Drivers and Points of Intervention for Obesity and Food Insecurity

HARVARD UNIVERSITY
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Drivers and Points of Intervention for Obesity and Food Insecurity

A dissertation presented

by

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Drivers and Points of Intervention for Obesity and Food Insecurity

Abstract

Poor nutrition is a leading cause of disease and death in the United States and around the world. Two key types of poor nutrition are food insecurity (a lack of reliable access to nutritious food) and obesity (excess adiposity). They are both prevalent, costly, and can have serious health consequences. This dissertation focuses on these interrelated public health nutrition issues, using rigorous epidemiological methods to examine their health effects and identify policy and programmatic approaches that may meaningfully reduce their burden in the population.

We first examine the potential impact of voluntary sugar reduction targets for packaged foods and drinks set by the National Salt and Sugar Reduction Initiative. Using nationally representative data from the National Health and Nutrition Examination Survey, we find that the targets are expected to result in meaningful reductions in added sugar intake among children and the initiative is not projected to widen existing diet-related disparities. Next, we examine the longitudinal relationship between food insufficiency – a screener measure related to food insecurity – and cardiovascular disease risk factors using data from the Coronary Artery Risk Development in Young Adults Study. We find that experiencing food insufficiency appears to worsen health over time, particularly among women and for obesity-related measures such as BMI and waist circumference. Finally, we leverage administrative data from the Massachusetts Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) to examine shopping patterns related to redemption of food package benefits. We find that retail-based initiatives may need to target a wide range of store types in order to reach all WIC households and that efforts aimed at improving redemption may be especially important for WIC shoppers relying on superstores.

While the focus and scope of these papers varies, they each identify drivers and points of intervention for food insecurity and obesity. This work underscores the importance of conducting epidemiological research to aid in the development of policies and programs to reduce the burden of food insecurity and obesity in the population.

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Dedication

This work is dedicated to my parents, who filled my childhood with opportunities to gain new knowledge, inspiring my love for learning and science. They also instilled in me a commitment to make the world a better place, motivating my desire to study public health.

List of Tables and Figures

Chapter 1: Introduction

Poor nutrition is a leading cause of disease and death in the United States (U.S.) and around the world.[1] Two key types of poor nutrition are food insecurity (a lack of reliable access to nutritious food) and obesity (excess adiposity). They are both prevalent, costly, and can result in serious health consequences. Moreover, they are largely preventable. In 2019, one in ten households in the U.S. experienced food insecurity – a problem that has more than doubled due to the COVID-19 pandemic.[2-4] A fifth of American children currently have obesity and a majority (57%) are projected to have obesity by the time they are age 35.[5,6] Both food insecurity and obesity disproportionately impact low-income populations and racial/ethnic minorities,[2,5,7] an important consideration as the U.S. becomes an increasingly diverse nation. Food insecurity is linked to poor physical and mental health,[8] while obesity has long been associated with heightened risk of cardiovascular disease, type 2 diabetes, some cancers, and a host of other adverse health outcomes.[9-11] Consequently, food insecurity is estimated to cost the health system $53 billion annually and the direct medical costs of obesity are about $150 billion each year.[12,13] This dissertation focuses on the interrelated public health nutrition issues of food insecurity and obesity, using rigorous epidemiological methods to examine their health effects and identify policy and programmatic approaches that may meaningfully reduce their burden in the population.

Chapter 2 examines the potential impact of voluntary sugar reduction targets for packaged foods and drinks. These targets, set by the National Salt and Sugar Reduction Initiative (NSSRI) and released in 2021, are intended to complement existing policy and programmatic efforts aimed at reducing U.S. added sugar intake (e.g., sugar-sweetened beverage excise taxes). Given that excessive added sugar intake is linked to weight gain, reducing added sugar intake among youth is critical to achieving a healthier generation and reducing the nation's burden of obesity. Using nationally representative data from the National Health and Nutrition Examination Survey, we describe trends in added sugar intake from NSSRI foods and beverages among children and estimate possible reductions in added sugar intake if industry were to meet the targets.

Chapter 3 examines whether experiencing food insufficiency – a screener measure related to food insecurity – worsens cardiovascular health over time. This study contributes to the growing empirical evidence base assessing whether targeting food insecurity could be a viable public health strategy to lower cardiovascular disease (CVD) risk in the population. Using data from the Coronary Artery Risk Development in Young Adults study, we examine longitudinal relationships between food insufficiency and several CVD risk factors, such as waist circumference and blood pressure.

Chapter 4 examines shopping patterns related to food package redemption among participants in the Massachusetts Special Supplemental Nutrition Program for Women, Infants, and Children (WIC). This knowledge is critical to inform efforts to maximize redemption, and thus maximize the positive impacts of WIC on children's health and development. Leveraging administrative data provided by WIC, we describe where Massachusetts WIC households redeem their food benefits, as well as variations in the extent of benefit redemption depending on a household's preferred WIC store type.

While the focus and scope of the papers vary, they each identify drivers and points of intervention for food insecurity and obesity. This work underscores the importance of conducting rigorous epidemiological research to aid in the development of policies and programs aimed at reducing the population burden of food insecurity and obesity.

Chapter 2:

Estimated reductions in added sugar intake among U.S. youth in response to sugar reduction targets for packaged foods and beverages

2.1 ABSTRACT

Introduction: In 2021, the National Salt and Sugar Reduction Initiative (NSSRI) released voluntary sugar reduction targets for packaged foods and drinks in the United States (U.S). The objectives of this study are to describe trends in added sugar intake from NSSRI foods and beverages among youth and estimate possible reductions if industry were to meet the targets.

Methods: We used data on U.S. youth aged 2–19 years from eight survey cycles (2003–2004 to 2017–2018) of the National Health and Nutrition Examination Survey (NHANES). Foods and beverages reported by participants were mapped to one of the NSSRI's categories or coded as a non-NSSRI item. Trends over time in added sugar intake were assessed using regression models. To assess possible reductions in added sugar intake if industry were to meet the targets, sales-weighted mean percent reductions for 2023 and 2026 were applied to NSSRI items in the 2017–2018 NHANES data. Subgroup analyses were conducted to compare differences by demographic characteristics.

Results: From 2003–2004 to 2017–2018, added sugar intake from NSSRI foods and beverages declined, but consumption remained high. In 2017–2018, NSSRI categories accounted for 70% of added sugar intake. If industry were meeting the NSSRI targets, U.S. youth would consume 7% (2023 targets) to 21% (2026 targets) less added sugar. Findings were similar across race/ethnicity, family income, and parental educational attainment.

Conclusion: The NSSRI targets are expected to result in meaningful reductions in added sugar intake and the initiative is not projected to widen existing disparities.

2.2 INTRODUCTION

Added sugar intake among children and adolescents in the United States (U.S.) is high, with 65% not meeting the 2020–2025 Dietary Guidelines for Americans' (DGA) recommendation to limit added sugar to less than 10% of total energy intake.[14] A large body of research links added sugar intake to adverse health outcomes including weight gain, diabetes, cardiovascular disease risk factors, and dental caries.[15] Reducing added sugar intake among youth is critical to achieving a healthier generation and reducing the nation's burden of diet-related diseases.[15-17]

Excessive intake of added sugar is driven by many factors, including the widespread availability of sweetened food and beverages, the high sugar content of these products, and their ubiquitous marketing.[18-20] Thus, a meaningful reduction in added sugar in the U.S. population will likely require a suite of complementary, multi-level strategies, which could include governmental policy, consumer education and counter-marketing, and industry efforts to reduce added sugar in the food supply. In recent years, some progress has been made to implement sugar-reduction policies. For example, in 2016, the Food and Drug Administration published final rules on the Nutrition Facts label, which includes new information about added sugars.[21] In the same year, the U.S. Department of Agriculture published final rules on Nutrition Standards for Foods Sold in Schools, which prohibit the sale of sugary drinks and set sugar limits on snack foods.[22] There has also been momentum in select states and municipalities, including sugar-sweetened beverage (SSB) excise taxes[23] and healthy beverage ordinances requiring restaurants to offer only healthy beverages instead of SSBs with children's meals.[24-26] These measures, together with growing media and public recognition of harms of SSBs in particular, have likely contributed to gradually declining added sugar consumption among U.S. children and adults.[27,28]

However, these declines are largely attributable to reductions in SSB intake (which still remains high), while decreases in added sugar from foods have been much smaller.[27,28]

The National Salt and Sugar Reduction Initiative (NSSRI) is a partnership of more than 100 local, state, and national health groups convened by the New York City Department of Health and Mental Hygiene ("Health Department") to encourage reductions in sodium and sugar in packaged foods. By creating changes at the level of the food supply, the initiative seeks to make it easier for all individuals to access healthier options, an upstream approach that may mitigate existing disparities in diet-related diseases.[29,30] Through analysis of national sales data, nutrition information, meetings with industry, and two public comment periods, the NSSRI developed voluntary sugar reduction targets for industry across 15 categories of packaged foods and drinks.[30] The creation of sugar reduction targets was based on the demonstrated success of the National Salt Reduction Initiative,[30] which itself was modeled on the United Kingdom's approach to reducing sodium.[31] Compared to total sugar levels in 2018 as the baseline, the 2023 sugar reduction targets are a 10% reduction in total sugar per 100 grams of the highest selling food and drink products, while the 2026 targets are a 20% reduction in total sugar per 100 grams for foods and 40% for drinks. Industry is encouraged to meet NSSRI targets; to do so, the mean sugar density of a company's products must be at or below the target. Companies can influence mean total sugar per 100 grams by reformulating existing products to be lower in total sugar, increasing sales of lower total sugar products, and introducing new, lower total sugar products.[32]

The public health impact of the NSSRI relies on whether and to what extent the targets capture major sources of added sugar in the U.S. diet. It is also of importance to document temporal trends in consumption of NSSRI foods and beverages prior to the initiative launch – understanding whether added sugar intake from NSSRI items is already changing will inform future evaluation efforts and may help identify and prioritize NSSRI foods and beverages for which added sugar intake is not already decreasing over time.

Thus, the objectives of this study were to use nationally representative data to: (1) describe trends in added sugar intake from NSSRI foods and beverages among children and adolescents aged 2–19 years between 2003–2004 and 2017–2018; (2) document to what extent food and drinks included in the NSSRI account for added sugar intake in the most recent years of data (2017–2018); and (3) estimate possible reductions in added sugar intake if industry had met the NSSRI sugar reduction targets in the most recent years of data (2017–2018). In order to understand potential effects that the initiative may have on diet-related disparities, we examined differences in the results for these aims by sociodemographic characteristics.

2.3 METHODS

Data and Study Population

This study pooled data from eight survey cycles (2003–2004 to 2017–2018) of the National Health and Nutrition Examination Surveys (NHANES), a repeated cross-sectional study released every two years and designed to represent the U.S. non-institutionalized population.[33] The study sample consisted of participants aged 2–19 years with complete data on all covariates and a valid first 24-hour dietary recall. While the NHANES administered two 24-hour dietary recalls, we limited our analysis to the first 24-hour recall to preserve sample size for subgroup analyses. A single 24-hour recall is sufficient to provide an estimate of *mean* intake in a population, while multiple 24-hour recalls are needed if estimating the *distribution* of intake.[34,35] Thus, since our study objective was to examine mean added sugar intake (and not the distribution of added sugar intake), it was appropriate to use a single 24-hour recall.[36] Because this study analyzed de-identified publicly available data, it does not constitute human subjects research and Institutional Review Board approval was not required.

Measures

Added Sugar Intake: Survey respondents reported all foods and beverages consumed in the previous 24-hour period, specifying the type, quantity, and source of each intake occasion. Responses for participants aged 2 to 11 years were provided or assisted by a parent/guardian, while participants aged 12 years and older responded independently. All reported foods and beverage items were systematically coded using the USDA Food and Nutrient Database for Dietary Studies (FNDDS) to obtain total calories and the Food Patterns Equivalents Database (FPED) to obtain added sugar. Given declines in reported energy intake over time in NHANES and concerns about measurement error,[37,38] our trends analyses were energy-adjusted by using percent of daily calories from added sugar as the primary outcome. We also examined grams of added sugar as a secondary outcome, energy-adjusted by including total calories as a continuous covariate in regression models.

NSSRI Categories*:* Methods used to develop the NSSRI targets are described in detail in **Supplementary Text 2.1**. Briefly, the NSSRI includes 15 packaged food and beverage categories aggregated to form seven meta-categories. Baseline sales-weighted mean (SWM) sugar density (grams of sugar per 100g of food or per 100mL of beverage) was calculated for each category using U.S. sales and nutrition data. SWM sugar density was calculated by dividing each product's sugar content in grams by its weight in 100-gram units (or volume in 100-milliliter units for liquids) and multiplying by the product's percent unit sales in the category.

The FNDDS codes corresponding to foods and beverages reported by NHANES participants were hand coded as a non-NSSRI item or mapped to one of the NSSRI's 15 food and beverage categories using added sugar amounts and item descriptions. This coding was checked by two authors and any discrepancies were discussed as a team. Because the NSSRI sets targets for packaged foods and beverages, we restricted our definition of NSSRI items to those reported by participants to be acquired from stores (grocery, supermarket, and convenience stores) or vending machines. Foods in NSSRI categories acquired from other sources (e.g., restaurants) were considered non-NSSRI foods. We allowed sugary beverages to be obtained from any source.

Covariates: To adjust for potential demographic shifts over time, analyses included the following covariates: age group (2–5 years, 6–11 years, 12–19 years), sex (male, female), race/ethnicity (non-Hispanic White, non-Hispanic Black, Mexican American, non-Mexican Hispanic, other race/ethnicity), family income (lower income, higher income), and parental educational attainment (lower education, higher education). Other race/ethnicity included individuals reporting a race other than White or Black or individuals reporting multi-racial identity. The other race/ethnicity category was primarily comprised of non-Hispanic Asian participants, a racial/ethnic category that NHANES only began distinguishing in 2011–2012. Lower income was defined as <130% of the Federal Poverty Line, while higher income was defined as ≥130% of the Federal Poverty Line. Lower education was defined as less than a college graduate, while higher education was defined as more than a college graduate.

Analyses

Trends analyses: All analyses were weighted to account for the multistage, clustered probability sampling of the NHANES. We conducted linear regressions to estimate the percent of daily calories from added sugar for each NSSRI category and meta-category over time. In these models, the primary outcome was percent of daily calories from added sugar from each NSSRI category and meta-category and covariates were a categorical survey year term, age group, sex, race/ethnicity, family income, and parental educational attainment. To obtain trend estimates within subgroups, separate models were fitted within each subgroup, adjusting for all other covariates.

To analyze the statistical significance of trends over time, models were fit with a continuous survey year term. To assess potential non-linearity in trends over time, quadratic and cubic year terms were also included as covariates, and we performed a joint Wald test of the quadratic and cubic terms. If the test was statistically significant, we reported the results from this model. If not, we concluded there was no evidence of non-linearity, and a model including only a linear term was fitted and the results from this model were reported. To account for multiple testing, we applied a Bonferroni correction wherein a p-value of <0.001 was considered statistically significant.

Trends analyses with secondary outcomes (added sugar intake in grams and total quantity of foods or beverages in grams) were conducted in an analogous manner.

<u>Estimated reductions</u>*:* Methods used to estimate reductions in added sugar intake if industry had met the 2023 and 2026 targets in 2017–2018 are described in detail in **Supplementary Text 2.2**. Briefly, following the approach of a previous study,[39] we calculated the ratio of the target SWM sugar to baseline SWM sugar for each NSSRI category, then multiplied this ratio by the amount of added sugar reported in that category for each participant. We used descriptive statistics (means, percent change) to summarize added sugar intake pre-NSSRI (2017–2018 data) and under 2023 and 2026 targets, overall and by subgroup.

Sensitivity Analyses: We conducted two sensitivity analyses related to allowable food sources for NSSRI items. The first sensitivity analysis only allowed sugary beverages acquired from stores and vending machines to be considered an NSSRI item, taking a more conservative approach and assuming no reformulation of beverages from non-store sources. The second sensitivity analysis placed no restrictions on food or beverage sources, taking a less conservative approach and assuming total reformulation of foods and beverages from all sources.

All analyses were conducted in 2020 using Stata, version 14.2.

2.4 RESULTS

The final analytic sample included 23,248 children and adolescents. **Table 2.1** reports unweighted sample sizes and proportions by demographic characteristics.

Table 2.1: Sample characteristics of children aged 2–19 years in the NHANES 2003–2004 to 2017–2018 (n=23,248)

Characteristic	N (%)
Sex	
Male	11,722 (50%)
Female	11,526 (50%)
Age	
2–5-years	5,522 (24%)
6–11-years	7,528 (32%)
12–19-years	10,198 (44%)
Race/Ethnicity	
Non-Hispanic White	6,915 (30%)
Non-Hispanic Black	6,256 (27%)
Mexican American	5,750 (25%)
Non-Mexican Hispanic	1,922 (8%)
Other Race/Ethnicity[1]	2,405 (10%)
Household Income[2]	
Lower income	10,311 (44%)
Higher income	12,937 (56%)
Parental Educational Attainment[3]	
Lower education	18,846 (81%)
Higher education	4,402 (19%)

[1]Other race/ethnicity included individuals reporting a race other than White or Black, including Asians, or individuals reporting multi-racial identity.
[2]Lower income was defined as an annual family income <130% of the federal poverty line, while higher income was defined as an annual family income ≥130% of the federal poverty line.
[3]Lower education was defined as child's parent respondent being less than a college graduate, while higher education was defined as child's parent respondent being a college graduate or above.

Between 2003–2004 and 2017–2018, added sugar intake from all NSSRI foods and beverages as a percent of daily calories declined (14.0% to 10.4%, p-for-trend<0.001), driven primarily by a reduction in percent calories from added sugar in drinks (9.0% to 5.8%, p-for-trend<0.001) (**Table 2.2)**. There was also a decrease over time in percent calories from added sugar for NSSRI foods (5.0% to 4.6%, p-for-trend<0.001), although many of the individual food categories did not experience a significant decrease. Trends were similar when examining grams of added sugar from NSSRI items as the outcome (**Supplementary Table 2.1**). There was also a decline in the quantity (total grams) of NSSRI foods and drinks consumed by participants (**Supplementary Table 2.2)**.

Between 2003–2004 and 2017–2018, added sugar as a percent of total calories from NSSRI items declined significantly across all age groups, most racial/ethnic groups, lower and higher income families, and those whose parents had both lower and higher educational attainment (**Table 2.3**). Across all years, 2–5-year-olds had the lowest percent intake of added sugar from NSSRI categories, while 12–19-year-olds had the highest intake. With respect to race/ethnicity, non-Hispanic White and Black children had the highest percent intake of added sugar from NSSRI categories across all years.

