Low-calorie- and calorie-sweetened beverages: diet quality, food intake, and purchase patterns of US household consumers[1–3]

Carmen Piernas, Michelle A Mendez, Shu Wen Ng, Penny Gordon-Larsen, and Barry M Popkin

ABSTRACT

Background: Few studies have investigated the diet quality of consumers of low-calorie-sweetened (LCS) and calorie-sweetened (CS) beverages.

Objective: The objective was to examine the dietary quality and adherence to dietary purchasing and consumption patterns of beverage consumers from 2000 to 2010.

Design: We analyzed purchases for 140,352 households from the Homescan longitudinal data set 2000–2010 and dietary intake from NHANES 2003–2010 (n = 34,393). We defined mutually exclusive consumer profiles as main exposures: LCS beverages, CS beverages, LCS & CS beverages, and non/low consumers. As main outcomes, we explored dietary quality by using total energy and macronutrients (kcal/d). We performed factor analyses and applied factor scores to derive dietary patterns as secondary outcomes. Using multivariable linear (NHANES) and random-effects (Homescan) models, we investigated the associations between beverage profiles and dietary patterns.

Results: We found "prudent" and "breakfast" patterns in Homescan and NHANES, "ready-to-eat meals/fast-food" and "prudent/snacks/LCS desserts" patterns in Homescan, and "protein/potatoes" and "CS desserts/sweeteners" patterns in NHANES. In both data sets, compared with non/low consumers, both CS- and LCS-beverage consumers had a significantly higher total energy from foods, higher energy from total and SFAs, and lower probability of adherence to prudent and breakfast patterns. In Homescan, LCS-beverage consumers had a higher probability of adherence to 2 distinct patterns: a prudent/snacks/LCS dessert pattern and a ready-to-eat meals/fast-food purchasing pattern.

Conclusions: Our findings suggest that overall dietary quality is lower in LCS-, CS-, and LCS & CS–beverage consumers relative to non/low consumers. Our study highlights the importance of targeting foods that are linked with sweetened beverages (either LCS or CS) in intervention and policy efforts that aim to improve nutrition in the United States. *Am J Clin Nutr* 2014;99:567–77.

INTRODUCTION

Consumption of low-calorie-sweetened (LCS)[4] foods and beverages alone or in combination with caloric sweeteners has increased dramatically over the past decade in the United States (1, 2). As consumers turn to lower sugar and calorie items, a better understanding of actual patterns of sweetened-beverage consumption—containing either LCS or caloric sweeteners—and determinants and consequences of these patterns is warranted.

Intake of caloric sweeteners in general, and sugar- or high-calorie-sweetened beverages (CS beverages) in particular, is commonly associated with poor health outcomes (3). However, the association between LCS consumption and the risk of obesity and cardiometabolic problems still remains controversial (4–7). Several biological mechanisms have been hypothesized to link LCS consumption to increased energy, sugar intake, and poor dietary quality (8–10). Behaviorally, consumption of LCS products could be linked to a higher intake of calories or larger portion sizes motivated by the general perception that these "diet" products are lower in calories and sugars, hence allowing some consumers to offset these beverages with less healthful foods. Such dietary patterns may be one pathway linking LCS consumption to health outcomes such as cardiometabolic disorders.

Although the physiologic causal pathways are not well understood and are difficult to test, few studies have explored in depth what dietary patterns are followed by consumers of LCS and CS beverages. Previous studies have typically examined the independent effects of LCS and CS beverages on metabolic outcomes after control or stratification by "Western" or "prudent" dietary patterns (4, 7, 11, 12). However, few have investigated the long-term adherence of LCS- and CS-beverage consumers relative to dietary patterns. Moreover, LCS consumption has typically been poorly assessed because of the lack of standardized ways to determine the presence of sweeteners in food products, partly because of the lack of access to product ingredient lists and to the lack of awareness of the presence of LCS, CS, or both sweeteners in food products as self-reported by participants.

In this study, we analyzed purchases by households included in the Nielsen Homescan Longitudinal data set 2000–2010, which captures >400,000 bar-coded food products (12). Each product is linked to detailed ingredient information to identify the

[1] From the Department of Nutrition, Gillings School of Global Public Health, University of North Carolina at Chapel Hill, Chapel Hill, NC.

[2] Supported by the Robert Wood Johnson Foundation (grant 70017) and the CPC 5 R24 HD050924.

[3] Address correspondence to BM Popkin, Carolina Population Center, University of North Carolina, 123 West Franklin Street, Chapel Hill, NC 27516. E-mail: popkin@unc.edu.

[4] Abbreviations used: CS, calorie sweetened; Homescan, Nielsen Homescan Panel; LCS, low-calorie sweetened; RTE, ready to eat.

Received July 24, 2013. Accepted for publication November 27, 2013.

First published online December 18, 2013; doi: 10.3945/ajcn.113.072132.

presence of LCS and CS in products currently sold in the United States. Because sweetened beverages are major sources of CS and LCS in the diet, we defined profiles to characterize households that purchase LCS beverages, CS beverages, both LCS & CS beverages, and non/low consumers of both beverage types. Then, we investigated overall food-purchasing patterns of the different beverage consumer profiles. In addition, we used NHANES data from 2003 to 2010 to explore dietary patterns of the same beverage consumer profiles. We hypothesized that consumers of LCS beverages would follow 2 distinct patterns: one characterized by a reduced energy intake and another characterized by a lower dietary quality and higher energy intake. We also hypothesized that consumers of CS beverages would have poorer dietary quality and higher energy intakes.

SUBJECTS AND METHODS

Study design and population

To capture both purchasing and dietary intake patterns, we used 2 different data sets: a longitudinal data set of household purchases from the Nielsen Homescan (The Nielsen Co) (12) 2000–2010 and cross-sectional data sets of individual dietary intake data from the USDA NHANES 2003–2010.

Food purchase data: the Nielsen Homescan Consumer Panel

The Nielsen Homescan Panel (Homescan) is an ongoing nationally representative longitudinal survey of 35,000–60,000 households per year that captures information on consumer purchases of >400,000 bar-coded products that are sold in the United States over this period. Homescan participants are provided with home scanners, with which they scan their purchases from every shopping event for ≥10–12 mo (we refer to this period as 1 y) and up to 10 y. The current study included all households with adults and children from Homescan (12) from 2000 to 2010 (n = 501,343 observations from 140,352 unique households and 408,458 individuals). An observation represented all purchases made by a single household over a period of ≥10 to 12 mo. Each uniquely bar-coded product captured in Homescan was linked with Nutrition Facts Panel data and ingredient information (13). Household socioeconomic status and other information, including sex and age of each family member and income, education, and race-ethnicity of the main head of the household were also available. Households included in Homescan are sampled and weighted to be nationally representative. Overall, calories from Homescan food-purchase data represent approximately two-thirds of the total calorie intake (14).

Dietary intake data: NHANES

The USDA NHANES capture dietary intake data for a nationally representative self-weighting, multistage, and stratified probability sample of noninstitutionalized US households (15–19). For this study, we included adults and children (n = 34,393) who had participated in 1 of 4 NHANES waves from 2003 to 2010: NHANES 2003–2004 (n = 8273), NHANES 2005–2006 (n = 8549), NHANES 2007–2008 (n = 8529), and NHANES 2009–2010 (n = 9042). Dietary intake data were collected by using 2 nonconsecutive 24-h recalls and was linked to the USDA food databases and food-composition tables, which provide nutrient information and food descriptions for each food item consumed by the participants (19). Sociodemographic information, such as age, sex, race-ethnicity, and income was also collected for each participant.

Classification of sweetened beverages and definition of consumer profiles

Sweetened beverages, including soda-type carbonated beverages and sweetened-flavored waters, were classified as LCS or CS beverages in each data set. In Homescan, we conducted keyword searches for CS and LCS (including terms such as "sugar," "high-fructose corn syrup," "sucralose," or "aspartame") using the ingredient lists provided for each bar-coded product purchased by participating households (20). In NHANES, we conducted keyword searches by looking at the food description of each food code that is captured by the USDA food database. We classified beverages as LCS if their food description included the following terms: "with low/no calorie sweetener," "sugar-free," and "dietetic/low sugar." Otherwise, they were considered CS beverages.

