder
Per Se	By or in itself
Point Estimate	A single value assigned to a parameter in estimation of a population
Preeclampsia	A complication during pregnancy characterized by high-blood pressure, headache, swelling, and protein in the urine
Prevalence	The percentage of a population afflicted with a particular disease or disorder at a particular point in time
Quartile	The 25^{th}, 50^{th}, and 75^{th} percentile points of a distribution that has been divided into four equal segments
Randomized study	A study in which the subjects are randomly allocated to each treatment group
Regression analysis	A statistical tool that investigates relationships between variables, and allows for consideration of the effects of differences between other variables
Satiety	The feeling of fullness or satisfaction after eating
Self-report	The reporting of characteristics or states of a subject by the subject himself/herself
Sensitivity Analysis	Sensitivity analysis is used to determine how a model is affected by changes in the value of the parameters of the model and to changes in the structure of the model
Statistical Significance	The statistical significance states the likelihood that a computed value could have been calculated simply due to chance. A statistically significant estimate is one that is most likely not due to chance, and therefore is likely to represent the true relationship.
Subsume	To contain or include within
Tanner Stage	Refers to the stages of the physical development that are defined by physical measurements based on external primary and secondary sex characteristics
Validation study	An analytical method that establishes that the performance characteristics of the method meet the requirements for the intended applications
Variance	A measure of statistical dispersion or spread of a distribution around its mean value

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