Table 2.2: Trends in added sugar intake as a percent of total energy intake[1] from each National Salt and Sugar Reduction Initiative category, meta-category, and all categories combined between 2003–2004 and 2017–2018 for children in the NHANES

	2003–2004	2005–2006	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016	2017–2018	p-value for linear trend[2]
All NSSRI Sugar Categories Combined	14.0 (13.1, 15.0)	13.0 (12.4, 13.6)	12.8 (12.0, 13.6)	12.1 (11.4, 12.8)	11.4 (11.0, 11.8)	11.2 (10.4, 12.0)	9.9 (9.4, 10.4)	10.4 (9.7, 11.1)	<0.001
All NSSRI Foods Combined (not Drinks)	5.0 (4.7, 5.3)	5.1 (4.8, 5.3)	4.9 (4.6, 5.3)	4.6 (4.3, 4.9)	4.2 (4.1, 4.4)	4.7 (4.4, 5)	4.3 (4.0, 4.6)	4.6 (4.2, 5.1)	<0.001
1. Drinks	9.0 (8.2, 9.8)	7.9 (7.3, 8.5)	7.9 (7.1, 8.6)	7.5 (6.9, 8.1)	7.2 (6.8, 7.6)	6.5 (5.7, 7.3)	5.5 (5.1, 5.9)	5.8 (5.3, 6.3)	<0.001
1.1 Sugary drinks	8.6 (7.8, 9.4)	7.6 (7, 8.1)	7.5 (6.8, 8.3)	7.0 (6.4, 7.7)	6.9 (6.4, 7.3)	6.2 (5.4, 7.1)	5.3 (4.9, 5.7)	5.5 (5.1, 6.0)	<0.001
1.2 Sweetened milk	0.4 (0.3, 0.4)	0.2 (0.2, 0.3)	0.3 (0.2, 0.4)	0.4 (0.3, 0.5)	0.3 (0.2, 0.4)	0.2 (0.2, 0.3)	0.2 (0.2, 0.3)	0.2 (0.1, 0.3)	0.001
1.3 Sweetened milk substitute	0 (0, 0)	0.1 (0, 0.1)	0 (0, 0.1)	0 (0, 0.1)	0.1 (0, 0.1)	0 (0, 0.1)	0 (0, 0.1)	0 (0, 0.1)	0.420
2. Grain-Based Desserts and Snack Bars	1.4 (1.2, 1.5)	1.6 (1.3, 1.8)	1.5 (1.3, 1.7)	1.5 (1.4, 1.6)	1.6 (1.4, 1.7)	1.5 (1.3, 1.8)	1.6 (1.4, 1.7)	1.5 (1.3, 1.8)	0.335
2.1 Breakfast pastries	0.4 (0.3, 0.4)	0.5 (0.4, 0.6)	0.5 (0.4, 0.6)	0.5 (0.4, 0.6)	0.5 (0.4, 0.6)	0.4 (0.3, 0.5)	0.5 (0.3, 0.6)	0.4 (0.3, 0.5)	0.460
2.2 Cakes	0.5 (0.3, 0.6)	0.5 (0.4, 0.6)	0.5 (0.3, 0.6)	0.4 (0.3, 0.5)	0.4 (0.2, 0.5)	0.4 (0.3, 0.5)	0.4 (0.3, 0.5)	0.5 (0.3, 0.7)	0.523
2.3 Cookies	0.4 (0.3, 0.5)	0.5 (0.4, 0.5)	0.4 (0.3, 0.5)	0.5 (0.4, 0.5)	0.6 (0.5, 0.7)	0.5 (0.4, 0.6)	0.5 (0.5, 0.6)	0.5 (0.4, 0.6)	0.012
2.5 Granola bars	0.1 (0.1, 0.1)	0.1 (0.1, 0.1)	0.1 (0.1, 0.1)	0.1 (0.1, 0.2)	0.2 (0.1, 0.2)	0.2 (0.1, 0.2)	0.1 (0.1, 0.2)	0.1 (0.1, 0.2)	0.015

Table 2.2 (Continued)

	2003–2004	2005–2006	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016	2017–2018	p-value for linear trend[2]
3. Refrigerated & Frozen Desserts[3]	0.9 (0.7, 1.2)	1.0 (0.8, 1.2)	1.1 (0.8, 1.3)	0.8 (0.7, 0.9)	0.5 (0.4, 0.6)	0.6 (0.5, 0.7)	0.6 (0.5, 0.7)	0.6 (0.5, 0.8)	<0.001
4. Candies	1.0 (0.8, 1.2)	0.8 (0.7, 0.9)	0.8 (0.7, 0.9)	0.7 (0.6, 0.8)	0.6 (0.5, 0.7)	1.0 (0.8, 1.1)	0.7 (0.6, 0.8)	0.8 (0.6, 0.9)	0.036
4.1 Sweet candies	0.6 (0.5, 0.7)	0.5 (0.4, 0.6)	0.5 (0.4, 0.6)	0.4 (0.3, 0.4)	0.3 (0.3, 0.4)	0.7 (0.6, 0.8)	0.4 (0.3, 0.5)	0.6 (0.5, 0.7)	0.699
4.2 Chocolate candies	0.4 (0.3, 0.5)	0.3 (0.3, 0.4)	0.3 (0.3, 0.4)	0.3 (0.2, 0.4)	0.2 (0.2, 0.3)	0.3 (0.2, 0.5)	0.3 (0.2, 0.3)	0.2 (0.1, 0.3)	0.003
5. Breakfast Cereals[3]	1.1 (1, 1.2)	1.0 (0.9, 1.1)	0.9 (0.8, 1.0)	1.0 (0.8, 1.1)	0.9 (0.8, 0.9)	0.9 (0.8, 1.0)	1 (0.9, 1.1)	1 (0.9, 1.1)	0.084
6. Condiments and Toppings	0.4 (0.3, 0.5)	0.5 (0.4, 0.6)	0.4 (0.3, 0.6)	0.4 (0.3, 0.5)	0.5 (0.3, 0.7)	0.5 (0.4, 0.5)	0.4 (0.3, 0.6)	0.6 (0.4, 0.7)	0.067
6.1 Condiments	0.1 (0.1, 0.1)	0.1 (0.1, 0.1)	0.1 (0.1, 0.1)	0.1 (0.1, 0.1)	0.1 (0.1, 0.1)	0.1 (0.1, 0.2)	0.1 (0.1, 0.1)	0.2 (0.1, 0.2)	0.057
6.2 Dessert syrups and toppings	0.3 (0.2, 0.4)	0.4 (0.3, 0.4)	0.3 (0.2, 0.4)	0.3 (0.2, 0.4)	0.4 (0.2, 0.6)	0.3 (0.3, 0.4)	0.3 (0.2, 0.5)	0.4 (0.3, 0.6)	0.170
7. Yogurt[3]	0.2 (0.1, 0.3)	0.2 (0.2, 0.3)	0.2 (0.1, 0.2)	0.3 (0.2, 0.3)	0.2 (0.2, 0.3)	0.2 (0.2, 0.3)	0.1 (0.1, 0.1)	0.1 (0.1, 0.2)	0.006
Non-NSSRI Items	3.6 (3.4, 3.9)	4.2 (3.9, 4.5)	4.3 (4, 4.5)	4.4 (4.2, 4.7)	4.7 (4.3, 5.1)	4 (3.9, 4.2)	4.4 (4, 4.9)	4.3 (4.1, 4.6)	non-linear[4]

[1]Outcome was constructed as (grams of added sugar per day * 4)/(total calories per day)*100%.
[2]To account for multiple testing, we applied a Bonferroni correction wherein a p-value of <0.001 was considered statistically significant.
[3]NSSRI meta category only contains a single category.
[4]Evidence of a non-linear trend in added sugar intake from non-NSSRI items over time, as indicated by statistically significant joint Wald test of the quadratic and cubic terms for survey year ($p<0.001$).
Notes: The margins command in Stata was used to estimate the predicted percent of daily calories from added sugar from each category and meta-category for each survey year, when all other covariates were set to their mean values.

Table 2.3: Trends in added sugar intake as a percent of total energy[1] from all National Salt and Sugar Reduction Initiative categories combined between 2003–2004 and 2017–2018 for children in the NHANES, by sociodemographic characteristics

	2003–2004	2005–2006	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016	2017–2018	p-value for linear trend[2]
Age									
2–5-years	11.1 (10.1, 12.2)	10.4 (9.7, 11.2)	10.2 (9.6, 10.8)	9.5 (9.1, 10.0)	9.7 (9.1, 10.4)	9.2 (8.4, 10.0)	8.1 (7.4, 8.9)	8.8 (7.2, 10.4)	<0.001
6–11-years	13.2 (12.1, 14.3)	11.6 (10.8, 12.4)	12.6 (11.8, 13.5)	11.3 (10.6, 12.0)	11.2 (10.6, 11.7)	10.4 (9.5, 11.3)	9.5 (8.7, 10.3)	10.3 (9.3, 11.4)	<0.001
12–19-years	16.1 (14.8, 17.4)	15.2 (14.4, 16.1)	14.2 (12.9, 15.6)	13.9 (12.5, 15.3)	12.4 (11.6, 13.3)	12.7 (11.4, 14.1)	11.0 (10.2, 11.9)	11.2 (10.1, 12.4)	<0.001
Race/Ethnicity									
Non-Hispanic White	14.4 (13.2, 15.6)	13.5 (12.4, 14.5)	13.4 (12.3, 14.4)	12.5 (11.5, 13.5)	12.1 (11.5, 12.7)	11.6 (10.1, 13.0)	10.1 (9.4, 10.8)	10.8 (9.6, 11.9)	<0.001
Non-Hispanic Black	15.1 (13.7, 16.6)	13.0 (12.1, 14.0)	13.5 (12.7, 14.3)	12.6 (11.5, 13.8)	11.8 (10.7, 13.0)	12.4 (11.2, 13.5)	11.0 (10.2, 11.9)	11.6 (10.8, 12.4)	<0.001
Mexican American	13.8 (12.7, 14.9)	11.9 (10.8, 13.1)	11.7 (10.8, 12.7)	11.8 (10.4, 13.3)	10.2 (9.1, 11.3)	9.6 (9.1, 10.2)	9.5 (8.7, 10.4)	9.5 (8.2, 10.7)	<0.001
Non-Mexican Hispanic	12.2 (9.5, 15.0)	12.3 (10.3, 14.3)	12.2 (9.8, 14.6)	11.5 (10.0, 13.0)	11.8 (10.7, 13.0)	10.7 (9.2, 12.2)	8.6 (7.4, 9.7)	8.1 (7.0, 9.2)	<0.001
Other Race/Ethnicity[3]	11.5 (9.0, 14.0)	12.3 (10.5, 14.1)	9.0 (7.5, 10.5)	9.0 (7.7, 10.3)	8.8 (7.1, 10.5)	8.6 (7.6, 9.6)	7.9 (6.9, 8.8)	9.3 (8.3, 10.3)	0.001

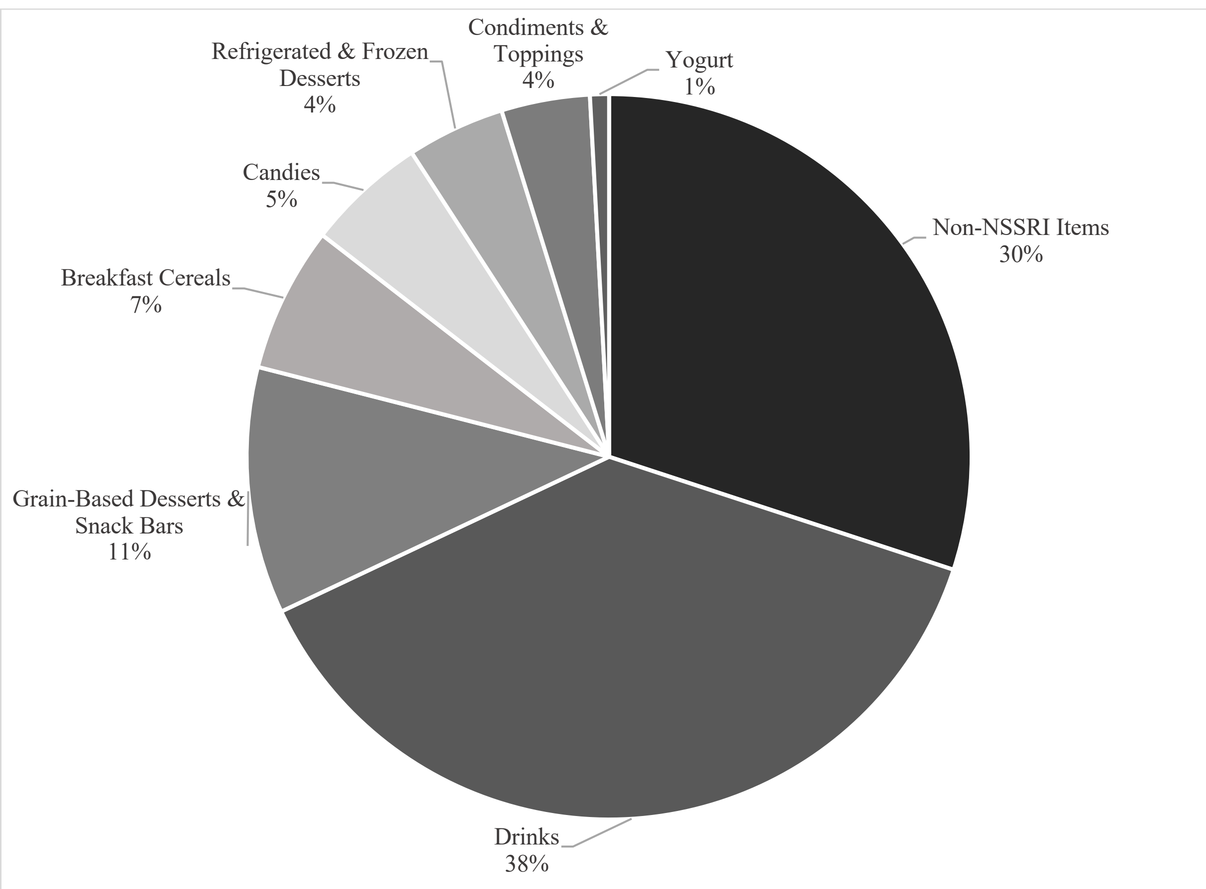
Table 2.3 (Continued)

	2003–2004	2005–2006	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016	2017–2018	p-value for linear trend[2]
Family Income[4]									
Lower income	14.2 (13.1, 15.2)	12.9 (12.2, 13.6)	13.4 (12.0, 14.8)	12.6 (11.8, 13.3)	12.1 (11.3, 12.9)	12.0 (10.6, 13.3)	10.1 (9.4, 10.9)	10.9 (9.8, 12.0)	<0.001
Higher income	14.0 (13.0, 15.1)	13.0 (12.3, 13.7)	12.5 (11.5, 13.4)	11.8 (10.8, 12.8)	11.1 (10.4, 11.7)	10.8 (10.0, 11.5)	9.7 (9.2, 10.3)	10.1 (9.3, 11.0)	<0.001
Parental Educational Attainment[5]									
Lower education	14.7 (13.7, 15.8)	13.4 (12.8, 14.1)	13.3 (12.5, 14.1)	12.6 (12.0, 13.2)	12.2 (11.6, 12.8)	11.7 (10.9, 12.5)	10.3 (9.8, 10.9)	11.0 (10.3, 11.7)	<0.001
Higher education	11.9 (10.5, 13.3)	11.9 (10.4, 13.3)	11.3 (10.4, 12.3)	10.7 (9.3, 12.1)	9.2 (8.5, 10.0)	9.7 (8.0, 11.4)	8.4 (7.7, 9.1)	8.7 (7.3, 10.2)	<0.001

[1]Outcome was constructed as (grams of added sugar per day * 4)/(total calories per day)*100.
[2]To account for multiple testing, we applied a Bonferroni correction wherein a p-value of <0.001 was considered statistically significant.
[3]Lower income was defined as an annual family income <130% of the federal poverty line, while higher income was defined as an annual family income ≥130% of the federal poverty line.
[4]Other race/ethnicity included individuals reporting a race other than White or Black, including Asians, or individuals reporting multi-racial identity.
[5]Lower education was defined as child's parent respondent being less than a college graduate, while higher education was defined as child's parent respondent being a college graduate or above.
Notes: To obtain trend estimates within subgroups, separate models were fitted within each subgroup, adjusting for all other covariates (e.g., model it among Non-Hispanic White children, adjusting for age, family income, and parental educational attainment). Negative predicted values were truncated at 0. The margins command in Stata was used to estimate the predicted percent of daily calories from added sugar for each survey year, when all other covariates were set to their mean values.

In 2017–2018, mean overall added sugar intake among children and adolescents was 70.8g, with the majority (49.5g, 70.0%) of this added sugar intake estimated to come from foods and beverages covered under the NSSRI (**Figure 2.1)**. Of the 21.3g (30.0%) of added sugar intake not covered by NSSRI categories in 2017–2018, about half was contributed by NSSRI items from non-allowable foods sources, while the remainder came from a variety of food and beverages not covered by the NSSRI such as dips/spreads/sauces, mixed dishes (e.g., pasta with tomato sauce), and salty snacks. In sensitivity analyses, the proportion of added sugar intake comprised by NSSRI items varied from 58% (assuming no reformulation in non-store sources) to 85% (assuming total reformulation in all sources).

Figure 2.1: Daily added sugar intake (percent) by National Salt and Sugar Reduction Initiative meta-category, for children aged 2–19 years in the NHANES 2017–2018



Assuming no substitution, daily added sugar intake would have been 7% lower if the 2023 NSSRI targets had been met and would have been 21% lower if the 2026 targets had been met (**Table 2.4**). Estimated reductions were comparable across population subgroups, although these differences were not tested statistically.

Table 2.4: Daily added sugar intake[1] (grams) in 2017–2018 and difference in intake if 2023 and 2026 NSSRI targets had been met

	2017–2018 added sugar intake (g)[1]	Estimated intake if industry were meeting 2023 targets (g)[1]	% change[2]	Estimated intake if industry were meeting 2026 targets (g)[1]	% change[2]
Overall	70.8	65.9	-6.9	55.7	-21.3
Age					
2–5-years	49.0	45.5	-7.1	39.7	-19.0
6–11-years	74.2	69.2	-6.7	59.6	-19.7
12–19-years	78.7	73.1	-7.1	60.3	-23.4
Race/Ethnicity					
Non-Hispanic White	74.9	69.6	-7.1	58.9	-21.4
Non-Hispanic Black	76.5	70.9	-7.3	59.6	-22.1
Mexican American	57.3	53.1	-7.3	44.6	-22.2
Non-Mexican Hispanic	62.5	58.9	-5.8	51.5	-17.6
Other Race/Ethnicity[3]	68.9	64.2	-6.8	54.1	-21.5
Family Income[4]					
Lower income	69.8	64.8	-7.2	54.4	-22.1
Higher income	71.3	66.4	-6.9	56.3	-21.0
Parental Education[5]					
Lower education	74.3	69.0	-7.1	57.7	-22.3
Higher education	62.1	58.2	-6.3	50.6	-18.5

[1]Added sugar intake refers to sum of both NSSRI and non-NSSRI items.
[2]Percent change calculated as (added sugar under targets – pre-NSSRI added sugar)/(pre-NSSRI added sugar)*100%.
[3]Other race/ethnicity included individuals reporting a race other than White or Black, including Asians, or individuals reporting multi-racial identity.
[4]Lower income was defined as an annual family income <130% of the federal poverty line, while higher income was defined as an annual family income ≥130% of the federal poverty line.
[5]Lower education was defined as child's parent respondent being less than a college graduate, while higher education was defined as child's parent respondent being a college graduate or above.

2.5 DISCUSSION

In 2017–2018, packaged foods and drinks covered under the NSSRI accounted for 70% of added sugar intake among children and youth in the U.S., with drinks comprising the largest proportion at 38%. While added sugar intake from NSSRI foods and drinks has declined over the past decade, added sugar intake from all sources remains high at about 71g per day (equivalent to roughly 17 teaspoons) and consumption of certain NSSRI categories has remained steady over time. Although many factors contribute to these trends, including widespread availability and promotion of sugary foods and beverages, our findings indicate that reducing sugar in the food supply could play a role in reducing added sugar intake among youth. If industry were meeting the NSSRI targets in 2017–2018, children and adolescents would have consumed 7% (2023 targets) to 21% (2026 targets) less added sugar. Estimated reductions were similar across demographic characteristics, suggesting the NSSRI categories capture key sources of added sugar intake among children from a variety of racial/ethnic and socioeconomic groups and is not projected to widen existing disparities.

Global evidence indicates that target setting initiatives like the NSSRI can work to promote public health goals through industry reformulation of the food supply. Following implementation of voluntary sugar targets in England, a 3.0% reduction in the SWM sugar content of food was observed in the first three years after implementation, with greater progress for some food categories (e.g., 13.3% reduction for cereals).[40] Lessons can also be learned from a larger body of research evaluating global sodium reduction initiatives. More than 50 countries have established national sodium content targets for products,[41] with important reductions in the SWM sodium content of products and population-level dietary sodium intake observed in many countries.[42] For example, in the U.S., a 7% reduction in the SWM sodium content of top-selling packaged foods was observed in the 5-year period during implementation of the National Salt Reduction Initiative's voluntary sodium reduction targets.[43] In countries where substantial reductions in dietary sodium intake have been observed, strong support from central government, as well as multi-pronged efforts encompassing public education campaigns and other complementary strategies have been keys to success.[44]

While this analysis focused on reductions in added sugar intake, it is important to consider other shifts in industry behavior and population dietary intake that may result from the NSSRI. First, industry might replace sugars with unhealthy ingredients such as non-nutritive sweeteners, which is problematic in light of evidence that exposure to non-nutritive sweeteners during childhood may impact future taste preferences and have implications for long-term health.[45] Second, companies might acquire existing lower-sugar brands to meet the targets, which would change the composition of their product portfolio but would not affect the composition of the food supply. Third, consumers may make product substitutions away from reformulated products in favor of higher sugar items. Fourth, because our analysis suggests that U.S. youth are consuming a decreasing quantity of NSSRI foods and beverages over time, reducing the added sugar content of these items might not have as strong of an effect as anticipated. The Health Department has the ability to monitor these potential changes over time by rebuilding their database to track ingredients and sugar content for the years before and after the initiative.

There are limitations of this work. We did not account for possible substitution that may take place during the initiative and assumed homogeneity in the impact of NSSRI across subgroups. We did not forecast the impact of the NSSRI targets on added sugar intake in 2023 and 2026, but instead used current population estimates to assess what added sugar intake could have looked like had industry already met the targets. Additionally, the NSSRI targets are for total sugar, not added sugar. However, for many categories (e.g., sugary drinks), added sugar and total sugar are equivalent, and in other categories (e.g., sweetened milk), targets used an adjustment factor to account for sugars that are naturally occurring. Because the 24-hour dietary recall for children under 12 years of age was completed or assisted by primary caregivers, added sugar intake may be underestimated if children consume items without their caregiver's knowledge.

Our study also has many strengths. We used eight survey cycles of nationally representative data, conducted extensive mapping of FNDDS food codes to NSSRI categories, and included several sensitivity analyses varying analytic assumptions.

Conclusions

Added sugar intake from packaged food and drinks among children and adolescents in the U.S. is high. By setting sugar reduction targets for industry, the NSSRI could contribute to reducing youth consumption of added sugars.

Chapter 3:

A longitudinal analysis of food insufficiency and cardiovascular disease risk factors in the Coronary Artery Risk Development in Young Adults Study

3.1 ABSTRACT

Introduction: Most prior studies on food insecurity and cardiovascular disease (CVD) risk factors are cross-sectional. Without longitudinal data, it is unclear whether food insecurity precedes poor health and how exposure timing affects these relationships.