As main exposures, we created beverage-consumer profiles based on purchases (Homescan) or intake (NHANES) of LCS and CS beverages, because these sweetened beverages were the major sources of LCS and CS sweeteners in the US population over the past decade (1). Our definitions of beverage consumer profiles captured an overall preferred consumption of LCS or CS beverages but were not restrictive to having balanced sample sizes across the different profiles. Because Homescan captures household purchases over an entire year, we divided the total volume of LCS and CS beverages purchased per year by the standard serving size of a can (12 oz, or 355 mL), and we found that those households in the top quartile of the population distribution had ∼208 servings of LCS beverages per year (∼4/wk, or 0.56/d). We classified households above the top quartile of purchases of either LCS or CS beverages as consumers of that beverage type (ie, ≥0.56 servings/d) if they also reported lower purchases of the other type of beverage per day (<0.14 servings/d). Households with ≥0.56 servings/d of any combination of LCS and CS beverages were classified as combined LCS & CS beverage consumer households. All other households were considered non/low consumers. Similarly in NHANES, we divided the average volume of LCS and CS beverages consumed per day by the standard serving size of a can (12 oz or 355 mL) and we found that individuals in the top intake decile for LCS beverages consumed an average of 0.5 servings/d. We classified individuals as regular consumers of either LCS or CS beverages if they consumed ≥0.5 servings/d of those beverages and <0.5 servings of the other type of beverage per day. Individuals who reported consuming both types of beverages, with ≥0.25 servings/d of both LCS and CS beverages, were classified as combined LCS & CS beverage consumers. All other participants were considered non/low consumers.

Factor analysis

Factor analysis is a data-driven approach to derive dietary patterns that represent patterns of purchases or intake of foods and beverages that are consumed in combination. We grouped all foods and beverages that were purchased or reported in 35 food groups (*see* Supplemental Table 1 under "Supplemental data" in the online issue). We created a food-grouping system that captured a sufficient number of food groups while addressing important issues related to the general population's diet (ie, reflects all food groups generally consumed by the population) and related to food selection in association with LCS and CS beverage consumption, so the main food groups were disaggregated into subgroups (ie, milk drinks sweetened with LCS or CS). Because Homescan food groups were reflecting the different departments of the grocery store, we regrouped all foods and beverages into a more meaningful nutritional food-grouping system that was comparable with the NHANES grouping system. Then, we performed factor analyses in each data set separately using standardized measures of purchases or intake of all food and beverage groups other than LCS and CS beverages. Intake variables were defined as the percentage of energy from each food group. For each factor, every food group had a specific factor loading, which is the correlation coefficient between each food group and that factor or diet pattern. Also, each participant had a score for each factor; with higher scores indicating higher adherence to that factor or pattern. We performed a varimax rotation after the factor analysis so that the emerging factors or patterns were as uncorrelated as possible. We retained 4 factors in each data set based on the Kaiser criterion (eigenvalue >1) and the interpretability of the resulting patterns. Then, factor loadings from each of those 4 factors with a z score >0.2 were extracted.

To create dietary patterns longitudinally in Homescan, we calculated applied factor scores by using the Bartlett method, which is considered the most refined method for creating unbiased and orthogonal factor scores over time (21). We used factor loadings from 2010 to obtain predicted factor scores for earlier years (2000–2009) using maximum likelihood estimates that were most likely to represent the true factor scores. Using applied factor scores, we were able to consistently define the same dietary pattern over the time period studied. We applied factor scores backward to better capture food groups that might be present in 2010 but not in 2000. Because the NHANES sample combines 4 cross-sectional waves of data, we performed a single factor analysis in the entire sample using standardized measures of intake (% of energy from each food group with respect to total energy, excluding LCS and CS beverages) with a varimax rotation.

Statistical analysis

All analyses were performed by using Stata 12 (release 12, 2011; StataCorp). Survey commands were used to account for survey design and weighting to generate nationally representative results. In both data sets, race-ethnicity was used to classify participants as Hispanic, non-Hispanic white, non-Hispanic African American, and Others. Age was used to separate adults ($<$19 y) and children (2–18 y). The ratio of family income to poverty threshold, calculated from self-reported household income, was used to categorize income according to the percentage of the poverty level: lower income, $<$185%; middle income, $\geq$185% to $<$400%; and higher income, $\geq$400%.

To examine dietary quality (main outcome) by beverage consumer profile (main exposure), we estimated measures of daily energy (including total daily calories, total calories excluding LCS and CS beverages, total food calories, and total beverage calories) and daily energy from macronutrients (including carbohydrates, total sugar, fat, protein, and SFA) using total yearly purchases in Homescan and average daily intake in NHANES. All the models used in Homescan were adjusted for confounders, such as household size, year, income and race-ethnicity, whereas the models used in NHANES were adjusted for age, sex, race-ethnicity, and income because all these variables were found to be differentially associated with sweetened-beverage consumption (1). In addition, we stratified all the analyses in Homescan by household structure, because there was a significant interaction between beverage profiles and household type (single-person, multiperson with adults only, and multiperson with children). We also stratified all analyses in NHANES to obtain estimates for adults and children separately. We used average marginal effects from random-effects longitudinal linear regression models in Homescan to investigate the associations between the beverage consumer profiles and energy and macronutrient composition of the household purchases over the period studied. In NHANES, we used average marginal effects from linear regression models to investigate the cross-sectional associations between beverage profiles and the dietary energy and macronutrient composition of each individual's diet.

Next, we examined the associations between beverage consumer profiles and dietary patterns derived from factor analyses within each data set. With the use of factor scores for each of the 4 patterns that were retained, we created categories based on tertiles for each pattern so that individuals in the highest tertile of each pattern were more likely to follow that particular pattern. In Homescan, we used average marginal effects from random-effects longitudinal logistic regression models to investigate the associations between beverage consumer profiles and subsequent dietary-purchasing patterns over the period studied. The model included a binary outcome (the highest tertile of a factor compared with the middle/lower tertile), time-varying variables such as categories of beverage consumer profile as the main exposure, the interaction between the beverage profile and household type, and confounder variables. Similarly in NHANES, we used average marginal effects from logistic regression models to investigate the cross-sectional associations between dietary intake patterns and beverage consumer profiles. The model also included a binary outcome (the highest tertile of a factor compared with the middle/lower tertile), and categories of beverage consumer profiles as the main exposure plus confounder variables. In each data set, margins commands were used after the fully adjusted models to predict the probability of being in the highest tertile of each dietary pattern given their beverage profile. Because this model had a categorical outcome, we obtained the predicted probability of the outcome based on the model coefficients of the main exposure plus further adjustments performed in the model. Aside from adherence to dietary patterns, we also investigated the mean percentage of energy from purchases or intake of key food groups that characterized the main dietary patterns identified by using multivariable random-effects longitudinal models (Homescan) and multivariable models (NHANES). Estimates (95% CIs) are presented as means ($\pm$SEMs) or predicted probabilities. Statistically significant differences were tested by using Student's t test with the Bonferroni correction. A 2-sided P value of 0.05 was set to denote statistical significance.

RESULTS

Sociodemographic characteristics and beverage consumption profiles in Homescan and NHANES

Previous research showed that both the Homescan and NHANES populations are predominantly non-Hispanic white (1). Compared with NHANES, Homescan had a higher proportion of middle-income individuals, whereas NHANES included a higher proportion of higher-income individuals than did Homescan (1). Our results showed that the 2 most common profiles in Homescan were non/low consumers of sweetened beverages (42%) followed by LCS & CS beverage consumers (28%) (**Table 1**). Households classified as LCS- or CS-beverage consumers had purchases of almost 2 servings/d per household of each beverage type. In NHANES, most individuals were classified as non/low consumers or CS-beverage consumers (**Table 2**). Adult consumers of LCS beverages or CS beverages in NHANES consumed on average almost 2 servings of the respective type of beverage per day.