Methods: Data from years 2000–2001, 2005–2006, and 2010–2011 of the Coronary Artery Risk Development in Young Adults study was used. Food insufficiency – a screener measure related to food insecurity – was assessed in 2000–2001 and 2005–2006 using a single item. CVD risk factors were objectively assessed in 2010–2011. The effects of food insufficiency patterns (food sufficient; food insufficient in 2000–2001 only; food insufficient in 2005–2006 only; food insufficient in both 2000–2001 and 2005–2006) on CVD risk factors were estimated using inverse probability weighting of marginal structural models (MSM). Covariates that change over time were adjusted for using stabilized weights, while baseline covariates were adjusted for in the MSM. Analyses were conducted in 2020.

Results: The baseline sample included 2596 participants (56% women, 47% White). In unadjusted analyses, all food insufficiency patterns were associated with higher BMI, waist circumference, and blood pressure compared to food sufficiency. After accounting for covariates, point estimates were attenuated, but still consistent with adverse effects of food insufficiency, particularly among women.

Conclusion: After covariate adjustment, food insufficiency was associated with several CVD risk factors. Findings from our study should be replicated in other settings and populations. If verified, this evidence could provide justification for intervening on food insecurity to reduce future CVD risk.

3.2 INTRODUCTION

Food insecurity, defined by the United States Department of Agriculture (USDA) as a "lack of consistent access to enough food for an active, healthy life",[46] is a leading public health issue around the world.[47] In the U.S., the prevalence of food insecurity has been systematically monitored since 1995,[48] and the federal government spends in excess of $95 billion each year on nutrition assistance programs aimed at improving food access for food insecure households.[49,50] Despite these efforts, 10.5% of U.S. households were food insecure at some point during 2019,[2] with this number rising to an estimated 22% during the first few months of the COVID-19 pandemic in 2020.[3,4]

A growing body of evidence indicates that food insecurity may lead to poor health.[47,51-55] Obesity has been examined most frequently, with multiple studies reporting a harmful association among women, but mixed findings for men and children.[53,56] Emerging evidence also suggests that food insecurity is associated with other CVD risk factors,[57-61] including high cholesterol and blood pressure.[61] Households with insufficient financial resources to purchase food may compensate by increasing reliance on cheap, energy-dense, and nutrient-poor foods, which can lead to metabolic dysregulation and fat accumulation.[54] Food insecurity may also affect cardiometabolic risk through non-dietary pathways such as by activating a physiological stress response, triggering harmful coping behaviors, and/or reducing the ability to manage chronic conditions.[62] Given that obesity and CVD are leading causes of morbidity and mortality worldwide,[63,64] robust scientific evaluation of food insecurity and its impact on these outcomes is needed for informing interventions and policy development in this area.

Substantial gaps in knowledge regarding food insecurity and health still exist. Importantly, available research among adults is largely cross-sectional. Longitudinal data are needed to understand the temporal ordering of food insecurity and poor health, as well as to distinguish whether adverse health effects are the result of cumulative damage from years of experiencing food insecurity ("persistent food insecurity") versus shorter-term adaptations to acute experiences of food insecurity ("transient food insecurity"). A few studies have attempted to estimate the cumulative effects of food insecurity over time,[65-67] but previous research is limited by methodological challenges related to handling time-varying confounding and selection bias.[68]

Here, longitudinal data from the Coronary Artery Risk Development in Young Adults (CARDIA) study was used to (1) examine longitudinal relationships of food insecurity (as assessed by food insufficiency, a related screener measure[69]) with CVD risk factors and (2) determine whether experiencing persistent versus transient food insecurity has differing relationships with CVD risk factors.

3.3 METHODS

Data and Study Population

CARDIA is a prospective cohort study of 5,115 Black and White adults aged 18-30 years at recruitment in 1985–1986.[70] CARDIA's goal is to examine determinants of clinical and subclinical CVD and their risk factors through interviewer-administered questionnaires, anthropometric assessments, imaging, and bio-sample collections. Study recruitment was intended to be balanced on age, sex, race, and educational attainment across four urban field centers: Birmingham, AL; Chicago, IL; Minneapolis, MN; and Oakland, CA. Participants provided written informed consent at every exam and Institutional Review Board approval was obtained by each field center.

Three CARDIA exams that assessed food insufficiency were used: year 15 (2000–2001), year 20 (2005–2006), and year 25 (2010–2011). The analysis included participants with complete 2000–2001 data on exposure and covariates and who, in 2000–2001, had no previous history of myocardial infarction or stroke, and were not currently pregnant. The sample was further restricted to participants with an annual household income <$100,000 in 2000–2001 because there were few food insufficient participants with higher incomes. This "baseline" analytic sample (n=2596, participant flowchart in **Supplementary Figure 3.1)** was further restricted to those who reported fasting ≥8 hours in 2000–2001 when examining fasting glucose as an outcome (n=2441) and to those who reported fasting ≥12 hours in 2000–2001 when examining LDL and triglycerides (n=2311).

Over follow-up, participants were censored in 2005–2006 or 2010–2011 if they were missing exposure, covariate, or outcome data (or reported an inadequate fast duration for fasting outcomes). Approximately three-quarters of the overall sample (n=1897) remained uncensored by the end of follow-up in 2010–2011 (**Supplementary Figure 3.2**).

Measures:

Food Insufficiency: CARDIA assessed food insufficiency, a validated single-item measure often used as a screener for food insecurity surveys.[69] Compared to food insecurity, food insufficiency is more limited in scope and tends to overestimate assessments of food insecurity.[71-73] At each time point (2000–2001 and 2005–2006), food insufficiency was assessed by asking participants to choose the statement that best describes the food eaten in their household during the last year: (1) We have enough food to eat and the kinds of food we want; (2) We have enough food to eat, but NOT always the kinds of food we want to eat; (3) Sometimes we don't have enough food to eat; or (4) Often, we don't have enough food to eat. In line with previous research,[73,74] responses were dichotomized, with food sufficiency defined as having adequate quantity and quality of food (response option 1), and food insufficiency defined as inadequate quantity or quality of food (response options 2–4).

Food insufficiency assessments from 2000–2001 and 2005–2006 were used to create four time-varying food insufficiency patterns: (1) “food sufficiency” (food sufficient in 2000–2001 and 2005–2006); (2) transient “food insufficiency only in 2000–2001”; (3) transient “food insufficiency only in 2005–2006”; and (4) “persistent food insufficiency” (food insufficient in 2000–2001 and 2005–2006).

Outcomes: All outcomes were measured by trained study staff at 2010–2011 using standardized techniques.[75] Body Mass Index (BMI) was calculated as weight in kilograms divided by height in meters squared. Waist circumference was measured in duplicate with a tape to the nearest 0.5 cm around the minimal abdominal girth. Blood pressure was measured three times after participants rested in a quiet room for five minutes and was calculated as the average of the last two measurements. Blood samples were collected from participants to assess total cholesterol, high-density lipoprotein cholesterol (HDL), low-density lipoprotein cholesterol (LDL), triglycerides, and fasting glucose. Participants were instructed to fast overnight and avoid smoking and strenuous physical activity for at least two hours before blood collection.

Covariates (described in detail in footnote of Table 3.1): Baseline covariates assessed at CARDIA’s initial examination were sex, race, age, and recruitment center. Time-varying covariates assessed in 2000–2001 and 2005–2006 included: household income, employment status, marital status, household size, cholesterol or blood pressure medication use, self-reported diabetes, smoking status, and physical activity score. Prior BMI in 2000–2001 and 2005–2006 was also adjusted for when examining BMI as the outcome in 2010–2011 (with prior values of other outcomes adjusted for in an analogous manner).

Analyses

Unadjusted Analyses: The distribution of outcomes across individuals was compared across food insufficiency status before taking into account covariates. Coefficients were estimated using linear regression models, where the dependent variable was a continuous version of each outcome in 2010–2011 and covariates were indicators for food insufficiency in 2000–2001, food insufficiency in 2005–2006, and an interaction term between the two food insufficiency indicators. The parameters of this model were used to compare outcomes across the four food insufficiency patterns.

Inverse Probability (IP) Weighting of Marginal Structural Models (MSM): Next, IP weighting of MSMs was used to compare outcome distributions, adjusted for baseline and time-varying covariates.[76,77] IP weighting was chosen as the analytic approach because it allows for estimation of the effects of exposures which vary over time and may affect, and be affected by, covariates that also vary over time.[78,79] IP weights were used to adjust for time-varying confounders, while baseline confounders were included directly in the MSM. In a similar manner, weights were used to account for selection bias due to censoring (i.e., bias induced by loss to follow-up and/or missing follow-up data). As in all observational analyses that attempt to make causal inferences, the validity of these findings is based on many untestable assumptions (see discussion of approach and assumptions in **Supplementary Text 3.1**).

To estimate coefficients of the MSM, weighted generalized linear regression models were fit among uncensored participants, but with all participants in the overall "baseline" sample contributing to the estimation of the weights using data prior to their censoring time. In these models, the dependent variable was the outcome in 2010–2011 and covariates were an indicator for food insufficiency in 2000–2001, an indicator for food insufficiency in 2005–2006, an interaction term between the two food insufficiency indicators, and baseline confounders (with time-varying confounders accounted for using IP weights). Because prior research suggests there may be sex differences in the effects of food insufficiency on health outcomes,[53,56] an interaction term between sex and each food insufficiency term was included. In secondary analyses, models with an interaction term instead between race and each food insufficiency term were fitted – this analysis was motivated by prior research suggesting food insufficiency may have differential effects by race due to socially-driven factors including differences in coping strategies and diet quality.[74,80,81] Due to small sample size, the analysis did not include interaction terms for effect modification by both race and sex.

Parameter estimates from the MSM were used to estimate differences in mean outcome values for each of the food insufficiency patterns compared to food sufficiency. 95% confidence intervals (CI) were constructed using non-parametric bootstrapping with 5000 replications.

All analyses were performed in 2020 using RStudio, version 1.3.959.

3.4 RESULTS

Table 3.1 reports characteristics of the analytic sample in 2000–2001 (n=2596). The sample was approximately half women and half White, with a mean age of 40 years. About 20% of participants reported food insufficiency at baseline. **Supplementary Table 1** reports baseline characteristics of the uncensored sample by food insufficiency pattern.

Table 3.1: Characteristics of analytic sample, by food insufficiency status at "baseline": CARDIA, 2000-2001

Characteristic	Total (N=2596)	Food insufficient (N=464)	Food sufficient (N=2132)	p-value
Sex				0.002
Women	1466 (56%)	293 (63%)	1173 (55%)	
Men	1130 (44%)	171 (37%)	959 (45%)	
Age (years)				0.003
Mean (SD)	40 .0 (± 3.7)	39.5 (± 3.9)	40.1 (± 3.7)	
Race				<0.001
White	1219 (47%)	146 (31%)	1073 (50%)	
Black	1377 (53%)	318 (69%)	1059 (50%)	
Employment status				<0.001
Full-time	1959 (75%)	303 (65%)	1656 (78%)	
Part-time	547 (21%)	127 (27%)	420 (20%)	
Unemployed	90 (3%)	34 (7%)	56 (3%)	
Smoking status				<0.001
Current	634 (24%)	168 (36%)	466 (22%)	
Former	459 (18%)	72 (16%)	387 (18%)	
Never	1503 (58%)	224 (48%)	1279 (60%)	
Household income				<0.001
<$5000	72 (3%)	38 (8%)	34 (2%)	
$5000-$11,999	123 (5%)	56 (12%)	67 (3%)	
$12,000-$15,999	99 (4%)	43 (9%)	56 (3%)	
$16,000-$24,999	226 (9%)	62 (13%)	164 (8%)	
$25,000-$34,999	309 (12%)	78 (17%)	231 (11%)	
$35,000-$49,000	532 (20%)	93 (20%)	439 (21%)	
$50,000-$74,999	743 (29%)	72 (16%)	671 (31%)	
$75,000-$99,999	492 (19%)	22 (5%)	470 (22%)	
Marital status				<0.001
No partner	1218 (47%)	270 (58%)	948 (44%)	
Partner	1378 (53%)	194 (42%)	1184 (56%)	
Household size				<0.001
1 person	444 (17%)	77 (17%)	367 (17%)	
2-4 people	1745 (67%)	286 (62%)	1459 (68%)	
5 people or more	407 (16%)	101 (22%)	306 (14%)	

Table 3.1 (Continued)

Characteristic	Total (N=2596)	Food insufficient (N=464)	Food sufficient (N=2132)	p-value
Diabetes				0.720
Yes	123 (5%)	20 (4%)	103 (5%)	
No	2473 (95%)	444 (96%)	2029 (95%)	
Cholesterol or BP Medication				0.103
Yes	247 (10%)	54 (12%)	193 (9%)	
No	2349 (90%)	410 (88%)	1939 (91%)	
Physical Activity tertile				<0.001
Low	935 (36%)	206 (44%)	729 (34%)	
Moderate	847 (33%)	151 (33%)	696 (33%)	
High	814 (31%)	107 (23%)	707 (33%)	
Recruitment Center				0.032
Birmingham	680 (26%)	130 (28%)	550 (26%)	
Chicago	497 (19%)	100 (22%)	397 (19%)	
Minneapolis	793 (31%)	146 (31%)	647 (30%)	
Oakland	626 (24%)	88 (19%)	538 (25%)	

Table values are N (%) for categorical variables and mean (SD) for continuous variables. The p-value for categorical variables is based on a chi-square test, while p-value for continuous variables is based on a t-test.

Notes: *Employment status*: participants were categorized as working "full-time" if they answered affirmatively to the question "Are you working full-time?"; otherwise, they were classified as "part-time or keeping house" if they responded affirmatively to questions about working part-time or keeping house full-time; and "unemployed" if they responded affirmatively to questions about being unemployed, laid off or currently looking for work. *Smoking status:* participants were classified as a "never smoker" if they reported never smoking any tobacco products or never smoking cigarettes regularly for at least 3 months (regularly defined as ≥5 cigarettes/week almost every week); "current smokers" if they reported smoking regularly now; and "former smokers" if they reported smoking regularly at some point in their life, but not now. *Income:* participants were asked to report their total combined family income from the past 12-months in 9 categories (with ≥$100,000 excluded for this analysis, leaving eight categories). *Marital status:* Participants were categorized as having a "partner" if they reported being married or living with someone in a marriage-like relationship and "no partner" if they reported being widowed, divorced, separated, never married, or other. *Household size:* Participants reported the total number of people currently living in their household, including themselves. *Diabetes:* Participants were asked "has a doctor or nurse ever told you that you have diabetes (high sugar in blood or urine)?". Thus, type 1 and type 2 diabetes were not distinguished. *Cholesterol/BP medication:* Participants were categorized as "Yes" if they responded affirmatively to either "are you taking medications for high blood pressure?" or "are you taking medications to lower your blood cholesterol?". *Physical Activity:* Participants completed the Physical Activity History, a brief questionnaire developed by CARDIA that asks about the frequency, intensity, and duration of 13 categories of sports/exercise over the past 12-months. Responses were used to determine a total physical activity score in units. Participants were then divided into tertiles based on their total physical activity score.

Abbreviations: BP=Blood Pressure; SD=Standard Deviation.

In unadjusted analyses, all food insufficiency patterns were associated with higher BMI and waist circumference compared to food sufficiency (**Figure 3.1**). After accounting for covariates, point estimates were attenuated, but directions were generally still consistent with adverse effects of food insufficiency compared to food sufficiency on adiposity (although estimates were imprecise with CIs often overlapping the null value of 0). When generating estimates for men and women separately, the estimated associations between food insufficiency and adiposity were often stronger among women, although differences in the effect estimates for women compared to men did not reach statistical significance at a two-sided alpha= 5% (**Supplementary Table 3.2**).

Figure 3.1: Unadjusted and IP-weighted estimates of mean differences in BMI and waist circumference (95% CI) in 2010–2011 for food insufficiency patterns in 2000–2001 and 2005–2006 compared to food sufficiency: CARDIA, 2000-2011

Panel A: BMI, kg/m²

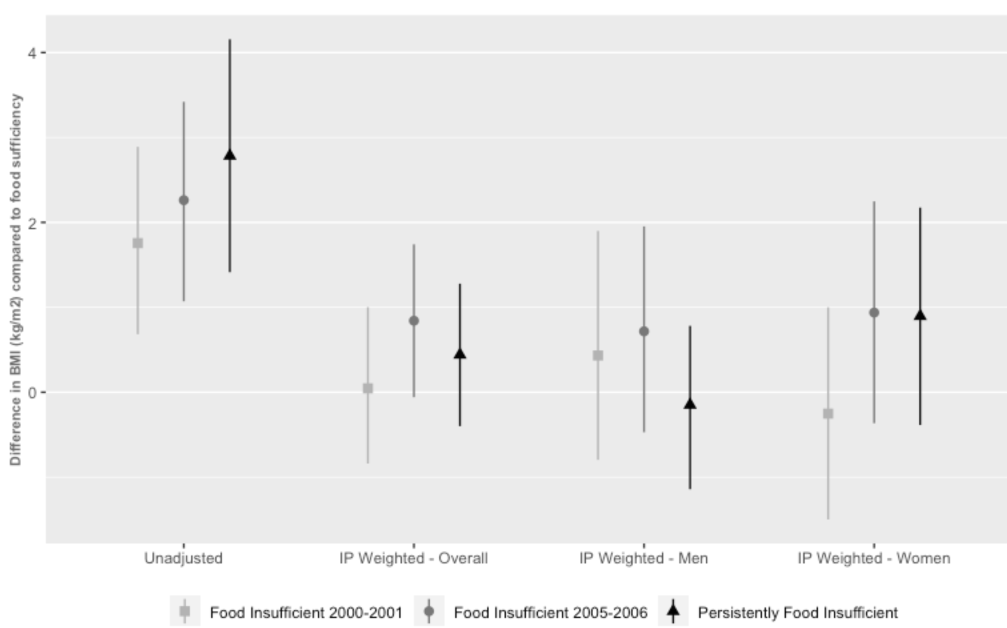
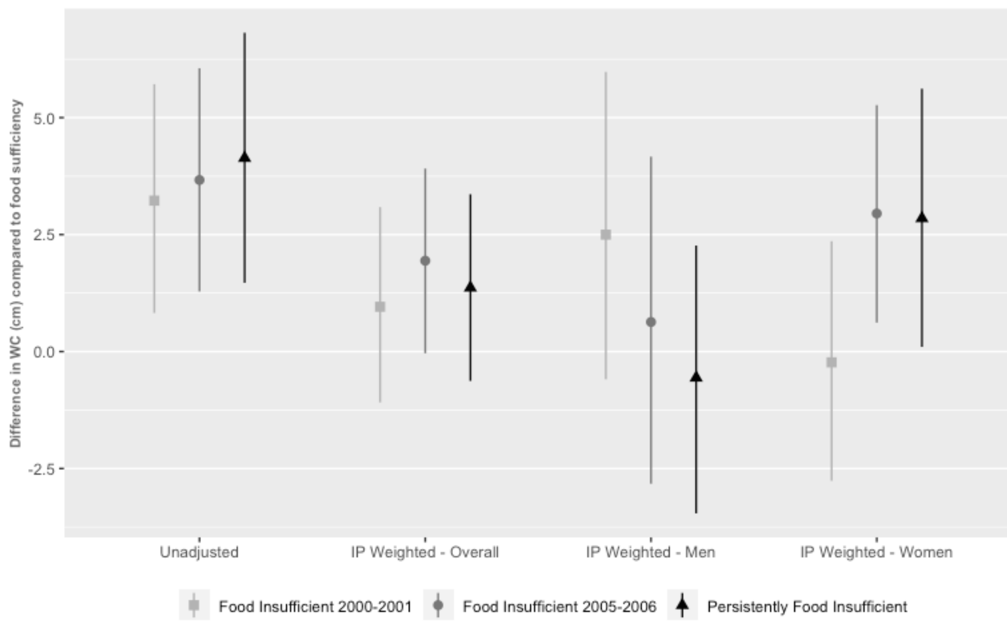


Figure 3.1 (continued)
Panel B: Waist Circumference, cm



Notes: Unadjusted analyses were conducted among participants with complete exposure and outcome information (no requirement for non-missing covariate data, no additional inclusion/exclusion criteria). IP-weighted analyses were conducted among participants with complete 2000–2001 data on exposure and covariates, who had not previously had a myocardial infarction or stroke, were not currently pregnant, and had an annual household income <$100,000. Covariates included: sex, race, age, recruitment center, household income, employment status, marital status, household size, cholesterol or blood pressure medication use, self-reported diabetes, smoking status, physical activity score, and prior BMI in 2000–2001 and 2005–2006 when examining BMI as the outcome in 2010–2011 (with prior values of other outcomes adjusted for in an analogous manner). Data from both censored and uncensored participants was used in construction of IP weights (n=2596). MSMs were fit among uncensored participants only (n=1897; no food insufficiency, n=1437; food insufficient 2000–2001, n=164; food insufficient 2005–2006, n=170; persistently food insufficient, n=126), using weighted data.
Abbreviations: BMI=Body Mass Index; CI = Confidence Interval; IP = Inverse probability, MSM = Marginal Structural Model; WC = Waist Circumference.

In unadjusted analyses, all food insufficiency patterns were associated with higher systolic and diastolic blood pressure compared to food sufficiency (**Table 3.2**). In IP-weighted results, no statistically significant differences in systolic or diastolic blood pressure were observed for any food insufficiency pattern, although point estimates for both transient food insufficiency patterns were consistent with higher blood pressure compared to food sufficiency. Some sex-specific associations emerged: for example, women with transient food insufficiency in 2005–2006 had significantly higher diastolic blood pressure compared to food sufficiency (an effect estimate that was significantly different from the effect observed among men).

Table 3.2: Unadjusted and IP-weighted estimates of mean differences in outcomes (95% CI) in 2010–2011 for food insufficiency patterns in 2000–2001 and 2005–2006 compared to food sufficiency, overall and by sex: CARDIA, 2000-2011

	Food Sufficiency: *Food sufficient in 2000–2001 and 2005–2006*	**Food Insufficient in 2000–2001 only** *Food insufficient in 2000–2001, food sufficient in 2005–2006*	**Food Insufficient in 2005–2006 only** *Food sufficient in 2000–2001, food insufficient in 2005–2006*	**Persistent Food Insufficiency:** *Food insufficient in 2000–2001 and 2005–2006*
Overall Sample				
Systolic blood pressure, mmHg				
Unadjusted	Ref.	4.08 (1.69, 6.56)	4.87 (2.57, 7.31)	4.24 (1.40, 7.07)
IP weighted – Overall	Ref.	1.91 (-0.62, 4.23)	1.62 (-0.64, 3.86)	-0.31 (-3.27, 2.40)
IP weighted – Men	Ref.	3.31 (-0.22, 6.66)	0.53 (-1.80, 2.90)	1.45 (-3.65, 6.10)
IP weighted – Women	Ref.	0.83 (-2.65, 4.14)	2.47 (-1.12, 6.08)	-1.66 (-4.97, 1.43)
Diastolic blood pressure, mmHg				
Unadjusted	Ref.	3.07 (1.38, 4.73)	3.33 (1.80, 4.95)	2.28 (0.45, 4.09)
IP weighted – Overall	Ref.	1.55 (-0.21, 3.26)	1.24 (-0.23, 2.72)	-0.37 (-2.54, 1.69)
IP weighted – Men	Ref.	2.67 (0.02, 5.28)	-0.81 (-2.85, 1.29)	1.19 (-2.96, 4.93)
IP weighted – Women	Ref.	0.68 (-1.60, 2.92)	2.83 (0.74, 4.97)	-1.57 (-3.73, 0.50)
Total cholesterol, mg/dL				
Unadjusted	Ref.	-2.20 (-7.75, 3.45)	1.08 (-4.79, 7.06)	-8.07 (-13.74, -2.31)
IP weighted – Overall	Ref.	-1.38 (-6.86, 3.95)	-2.00 (-7.66, 3.78)	-2.67 (-8.41, 2.95)
IP weighted – Men	Ref.	-1.89 (-10.91, 6.68)	-5.60 (-14.61, 3.36)	-1.07 (-11.17, 8.94)
IP weighted – Women	Ref.	-0.98 (-8.07, 6.04)	0.77 (-6.61, 8.38)	-3.91 (-11.05, 2.90)
HDL cholesterol, mg/dL				
Unadjusted	Ref.	0.26 (-2.76, 3.59)	-1.66 (-3.94, 0.71)	-3.59 (-5.94, -1.26)
IP weighted – Overall	Ref.	0.39 (-2.60, 3.53)	-0.61 (-2.42, 1.25)	-3.70 (-6.08, -1.28)
IP weighted – Men	Ref.	-1.98 (-5.14, 1.17)	3.40 (0.68, 6.53)	-2.75 (-6.51, 1.13)
IP weighted – Women	Ref.	2.22 (-2.39, 7.24)	-3.71 (-6.14, -1.21)	-4.44 (-7.59, -1.38)
Fasting Sample (≥12 hours)				
Triglycerides, mg/dL				
Unadjusted	Ref.	2.14 (-10.74, 16.34)	0.88 (-9.18, 11.77)	2.82 (-10.69, 19.56)

Table 3.2 (Continued)

	Food Sufficiency: *Food sufficient in 2000–2001 and 2005–2006*	**Food Insufficient in 2000–2001 only** *Food insufficient in 2000–2001, food sufficient in 2005–2006*	**Food Insufficient in 2005–2006 only** *Food sufficient in 2000–2001, food insufficient in 2005–2006*	**Persistent Food Insufficiency:** *Food insufficient in 2000–2001 and 2005–2006*
IP weighted – Overall	Ref.	-4.63 (-15.93, 8.10)	1.55 (-7.70, 11.11)	-1.98 (-12.51, 9.64)
IP weighted – Men	Ref.	-1.40 (-20.90, 22.60)	-11.82 (-26.65, 4.13)	-11.82 (-26.65, 4.13)
IP weighted – Women	Ref.	-7.03 (-19.17, 5.85)	11.49 (-0.89, 23.83)	2.83 (-8.22, 13.88)
LDL cholesterol, mg/dL				
Unadjusted	Ref.	-3.07 (-8.08, 2.05)	3.06 (-2.65, 9.01)	-3.25 (-8.22, 1.71)
IP weighted – Overall	Ref.	-0.52 (-6.65, 5.56)	2.42 (-3.74, 8.89)	-2.73 (-8.67, 3.16)
IP weighted – Men	Ref.	0.10 (-7.75, 8.78)	-0.22 (-10.01, 10.48)	-3.18 (-12.27, 6.11)
IP weighted – Women	Ref.	-0.98 (-9.67, 7.49)	4.39 (-4.12, 12.50)	-2.39 (-10.06, 5.09)
Fasting Sample (≥ 8 hours)				
Fasting plasma glucose, mg/dL				
Unadjusted	Ref.	-1.11 (-4.64, 2.78)	3.39 (-1.21, 8.51)	5.39 (-0.25, 11.70)
IP weighted – Overall	Ref.	-3.87 (-7.25, -0.44)	0.43 (-4.27, 5.59)	2.14 (-3.34, 7.87)
IP weighted – Men	Ref.	-2.26 (-7.22, 2.99)	-3.42 (-9.00, 2.76)	4.05 (-4.92, 14.64)
IP weighted – Women	Ref.	-5.09 (-9.64, -0.56)	3.37 (-3.64, 11.23)	0.69 (-5.99, 7.92)

Notes: Unadjusted analyses in overall sample were conducted among participants with complete exposure and outcome information (no requirement for non-missing covariate data, no additional inclusion/exclusion criteria). Unadjusted analyses in fasting samples were conducted among participants with complete exposure and outcome information who had fasted for the adequate time period in 2010–2011 (≥12 hours for triglycerides and LDL; ≥8 hours for plasma glucose) (no requirement for non-missing covariate data, no additional inclusion/exclusion criteria). IP-weighted analyses in overall sample were conducted among participants with complete 2000–2001 data on exposure and covariates, who had not previously had a myocardial infarction or stroke, were not currently pregnant, and had an annual household income <$100,000. IP-weighted analyses in fasting sample were conducted among participants with complete 2000–2001 data on exposure and covariates, who had not previously had a myocardial infarction or stroke, were not currently pregnant, had an annual household income <$100,000 and who had fasted for the adequate time period (≥12 hours for triglycerides and LDL; ≥8 hours for plasma glucose). Covariates included: sex, race, age, recruitment center, household income, employment status, marital status, household size, cholesterol or blood pressure medication use, self-reported diabetes, smoking status, physical activity score, and prior BMI in 2000–2001 and 2005–2006 when examining BMI as the outcome in 2010–2011 (with prior values of other outcomes adjusted for in an analogous manner). Data from both censored and uncensored participants was used in construction of IP weights (n=2596 for systolic blood pressure, diastolic blood pressure, total cholesterol, and HDL; n=2311 for LDL and triglycerides; n=2441 for fasting plasma glucose). MSMs were fit among uncensored participants only. For systolic blood pressure, diastolic blood pressure, total cholesterol, and HDL, this included n=1897

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Table 3.2 (Continued)

participants (no food insufficiency, n=1437; food insufficient 2000–2001, n=164; food insufficient 2005–2006, n=170; persistently food insufficient, n=126). For LDL and triglycerides, this included n=1379 participants (no food insufficiency, n=1072; food insufficient 2000–2001, n=102; food insufficient 2005–2006, n=114; persistently food insufficient, n=91). For fasting plasma glucose, this included n=1605 participants (no food insufficiency, n=1232; food insufficient 2000–2001, n=128; food insufficient 2005–2006, n=141; persistently food insufficient, n=104).

Abbreviations: HDL= High-density lipoprotein; LDL=Low-density lipoprotein; MSM=Marginal Structural Model.

Point estimates of associations between food insufficiency and lipids were less consistent, with wide confidence intervals and estimates that varied in direction and magnitude depending on the food insufficiency pattern and sex. In IP-weighted results, persistent food insufficiency was associated with lower HDL compared to food sufficiency. Compared to food sufficiency, both food insufficiency in 2005–2006 and persistent food insufficiency were associated with significantly lower HDL among women, whereas food insufficiency in 2005–2006 was associated with significantly higher HDL among men.

In secondary analyses, where the effects of food insufficiency were estimated by race, some race-specific associations emerged: for example, Black participants with food insufficiency in 2005–2006 had significantly higher systolic and diastolic blood pressure compared to food sufficiency (**Supplementary Table 3.3**). While this effect on blood pressure of food insufficiency in 2005–2006 vs. food sufficiency was significantly higher among Black participants compared to White participants, no other differences in effect estimates by race reached statistical significance (**Supplementary Table 3.4**).

3.5 DISCUSSION

This study analyzed longitudinal relationships between food insufficiency – a screener measure of food insecurity – and several CVD risk factors. Compared to food sufficiency, food insufficiency patterns were generally associated with higher BMI, waist circumference, and blood pressure, and lower HDL, with some sex- and race-specific patterns. These longitudinal findings are unique to the literature because they were generated with an analytic approach which can be used to estimate the effects of exposures in the presence of time-varying confounding and selection bias.[76,77] The findings also have important health policy implications: now more than ever, research linking food insecurity to poor health outcomes is needed to guide nutrition policies and programs. Additional policy implications are discussed in **Supplementary Text 3.2** and **Supplementary Table 3.5.**

Consistent with prior cross-sectional studies,[53] food insufficiency was associated with higher BMI and larger waist circumference compared to food sufficiency (particularly among women). Longitudinal studies examining this relationship are limited and have reported mixed results.[65-67,82,83] Differences between this study's findings and previous longitudinal studies that reported null results may be explained by different exposure assessments (other studies assessed food insecurity), distinct study populations (several only included pregnant women and/or young mothers), shorter follow-up periods (all were less than 5 years), and differing analytic approaches (none adjusted for time-varying confounding). Contrary to the study's hypothesis, no clear evidence was found that persistent food insecurity is worse for health than transient food insecurity, a finding that could be a true effect (e.g., due to development of more effective coping mechanisms over time) or due to bias (e.g., residual confounding and selection bias).

Researchers have proposed a number of possible mechanisms by which food insecurity may increase adiposity and CVD risk. Food insecure households often cycle between periods of food adequacy and scarcity,[54] resulting in the development of compensatory strategies (e.g., overconsumption of calories when available or skipping meals when food is limited) and constrained food choices (e.g., a reliance on cheap, nutrient-poor foods).[54] In particular, studies have found that food insecure individuals have lower micronutrient intakes (e.g., iron),[84-86] eat fewer fruits and vegetables,[87-89] and consume more added sugars.[90,91] These dietary behaviors may lead to metabolic dysregulation and adipose accumulation.[62] Food insecurity may also act as a chronic stressor which can elevate CVD risk factors either directly or by triggering unhealthful coping behaviors (e.g., smoking or excessive drinking).[62] More research is needed to examine which behavioral or physiological responses to food insecurity are most related to disease risk.

In line with prior research,[53,56] this study's findings suggest that women may experience more adverse effects on adiposity (particularly waist circumference) from food insufficiency compared to food sufficiency. While CARDIA does not distinguish between biological sex and gender, it is possible that both are contributors to observed differences in this study. For example, societal gender norms may mean that mothers feel pressure to put their children's needs first, which may result in adoption of unhealthy coping strategies to protect their family when the food supply is threatened (e.g., skipping meals).[92,93] With respect to biological sex, the accumulation of fat as a physiologically regulated response to a reduced food supply may happen disproportionately among women because of the important role adiposity plays in reproduction and offspring survival.[94] More research is needed to understand what mechanisms are driving effect modification by sex and/or gender in order to develop targeted strategies to reduce the disproportionate impact of food insecurity among females/women.

This study's findings also have health equity implications. First, this study contributes to mounting evidence on racial disparities in the burden of food insecurity,[2,95] with 23% of Black participants reporting food insufficiency at baseline, compared to 12% of White participants. Second, this study reports some race-specific findings for the effects of food insufficiency on CVD risk factors, with transient food insufficiency associated with higher blood pressure compared to food sufficiency among Black participants. Some possible explanations for this variation in findings by race include differences in neighborhood food environment and different coping strategies and diet quality during times of food insecurity.[80,96,97] Moving forward, there is a need for adequately power longitudinal studies to examine research questions around how structural racism may contribute to differences in the effects of food insecurity on health.

This study has multiple limitations. First, CARDIA assessed food insufficiency, not food insecurity. Moreover, due to small sample sizes, responses reporting a lack of sufficient quantity or quality of food were collapsed together, meaning it was not possible to assess effects by food insufficiency severity. Next, because CARDIA does not ask participants about participation in nutrition assistance programs and dietary data are only available for a subset of years, it was not possible to incorporate these factors into the analysis. Additionally, it was assumed that smoking and physical activity were confounders, but it is plausible that they are instead mediators.[98,99] Additionally, while this study's interpretation of results did not focus on statistical significance, it examined a number of different, but correlated, outcomes, which may raise concerns about multiple comparisons. Finally, this study's primary analysis did not account for interim CVD events (e.g., stroke). However, in sensitivity analyses treating interim CVD events as a censoring criterion and a time-varying covariate (**Supplementary Tables 3.6** and **3.7)**, results did not vary meaningfully.

Despite these limitations, the study has many strengths. CARDIA's study design allowed for examination relationships prospectively over 10 years of follow-up, increasing confidence in the temporal ordering of exposure before outcome. Additionally, an analytic method was used which can be used to estimate the effects of exposures in the presence of time-varying confounding and selection bias.[76,77]

Conclusion

Food insufficiency – one measure of food insecurity – was associated with several CVD risk factors. Findings from this study should be replicated in other settings and populations. If verified, these associations could provide further justification for intervening on food insecurity.

Chapter 4:

A Descriptive Analysis of Redemption Patterns by Vendor Type among WIC Participants in Massachusetts

4.1 ABSTRACT

Introduction: The retail environment is an important determinant of food package redemption in the Special Supplemental Nutrition Program for Women, Infants and Children (WIC). The objectives of this study were to describe (1) where Massachusetts (MA) WIC households redeem their food benefits and (2) variations in benefit redemption depending on a household's preferred type of WIC vendor.

Methods: Administrative data provided by MA WIC included monthly household-level redemption data for approximately 200,000 MA households shopping at about 1,000 unique vendors between January 2015 and August 2019. For each month, households were classified as using one of 8 vendor types. For each year, the percentage of households redeeming at each vendor type was calculated, as well as average percent redemption for each benefit category by vendor type. Analyses were conducted in 2020.

Results: Over half of MA WIC households relied only on large vendors (superstores, supermarkets, and large grocery stores) when redeeming benefits in 2019, while less than 5% relied only on small grocery or convenience stores. Between 2015–2019, reliance on large vendors appeared to increase, while reliance on small grocery and convenience stores appeared to decrease. Compared to other vendor types, households that redeemed benefits only at superstores had lower redemption levels for most benefit categories, while households that relied only on small grocery stores had lower redemption for yogurt and the cash value benefit.

Conclusions: Results suggest that retail-based efforts to increase redemption should consider vendor type preferences and that strategies to increase redemption may be especially important for WIC shoppers relying on superstores.

4.2 INTRODUCTION

The Special Supplemental Nutrition Program for Women, Infants and Children (WIC) is a federally-funded program administered by states that provides food packages, nutrition education, screening, and health service referrals to low-income women (pregnant, breastfeeding, and postpartum), infants (0–1 years old), and children (up to 5^{th} birthday).[100] In most states, WIC participants are provided with an Electronic Benefits Transfer (EBT) card that enables the redemption of a monthly quantity of WIC-approved foods from authorized vendors (e.g., a dozen eggs). In FY2019, WIC had over $5 billion in program costs and served nearly 6.4 million people, reaching more than half of all infants and about a quarter of all children in the United States (US).[101]

The current WIC food packages reflect revisions initiated by the US Department of Agriculture (USDA) in 2007 and finalized in 2014 to align the program more closely with evidence-based recommendations from the Dietary Guidelines for Americans.[102-104] Key changes included expanding whole grain options, creating a cash value benefit (CVB) for fruits and vegetables, decreasing the juice allotment, and reducing the fat content of milk and yogurt.[102,103] A growing body of evidence indicates the revised packages improved participants' diet quality[105-107] and may have reduced obesity among children in the program aged 2–4 years old.[108,109] However, such positive health impacts are only seen among those who continue to utilize the program; not all participants redeem everything in their monthly food package,[110,111] suggesting they may face barriers to fully utilizing their WIC benefits.

Experiences within the retail environment may be an important determinant of incomplete food package redemption.[112-119] Prior research has identified retail factors that may influence redemption including "decision fatigue" in identifying allowable foods, negative employee-participant interactions, and vendor characteristics such as size and ease of access.[112-117] The majority of research in this area has been qualitative, utilizing interviews and focus groups among a small number of WIC participants to identify vendor-related barriers to redemption. Comprehensive and systematically collected data from a large number of WIC participants spanning several years is needed to further tease out the role of vendors in influencing redemption. While a previous Economic Research Services (ERS) report examined WIC food dollar redemption patterns by vendor type in FY2012,[120] those data are now nearly a decade old and the analysis did not directly examine redemption of individual components of the WIC food package. Thus, this paper will build on the ERS report to provide previously unknown visibility around WIC shopping patterns. This knowledge is critical for helping to inform efforts to maximize redemption, and thus maximize the positive impacts of WIC on children's health and development.

The objectives of this study were to use existing administrative data on participants from Massachusetts (MA) WIC to describe (1) where households in MA WIC redeem their benefits and (2) variations in benefit redemption depending on a household's preferred type of WIC vendor. The longitudinal nature of this data allowed for examination of patterns using the most recently available data (2019), as well as over time (2015–2019).

4.3 METHODS

Data Source & Study Population

The MA WIC state agency provided de-identified monthly, household-level redemption data from January 2015 to August 2019. The data included detailed information on the quantity of food benefits issued and redeemed for approximately 200,000 MA WIC households shopping at about 1,000 authorized vendors across the state. Compared to other states, MA WIC is ranked around 20th for state-level food costs and participation, with about 100,000 participants taking part in the program on a given month in 2019.[121]

Because benefits are issued to households on a monthly basis, the unit of analysis was household-months (n=4,190,577 total household-months). Data were included from households during months they: 1) participated and were issued benefits in WIC and 2) redeemed at least some benefits. Data from months that households did not redeem any benefits were excluded because, without redemption information, it would not be possible to identify the household's preferred type of WIC vendor for that month (n=203,302 household-months; 4.6% of total household-months).

The study protocol was reviewed and approved by the Institutional Review Boards for the MA Department of Public Health and the Harvard T. H. Chan School of Public Health.

Measures

Benefit Categories: WIC food benefit categories include juice, milk, breakfast cereal, cheese, eggs, fruit and vegetable CVB, whole wheat bread, fish, legumes or peanut butter, infant cereal, infant meats, infant fruits and vegetables, and infant formula.[122] The quantity and type of foods in each food package depends on whether the participant is an infant, child, or pregnant/breastfeeding/postpartum mother, as well as nutritional needs and participant preferences (food package details provided elsewhere[123]). Depending on the household size, the average monthly value of food benefits to a MA WIC family is estimated to be between $100 to $200.[124]

Vendor Type: MA WIC vendors were classified into one of 8 vendor types: superstores, supermarkets, large grocery stores, medium grocery stores, small grocery stores, convenience stores, commissaries, and pharmacies. Vendors were categorized based on classifications from the SNAP Retailers Database (a dataset maintained by the Center on Budget and Policy Priorities),[125] with additional information updated by MA WIC based on internal knowledge of vendors in the state (e.g., number of cash registers). Due to small sample sizes, data from households who redeemed any benefits at a commissary (i.e., store operated by the military) in a given month were excluded (n=1,661 household-months; 0.04% of total household-months).

Overall vendor type: For each month of the data, households were classified based on the vendor type they relied on when redeeming their WIC food benefits that month (**Supplementary Figure 4.1**). Households that redeemed their benefits at only one vendor type that month were mapped to that vendor type (e.g., supermarket only). Households that redeemed their benefits at more than one vendor type that month were mapped to one of three combination vendor types: "both supermarket and superstore", "both supermarket and grocery store" (including small, medium, and large grocery stores), or "other combination of vendor types".