Beverage profiles and energy and macronutrient composition of food purchases and intakes

In Homescan, compared with non/low consumers, households purchasing larger amounts of any type of sweetened beverage had significantly higher average total daily energy and total daily energy intakes from foods only and higher energy from each macronutrient (**Figure 1**A; *see* Supplemental Table 2 under "Supplemental data" in the online issue). In NHANES, individuals who consumed any type of sweetened beverage also had higher daily energy intakes from foods and from total fat, SFA, and protein (Figure 1B; *see* Supplemental Table 3 under "Supplemental data" in the online issue).

Dietary patterns based on food purchases and intakes obtained from factor analyses

Four dietary patterns or factors explaining the maximum variability in each population were retained (**Table 3**). We found

TABLE 1

Population demographics, sample sizes, and average sweetened beverage consumption by consumer profile in Homescan 2000–2010[1]

Homescan 2000–2010, household level	Definition of consumer profiles: Non/low consumers	LCS beverages	CS beverages	LCS & CS beverages[2]	Total sample[3]
LCS beverages (servings/d)	0 to <0.28	≥0.56	<0.14	≥0.28 or ≥0.42 or ≥0.14	
CS beverages (servings/d)	0 to <0.28	<0.14	≥0.56	≥0.28 or ≥0.14 or ≥0.42	
Total observations, 2000–2010 [*n* (%)]	221,023 (42.1)	53,955 (9.0)	88,176 (21.1)	138,189 (27.8)	501,343
Single person	88,001 (61.8)	16,520 (11.3)	15,981 (14.4)	15,509 (12.5)	136,011
Multiperson without children	95,061 (37.4)	30,616 (11.1)	41,420 (19.9)	74,502 (31.6)	241,599
Multiperson with children	37,961 (31.2)	6819 (4.7)	30,775 (28.1)	48,178 (36.0)	123,733
Household sociodemographic characteristics [*n* (%)]					
White[4]	179,783 (40.6)	49,512 (10.2)	69,769 (19.8)	120,484 (29.4)	419,548
African American	22,955 (51.0)	1607 (3.3)	10,549 (28.2)	7569 (17.4)	42,680
Hispanic	10,133 (39.7)	1789 (6.0)	5453 (25.6)	7010 (28.8)	24,385
Lower income, <185%[5]	39,403 (41.9)	6633 (6.0)	20,578 (27.3)	21,994 (24.8)	88,608
Middle income, ≥185 to <400%	91,833 (41.3)	19,944 (7.6)	40,652 (22.8)	59,528 (28.3)	211,957
Higher income, ≥400%	89,787 (42.9)	27,378 (12.2)	26,946 (15.6)	56,667 (29.2)	200,778
Household size	2.1 ± 0.0[6]	2.0 ± 0.0	2.8 ± 0.0	2.9 ± 0.0	501,343
LCS beverages per household (servings/d)					
All households	0.09 ± 0.00	1.83 ± 0.01	0.03 ± 0.00	1.31 ± 0.00	501,343
Single person	0.08 ± 0.00	1.63 ± 0.01	0.02 ± 0.00	1.13 ± 0.01	136,011
Multiperson without children	0.10 ± 0.00	1.91 ± 0.01	0.03 ± 0.00	1.35 ± 0.01	241,599
Multiperson with children	0.09 ± 0.00	1.91 ± 0.02	0.03 ± 0.00	1.30 ± 0.01	123,733
CS beverages per household (servings/d)					
All households	0.15 ± 0.00	0.05 ± 0.00	1.74 ± 0.00	1.13 ± 0.00	501,343
Single person	0.11 ± 0.00	0.04 ± 0.00	1.45 ± 0.01	0.80 ± 0.01	136,011
Multiperson no children	0.16 ± 0.00	0.05 ± 0.00	1.72 ± 0.01	1.06 ± 0.00	241,599
Multiperson children	0.21 ± 0.00	0.06 ± 0.00	1.94 ± 0.01	1.35 ± 0.01	123,733

[1] Estimates were weighted to adjust for unequal probability of sampling. One serving equals the size of a can (12 oz, or 355 mL). CS, calorie sweetened; Homescan, Nielsen Homescan Panel; LCS, low-calorie sweetened.

[2] Consumers of LCS & CS beverages had any combination of LCS and CS per day: ≥0.28 of LCS and CS, or ≥0.42 of LCS and ≥0.14 of CS, or ≥0.14 of LCS and ≥0.42 of CS.

[3] Total sample indicates the total number of observations for each socioeconomic group from 140,352 households included in Homescan from 2000 to 2012. An observation in Homescan represents all purchases made by a single household over a period >10–12 mo.

[4] Race-ethnicity is self-reported by the head of the household in Homescan.

[5] Ratio of family income to poverty threshold (calculated from self-reported household or individual income) was used to categorize income according to the percentage of the poverty level.

[6] Mean ± SEM (all such values).

TABLE 2
Population demographics, sample sizes, and average sweetened beverage consumption by consumer profile in NHANES 2003–2010[1]

	Definition of consumer profiles				
NHANES 2003–2010, individual level	Non/low consumers	LCS beverages	CS beverages	LCS & CS beverages	Total sample
LCS beverages (servings/d)	0 to <0.25	≥0.50	<0.50	≥0.25	
CS beverages (servings/d)	0 to <0.25	<0.50	≥0.50	≥0.25	
Total population [n (%)]	15,236 (40.6)	3220 (14.4)	14,188 (38.0)	1749 (7.0)	34,393
Adults	8828 (38.7)	2889 (17.9)	8145 (36.5)	1109 (6.9)	20,971
Children	6408 (46.6)	331 (3.6)	6043 (42.4)	640 (7.4)	13,422
Individual sociodemographic characteristics [n (%)]					
Male	6663 (34.6)	1437 (12.1)	7996 (45.9)	862 (7.3)	16,958
Female	8573 (46.1)	1783 (16.6)	6192 (30.6)	887 (6.7)	17,435
White[2]	6153 (39.7)	2128 (18.0)	5030 (34.5)	924 (7.8)	14,235
African American	3566 (41.3)	406 (5.6)	3780 (48.2)	303 (5.0)	8055
Hispanic	3264 (37.1)	443 (6.6)	3897 (51.2)	346 (5.1)	7950
Lower income, <185%[3]	6936 (40.2)	925 (7.6)	7279 (46.3)	661 (5.9)	15,801
Middle income, ≥185 to <400%	4109 (40.4)	954 (14.2)	3730 (37.6)	560 (7.8)	9353
Higher income, ≥400%	4191 (41.2)	1341 (20.4)	3179 (31.2)	528 (7.3)	9239
LCS beverages (servings/d)					
All	0.02 ± 0.00[4]	1.89 ± 0.04	0.00 ± 0.00	1.24 ± 0.06	34,393
Adults	0.02 ± 0.00	1.93 ± 0.04	0.00 ± 0.00	1.39 ± 0.07	20,971
Children	0.02 ± 0.00	1.27 ± 0.14	0.00 ± 0.00	0.83 ± 0.04	13,422
CS beverages (servings/d)					
All	0.06 ± 0.00	0.00 ± 0.00	1.88 ± 0.03	1.26 ± 0.04	34,393
Adults	0.05 ± 0.00	0.00 ± 0.00	1.99 ± 0.04	1.27 ± 0.05	20,971
Children	0.10 ± 0.00	0.01 ± 0.00	1.58 ± 0.04	1.23 ± 0.05	13,422

[1] Estimates were weighted to adjust for unequal probability of sampling. One serving equals the size of a can (12 oz, or 355 mL). CS, calorie sweetened; Homescan, Nielsen Homescan Panel; LCS, low-calorie sweetened.
[2] Race-ethnicity is self-reported by the head of the household in Homescan or by each participant in the NHANES data sets.
[3] Ratio of family income to poverty threshold (calculated from self-reported household or individual income) was used to categorize income according to the percentage of the poverty level.
[4] Mean ± SEM (all such values).

that the prudent and breakfast patterns were common in both Homescan and NHANES. The prudent pattern was characterized by positive factor loadings for food groups that reflected more like "home-cooking" eating habits, with more whole/plain foods such as fruit, vegetables, grains, cooking fat, and others; negative loadings for processed food groups such as salty