Food-specific vendor type: To capture further details of households redeeming benefits at more than one vendor type, food-specific vendor types were also assigned to each household for each month of the data. For example, a household that redeemed benefits at both supermarkets and superstores could have redeemed milk only at supermarkets and redeemed cheese only at superstores that month.

Analyses

For each month of the data, the percentage of households that relied on each vendor type when redeeming benefits (i.e., overall vendor type) was calculated. For example, in March 2017, what percentage of households redeemed that month's benefits only at superstores? In a similar manner, for each month of the data, the percentage of households that relied on each vendor type when redeeming individual components of the food package (i.e., food-specific vendor type) was calculated. For example, in March 2017, what percentage of households redeemed that month's cheese benefits only at superstores? The averages of these percentages were then computed for each of the 5 years of the data. Estimates from 2019 (the most recent year of the data) were reported first. To contextualize these 2019 estimates, estimates from 2015–2019 were also reported, including estimating an annual percentage point change (details on this calculation provided in table footnotes). To further contextualize these findings, the number and percentage of MA WIC-authorized vendors categorized as each vendor type for each year of the data were also reported.

Next, for each month of the data and each benefit category, the average percent redemption by the household's overall vendor type was reported. For example, in March 2017, what was the average percent redemption for cheese among households who relied only on superstores when redeeming their benefits? Redemption percentages were calculated as the percentage of the benefit quantity issued to a household in a given month that was actually redeemed (e.g., if a household redeemed 1 dozen eggs of out 2 dozen issued, then the average percent redemption for eggs was 50%). As above, the average of these percentages was computed for each year of the data and an annual change measure was estimated.

Analytic sample sizes are reported in **Supplementary Table 4.1**. Because the data was a census of all MA WIC households, it was not appropriate to conduct inferential tests, which are applied only to sample statistics.

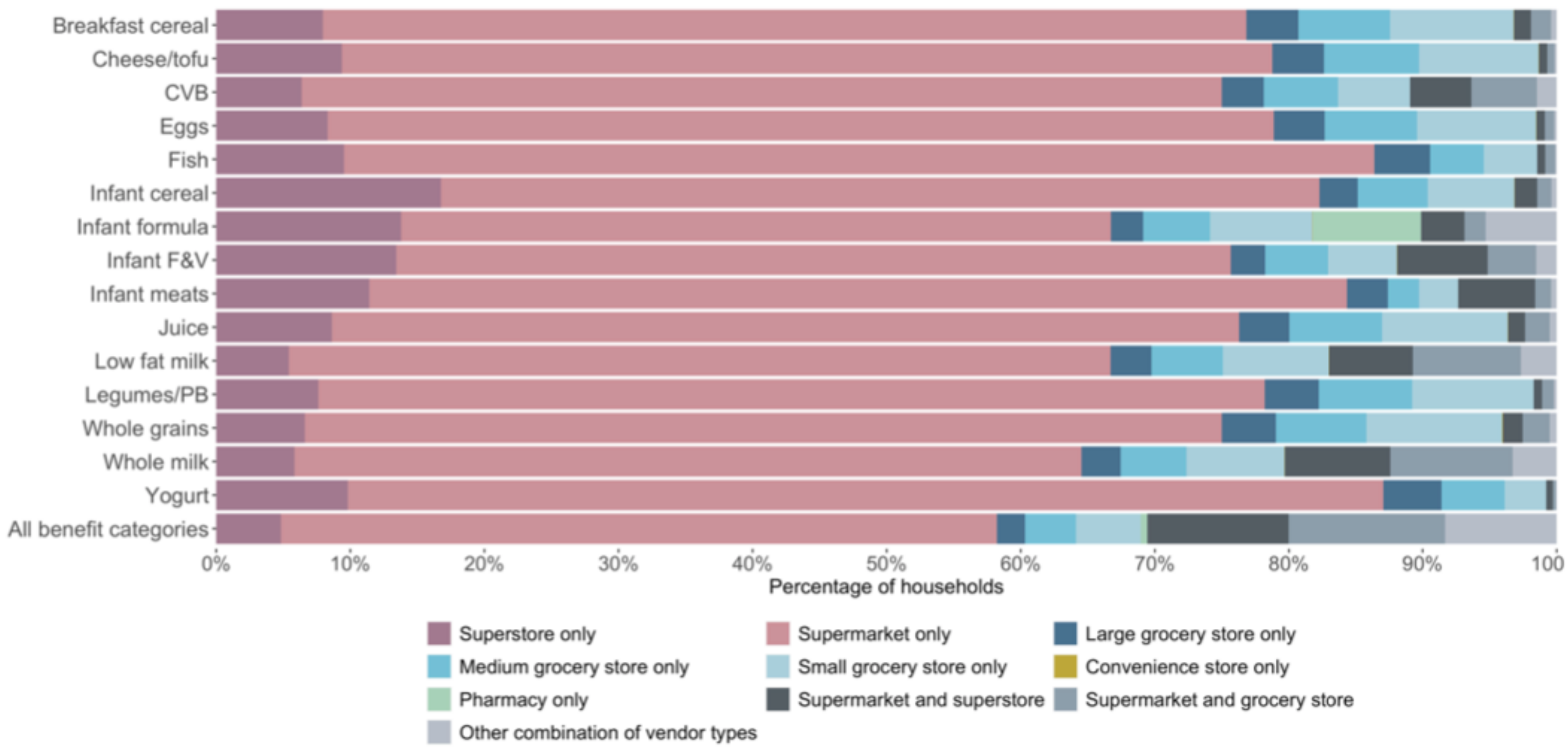
Analyses were conducted using Stata (Version 16) and RStudio (Version 1.3.959) in 2020.

4.4 RESULTS

In 2019, approximately two-thirds of MA WIC households relied on a single vendor type when redeeming benefits in a given month, with the majority of these households redeeming only at supermarkets (53.4%), followed by superstores (4.8%) and small grocery stores (4.8%) (**Figure 4.1**). Approximately one-third of households redeemed benefits at more than one vendor type in a given month, with 12% of households redeeming benefits from both supermarkets and grocery stores (large, medium or small), 11% of households redeeming benefits from both supermarkets and superstores, and the remaining 8% of households redeeming benefits from some other combination of vendor types.

Figure 4.1 shows some variation in the food-specific vendor type households relied on when redeeming benefits in 2019. For example, the percentage of households who relied only on supermarkets ranged from 53% when redeeming infant formula to 77% when redeeming yogurt or fish benefits. A higher percentage of households relied on more than one vendor type when redeeming milk and the CVB compared to other benefit categories.

Figure 4.1: Average percentage[1] of MA WIC households that redeemed food benefits at each vendor type[2] in a given month in 2019, for all benefit categories combined and separately for each benefit category



[1]Percentages are calculated only among households that were issued and redeemed at least some benefits for benefit category that month. For example, in a given month in 2019, 68% of the households that redeemed any of their juice benefit did so at supermarkets only.
[2]Vendor Type for "all benefit categories" row of figure refers to "overall vendor type", while vendor type for all other rows of figure refers to the "food-specific vendor type".
<u>Abbreviations</u>: CVB=Cash Value Benefit, F&V= Fruit and Vegetable, MA = Massachusetts; PB = Peanut Butter, WIC = Special Supplemental Nutrition Program for Women, Infants and Children.

Between 2015–2019, the percentage of households who relied only on superstores, supermarkets, and large grocery stores appeared to increase (annual average percentage point increase of 0.3, 0.4 and 0.2, respectively), while the percentage of households who relied only on small grocery and convenience stores appeared to decrease (annual average percentage point decrease of 0.8 and 0.2, respectively) (**Table 4.1**). Results were similar when examining vendor type reliance for redemption of individual components of the food package (**Supplementary Table 4.2**).

Over the same time period, there looked to be modest increases the number and percentage of WIC-authorized supermarkets (annual average increase in number of vendors of 3.5), while there was little change for superstores and large grocery stores (annual average change in number of vendors of -1.2 and 1.0, respectively). Additionally, there appeared to be decreases in the number and percentage of WIC-authorized small grocery stores and convenience stores (annual average decrease in number of vendors of 28 and 8.3, respectively).

Table 4.1: Number and percentage of MA WIC vendors by vendor type[1] and percentage of WIC households that redeemed food benefits at each vendor type in a given month, 2015–2019

Vendor Type	Definition	Year	Number (%) of MA WIC vendors[2]	Percentage of households that relied only on vendor type when redeeming benefits in a given month[3]	Percentage of households that redeemed at least some benefits at vendor type in a given month[4]
Large Stores					
Superstores	Very large supermarkets, 'big box' stores, super stores and food warehouses primarily engaged in the retail sale of a wide variety of grocery and other store merchandise. Examples: Target, Walmart	2015	53 (5.3)	3.6	15.7
		2016	54 (5.5)	3.7	16.9
		2017	54 (5.6)	3.9	17.3
		2018	50 (5.5)	4.4	17.9
		2019	49 (5.5)	4.8	18.9
		Δ *per year*[5]	*-1.2*	*0.3*	*0.8*
Supermarkets	Extensive variety of grocery and other store merchandise… typically has 10 or more checkout lanes with registers, bar code scanners, and conveyor belts. Examples: Stop & Shop, Star Market	2015	351 (35.1)	52.3	78.5
		2016	377 (38.1)	51.9	79.8
		2017	371 (38.1)	52.8	80.6
		2018	368 (40.3)	53.7	81.1
		2019	373 (42.0)	53.4	80.9
		Δ *per year*[5]	*3.5*	*0.4*	*0.7*
Large grocery stores	Carries a wide selection of all four staple food categories… may sell ineligible items as well, but their primary stock is food items. Example: Sebra Foods	2015	12 (1.2)	1.3	3.6
		2016	13 (1.3)	1.5	4.3
		2017	15 (1.5)	1.8	5.1
		2018	15 (1.6)	2.0	5.4
		2019	15 (1.7)	2.1	5.8
		Δ *per year*[5]	*1.0*	*0.2*	*0.6*

Table 4.1 (continued)

Vendor Type	Definition	Year	Number (%) of MA WIC vendors[2]	Percentage of households that relied only on vendor type when redeeming benefits in a given month[3]	Percentage of households that redeemed at least some benefits at vendor type in a given month[4]
Small Stores					
Medium grocery stores	Carries a moderate selection of all four staple food categories… may sell ineligible items as well, but their primary stock is food items. Example: Adam's Hometown Market	2015	36 (3.6)	3.8	9.9
		2016	37 (3.7)	3.7	10.5
		2017	37 (3.8)	3.7	10.5
		2018	36 (3.9)	3.6	10.3
		2019	37 (4.2)	3.8	10.7
		Δ per year[5]	*0.1*	*0.0*	*0.1*
Small grocery stores	Carries a small selection of all four staple food categories… may sell ineligible items as well, but their primary stock is food items. Example: Aksel Market	2015	298 (29.8)	7.9	19.3
		2016	265 (26.8)	6.7	18.7
		2017	254 (26.1)	6.1	17.2
		2018	219 (24.0)	5.4	15.4
		2019	181 (20.4)	4.8	14.0
		Δ per year[5]	*-28*	*-0.8*	*-1.4*
Convenience stores	Offers a limited line of convenience items and are typically open long hours to provide easy access for customers. Example: 7-Eleven	2015	37 (3.7)	0.7	3.6
		2016	32 (3.2)	0.4	2.7
		2017	29 (3.0)	0.2	1.6
		2018	15 (1.6)	0.1	0.5
		2019	4 (0.5)	0.0	0.1
		Δ per year[5]	*-8.3*	*-0.2*	*-1.1*

Table 4.1 (continued)

Vendor Type	Definition	Year	Number (%) of MA WIC vendors[2]	Percentage of households that relied only on vendor type when redeeming benefits in a given month[3]	Percentage of households that redeemed at least some benefits at vendor type in a given month[4]
Other Stores					
Pharmacies	Only authorized to provide infant formula, exempt infant formula, or other WIC-eligible medical foods, Examples: CVS, Walgreens	2015	212 (21.2)	0.4	3.5
		2016	211 (21.3)	0.4	3.4
		2017	213 (21.9)	0.4	3.2
		2018	211 (23.1)	0.5	3.7
		2019	229 (25.8)	0.5	3.9
		Δ per year[5]	*3.4*	*0.0*	*0.0*

[1]Vendors were categorized based on classifications from the SNAP Retailers Database (a dataset maintained by the Center on Budget and Policy Priorities which categorizes SNAP vendors into vendor types), with additional information updated by the MA WIC vendor manager based on internal knowledge of vendors in the state (e.g., number of cash registers). Descriptions in "definitions" column are based on definitions included in SNAP Retailers Database.
[2]Number of distinct WIC-authorized vendors in Massachusetts where at least once WIC redemption took place that year. Percentages refer to percentage of total vendors that were classified as each vendor type for that year. For example, 25.8% of all MA WIC vendors in 2019 were classified as pharmacies.
[3]"Percentage of households that relied only on vendor type when redeeming benefits in a given month" refers to the overall vendor type classification, as defined in the methods. Percentages in this column will not sum to 100% because some households redeemed at more than one vendor type in a given month.
[4]"Percentage of households that redeemed at least some benefits at vendor type in a given month" refers to a household partially or fully relying on that vendor type in a given month. For example, in a given month a household may redeem some benefits at a convenience store (e.g., milk) and some benefits at a superstore (e.g., eggs). We would consider this household to "redeem partially" at both the superstore and convenience store vendor types.
[5]For the "number (%) of WIC vendors" column, Δ per year refers to the annual change in number of vendors. This was estimated using a linear regression model where the outcome variable was the number of vendors classified as a given vendor type and the only predictor variable was a continuous year term. The coefficient of the continuous year term was interpreted as the estimated annual change in the number of vendors for that vendor type. For example, the average number of superstores decreased by about 1.2 vendors per year between 2015–2019. For the last 2 columns in the table, Δ per year refers to estimated annual percentage point change in the percentage of households relying on each vendor type. This was estimated using a logistic regression model where the outcome variable was a binary indicator (yes/no) for whether or not a household redeemed at a given vendor type and the only predictor variable was a continuous year term. After fitting the model, Stata's margins dydx command was used to predict the average percentage point change per year. For example, the percentage of households that relied only on superstores when redeeming benefits in a given month increased by about 0.3 percentage points per year between 2015 to 2019.
Abbreviations: MA = Massachusetts; SNAP = Supplemental Nutrition Assistance Program; WIC= Special Supplemental Nutrition Program for Women, Infants and Children.

In 2019, average percent redemption was lowest for infant meats, fish, and yogurt, while average percent redemption was highest for infant formula and the CVB (**Figure 4.2**). Average percent redemption appeared to vary by overall vendor type. Compared to other vendor types, households that redeemed benefits only at superstores had lower redemption for most benefit categories, households that relied only on small grocery stores had lower redemption for yogurt and the cash value benefit, and households that redeemed benefits at more than one vendor type appeared to have higher redemption of the CVB, infant fruits and vegetables, and fish.

Figure 4.2: Average percent redemption[1] in a given month in 2019 among MA WIC households redeeming at different overall vendor types, by food benefit category

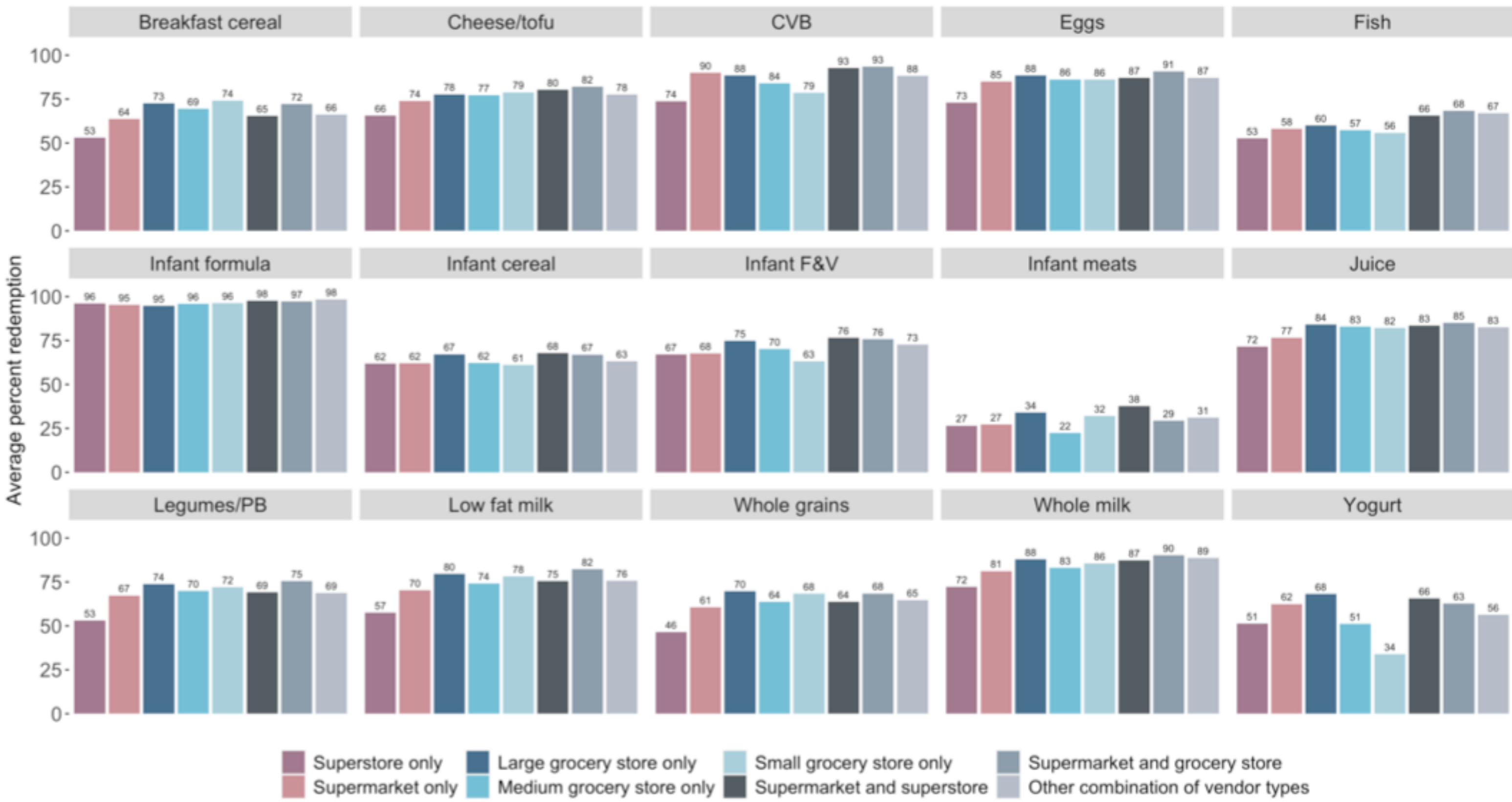


Figure 4.2 (continued)

[1]Average percent redemption refers to the percentage of benefit quantity issued to a household that is redeemed per month. For example, if a household is issued 2 dozen eggs and redeemed 2 dozen eggs, their redemption percentage would be 100%. If a household is issued 2 dozen eggs and redeemed 1 dozen eggs, their redemption percentage would be 50%. These percentages are only calculated among households that were issued benefit in that month (e.g., redemption percentage for eggs does not include participants who were not issued eggs that month).
[2]Vendor Type refers to the overall vendor type from which a household redeemed their WIC benefits in a given month. For example, the average percent redemption for breakfast cereal was about 53% in 2019 for households that redeemed their benefits only at superstores.
Notes: Due to small sample sizes, this analysis excluded households that redeemed benefits only from pharmacies or convenience stores.
Abbreviations: CVB=Cash Value Benefit, F&V= Fruit and Vegetable, MA = Massachusetts, PB = Peanut Butter, WIC = Special Supplemental Nutrition Program for Women, Infants and Children.

There was an apparent decrease in average percent redemption between 2015–2019 for most benefit categories, with the exception of the CVB and yogurt (**Supplementary Table 4.3**). There were some differences in these results by overall vendor type. For example, while yogurt redemption increased across all vendor types, the largest increases were for households redeeming benefits only at small grocery stores (annual average percentage point increase of 6.9).

4.5 DISCUSSION

In this study of approximately 200,000 MA households participating in WIC between 2015 and 2019, a large and increasing share of households redeemed benefits only at larger stores (superstores, supermarkets, and large grocery stores), while a small and decreasing portion of households redeemed benefits only at small grocery and convenience stores. There was also variability in average percent redemption of benefits depending on which vendor type households relied on when redeeming benefits, with households that redeemed benefits only at superstores having the lowest redemption of most benefit categories compared to other vendor types. These findings suggest that retail-based efforts to increase redemption should consider vendor type preferences and that strategies to increase redemption may be especially important for WIC shoppers relying on superstores.

This study found that many MA WIC households rely only on supermarkets for benefit redemption, consistent with national redemption patterns in 2012.[120] Compared to smaller outlets, supermarkets often offer considerably lower prices for most benefit categories.[126] While WIC households are theoretically price-insensitive when redeeming benefits (with the exception of the CVB), benefits typically do not cover all the food a family requires and an estimated 85% of WIC participants do their WIC shopping at the same vendor where they purchase their other groceries.[127] Thus, lower prices may still motivate WIC households to seek out supermarkets when redeeming benefits. Furthermore, we found that 42% of all authorized WIC vendors are supermarkets, suggesting that the pervasiveness of these large stores in the MA WIC retail landscape may make it more convenient for participants to redeem benefits at them.

This study also found that a small and declining percentage of WIC households rely on small grocery and convenience stores (about 5% in 2019), a finding that could be driven by the shrinking availability of these vendors in MA WIC over the past 5 years. There are many possible reasons for declines in the number of small WIC vendors. WIC-authorized vendors must meet minimum stocking requirements,[128] a factor which may be a greater challenge for small vendors with limited shelf space and equipment to keep perishable foods fresh. Thus, it is possible that stocking requirements and other compliance challenges faced by small vendors make it no longer worthwhile to maintain WIC-authorized status. Alternatively, it is possible that observed changes in the composition of MA WIC-authorized vendors could be driven by secular retailer trends independent of WIC – unfortunately, data on trends in retailer composition in MA are limited, although previous research using national-level data found a decline in independent grocery stores over time.[129] More research is needed in MA and elsewhere to document factors influencing small store participation in WIC.

The results of this study indicate that WIC households that relied only on superstores had the lowest redemption levels for most benefit categories. This is consistent with previous qualitative work which has highlighted challenges that WIC households face when redeeming benefits from very large vendors like superstores.[112] WIC-eligible items may be harder to locate in superstores and, if an ineligible item (e.g. incorrect brand or size) is not accepted at the cash register, shoppers are more reluctant to go back through the large store to replace it with a WIC-eligible product.[112] An alternative explanation for this finding is that households choosing to shop at superstores may have different characteristics or preferences that drive the extent of their redemption, independent of the effect of store type on redeeming benefits. Future research should investigate whether there is something about the superstore environment that reduces redemption versus whether it is a compositional effect based on who self-selects into shopping at superstores. If findings suggest that it is the superstore environment that is driving lower redemption, an additional lane of research inquiry could be to investigate how superstores can improve vendor practices to make redemption easier for participants (e.g., improved check-out process or labeling). In the meantime, relying on superstores can be viewed as a marker of risk for under-redeeming benefits; WIC may consider targeting these WIC shoppers with additional education efforts or other strategies to improve redemption.

This study also found that households that redeem benefits only at small grocery stores had lower redemption of the CVB and yogurt. This is in line with previous research suggesting that small vendors are typically characterized by limited availability of healthy, perishable food items.[130] Encouragingly, redemption percentages of the CVB and yogurt appear to have increased over the past 5 years among households relying on small grocery stores, suggesting that vendor practices to promote redemption of these benefit categories may be improving.

This study provides important information needed to understand the best targets for WIC quality improvement initiatives or future interventions. While these findings suggest that targeting supermarkets is likely to reach the greatest number of WIC households in MA, a sizeable portion of WIC participants redeem at least some benefits from small stores in a given month, suggesting that vendor initiatives focused only on large stores would fail to reach a considerable number of households. This insight has important implications for equity in future vendor initiatives. For example, there is growing interest in enabling online shopping for WIC redemptions, including the Food and Nutrition Service's recent $2.5 million investment in a pilot project to develop and test an online ordering model for WIC.[131] While this type of initiative has important potential to reduce barriers to WIC benefit redemption, households who are not relying on superstores and supermarkets may not benefit from online purchase initiatives, which are likely to be implemented first among larger vendors. Moving forward, it will be important for future research to investigate whether there are inequities in who has access to online shopping initiatives.

This study has a number of limitations. First, because the data were limited to a single state, findings may not generalize to states with different demographic profiles or distributions of vendor types. However, the findings from this study are comparable to studies conducted in other states,[120] suggesting these results may have relevance beyond MA. Second, the data were collected prior to the COVID-19 pandemic, which has resulted in major changes to shopping behaviors.[132-134] Third, this analysis is purely descriptive and thus is not intended to make causal inferences about the effects of vendor type on redemption. Despite these limitations, this study contributes important new quantitative evidence which can be used as a launching point for future research in this area and for informing current practice.

Conclusion

This study provides important new evidence on where and to what extent households in MA redeem their WIC food benefits. Results suggest that retail-based efforts to increase redemption should consider vendor type preferences and that strategies to increase redemption may be especially important for WIC shoppers relying on superstores.

Chapter 5: Conclusion

Food insecurity and obesity – two key types of poor nutrition – are prevalent, costly, and can result in serious health consequences. In these chapters, we underscored the importance of conducting rigorous epidemiological research to examine their health impacts and identify policy and programmatic approaches that may meaningfully reduce their burden in the population.

In **Chapter 2**, we described trends in added sugar intake from foods and beverages covered under the NSSRI sugar reduction targets and estimated possible reductions if industry were to meet the targets. We showed that, while added sugar intake from NSSRI foods and drinks has declined over the past decade, total added sugar intake remains high and consumption of certain NSSRI categories has remained steady over time. Although many factors contribute to sugar intake, our findings indicate that reducing sugar in the food supply could play a role in lowering added sugar intake among youth. Estimated reductions were similar across demographic characteristics, suggesting the NSSRI captures key sources of added sugar intake among children from a variety of racial/ethnic and socioeconomic groups and is not projected to widen existing diet-related disparities. Once implemented, these targets stand to complement current policy and programmatic efforts aimed at reducing added sugar intake.

In **Chapter 3,** we examined whether experiencing food insufficiency – a screener measure related to food insecurity – worsens cardiovascular health over time. Compared to food sufficiency, we found that food insufficiency patterns were generally associated with higher BMI, waist circumference, and blood pressure, and lower HDL, with some sex- and race-specific patterns. Findings from our study should be replicated in other settings and populations. If verified, this evidence could provide further justification for intervening on food insecurity to reduce future CVD risk.

In **Chapter 4**, we examined shopping patterns related to food package redemption among participants in the WIC program. We provided previously unknown visibility around WIC shopping patterns, highlighting that retail-based efforts to increase redemption may need to target a wide range of vendor types to reach all WIC households, but could be especially important for shoppers relying on superstores. More research in this area is critical to inform efforts to maximize redemption, and thus maximize the positive impacts of WIC on children's health and development.

While the focus and scope of each of these three chapters varied, they each identified drivers and points of intervention for obesity and food insecurity. This work underscores the importance of conducting rigorous epidemiological research to aid in the development of policies and programs aimed at reducing the population burden of food insecurity and obesity.

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Appendix

Supplementary Text 2.1: Development of targets

The National Salt and Sugar Reduction Initiative (NSSRI) categories were identified through an iterative process that considered added sugar contribution, opportunities and technical challenges for sugar reduction, and comments from industry. After the targets are released, the Health Department will continue ongoing efforts to monitor sugar supply in packaged foods as well as encourage companies to meet them. The targets include 15 packaged food and beverage categories spanning 7 meta-categories. Baseline sales-weighted mean (SWM) sugar density (defined as grams of sugar per 100g of food or per 100mL of beverage) was calculated for each category using 2017 sales data from Nielson and nutrition data from Label Insight and manufacturer websites. SWM sugar density was calculated by dividing each product's sugar content in grams by its weight in 100-gram units (or 100-millilitter of liquid) and multiplying by the product's percent unit sales in the category. Thus, more frequently purchased foods and beverages contribute more to the SWM sugar density than less frequently purchased foods and beverages. The 2023 targets reflect a 10% reduction in the SWM sugar density for both food and drinks, while the 2026 targets reflect a 20% reduction in the SWM sugar density for foods and a 40% for drinks. For example, sugary drinks were estimated to have a baseline SWM sugar density of 8.9g per 100g; thus, the 2023 target was set at 8.0g and the 2026 target was set at 5.3g.

Supplementary Text 2.2: Application of targets to NHANES data

To estimate reductions in added sugar intake if companies were to meet the 2023 and 2026 targets, we first restricted our sample to the most recently available data (2017–2018). Next, we calculated the ratio of the target to baseline SWM sugar density for each NSSRI category. For example, the baseline SWM sugar density for the breakfast pastries categories was 27.2g per 100g, while the 2023 target was 24.5g per 100g; thus, the ratio of the 2023 target to baseline was 0.90. Next, we multiplied the applicable ratio of the target to the baseline SWM sugar density by the amount of added sugar reported for that NSSRI category by each participant. For example, if a participant reported consuming a total of 5g of sugar from the breakfast pastries category, their predicted intake under the 2023 targets would be 0.90*5g =4.5g.

It should be noted that the NSSRI targets are based on total sugar – however, for most categories (e.g., sugary drinks), added sugar and total sugar are equivalent and for products that contain natural sugars (e.g., sweetened milk drinks), allowances for natural sugar have been made as part of the targets. Thus, we applied the total sugar NSSRI target reductions to the added sugar NHANES values.

Supplementary Table 2.1: Energy-adjusted[1] trends in daily added sugar intake (grams) from each National Salt and Sugar Reduction Initiative category, meta-category, and all categories combined between 2003–2004 and 2017–2018 for children in the NHANES

	2003–2004	2005–2006	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016	2017–2018	p-value for linear trend[2]
All NSSRI Sugar Categories Combined	70.1 (65.6, 74.7)	65.4 (61.1, 69.8)	63.4 (59.1, 67.8)	61.9 (58.6, 65.2)	55.5 (54.1, 57.0)	55.4 (52.4, 58.4)	49.7 (47.2, 52.2)	52.3 (48.9, 55.7)	<0.001
All NSSRI Foods Combined (not Drinks)	24.8 (23.0, 26.5)	24.6 (23.3, 25.9)	24.2 (22.0, 26.4)	23.0 (21.4, 24.5)	20.5 (19.3, 21.7)	22.6 (21.1, 24.1)	21.4 (20.0, 22.8)	23.5 (21.4, 25.6)	0.005
1. Drinks	45.4 (41.7, 49.1)	40.8 (36.6, 45.1)	39.2 (35.7, 42.8)	39.0 (36.0, 41.9)	35.0 (33.2, 36.8)	32.8 (29.6, 36.0)	28.3 (26.2, 30.4)	28.8 (26.8, 30.8)	<0.001
1.1 Sugary drinks	43.5 (39.8, 47.2)	39.5 (35.3, 43.6)	37.7 (34.0, 41.3)	36.9 (33.7, 40.0)	33.6 (31.6, 35.5)	31.5 (28.2, 34.7)	27.1 (25.0, 29.1)	27.7 (25.9, 29.5)	<0.001
1.2 Sweetened milk	1.8 (1.3, 2.3)	1.1 (0.9, 1.4)	1.4 (1.1, 1.7)	2 (1.5, 2.5)	1.2 (0.7, 1.7)	1.1 (0.9, 1.3)	1.0 (0.8, 1.2)	1.0 (0.6, 1.3)	0.001
1.3 Sweetened milk substitute	0.1 (0.0, 0.1)	0.2 (0.0, 0.4)	0.2 (0.1, 0.3)	0.2 (0.1, 0.3)	0.2 (0.1, 0.4)	0.2 (0.0, 0.5)	0.2 (0.1, 0.3)	0.2 (0.1, 0.3)	0.194
2. Grain-Based Desserts and Snack Bars	6.8 (5.9, 7.6)	7.8 (6.6, 8.9)	7.6 (6.5, 8.6)	7.6 (7.0, 8.1)	8.0 (7.1, 9.0)	8.1 (6.8, 9.4)	8.1 (7.4, 8.9)	8.2 (7.0, 9.5)	0.049
2.1 Breakfast pastries	1.8 (1.5, 2.2)	2.4 (1.8, 2.9)	2.7 (2.2, 3.3)	2.7 (2.2, 3.2)	2.6 (2.0, 3.1)	2.2 (1.7, 2.6)	2.6 (1.8, 3.3)	2.4 (1.8, 2.9)	0.422
2.2 Cakes	2.5 (1.8, 3.2)	2.8 (2.0, 3.6)	2.5 (1.7, 3.2)	1.9 (1.4, 2.4)	1.9 (1.2, 2.5)	2.5 (1.8, 3.3)	2.1 (1.6, 2.7)	2.8 (1.7, 3.8)	0.78

Supplementary Table 2.1 (Continued)

	2003–2004	2005–2006	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016	2017–2018	p-value for linear trend[2]
2.3 Cookies	2.0 (1.5, 2.4)	2.1 (1.8, 2.5)	1.9 (1.4, 2.4)	2.4 (2.0, 2.7)	2.9 (2.4, 3.4)	2.6 (2.1, 3.1)	2.8 (2.3, 3.3)	2.5 (2.0, 2.9)	0.003
2.5 Granola bars	0.5 (0.2, 0.7)	0.4 (0.3, 0.6)	0.5 (0.3, 0.7)	0.5 (0.4, 0.7)	0.7 (0.4, 1.0)	0.8 (0.6, 1.0)	0.7 (0.5, 0.9)	0.6 (0.4, 0.9)	0.015
3. Refrigerated and Frozen Desserts[3]	4.5 (3.4, 5.6)	4.7 (3.8, 5.6)	5.5 (4.1, 6.8)	4.1 (3.6, 4.7)	2.4 (2.0, 2.9)	3.0 (2.2, 3.8)	2.8 (2.3, 3.3)	3.2 (2.4, 4.1)	<0.001
4. Candies	5.1 (4.1, 6.0)	4.1 (3.4, 4.7)	4.1 (3.7, 4.5)	3.5 (2.9, 4.1)	2.7 (2.2, 3.2)	4.6 (3.9, 5.3)	3.4 (2.9, 4.0)	3.9 (3.3, 4.6)	0.032
4.1 Sweet candies	3.0 (2.0, 3.9)	2.4 (1.8, 3.0)	2.4 (1.9, 2.9)	2.0 (1.6, 2.4)	1.5 (1.1, 1.8)	2.9 (2.4, 3.5)	1.9 (1.6, 2.2)	2.7 (2.1, 3.2)	0.382
4.2 Chocolate candies	2.1 (1.6, 2.6)	1.6 (1.5, 1.8)	1.7 (1.4, 2.0)	1.5 (1.2, 1.8)	1.2 (0.9, 1.5)	1.7 (0.8, 2.5)	1.5 (1.1, 2.0)	1.2 (0.9, 1.6)	0.024
5. Breakfast Cereals[3]	5.6 (4.8, 6.3)	4.7 (4.2, 5.2)	4.1 (3.7, 4.5)	4.4 (3.7, 5.1)	3.9 (3.5, 4.3)	3.7 (3.3, 4.1)	4.2 (3.7, 4.7)	4.7 (4.1, 5.2)	non-linear[4]
6. Condiments and Toppings	1.8 (1.3, 2.3)	2.3 (1.7, 2.8)	2.2 (1.6, 2.8)	2.2 (1.9, 2.6)	2.3 (1.3, 3.4)	2.2 (1.9, 2.6)	2.4 (1.8, 3.0)	2.9 (2.3, 3.6)	0.03
6.1 Condiments	0.5 (0.4, 0.6)	0.5 (0.4, 0.6)	0.6 (0.4, 0.7)	0.5 (0.4, 0.6)	0.4 (0.3, 0.5)	0.5 (0.4, 0.6)	0.6 (0.5, 0.7)	0.7 (0.6, 0.9)	0.035
6.2 Dessert syrups and toppings	1.4 (0.8, 1.9)	1.8 (1.2, 2.3)	1.6 (1.1, 2.2)	1.7 (1.3, 2.1)	1.9 (0.8, 2.9)	1.8 (1.4, 2.1)	1.8 (1.2, 2.4)	2.2 (1.6, 2.9)	0.079

Supplementary Table 2.1 (Continued)

	2003–2004	2005–2006	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016	2017–2018	p-value for linear trend[2]
7. Yogurt	1.0 (0.6, 1.3)	1.0 (0.8, 1.3)	0.7 (0.6, 0.9)	1.1 (0.9, 1.4)	1.1 (0.8, 1.3)	1.0 (0.7, 1.2)	0.5 (0.3, 0.6)	0.6 (0.4, 0.7)	0.002
Non-NSSRI Items	17.6 (16.3, 18.9)	20.9 (19.2, 22.6)	21.3 (19.9, 22.7)	21.4 (20.3, 22.5)	23.7 (22.0, 25.5)	20.4 (19.4, 21.4)	23.1 (20.7, 25.5)	22.1 (20.6, 23.5)	<0.001

[1]Energy adjustment was conducted by including total calories as a continuous covariate in regression models.

[2]To account for multiple testing, we applied a Bonferroni correction wherein a p-value of <0.001 was considered statistically significant.

[3]Meta category only contains a single category; thus, results are not repeated in this row.

[4]Evidence of a non-linear trend in added sugar intake from breakfast cereals over time, as indicated by statistically significant joint Wald test of the quadratic and cubic terms for survey year (p=0.0004)

Notes: Negative predicted values were truncated at 0.

Supplementary Table 2.2: Trends in daily intake (grams of food or drink) from each National Salt and Sugar Reduction Initiative meta-category and all categories combined between 2003–2004 and 2017–2018 for children in the NHANES

	2003–2004	2005–2006	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016	2017–2018	p-value for linear trend[1]
All NSSRI Categories Combined	693.0 (644.4, 741.7)	630.5 (568.0, 693.1)	576.5 (538.3, 614.6)	560.2 (524.4, 596.0)	514.3 (487.4, 541.1)	464.1 (429.9, 498.3)	407.3 (380.4, 434.2)	431.8 (403.8, 459.7)	<0.001
All NSSRI Foods Combined	106.4 (97.8, 115.0)	106.0 (99.5, 112.5)	105.5 (97.7, 113.2)	100.0 (91.9, 108.1)	87.4 (82.0, 92.9)	90.9 (84.7, 97.0)	90.1 (84.1, 96.2)	96.5 (87.1, 105.8)	<0.001
1. Drinks	586.6 (542.1, 631.2)	524.5 (463.2, 585.9)	471.0 (432.3, 509.8)	460.2 (423.8, 496.6)	426.8 (399.2, 454.4)	373.2 (340.0, 406.4)	317.2 (289.8, 344.5)	335.3 (309.5, 361.1)	<0.001
2. Grain-Based Desserts and Snack Bars	25.7 (23.2, 28.1)	26.1 (23.0, 29.2)	25.5 (22.4, 28.6)	26.3 (23.5, 29.1)	28.1 (25.0, 31.2)	25.5 (21.3, 29.6)	27.0 (23.7, 30.3)	27.8 (23.4, 32.2)	0.363
3. Refrigerated and Frozen Desserts	26.7 (21.5, 31.8)	26.4 (22.0, 30.8)	27.2 (22.3, 32.0)	21.6 (18.5, 24.6)	14.6 (12.0, 17.2)	17.4 (12.9, 21.9)	16.4 (13.5, 19.2)	17.1 (12.8, 21.5)	<0.001
4. Candies	10.3 (8.5, 12.1)	9.3 (8.1, 10.5)	9.1 (7.9, 10.2)	8.2 (7.3, 9.0)	7.1 (5.8, 8.4)	8.3 (7.0, 9.7)	6.1 (5.1, 7.2)	6.9 (5.7, 8.0)	<0.001
5. Breakfast Cereals	21.2 (19.1, 23.3)	20.2 (17.7, 22.7)	21.4 (17.8, 25.0)	18.9 (16.7, 21.1)	17.2 (15.3, 19.0)	16.9 (14.8, 19.1)	17.9 (15.9, 20.0)	18.2 (16.3, 20.2)	0.001
6. Condiments and Toppings	14.4 (9.5, 19.2)	14.3 (10.5, 18.1)	16.0 (12.0, 20.1)	14.8 (11.3, 18.2)	10.6 (7.2, 13.9)	12.2 (9.2, 15.2)	13.4 (9.4, 17.4)	15.9 (12.5, 19.3)	0.704

Supplementary Table 2.2 (Continued)

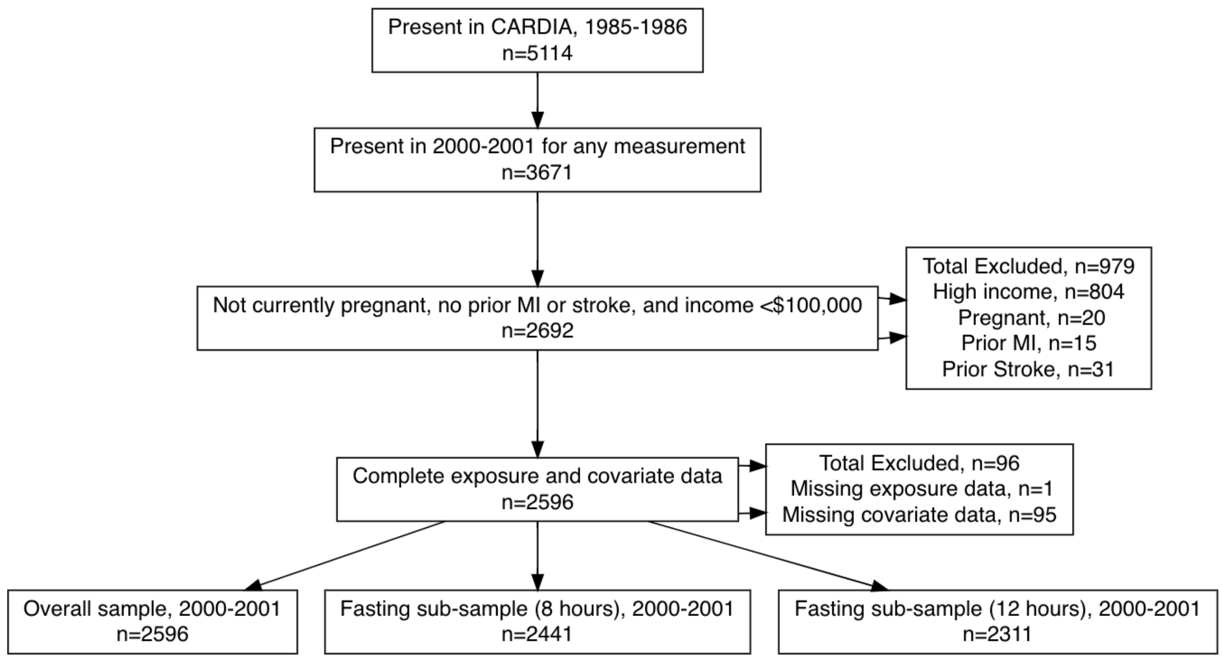
	2003–2004	2005–2006	2007–2008	2009–2010	2011–2012	2013–2014	2015–2016	2017–2018	p-value for linear trend[1]
7. Yogurt	8.2 (5.9, 10.5)	9.6 (7.2, 12.0)	6.3 (4.9, 7.8)	10.3 (7.7, 12.9)	9.9 (7.9, 11.8)	10.6 (8.1, 13.0)	9.3 (6.6, 12.0)	10.6 (7.8, 13.3)	0.111
Non-NSSRI	337.6 (320.2, 355.0)	281.8 (269.3, 294.2)	280.2 (263.3, 297.0)	289.7 (270.7, 308.7)	337.0 (324.4, 349.6)	296.4 (283.7, 309)	314.5 (293.5, 335.5)	308.7 (290.7, 326.8)	non-linear[2]

[1]To account for multiple testing, we applied a Bonferroni correction wherein a p-value of <0.001 was considered statistically significant. To assess the presence of non-linearity in trends, we included linear, quadratic and cubic year terms in our models. We conducted a joint Wald test of the significance of the quadratic and cubic terms. If these terms were significant, we concluded non-linearity. If these terms were not significant, we concluded there was no evidence of non-linearity and reported the results from a model that only included a linear year term.