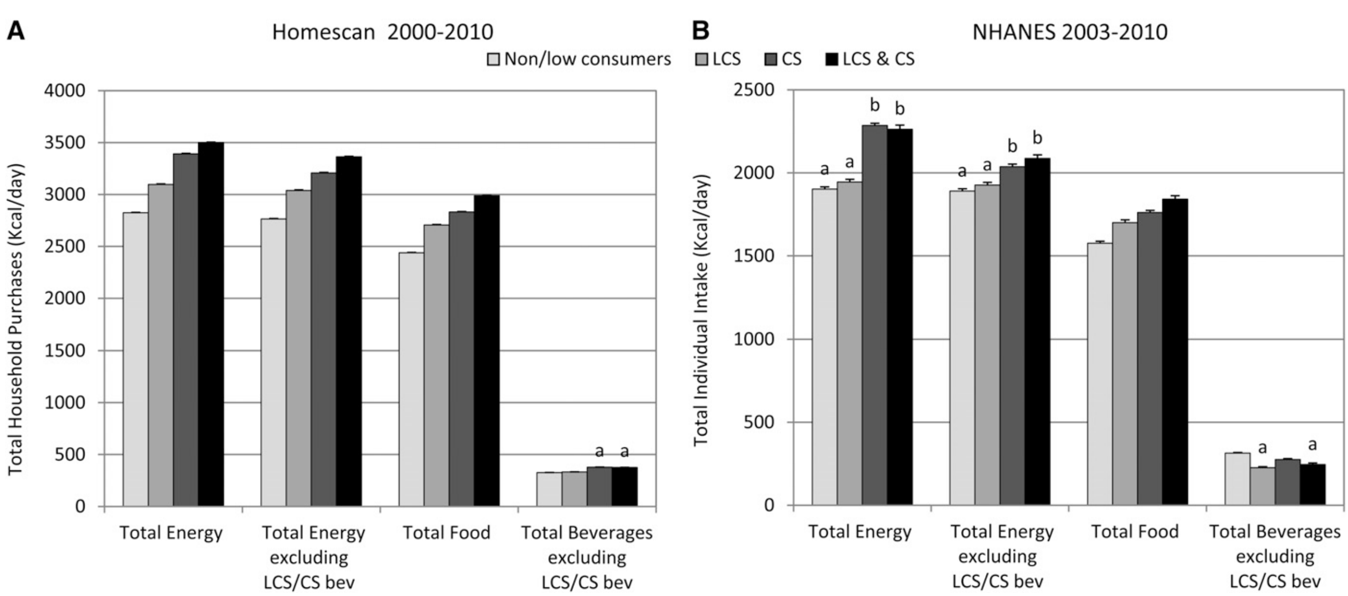

FIGURE 1. Average total daily household purchases in Homescan (A) and individual intakes in NHANES (B). A: non/low consumers, n = 221,023 observations; LCS, n = 53,955 observations; CS, n = 88,176 observations; LCS & CS, n = 138,189 observations. B: non/low consumers, n = 15,236 individuals; LCS, n = 3220 individuals; CS, n = 14,188 individuals; LCS & CS, n = 1749 individuals. Bars with different lowercase letters are significantly different at the 5% level (Bonferroni-adjusted Student's t test). bev, beverages; CS, calorie sweetened; Homescan, Nielsen Homescan Panel; LCS, low-calorie sweetened.

TABLE 3
Dietary and purchasing patterns derived from factor analysis in the Homescan and NHANES populations[1]

	Homescan dietary purchasing patterns				NHANES dietary intake patterns			
Food groups	Factor 1: prudent	Factor 2: breakfast	Factor 3: RTE meals/fast food	Factor 4: prudent/snacks/LCS desserts	Factor 1: prudent	Factor 2: breakfast	Factor 3: protein/potatoes	Factor 4: CS desserts/CS sweetener
Water/other drinks, unsweetened								
Juice, sweetened, LCS								
Juice, sweetened, CS		0.29				0.25		
Milk, unsweetened		0.50		−0.21		0.71		
Milk, sweetened, LCS								
Milk, sweetened, CS								
Coffee/tea, unsweetened					0.28	−0.33		
Coffee/tea, sweetened, LCS								
Coffee/tea, sweetened, CS						−0.22		
Alcohol		−0.25				−0.33		−0.28
Yogurt, plain/unsweetened								
Yogurt, sweetened, LCS								
Yogurt, sweetened, CS								
Cheese, all types	0.25	−0.24	0.20				0.27	
Cooking fat/oil	0.28	−0.34	−0.52	−0.23	0.25		0.22	0.36
Nuts				0.65	0.22			
Dressings/sauces	0.24	−0.36					0.28	
Protein group; meat/fish/eggs	0.31	−0.38		−0.28		−0.26	0.55	−0.29
Vegetables	0.38			0.26	0.49			
Potatoes		−0.25		−0.27	−0.28		0.38	
Fruit, plain	0.20			0.44	0.46	0.31		
Fruit, processed and sweetened, LCS								
Fruit, processed and sweetened, CS								
RTE mixed/frozen meals			0.67	−0.27			−0.84	
Fast-food meals			0.45	−0.26	−0.61			
Grains, pasta/rice	0.40		−0.47		0.60			
RTE cereal, sweetened, LCS		0.31						
RTE cereal, sweetened, CS		0.71				0.68		
Salty snacks	−0.27	−0.22		0.20	−0.25			
Desserts/sweet snacks, LCS				0.31				
Desserts/sweet snacks, CS	−0.92							0.72
Sweeteners, LCS								
Sweeteners, CS			−0.53	−0.30				0.60
Other			−0.24					

[1] Factor loadings were estimated for all food and beverage groups, excluding LCS and CS beverages in each data set separately by using standardized measures of purchases (Homescan) or intake (NHANES): percentage of energy from each food group with respect to the total energy, excluding LCS and CS beverages. A varimax rotation was performed after the factor analysis so that the emerging factors are as different as possible and less correlated with one another. Four factors are retained in each data set based on the Kaiser criterion (eigenvalue >1) and the interpretability of the resulting patterns. Factor loadings <0.20 are not shown. CS, calorie sweetened; Homescan, Nielsen Homescan Panel; LCS, low-calorie sweetened; RTE, ready to eat.

snacks; and fast-food meals only in NHANES. The breakfast pattern was characterized by positive loadings for unsweetened milk, juice, and ready-to-eat (RTE) cereals. In addition, we found an "RTE meals/fast-food" purchasing pattern characterized by positive loadings for mixed, frozen, and fast-food meals and a "prudent/snacks/LCS desserts" purchasing pattern with positive loadings for fruit, nuts, vegetables and also snacks and LCS desserts in Homescan. In NHANES, we found a "protein/potatoes" pattern with positive loadings for meat, poultry, and potatoes including French fries and finally a "CS desserts/sweetener" pattern with positive loadings for CS desserts and sweeteners.

Associations between beverage profiles and overall dietary patterns

Households purchasing any type of sweetened beverage had significantly lower probability of adherence to the prudent or breakfast purchasing pattern compared with non/low consumers (**Figure 2**A). Although households that purchased LCS or LCS & CS beverages had a higher adherence to the RTE meals/fast-food purchase pattern, those that purchased mainly LCS beverages had a particularly higher probability of following the prudent/snacks/LCS desserts, whereas those that purchased either CS or LCS & CS beverages had a lower probability of following this pattern. Although these associations were consistent across the different types of households, the magnitude of the adherence to each pattern varied depending on the type of household (Figure 2, B–D). The breakfast and the RTE meals/fast-food patterns were more predominant among households with children. These results were also found in NHANES, where individuals consuming any type of sweetened beverage had lower predicted probabilities of adherence to a prudent or breakfast intake pattern compared with non/low consumers (**Figure 3**, A–C). We also found that sweetened-beverage consumers of any type had a higher probability of adherence to the protein/potatoes intake pattern. However, no significant differences were found between sweetened-beverage consumers and non/low consumers in adherence to the CS desserts/sweeteners pattern except for LCS-beverage consumers, who had a lower probability.

Additional analyses were performed in which beverage consumers were categorized based on high adherence (ie, being in the highest tertile) to only 1 of the 4 patterns, and the proportion of the sample of each beverage profile was calculated for each of

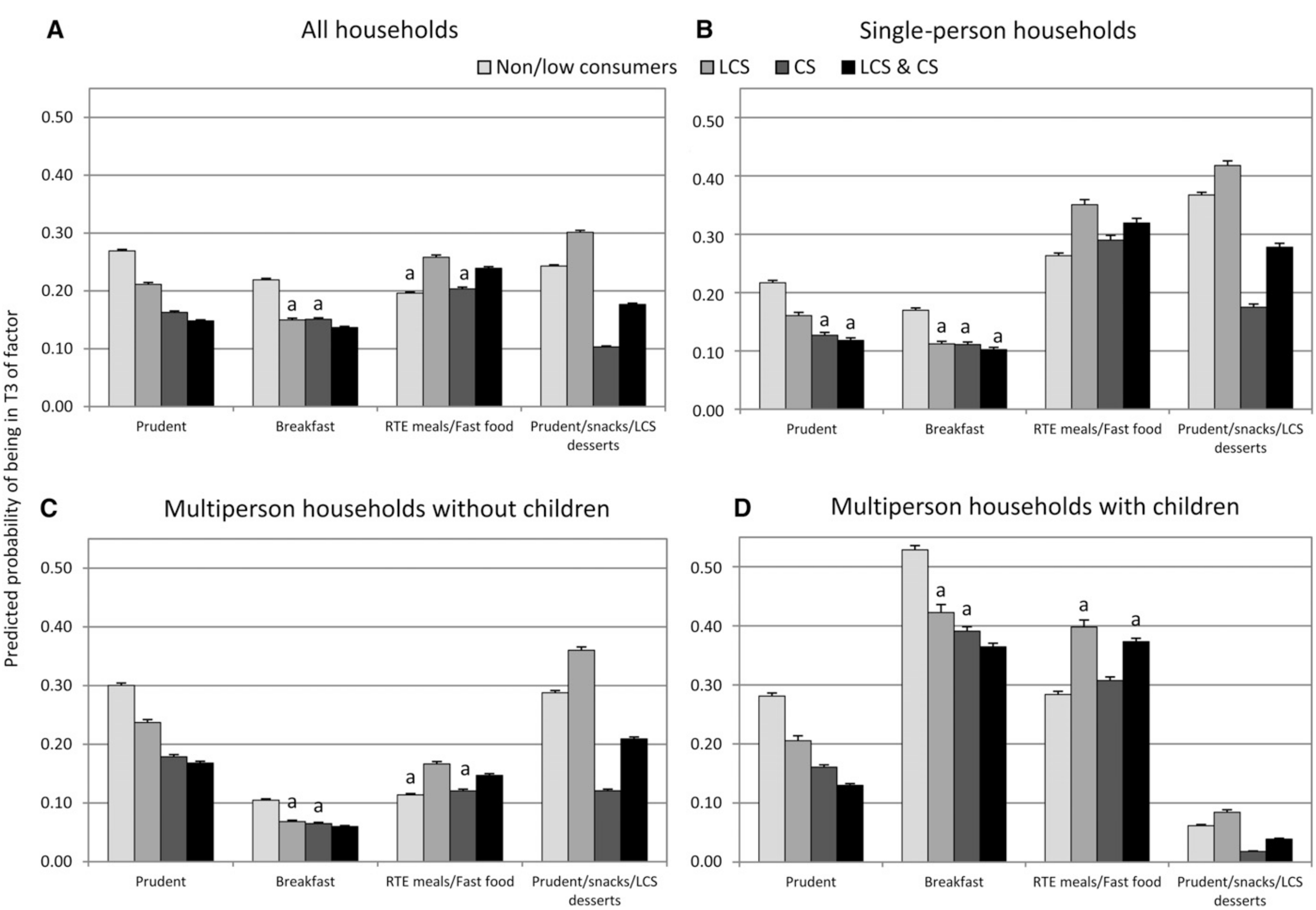

FIGURE 2. Relations between beverage consumption profiles and dietary purchasing patterns, Homescan 2000–2010. A: All households (n = 501,343 observations). B: Single-person households (n = 136,011 observations). C: Multiperson households without children (n = 241,599 observations). D: Multiperson households with children (n = 123,733 observations). Values represent the predicted probability of being in the highest tertile (T3) for each dietary pattern from random-effects longitudinal logistic regression models, adjusted for household size, year, income, and race-ethnicity with interaction between the beverage profile and household type (B-D). Bars with different lowercase letters are significantly different at the 5% level (Bonferroni-adjusted Student's t test). CS, calorie sweetened; Homescan, Nielsen Homescan Panel; LCS, low-calorie sweetened RTE, ready to eat; T, tertile.

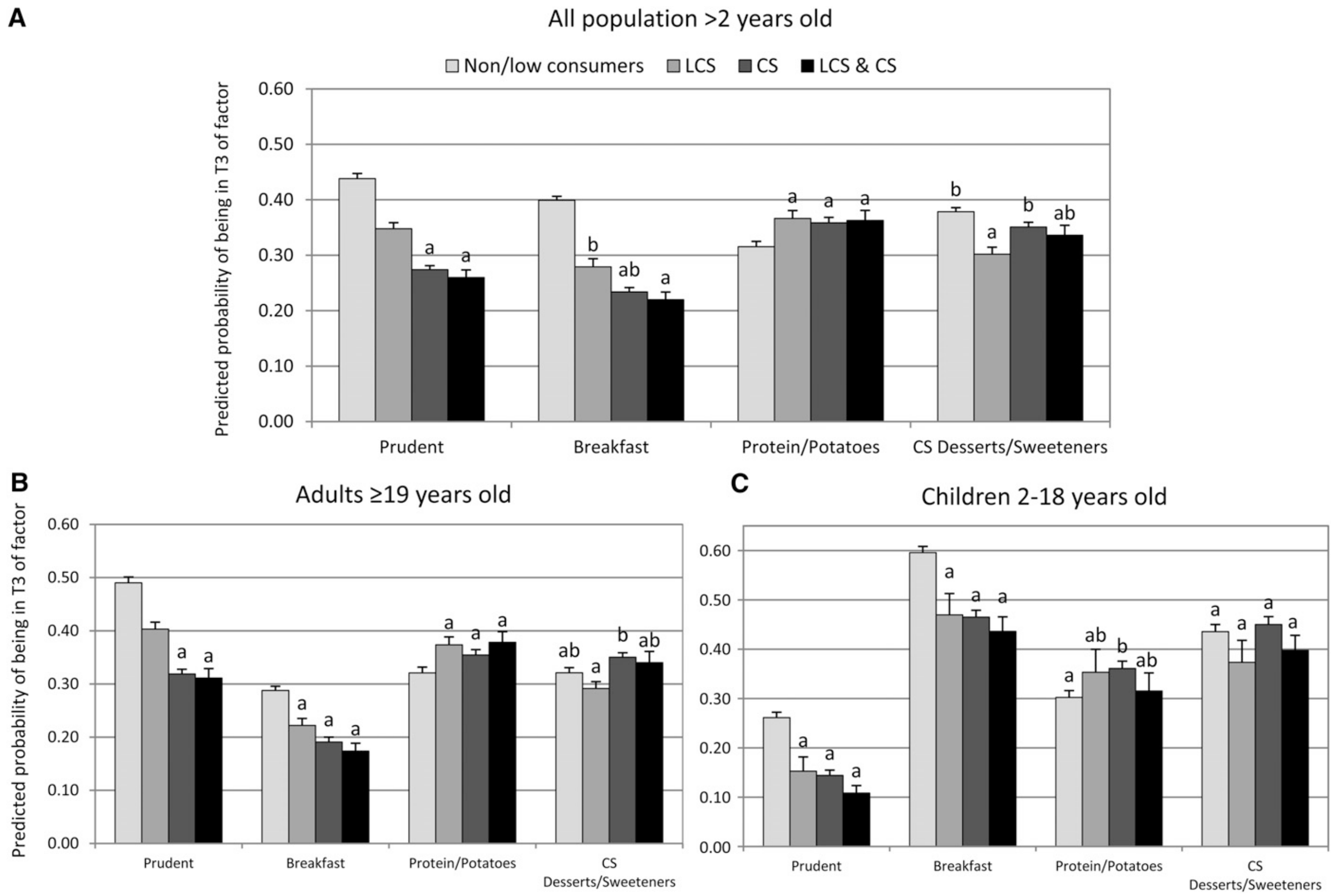

FIGURE 3. Relations between beverage consumption profiles and dietary intake patterns, NHANES 2003–2010. A: All population >2 y old (n = 34,393). B: Adults ≥19 y old (n = 20,971). C: Children 2–18 y old (n = 13,422). Values represent the predicted probability of being in the highest tertile (T3) for each dietary pattern from logistic regression models, adjusted for age, sex, race-ethnicity, and income. Stratified models were performed to obtain estimates for adults and children separately (B and C). Bars with different lowercase letters are significantly different at the 5% level (Bonferroni-adjusted Student's t test). CS, calorie sweetened; LCS, low-calorie sweetened; T, tertile.