[2]Evidence of a non-linear trend in grams of non-NSSRI items over time, as indicated by statistically significant joint Wald test of the quadratic and cubic terms for survey year ($p<0.001$).

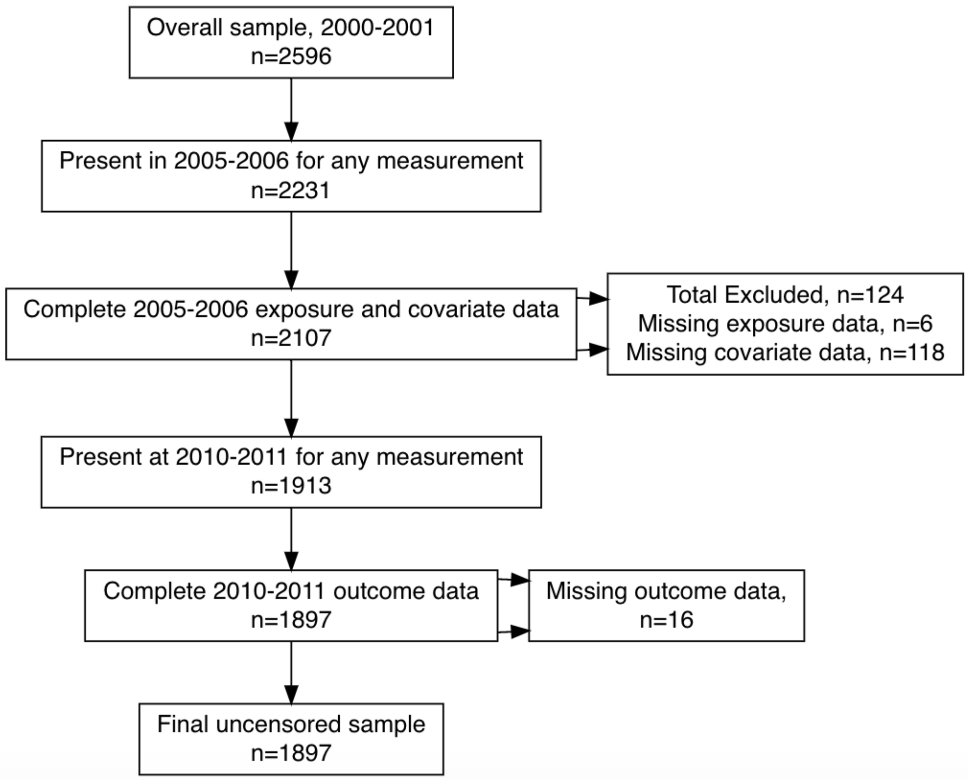
Notes: Negative predicted values were truncated at 0.

Supplementary Figure 3.1: Flowchart outlining criteria leading to selection of "baseline" analytic sample: CARDIA, 2000–2001



Notes: Participants with complete 2000–2001 data on exposure and covariates and who, in 2000–2001, had no previous history of myocardial infarction or stroke, were not currently pregnant, and had an annual household income <$100,000 were included in the overall "baseline" analytic sample (n=2296). In line with cohort recommendations, this "baseline" analytic sample was further limited to those who reported fasting ≥8 hours in 2000–2001 when examining fasting glucose as an outcome (n=2441) and to those who reported fasting ≥12 hours in 2000–2001 when examining LDL and triglycerides as outcomes (n=2311). Sub-categories in "Total Excluded, n=979" box do not sum to 979 because of missing values for income or pregnancy/prior MI/stroke status.
Abbreviations: MI = Myocardial Infarction.

Supplementary Figure 3.2: Flowchart outlining criteria leading from overall "baseline" analytic sample in 2000–2001 to selection of final "uncensored" sample in 2010–2011: CARDIA: 2000–2011



Notes: Over follow-up, participants were censored in 2005–2006 or 2010–2011 if they were missing exposure, covariate, or outcome data. Thus, "uncensored" means that the participant remained in the sample throughout follow-up and had complete data on all exposure, covariate and outcome information. The above flowchart illustrates censoring for the overall sample. When examining fasting outcomes, participants were additionally censored for not fasting the appropriate duration of time (i.e., either 8-hours or 12-hours). The final uncensored sample size was n=1605 for participants fasting ≥8 hours and n=1379 for participants fasting ≥12 hours.

Supplementary Text 3.1: Details on analytic approach

To identify the causal effect of food insufficiency on cardiometabolic health, outcome values must be known under both the presence and absence of food insufficiency. However, since we cannot observe outcomes of food sufficient individuals under the state of food insufficiency (and vice versa), we must compare outcomes in populations with different levels of food sufficiency but presumed to be exchangeable on all other factors. Since food insufficiency is not randomly distributed in the population and there are obvious ethical and logistical factors that make random assignment unfeasible, analyses of observational data provide an alternative approach to making this comparison. Inverse Probability (IP) weighting – once such analytic approach – was chosen because it allows for estimation of the effects of exposures which vary over time and may affect, and be affected by, covariates that also vary over time.

<u>Inverse Probability (IP) of Treatment Weights</u>

Denominator of Weights: In its most basic form ("unstabilized treatment weights"), IP of treatment weighting intends to "simulate" what would have happened had we implemented an intervention that ensured everyone in the study population was food insufficient (exposed) versus food sufficient (unexposed). Provided all relevant baseline and time-varying confounders are measured and included in weight models and these models are correctly specified, this weighting scheme creates a pseudopopulation twice the size of the original sample where food insufficiency is independent of past measured confounders. In practice, the pseudopopulation is created by weighting each participant by the inverse of the probability of receiving the exposure that he/she actually received, conditional on his/her exposure and confounder history. To estimate these weights, we fit a logistic regression model for the log odds of food insufficiency (see below), then use the estimated coefficients from this model to "predict" each participant's probability of being food sufficient (if they reported being food sufficient) or food insufficient (if they reported being food insufficient). The weights are the inverse of these probabilities.

Numerator of Weights: To make a more stable version of these weights ("stabilized treatment weights"), a numerator can be included. With stabilized weights, the pseudopopulation is the same size as the original sample, but exposure remains independent of measured confounders. Compared to unstabilized weights, stabilized weights typically have a smaller range and result in narrower 95% confidence intervals. The numerator is a participant's probability of receiving the exposure that he/she actually received, conditional on exposure history and a subset of the "baseline" confounders. The more components that are included in this subset, the more stable the weights will be. Thus, we chose to include all 2000–2001 confounders in this subset for our models. As before, we fit a logistic regression for the log odds of food insufficiency (see below), then use the coefficients from this model to "predict" each participant's probability of being food sufficient (if they reported being food sufficient) or food insufficient (if they reported being food insufficient). This probability is included as the numerator of the participant's weight.

Weights in Time Varying Settings: IP weights can be generalized for time-varying exposures by creating separate weights at each time point, then taking the product of these weights.

Let A_0 denote food insufficiency in 2000–2001 (1=food insufficient, 0=food sufficient), A_1 denote food insufficiency in 2005–2006 (1=food insufficient, 0=food sufficient), L_0 denote a vector of covariates measured at baseline (2000–2001), L_1 denote a vector of time-varying covariates measured in 2005–2006, and C_1 denote censoring by 2005–2006 (1= censored, 0 =uncensored).

$$\frac{P(A_0 = a_0|L_0 = l_0)}{P(A_0 = a_0|L_0 = l_0)} x \frac{P(A_1 = a_1|C_1 = 0, A_0 = a_{0,} L_0 = l_0)}{P(A_1 = a_1|C_1 = 0, A_0 = a_0, L_0 = l_0, L_1 = l_1)}$$

Treatment weight in 2000–2001[1]   Treatment weight in 2005–2006

Weight Component	Logistic Regression Model
Numerator of treatment weight in 2000–2001[2]	$logit(P[A_0 = 1|L_0 = l_0]) = \beta_0 + \beta_1 L_0$
Denominator of treatment weight in 2000–2001[2]	$logit(P[A_0 = 1|L_0 = l_0]) = \beta_0 + \beta_1 L_0$
Numerator of treatment weight in 2005–2006[3]	$logit(P[A_1 = 1|C_1 = 0, A_0 = a_0, L_0 = l_0]) = \beta_0 + \beta_1 a_0 + \beta_2 l_0$
Denominator of treatment weight in 2005–2006[3]	$logit(P[A_1 = 1|C_1 = 0, A_0 = a_0, L_0 = l_0, L_1 = l_1)] = \beta_0 + \beta_1 a_0 + \beta_2 l_0 + \beta_3 l_1$

[1]The stabilized treatment weight at the first time point will be 1 because the numerator and denominator cancel out. For this reason, baseline covariates need to be adjusted for in the Marginal Structural Model (MSM).
[2]Because food insufficiency was not assessed prior to 2000–2001 in CARDIA, we did not include food insufficiency history as a covariate in the numerator or denominator treatment weights in 2000–2001 models.
[3]Only participants who remained uncensored by 2005–2006 were used to fit model for the numerator and denominator of treatment weights in 2005–2006. This is the reason that the models are conditioned on $C_1 = 0$.

Inverse Probability of Censoring Weights

Over follow-up, participants were censored at the first time point in which s/he was missing exposure, covariate, or outcome data. For example, if a participant was missing food insufficiency data in 2005–2006, they were censored in 2005–2006. If a participant was missing BMI data in 2010–2011, they were censored in 2010–2011. When examining fasting outcomes, participants were also censored at the first time point in which they did not report fasting for a sufficient amount of time (i.e., either 8-hours or 12-hours). Because loss to follow-up and missing data can introduce selection bias, we created stabilized IP weights for censoring. This creates a pseudopopulation the same size as the original sample *after* censoring, but censoring occurs at random with respect to measured covariates. In practice, the pseudopopulation is created by weighting each participant by the inverse of the probability of being uncensored, conditional on food insufficiency and covariate history. As with the treatment weights, these probabilities are estimated by fitting logistic regression models (see below). As before, we can extend IP weights for censoring to the time-varying setting by taking the product of the weights at each time point.

Let A_0 denote food insufficiency in 2000–2001 (1=food insufficient, 0=food sufficient), A_1 denote food insufficiency in 2005–2006 (1=food insufficient, 0=food sufficient), L_0 denote a vector of covariates measured in 2000–2001, L_1 denote a vector of time-varying covariates measured in 2005–2006, C_1 denote censoring by 2005–2006 (1= censored, 0 =uncensored), and C_2 denote censoring by 2010–2011 (1= censored, 0 =uncensored).

$$\frac{P(C_1 = 0 \mid A_0 = a_0, L_0 = l_0)}{P(C_1 = 0 | A_0 = a_0, L_0 = l_0)} x \frac{P(C_2 = 0 \mid C_1 = 0,\ A_0 = a_0, A_1 = a_1, L_0 = l_0)}{P(C_2 = 0 | C_1 = 0, A_0 = a_0, A_1 = a_{1,} L_0 = l_0, L_1 = l_1,)}$$

Censoring weight by 2005–2006[1] Censoring weight by 2010–2011

Weight	**Logistic Regression**
Numerator of censoring in 2005–2006 weight	$logit(P[C_1 = 0 \mid A_0 = a_0, L_0 = l_0]) = \beta_0 + \beta_1 a_0 + \beta_2 L_0$
Denominator of censoring in 2005–2006 weight	$logit(P\left[C_1 = 0 \mid A_0 = a_{0,} L_0 = l_0\right]) = \beta_0 + \beta_1 a_0 + \beta_2 L_0$
Numerator of censoring in 2010–2011 weight[2]	$logit(P[C_2 = 0 \mid C_1 = 0, A_0 = a_0,\ A_1 = a_1, L_0 = l_0]) = \beta_0 + \beta_1 a_0 + \beta_2 a_1 + \beta_3 L_0$
Denominator of censoring in 2010–2011 weight[2]	$logit(P\left[C_2 = 0 \mid C_1 = 0, A_0 = a_{0,}\ A_1 = a_{1,} L_0 = l_0, L_1 = l_1)\right] = \beta_0 + \beta_1 a_0 + \beta_2 a_1 + \beta_3 L_0 + \beta_4 L_1$

[1]The censoring weight at the first time point will be 1 because the numerator and denominator cancel out. For this reason, baseline covariates need to be adjusted for in the MSM.
[2]Only participants who remained uncensored in 2005–2006 were used to fit model for the censoring weight in 2010–2011.

<u>Overall Weight Construction</u>

To obtain an uncensored participant's overall weight, we multiply the treatment and censoring weights together. Censored participants receive a weight of 0.

Fitting the Marginal Structural Model (MSM) and Estimating Means

Let $E[Y^{a0,a1}]$ denote the mean of the outcome under a hypothetical intervention that sets $\bar{A}_k$=(A_0, A_1) equal to some set of fixed values $\bar{a}_k$=(a_0, a_1), where a_k is a possible realization of A_k (either 1 or 0) and k is the measurement interval (2000–2001 or 2005–2006). The MSM is a model for the mean of the counterfactual outcome $E[Y^{a0,a1}]$ conditional on baseline covariates (i.e., the suite of baseline covariates L_0, including the baseline covariate "sex" which is considered to be both a confounder and effect modifier in our analysis). The MSM encodes causal effects. For example, the average causal effect of an intervention "food insufficiency in 2000–2001 only" vs. "food sufficiency" is $E[Y^{a0=1, a1=0}]$ - $E[Y^{a0=0, a1=0}]$.

We assume the following MSM:

$$E[Y^{a0,a1}|L_0] = \beta_0 + \beta_1 a_0 + \beta_2 a_1 + \beta_3 a_0 a_1 + \beta_4 female + \beta_5 a_0 * female + \beta_6 a_1 * female + \beta_7 a_0 a_1 female + \beta_8 L_0$$

IP weighting is a g-method that can be used to estimate the coefficients of this model. More specifically, an IP weighted outcome regression model can be fit among uncensored participants, where the treatment and censoring weights are defined as above. Under certain assumptions (including conditional exchangeability, positivity, and consistency; correct specification of denominator of weight models and the MSM; and no measurement error), the estimated coefficients of the IP weighted outcome regression model can be used to estimate causal effects.

Estimating Means

We can use the parameter estimates from the MSM to estimate differences in mean BMI or CVD risk factor for various causal contrasts as follows:

Among Males:

(1) β_1 = Difference in mean value of outcome if all participants had food insufficiency in 2000–2001 compared to if all participants had food sufficiency at both time points.

(2) β_2= Difference in mean value of outcome if all participants had food insufficiency in 2005–2006 compared to if all participants had food sufficiency at both time points.

(3) $\beta_1 + \beta_2 + \beta_3$= Difference in mean value of outcome if all participants had persistent food insufficiency compared to if all participants had food sufficiency at both time points.

Among Females:

(1) $\beta_1 + \beta_5$ = Difference in mean value of outcome if all participants had food insufficiency in 2000–2001 compared to if all participants had food sufficiency at both time points.

(2) $\beta_2 + \beta_6$= Difference in mean value of outcome if all participants had food insufficiency in 2005–2006 compared to if all participants had food sufficiency at both time points.

(3) $\beta_1 + \beta_2 + \beta_3 + \beta_5 + \beta_6 + \beta_7$= Difference in mean value of outcome if all participants had persistent food insufficiency compared to if all participants had food sufficiency at both time points.

Overall (weighted-average of sex-specific effects)

Note: proportion of males and females is calculated in the "baseline" (2000–2001) sample (56% female, 44% male).

(1) $(\beta_1)(proportion\ of\ males)$ + $(\beta_1 + \beta_5)(proportion\ of\ females)$ = Difference in mean value of outcome if all participants had food insufficiency in 2000–2001 compared to if all participants had food sufficiency at both time points.

(2) $(\beta_2)(proportion\ of\ males)$ + $(\beta_2 + \beta_6)(proportion\ of\ females)$ = Difference in mean value of outcome if all participants had food insufficiency in 2005–2006 compared to if all participants had food sufficiency at both time points.

(3) $(\beta_1 + \beta_2 + \beta_3)(proportion\ of\ males)$ + $(\beta_1 + \beta_2 + \beta_3 + \beta_5 + \beta_6 + \beta_7)(proportion\ of\ females)$ = Difference in mean value of outcome if all participants had persistent food insufficiency compared to if all participants had food sufficiency at both time points.

Assumptions

As in all observational analyses that attempt to make causal inferences, the validity of this approach is based on many untestable assumptions. The key assumptions for IP weighting of MSM include conditional exchangeability, positivity, and consistency; correct specification of denominator of weight models and the MSM; and no measurement error. Conditional exchangeability – which requires no unmeasured confounding or selection bias – is always an approximation at best. While CARDIA includes many possible covariates to control for confounding and selection bias, the food insufficiency assessments were 5-years apart, a study design which may fail to capture important time-varying changes in exposure and confounders within each interval. Additionally, we did not observe extreme weights (one possible diagnostic for positivity violations) and conducted different analyses varying the specification of weight models and the MSM.

It is of interest to note that in many cases our approach makes weaker assumptions than traditional regression approaches. For example, because we used a bootstrap for the variance estimator, the usual normality assumption is not required. Similarly, our use of IP weighting means we don’t require the usual assumptions about the functional form between time-varying covariates and the outcome.