the 4 dietary patterns (data not shown). We found that a higher proportion of non/low consumers fell in the prudent pattern (30% in Homescan and 31% in NHANES), whereas a lower proportion of them fell in the RTE meals/fast-food pattern (19% in Homescan and 18% in NHANES). In contrast, LCS-beverage consumers in Homescan fell mostly in the prudent/snacks/LCS desserts (36%) and RTE meals/fast-food (30%) patterns and in the protein/potatoes pattern in NHANES (29%). CS-beverage consumers in Homescan fell mostly in the breakfast (31%) and RTE meals/fast-food (30%) patterns and in the protein/potatoes pattern in NHANES (33%). LCS & CS-beverage consumers in Homescan fell in the RTE meals/fast-food (34%) and in the protein/potatoes (34%) and CS desserts/sweeteners (31%) patterns in NHANES.

Associations between beverage profiles and food group purchases or intakes

Comparing food group patterns by beverage consumer profile in Homescan and NHANES (**Table 4**), we found that households and individuals purchasing or drinking any type of sweetened beverage, compared with non/low consumers, had higher purchases and intakes (% of energy) of protein groups (meat, fish, eggs, etc), RTE and fast-food meals, salty snacks, and, in Homescan, desserts. Across both data sets, non/low consumers of CS or LCS beverages had a higher proportion of energy from milk, CS juice, fruit and vegetables, grains, and RTE cereal (these last 2 groups were not different between non/low consumers and LCS-beverage consumers in NHANES). In both data sets, compared with CS- and LCS & CS–beverage profiles, consumers of LCS beverages had higher percentages of energy from fruit and vegetables and RTE cereal. In Homescan, compared with non/low consumers, LCS-beverage consumers had a higher percentage of energy from CS desserts, whereas LCS-beverage consumers in NHANES reported a lower percentages of energy from CS desserts.

DISCUSSION

In the context of emerging evidence from both human and animal studies that the consumption of sweeteners, and more recently LCS, may be associated with increased health risks, we found that consumers of any sweetened beverage—LCS, CS, or a combination of the two—are less likely to follow either prudent or breakfast food-purchasing and consumption patterns. This lower adherence was greatest among beverage profiles that

TABLE 4
Comparison of food group patterns by beverage consumption profile in the Homescan and NHANES populations[1]

Food groups	Homescan household purchases				NHANES individual intake			
	Non/low consumers	LCS beverages	CS beverages	LCS & CS beverages	Non/low consumers	LCS beverages	CS beverages	LCS & CS beverages
	% of energy				% of energy			
Juice, sweetened CS	3.11 ± 0.01	2.65 ± 0.01	3.00 ± 0.01	2.87 ± 0.01	4.45 ± 0.10	2.46 ± 0.11[a]	2.89 ± 0.08[b]	2.55 ± 0.17[a,b]
Milk, unsweetened	4.73 ± 0.01[a]	4.44 ± 0.02	4.75 ± 0.01[a]	4.52 ± 0.01	5.32 ± 0.11	3.45 ± 0.13[a]	3.55 ± 0.10[a]	3.14 ± 0.16[a]
Cooking fats/oils	7.29 ± 0.01	7.14 ± 0.02	7.44 ± 0.02	7.23 ± 0.02	0.93 ± 0.03[b]	0.75 ± 0.04[a]	0.91 ± 0.03[b]	0.79 ± 0.05[a,b]
Nuts	2.31 ± 0.01	2.49 ± 0.02	1.88 ± 0.01	2.09 ± 0.01	2.28 ± 0.08[b]	2.06 ± 0.13[a,b]	1.51 ± 0.08[c]	1.70 ± 0.19[a,c]
Protein groups	6.05 ± 0.01	6.34 ± 0.02	6.20 ± 0.01	6.29 ± 0.01	12.56 ± 0.17	14.79 ± 0.35[a]	14.11 ± 0.23[a]	14.35 ± 0.36[a]
Fruit and vegetables	3.16 ± 0.01	3.08 ± 0.01	2.71 ± 0.01	2.82 ± 0.01	6.30 ± 0.11	5.14 ± 0.16	3.99 ± 0.08[a]	3.91 ± 0.16[a]
RTE and fast-food meals	8.05 ± 0.02	8.14 ± 0.02	8.39 ± 0.02	8.31 ± 0.02	19.87 ± 0.26	23.25 ± 0.48[b]	24.93 ± 0.3[a]	24.85 ± 0.65[a,b]
Potatoes	1.72 ± 0.00[a]	1.71 ± 0.01[a]	1.90 ± 0.01	1.85 ± 0.00	3.06 ± 0.08	3.78 ± 0.18	4.35 ± 0.11[a]	4.64 ± 0.23[a]
Grains	6.06 ± 0.01	5.77 ± 0.02	5.71 ± 0.02[a]	5.69 ± 0.01[a]	11.16 ± 0.15[b]	10.62 ± 0.23[a,b]	10.18 ± 0.16[a]	10.29 ± 0.26[a]
RTE cereal, sweetened CS	4.87 ± 0.01	4.78 ± 0.02	4.53 ± 0.02	4.63 ± 0.01	3.82 ± 0.09[b]	3.52 ± 0.13[b]	2.79 ± 0.09[a]	2.79 ± 0.15[a]
Salty snacks	2.61 ± 0.01	2.86 ± 0.01[a]	2.71 ± 0.01	2.83 ± 0.01[a]	3.95 ± 0.08	5.43 ± 0.18[a]	4.81 ± 0.10[a]	5.61 ± 0.26
Desserts/sweeteners, LCS	0.74 ± 0.00	1.13 ± 0.01	0.55 ± 0.01	0.78 ± 0.00	0.42 ± 0.03[a]	0.75 ± 0.07[b]	0.27 ± 0.02	0.59 ± 0.12[a,b]
Desserts/sweeteners, CS	32.27 ± 0.03	32.58 ± 0.04	33.46 ± 0.04	33.33 ± 0.03	12.63 ± 0.18[b]	11.51 ± 0.31[a]	13.20 ± 0.21[b]	12.85 ± 0.44[a,b]

[1] All values are means ± SEMs. Multivariable longitudinal linear regression random-effects models were adjusted for year, race, income, and household size (Homescan), and multivariable linear regression models were adjusted for year, age, sex, race, and income (NHANES). Estimates in the same row with different superscript letters are significantly different at the 5% level (Bonferroni-adjusted Student's *t* test). CS, calorie sweetened; Homescan, Nielsen Homescan Panel; LCS, low-calorie sweetened; RTE, ready to eat.

include CS beverages. Adherence to the RTE meals/fast-food pattern was increased only among beverage profiles that included LCS (either LCS or LCS & CS) in Homescan. In NHANES, any sweetened-beverage profile was associated with a higher adherence to the protein/potatoes pattern. In both data sets, compared with non/low consumers, consumers of any type of sweetened beverage had higher total energy from food and energy from total fat and SFA. Also, compared with non/low consumers, consumers of sweetened beverages had higher average energy intakes from purchases or intake of energy-dense food groups, such as salty snacks, fast-food meals, and, in Homescan data, desserts. Importantly, households and individuals purchasing or consuming both LCS and CS beverages had the highest amount of energy per day and the lowest adherence to the prudent and breakfast patterns. Overall, non/low consumers of sweetened beverages had the lowest total energy intake and higher adherence to prudent and breakfast patterns. LCS-beverage consumers had a significantly higher probability of following a prudent+snacks/LCS desserts pattern and had average higher intakes of fruit, vegetables, and nuts compared with the other beverage profiles. Consistent with what we had hypothesized, LCS-beverage consumers seem to follow 2 distinct dietary patterns that are characterized by both high- and low-calorie food groups.

Consumption of CS beverages has been extensively associated with poor health outcomes independently of energy intake and dietary patterns. Some of their attributed effects include incomplete compensatory reduction of intake at subsequent meals, increased insulin response because of a higher glycemic index, and the potential metabolic effects of fructose typically contained in some CS beverages (3, 22–25). Consistent with our results, other studies that examined the effect of CS beverages on overall diet have found positive associations with nonbeverage calories, lower intakes of fruit and vegetables, and higher intakes of fast foods and snacks (4, 26–28). Through the aforementioned direct and indirect effects, CS beverages are potential sources of excess calories and currently constitute one of the major public health targets to improve dietary quality and health in the US population (29).

Despite the fact that LCS in foods and beverages help reduce the sugar and calorie contents of products, widespread controversy still exists regarding the consumption of LCS beverages and its effects on metabolic health (23, 25). Some researchers suggested different effects of LCS, such as enhanced sweetness preference, disrupted biochemical pathways that control hunger and satiety, and increased insulin concentration after preloads of aspartame (8–10). Although several large epidemiologic studies have found an increased risk of diabetes and metabolic syndrome (22, 30–32), residual confounding and reverse causality were hypothesized to explain such effects (7, 33). A cohort analysis of the Health Professionals study found that adjustment for BMI and diet strongly attenuated a previously significant LCS-beverage effect on type 2 diabetes (6). However, a recent study found an increased risk of type 2 diabetes even after adjustment for BMI, energy intake, and dietary patterns (11). Another study found that dietary patterns rather modify the association between LCS beverage intake and the risk of health outcomes. Those consuming LCS beverages in the context of a prudent-style diet had a reduced risk of cardiometabolic outcomes (4). Results from a recent short-term randomized controlled trial found that those randomly assigned to substitute CS beverages with water or LCS beverages did not increase their overall energy intake or their calories from sweets or desserts compared with water (34). In relation to food-purchasing patterns, a cross-sectional study in the Homescan population found that, among single-person households in 1999, those that purchased LCS beverages made better nutrition choices regarding the energy content of foods compared with CS-beverage consumers (35). Our study showed that, compared with non/low consumers, consumers of LCS beverages had a lower probability of following a prudent pattern but a higher adherence to an RTE meals/fast-food pattern. Also, LCS-beverage consumers had an especially high probability of following a pattern characterized by healthy food groups such as fruit and vegetables, but also salty snacks and desserts with LCS. Clearly more research is needed to establish the biochemical pathways that can directly relate LCS with obesity and health outcomes. However, we have identified potential dietary patterns that link LCS consumption to increased energy intake and poor dietary quality, which could indirectly mediate the effects of LCS beverages on overall health.

We approached this topic from 2 different perspectives, one looking at the long-term household purchasing patterns and the other looking at the overall individual diet. Household-level food-purchasing surveys such as Homescan are useful data sets to study home food availability, and, although Homescan does not provide measures of an individual's food intake, it still captures the wide variability in the home food patterns that the members of the households are exposed to (36, 37). In this context it is difficult to know, within a household that purchases both LCS and CS beverages, which person in the household is consuming LCS or CS beverages. However, regardless of the actual eating patterns of each household member, we found that households purchasing any type of sweetened beverage are more likely to be exposed to worse dietary patterns. Unlike other studies, we were able to identify sweeteners using ingredients lists in the Homescan data set. For NHANES, we rely on the food description and the awareness of each person in their self-reported dietary intake to determine whether a product has LCS or CS. Moreover, Homescan captures long-term usual patterns by including measures of purchases over 10 mo and up to 10 y. However, Homescan does not capture food and drinks purchased from fast-food chains and other restaurants, which might have resulted in an underestimate of sweetened-beverage consumption, in general, as well as total energy and macronutrient intakes. NHANES, though, represents cross-sectional patterns of eating that reflect not only home eating but also away-from-home eating. Although we were unable to include either nonstore sources of foods or random weight products without bar codes (eg, loose fruit, vegetables, and nuts), packaged foods still constitute a high percentage of the total energy purchase and intake (15). In addition, the application of dietary-pattern techniques to nutritional epidemiology studies offers unique advantages, such as the identification of combinations of food groups that are typically consumed together and better represent the eating behaviors of a population (38, 39). Factor analysis is a data-driven method that is particularly valid for studies that aim to identify the major dietary patterns of a particular sample and to reproduce these dietary patterns longitudinally (38). However, factor analysis involves subjectivity in creating the final food groups and when retaining and naming the resulting factors. Also, we could not separate different types of grains, fats, or protein groups, so that patterns with those groups, such as the prudent pattern, might be more or less healthy depending on the household food choices. On the other hand, in both Homescan and NHANES we encountered several sources of bias. Households that participate in Homescan must scan all groceries at home, so the process of recording the data might be time consuming, which could result in the underreporting of data. Despite the potential for misreporting errors, several reports pointed out that the overall accuracy of the data set is consistent with other economic data sets (40, 41). Dietary intake surveys are not exempt from both random and systematic bias. By including only 2 days of dietary intake, the NHANES data set might not capture usual intake patterns. Also, given the widespread perception that sweetened beverages and desserts are items that should be reduced in our diets, these food groups could potentially be underreported by both Homescan and NHANES participants, which is a potential explanation of the conflicting results shown in Table 3 (in percentage of energy) from CS desserts between the 2 data sets. Overall, our analyses of associations of dietary patterns do not establish causal effects, and we were unable to disentangle whether the dietary pattern is a determinant of the beverage pattern or vice versa.

Our results have important public health and nutritional implications, particularly given the controversy surrounding consumption of LCS beverages. Despite the common perception that sweetened beverages, particularly CS beverages and more recently LCS beverages, can have a direct effect in the risk of obesity and other cardiometabolic outcomes, this study helped us to understand other ways to indirectly link consumption of LCS and CS beverages with poor diet quality and health. We found that all of the sweetened-beverage consumption profiles were associated with poorer dietary purchasing and dietary intake patterns. LCS-beverage consumers seem to follow 2 different directions, one pattern of purchases consisting of fruit, vegetables, and nuts but also salty snacks and desserts and another pattern characterized by more convenient food groups such as RTE meals and fast foods. Consumers of both LCS and CS beverages, which currently constitute an important proportion of sweetened-beverage consumers, had the highest amount of total daily energy from food sources, SFA, and total fat and the lowest probability of adherence to the prudent and breakfast patterns in both data sets. In conclusion, although causal associations need to be further studied, this study highlights the importance of other food groups that seem to be eaten in combination with sweetened beverages, which need to be taken into consideration in many intervention and policy efforts that aim to reduce calories and improve the quality of the American diet.

We thank the entire University of North Carolina Food Research Program for their assistance. We especially thank Donna Miles for exceptional assistance with the data management and programming, Frances L Dancy for administrative assistance, and David Guilkey for his contributions to reviewing and improving this work.

The authors' responsibilities were as follows—CP and BMP: designed the research (project conception, development of overall research plan, and study oversight) and conducted the research (hands-on conduct of the experiments and data collection); and CP, MAM, SWN, PG-L, and BMP: analyzed the data or performed the statistical analysis and wrote the manuscript (only authors who made a major contribution) and had primary responsibility for the final content. CP, MAM, SWN, PG-L, and BMP had no conflicts of interest of any type with respect to this article. The authors alone are responsible for the content and writing of the manuscript.

REFERENCES

1. Johnston KM, Gustafson P, Levy AR, Grootendorst P. Use of instrumental variables in the analysis of generalized linear models in the presence of unmeasured confounding with applications to epidemiological research. Stat Med 2008;27:1539–56.
2. Sylvetsky AC, Welsh JA, Brown RJ, Vos MB. Low-calorie sweetener consumption is increasing in the United States. Am J Clin Nutr 2012; 96:640–6.
3. Malik VS, Hu FB. Sweeteners and risk of obesity and type 2 diabetes: the role of sugar-sweetened beverages. Curr Diab Rep (Epub ahead of print 31 January 2012) .
4. Duffey KJ, Steffen LM, Van Horn L, Jacobs DR Jr, Popkin BM. Dietary patterns matter: diet beverages and cardiometabolic risks in the longitudinal Coronary Artery Risk Development in Young Adults (CARDIA) Study. Am J Clin Nutr 2012;95:909–15.
5. Anderson GH, Foreyt J, Sigman-Grant M, Allison DB. The use of low-calorie sweeteners by adults: impact on weight management. J Nutr 2012;142:1163S–9S.
6. de Koning L, Malik VS, Kellogg MD, Rimm EB, Willett WC, Hu FB. Sweetened beverage consumption, incident coronary heart disease and biomarkers of risk in men. Circulation. 2012;125:1735–41.
7. de Koning L, Malik VS, Rimm EB, Willett WC, Hu FB. Sugar-sweetened and artificially sweetened beverage consumption and risk of type 2 diabetes in men. Am J Clin Nutr 2011;93:1321–7.
8. Fowler SP, Williams K, Resendez RG, Hunt KJ, Hazuda HP, Stern MP. Fueling the obesity epidemic? Artificially sweetened beverage use and long-term weight gain. Obesity (Silver Spring) 2008;16:1894–900.
9. Anton SD, Martin CK, Han H, Coulon S, Cefalu WT, Geiselman P, Williamson DA. Effects of stevia, aspartame, and sucrose on food intake, satiety, and postprandial glucose and insulin levels. Appetite 2010;55:37–43.
10. Blundell JE, Hill AJ. Paradoxical effects of an intense sweetener (aspartame) on appetite. Lancet 1986;1:1092–3.
11. Fagherazzi G, Vilier A, Saes Sartorelli D, Lajous M, Balkau B, Clavel-Chapelon F. Consumption of artificially and sugar-sweetened beverages and incident type 2 diabetes in the Etude Epidemiologique aupres des femmes de la Mutuelle Generale de l'Education Nationale-European Prospective Investigation into Cancer and Nutrition cohort. Am J Clin Nutr 2013;97:517–23.
12. The Nielsen Co. Nielsen Consumer Panel and retail measurement. Available from: http://wwwnielsencom/us/en/measurement/retail-measurementhtml (cited 1 November 2012).
13. Ng SW, Popkin BM. Monitoring foods and nutrients sold and consumed in the United States: dynamics and challenges. J Acad Nutr Diet 2012;112:41–5.
14. Slining MM, Ng SW, Popkin BM. Food companies' calorie-reduction pledges to improve U.S. diet. Am J Prev Med 2013;44:174–84.
15. USDA ARS, Beltsville Human Nutrition Research Center, Food Surveys Research Group. What we eat in America, NHANES 2007-2008. 2008. Available from: http://www.cdc.gov/nchs/about/major/nhanes/nhanes2007-2008/dr1tot_c.xpt (cited 11 September 2011).
16. USDA ARS, Beltsville Human Nutrition Research Center, Food Surveys Research Group. What we eat in America, NHANES 2009-2010. 2010. Available from: http://www.cdc.gov/nchs/about/major/nhanes/nhanes2009-2010/dr1tot_c.xpt (cited 11 January 2012).
17. USDA ARS, Beltsville Human Nutrition Research Center, Food Surveys Research Group. What we eat in America, NHANES 2005-2006. 2005. Available from: http://www.cdc.gov/nchs/about/major/nhanes/nhanes2005-2006/dr1tot_c.xpt (cited December 2011).
18. USDA ARS, Beltsville Human Nutrition Research Center, Food Surveys Research Group. What we eat in America, NHANES 2003-2004. 2003. Available from: http://www.cdc.gov/nchs/about/major/nhanes/nhanes2003-2004/dr1tot_c.xpt (cited December 2011).
19. USDA. The USDA food and nutrient database for dietary studies. 4.1. Documentation and user guide. Beltsville, MD: USDA, 2010.
20. Ng SW, Slining MM, Popkin BM. Use of caloric and noncaloric sweeteners in us consumer packaged foods, 2005-2009. J Acad Nutr Diet. 2012;112:1828–34.
21. DiStefano C, Zhu M, Mindrila D. Understanding and using factor scores: considerations for the applied researcher. Pract Assess Res Eval 2009;14:1–11.
22. Malik VS, Schulze MB, Hu FB. Intake of sugar-sweetened beverages and weight gain: a systematic review. Am J Clin Nutr 2006;84:274–88.
23. Mattes R. Effects of aspartame and sucrose on hunger and energy intake in humans. Physiol Behav 1990;47:1037–44.
24. Mattes R. Fluid calories and energy balance: the good, the bad, and the uncertain. Physiol Behav 2006;89:66–70.
25. Mattes RD, Popkin BM. Nonnutritive sweetener consumption in humans: effects on appetite and food intake and their putative mechanisms. Am J Clin Nutr 2009;89:1–14.
26. Mrdjenovic G, Levitsky DA. Nutritional and energetic consequences of sweetened drink consumption in 6- to 13-year-old children. J Pediatr 2003;142:604–10.
27. Frary CD, Johnson RK, Wang MQ. Children and adolescents' choices of foods and beverages high in added sugars are associated with intakes of key nutrients and food groups. J Adolesc Health 2004;34:56–63.
28. Mathias KC, Slining MM, Popkin BM. Foods and beverages associated with higher intake of sugar-sweetened beverages. Am J Prev Med 2013;44:351–7.
29. Elbel B, Cantor J, Mijanovich T. Potential effect of the New York City policy regarding sugared beverages. N Engl J Med 2012;367:680–1.
30. Nettleton JA, Lutsey PL, Wang Y, Lima JA, Michos ED, Jacobs DR Jr. Diet soda intake and risk of incident metabolic syndrome and type 2 diabetes in the Multi-Ethnic Study of Atherosclerosis (MESA). Diabetes Care 2009;32:688–94.
31. Lutsey PL, Steffen LM, Stevens J. Dietary intake and the development of the metabolic syndrome: the Atherosclerosis Risk in Communities study. Circulation 2008;117:754–61.
32. Dhingra R, Sullivan L, Jacques PF, Wang TJ, Fox CS, Meigs JB, D'Agostino RB, Gaziano JM, Vasan RS. Soft drink consumption and risk of developing cardiometabolic risk factors and the metabolic syndrome in middle-aged adults in the community. Circulation 2007; 116:480–8.
33. Elfhag K, Tynelius P, Rasmussen F. Sugar-sweetened and artificially sweetened soft drinks in association to restrained, external and emotional eating. Physiol Behav 2007;91:191–5.
34. Arellano M, Bond S. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev Econ Stud 1991;58:277–97.
35. Binkley J, Golub A. Comparison of grocery purchase patterns of diet soda buyers to those of regular soda buyers. Appetite 2007;49:561–71.
36. Harris JM. Using Nielsen Homescan data and complex design techniques to analyze convenience food expenditures. Milwaukee, WI: American Agricultural Economics Association, 2005.
37. Fan JX, Brown BB, Kowaleski-Jones L, Smith KR. Household food expenditure patterns: a cluster analysis. Mon Labor Rev 2007;130:38.
38. Michels KB, Schulze MB. Can dietary patterns help us detect diet-disease associations? Nutr Res Rev 2005;18:241–8.
39. Jacques PF, Tucker KL. Are dietary patterns useful for understanding the role of diet in chronic disease? Am J Clin Nutr 2001;73:1–2.
40. Einav L, Leibtag E, Nevo A. On the accuracy of Nielsen Homescan data. Washington, DC: US Department of Agriculture, Economic Research Service, 2008.
41. Zhen C, Taylor JL, Muth MK, Leibtag E. Understanding differences in self-reported expenditures between household scanner data and diary survey data: a comparison of Homescan and consumer expenditure survey. Appl Econ Perspect Pol 2009;31:470–92.