Supplementary Table 3.1: Characteristics of uncensored sample, by food insufficiency pattern

Characteristic	Total (N=1897)	Food Sufficiency (N=1437)	Food Insufficient in 2000–2001 only (N=164)	Food Insufficient in 2005–2006 only (N=170)	Persistent Food Insufficiency (N=126)
Sex					
Women	1101 (58%)	809 (56%)	101 (62%)	101 (59%)	90 (71%)
Men	796 (42%)	628 (44%)	63 (38%)	69 (41%)	36 (29%)
Age (years)					
Mean (SD)	40.1 (± 3.68)	40.3 (± 3.60)	39.6 (± 4.04)	39.4 (± 3.86)	39.7 (± 3.67)
Race					
White	954 (50%)	789 (55%)	61 (37%)	62 (36%)	42 (33%)
Black	943 (50%)	648 (45%)	103 (63%)	108 (64%)	84 (67%)
Employment status					
Full-time	1465 (77%)	1135 (79%)	122 (74%)	128 (75%)	80 (63%)
Part-time	384 (20%)	276 (19%)	31 (19%)	37 (22%)	40 (32%)
Unemployed	48 (3%)	26 (2%)	11 (7%)	5 (3%)	6 (5%)
Smoking status					
Current	409 (22%)	271 (19%)	47 (29%)	50 (29%)	41 (33%)
Former	346 (18%)	275 (19%)	33 (20%)	19 (11%)	19 (15%)
Never	1142 (60%)	891 (62%)	84 (51%)	101 (59%)	66 (52%)
Household income					
<$5000	39 (2%)	19 (1%)	7 (4%)	5 (3%)	8 (6%)
$5000-$11,999	73 (4%)	28 (2%)	12 (7%)	13 (8%)	20 (16%)
$12,000-$15,999	62 (3%)	33 (2%)	11 (7%)	4 (2%)	14 (11%)
$16,000-$24,999	160 (8%)	103 (7%)	16 (10%)	21 (12%)	20 (16%)
$25,000-$34,999	226 (12%)	142 (10%)	35 (21%)	27 (16%)	22 (17%)
$35,000-$49,000	389 (21%)	296 (21%)	34 (21%)	35 (21%)	24 (19%)
$50,000-$74,999	559 (29%)	468 (33%)	32 (20%)	43 (25%)	16 (13%)
$75,000-$99,999	389 (21%)	348 (24%)	17 (10%)	22 (13%)	2 (2%)
Marital status					
No partner	862 (45%)	608 (42%)	84 (51%)	90 (53%)	80 (63%)
Partner	1035 (55%)	829 (58%)	80 (49%)	80 (47%)	46 (37%)
Household size					
1 person	312 (16%)	237 (16%)	30 (18%)	23 (14%)	22 (17%)
2-4 people	1290 (68%)	1010 (70%)	99 (60%)	111 (65%)	70 (56%)
5 people or more	295 (16%)	190 (13%)	35 (21%)	36 (21%)	34 (27%)

Supplementary Table 3.1 (Continued)

Characteristic	Total (N=1897)	Food Sufficiency (N=1437)	Food Insufficient in 2000–2001 only (N=164)	Food Insufficient in 2005–2006 only (N=170)	Persistent Food Insufficiency (N=126)
Diabetes					
Yes	87 (5%)	70 (5%)	6 (4%)	5 (3%)	6 (5%)
No	1810 (95%)	1367 (95%)	158 (96%)	165 (97%)	120 (95%)
Cholesterol or BP Medication					
Yes	166 (9%)	120 (8%)	18 (11%)	17 (10%)	11 (9%)
No	1731 (91%)	1317 (92%)	146 (89%)	153 (90%)	115 (91%)
Physical Activity tertile					
Low	667 (35%)	470 (33%)	67 (41%)	74 (44%)	56 (44%)
Moderate	624 (33%)	467 (32%)	59 (36%)	54 (32%)	44 (35%)
High	606 (32%)	500 (35%)	38 (23%)	42 (25%)	26 (21%)
Recruitment Center					
Birmingham	495 (26%)	361 (25%)	41 (25%)	55 (32%)	38 (30%)
Chicago	374 (20%)	261 (18%)	34 (21%)	44 (26%)	35 (28%)
Minneapolis	563 (30%)	438 (30%)	55 (34%)	34 (20%)	36 (29%)
Oakland	465 (25%)	377 (26%)	34 (21%)	37 (22%)	17 (13%)

Supplementary Table 3.2: Differences in IP-weighted estimates of mean differences in outcomes (95% CI) in 2010–2011 for food insufficiency patterns in 2000–2001 and 2005–2006 compared to food sufficiency comparing women vs. men: CARDIA, 2000-2011

	Difference in IP Weighted Estimate Comparing Women vs. Men		
	Food Insufficient in 2000–2001 only vs. food sufficiency	**Food Insufficient in 2005–2006 only vs. food sufficiency**	**Persistent Food Insufficiency vs. food sufficiency**
Overall Sample			
BMI, kg/m^2	-0.68 (-2.58, 1.04)	0.22 (-1.60, 1.97)	1.05 (-0.50, 2.61)
Waist circumference, cm	-2.73 (-6.92, 1.32)	2.32 (-2.10, 6.59)	3.41 (-0.38, 7.31)
Systolic blood pressure, mmHg	-2.48 (-7.34, 2.36)	1.94 (-2.31, 6.25)	-3.11 (-8.89, 2.73)
Diastolic blood pressure, mmHg	-1.99 (-5.41, 1.48)	3.64 (0.59, 6.64)	-2.77 (-7.04, 1.87)
Total cholesterol, mg/dL	0.91 (-10.04, 12.18)	6.37 (-5.36, 18.04)	-2.85 (-15.07, 9.65)
HDL cholesterol, mg/dL	4.20 (-1.50, 10.12)	-7.11 (-11.06, -3.24)	-1.69 (-6.72, 3.22)
Fasting Sample (≥12 hours)			
Triglycerides, mg/dL	-5.64 (-32.64, 18.04)	23.31 (2.64, 42.28)	11.27 (-14.43, 33.48)
LDL cholesterol, mg/dL	-1.08 (-13.10, 10.45)	4.62 (-9.09, 17.60)	0.79 (-11.06, 12.10)
Fasting Sample (≥ 8 hours)			
Fasting plasma glucose, mg/dL	-2.83 (-9.73, 3.79)	6.79 (-2.63, 16.46)	-3.36 (-15.82, 8.50)

Notes: These results were generated from models which included an interaction term between each food insufficiency pattern and sex. The difference in IP weighted estimates comparing women to men was obtained by subtracting the estimate for the effect of a given food insufficiency pattern compared to food sufficiency among men from the estimate for the effect of a given food insufficiency pattern compared to food sufficiency among women. Bootstrapping with 5000 replications was used to obtain the 95% CI.

Abbreviations: IP = Inverse Probability; HDL= High-density lipoprotein; LDL=Low-density lipoprotein.

Supplementary Table 3.3: IP-weighted estimates of mean differences in outcomes (95% CI) in 2010–2011 for food insufficiency patterns in 2000–2001 and 2005–2006 compared to food sufficiency, overall and by race: CARDIA, 2000-2011

	Food Sufficiency: *Food sufficient in 2000–2001 and 2005–2006*	**Food Insufficient in 2000–2001 only:** *Food insufficient in 2000–2001, food sufficient in 2005–2006*	**Food Insufficient in 2005–2006 only:** *Food sufficient in 2000–2001, food insufficient in 2005–*	**Persistent Food Insufficiency:** *Food insufficient in 2000–2001 and 2005–2006*
Overall Sample				
BMI, kg/m^2				
IP weighted - Black participants	Ref.	-0.03 (-1.38, 1.43)	0.68 (-0.49, 1.83)	0.70 (-0.48, 1.91)
IP weighted - White participants	Ref.	0.09 (-0.85, 1.08)	1.11 (-0.34, 2.69)	0.25 (-1.14, 1.73)
Waist circumference, cm				
IP weighted - Black participants	Ref.	0.28 (-2.52, 3.21)	1.29 (-1.44, 3.94)	0.72 (-1.91, 3.31)
IP weighted - White participants	Ref.	1.70 (-0.96, 4.45)	2.81 (-0.39, 6.10)	3.27 (-0.22, 6.81)
Systolic blood pressure, mmHg				
IP weighted - Black participants	Ref.	2.48 (-1.18, 5.89)	3.45 (0.39, 6.54)	-0.59 (-4.26, 3.10)
IP weighted - White participants	Ref.	1.06 (-1.89, 3.96)	-1.22 (-4.42, 2.09)	-0.27 (-4.09, 3.40)
Diastolic blood pressure,				
IP weighted - Black participants	Ref.	1.85 (-0.51, 4.16)	2.55 (0.53, 4.56)	-1.21 (-3.63, 1.15)
IP weighted - White participants	Ref.	1.04 (-1.49, 3.55)	-0.80 (-3.05, 1.48)	0.49 (-2.62, 3.42)
Total cholesterol, mg/dL				
IP weighted - Black participants	Ref.	2.75 (-3.85, 9.74)	-3.13 (-11.10, 4.92)	-2.43 (-9.68, 4.82)
IP weighted - White participants	Ref.	-7.99 (-16.75, 0.32)	0.37 (-8.28, 9.15)	-3.78 (-12.89, 5.37)
HDL cholesterol, mg/dL				
IP weighted - Black participants	Ref.	1.90 (-2.42, 6.83)	0.30 (-2.19, 2.94)	-4.01 (-7.22, -0.76)
IP weighted - White participants	Ref.	-1.62 (-4.79, 1.62)	-1.84 (-4.56, 0.90)	-3.01 (-6.45, 0.27)
Fasting Sample (≥12 hours)				
Triglycerides, mg/dL				
IP weighted - Black participants	Ref.	-7.72 (-20.70, 7.45)	1.80 (-10.23, 13.31)	2.30 (-9.51, 14.92)
IP weighted - White participants	Ref.	0.07 (-19.32, 21.01)	0.81 (-14.41, 17.72)	-9.21 (-27.46, 9.03)

Supplementary Table 3.3 (Continued)

LDL cholesterol, mg/dL				
IP weighted - Black participants	Ref.	2.01 (-6.39, 10.46)	3.88 (-5.15, 13.43)	-1.82 (-9.60, 5.63)
IP weighted - White participants	Ref.	-4.13 (-12.98, 4.99)	0.54 (-7.62, 8.87)	-3.85 (-13.55, 6.00)
Fasting Sample (≥ 8 hours)				
Fasting plasma glucose, mg/dL				
IP weighted - Black participants	Ref.	-6.04 (-10.66, -1.39)	-0.86 (-7.46, 6.72)	0.90 (-6.56, 8.93)
IP weighted - White participants	Ref.	-1.03 (-5.75, 4.04)	2.16 (-3.91, 9.56)	2.70 (-3.81, 10.61)

Notes: Results were generated from a model which included an interaction term between each food insufficiency pattern and race (but not sex).

Abbreviations: IP = Inverse Probability; HDL= High-density lipoprotein; LDL=Low-density lipoprotein.

Supplementary Table 3.4: Differences in IP-weighted estimates of mean differences in outcomes (95% CI) in 2010–2011 for food insufficiency patterns in 2000–2001 and 2005–2006 compared to food sufficiency comparing Black participants vs. White participants: CARDIA, 2000-2011

	Difference in IP Weighted Estimate Comparing Black participants vs. White participants		
	Food Insufficient in 2000–2001 only vs. food sufficiency	**Food Insufficient in 2005–2006 only vs. food sufficiency**	**Persistent Food Insufficiency vs. food sufficiency**
Overall Sample			
BMI, kg/m^2	-0.12 (-1.77, 1.61)	-0.43 (-2.50, 1.45)	0.44 (-1.44, 2.31)
Waist circumference, cm	-1.42 (-5.39, 2.73)	-1.52 (-5.76, 2.71)	-2.55 (-7.01, 1.77)
Systolic blood pressure, mmHg	1.42 (-3.21, 5.89)	4.67 (0.20, 9.08)	-0.32 (-5.41, 4.81)
Diastolic blood pressure, mmHg	0.81 (-2.51, 4.31)	3.35 (0.31, 6.28)	-1.70 (-5.43, 2.21)
Total cholesterol, mg/dL	10.74 (0.16, 21.39)	-3.51 (-15.68, 8.46)	1.34 (-10.71, 12.69)
HDL cholesterol, mg/dL	3.51 (-1.77, 9.24)	2.14 (-1.62, 5.97)	-0.99 (-5.51, 3.73)
Fasting Sample (≥12 hours)			
Triglycerides, mg/dL	-7.79 (-31.56, 17.28)	1.00 (-19.64, 20.12)	11.51 (-9.81, 33.73)
LDL cholesterol, mg/dL	6.15 (-6.34, 18.27)	3.34 (-9.05, 15.97)	2.03 (-10.48, 14.10)
Fasting Sample (≥ 8 hours)			
Fasting plasma glucose, mg/dL	-5.01 (-12.08, 1.68)	-3.02 (-12.99, 6.43)	-1.80 (-12.92, 8.90)

Notes: These results were generated from models which included an interaction term between each food insufficiency pattern and race. The difference in IP weighted estimates comparing Black participants to White participants was obtained by subtracting the estimate for the effect of a given food insufficiency pattern compared to food sufficiency among white participants from the estimate for the effect of a given food insufficiency pattern compared to food sufficiency among black participants. Bootstrapping with 5000 replications was used to obtain the 95% CI.
Abbreviations: IP = Inverse Probability; HDL= High-density lipoprotein; LDL=Low-density lipoprotein.

Supplementary Text 3.2: Methodological considerations

Our study has several important methodological considerations. First, our primary analysis poses a static deterministic research question comparing health effects had we implemented interventions to ensure persistent or transient (versus no) food insufficiency in the study population. In practice, only one side of this comparison – a hypothetical intervention to ensure no food insufficiency in the entire population – is policy relevant and (somewhat) realistic. For example, one might imagine an expanded suite of federal nutrition assistance programs that acts to eliminate food insufficiency in the U.S. The other side of the comparison – a hypothetical intervention to ensure food insufficiency in the entire population – is less realistic and is clearly not desirable from a public health perspective. This has two important implications/limitations. First, existing data may not support this type of research question being posed, which could lead to positivity violations (i.e., no or very few people in our dataset who have food insufficiency for certain levels of covariates, like income). For example, does it make sense to consider an intervention that "forces" a 1-person household with $90,000 annual income to be food insufficient? The second important implication is that, given that one side of this comparison is an unrealistic hypothetical situation, this may not be the most policy relevant research question that can be posed. Future researchers aiming to generate more policy-relevant findings may instead consider constructing alternate comparisons that depend on time-evolving risk factors (e.g., income) or are based on realistic changes in food insecurity (e.g., a 30% reduction in food insecurity, consistent with estimated impact of Supplemental Nutrition Assistance Program).

Despite these limitations, we still chose to pose this comparison in our primary analysis for a number of reasons. With respect to potential positivity violations, we limited our analysis to participants with annual family incomes ≤\$100,000 and we did not find evidence of positivity violations for other covariates. With respect to posing the most policy relevant research question, our priority was to first establish longitudinal associations between food insufficiency and adverse health outcomes before evaluating these relationships under these more realistic conditions.

An alternate analysis that may estimate more meaningful effects and is less subject to positivity violations is to compare health effects had we implemented interventions to ensure no food insufficiency in the study population (i.e., one side of the current comparison conducted in main analysis) vs. the "natural course" (i.e., no intervention). Because this does not enforce a hypothetical intervention to ensure food insufficiency in the entire population, it is more realistic and less susceptible to positivity violations. To estimate the mean outcome value under a hypothetical intervention that ensures no food insufficiency, we used the same IP-weighted MSM as in the primary analysis. Parameter estimates from the MSM were then used to predict the mean value of the outcome for each individual present at baseline given their baseline covariate values and setting their exposure to "never food insufficient". To estimate the mean outcome value under the "natural course", we calculated the censoring-weighted mean outcome value across all uncensored participants. Results for this alternate analysis are displayed in **Supplementary Table 3.5**:

Supplementary Table 3.5: Mean difference in outcomes (95% CI) in 2010–2011 for No Food Insufficiency in 2000–2001 and 2005–2006 vs. "Natural Course": CARDIA, 2000–2011

	No Food Insufficiency vs. "Natural Course'
Overall Sample	
BMI, kg/m^2	-0.02 (-0.33, 0.27)
Waist Circumference, cm	0.01 (-0.64, 0.65)
Systolic blood pressure, mmHg	0.16 (-0.38, 0.71)
Diastolic blood pressure, mmHg	0.13 (-0.23, 0.51)
Total cholesterol, mg/dL	-0.13 (-1.46, 1.17)
HDL cholesterol, mg/dL	0.29 (-0.38, 0.96)
Fasting Sample (≥12 hours)	
Triglycerides, mg/dL	0.67 (-1.81, 3.27)
LDL cholesterol, mg/dL	-1.04 (-2.51, 0.32)
Fasting Sample (≥ 8 hours)	
Fasting plasma glucose, mg/dL	0.63 (-0.54, 1.75)

Supplementary Table 3.6: IP-weighted estimates of mean differences in outcomes (95% CI) in 2010–2011 for food insufficiency patterns in 2000–2001 and 2005–2006 compared to food sufficiency treating interim CVD events as a censoring variable, overall and by sex: CARDIA, 2000-2011

	Food Sufficiency: *Food sufficient in 2000–2001 and 2005–2006*	**Food Insufficient in 2000–2001 only:** *Food insufficient in 2000–2001, food sufficient in 2005–2006*	**Food Insufficient in 2005–2006 only:** *Food sufficient in 2000–2001, food insufficient in 2005–2006*	**Persistent Food Insufficiency:** *Food insufficient in 2000–2001 and 2005–2006*
BMI, kg/m^2				
IP weighted - Overall	Ref.	0.01 (-0.97, 1.04)	0.50 (-0.42, 1.44)	0.31 (-0.59, 1.19)
IP weighted - Males	Ref.	0.58 (-0.75, 2.13)	0.48 (-0.72, 1.75)	-0.23 (-1.32, 0.81)
IP weighted - Females	Ref.	-0.44 (-1.74, 0.93)	0.52 (-0.83, 1.87)	0.72 (-0.57, 2.02)
Waist circumference, cm				
IP weighted - Overall	Ref.	0.59 (-1.61, 2.90)	1.23 (-0.71, 3.18)	1.15 (-1.04, 3.32)
IP weighted - Males	Ref.	2.50 (-1.06, 6.32)	0.15 (-3.26, 3.69)	-0.83 (-4.08, 2.36)
IP weighted - Females	Ref.	-0.88 (-3.65, 1.81)	2.06 (-0.25, 4.33)	2.67 (-0.26, 5.57)
Systolic blood pressure, mmHg				
IP weighted - Overall	Ref.	1.34 (-1.25, 3.84)	2.02 (-0.34, 4.42)	0.13 (-3.01, 3.04)
IP weighted - Males	Ref.	2.41 (-1.00, 5.88)	-0.02 (-2.42, 2.48)	1.88 (-3.68, 7.16)
IP weighted - Females	Ref.	0.51 (-3.12, 4.09)	3.59 (-0.15, 7.45)	-1.22 (-4.67, 2.10)
Diastolic blood pressure, mmHg				
IP weighted - Overall	Ref.	1.29 (-0.53, 3.10)	1.57 (0.05, 3.10)	-0.35 (-2.73, 1.88)
IP weighted - Males	Ref.	2.06 (-0.48, 4.65)	-1.18 (-3.27, 1.00)	1.40 (-3.23, 5.51)
IP weighted - Females	Ref.	0.69 (-1.79, 3.12)	3.69 (1.52, 5.91)	-1.70 (-3.98, 0.52)

Supplementary Table 3.6 (Continued)

Total cholesterol, mg/dL				
IP weighted - Overall	Ref.	0.29 (-5.11, 5.88)	-1.41 (-7.39, 4.62)	-2.78 (-8.53, 3.17)
IP weighted - Males	Ref.	0.24 (-8.88, 9.53)	-4.97 (-13.89, 4.06)	1.63 (-8.17, 11.58)
IP weighted - Females	Ref.	0.33 (-6.44, 7.49)	1.33 (-6.91, 9.42)	-6.18 (-13.61, 0.99)
HDL cholesterol, mg/dL				
IP weighted - Overall	Ref.	-0.79 (-3.78, 2.50)	-0.78 (-2.52, 1.07)	-3.34 (-5.81, -0.76)
IP weighted - Males	Ref.	-1.78 (-5.02, 1.64)	2.77 (0.40, 5.34)	-1.84 (-5.88, 2.25)
IP weighted - Females	Ref.	-0.02 (-4.56, 5.24)	-3.52 (-6.05, -0.91)	-4.49 (-7.73, -1.31)
Fasting Sample (≥12 hours)				
Triglycerides, mg/dL				
IP weighted - Overall	Ref.	-4.85 (-16.52, 8.72)	4.22 (-5.64, 14.08)	-2.95 (-12.82, 7.32)
IP weighted - Males	Ref.	-1.19 (-22.30, 24.83)	-9.80 (-25.18, 6.15)	-9.80 (-25.18, 6.15)
IP weighted - Females	Ref.	-7.58 (-19.99, 5.82)	14.65 (1.38, 27.77)	1.52 (-10.24, 13.63)
LDL cholesterol, mg/dL				
IP weighted - Overall	Ref.	1.43 (-4.55, 7.49)	3.11 (-3.46, 9.87)	-3.34 (-9.18, 2.92)
IP weighted - Males	Ref.	1.22 (-6.54, 9.88)	0.13 (-9.74, 11.02)	-0.90 (-10.56, 9.78)
IP weighted - Females	Ref.	1.59 (-6.93, 9.95)	5.32 (-3.75, 14.01)	-5.15 (-12.35, 2.00)
Fasting Sample (≥ 8 hours)				
Fasting plasma glucose, mg/dL				
IP weighted - Overall	Ref.	-3.00 (-6.57, 0.69)	0.18 (-4.26, 5.00)	1.81 (-4.04, 8.19)
IP weighted - Males	Ref.	-0.99 (-6.19, 4.69)	-2.90 (-8.34, 3.12)	6.40 (-3.85, 18.89)
IP weighted - Females	Ref.	-4.54 (-9.30, 0.16)	2.53 (-4.06, 10.03)	-1.70 (-8.14, 5.14)

Note: In our primary analyses, we did not censor participants who experienced an interim CVD event (i.e., myocardial infarction, stroke). Thus, our findings can be interpreted as "total effects" that capture the effects of food insufficiency patterns on outcomes through all possible pathways, including possibly through exposure effects on interim CVD events. In contrast, in this sensitivity analyses, we instead censor participants at the time point by which they experienced an interim CVD event. Thus, this analysis does not allow for food insufficiency to affect CVD risk factors via interim CVD events. Results do not meaningfully differ from primary analyses.

Supplementary Table 3.7: IP-weighted estimates of mean differences in outcomes (95% CI) in 2010–2011 for food insufficiency patterns in 2000–2001 and 2005–2006 compared to food sufficiency treating interim CVD events as a confounding variable, overall and by sex: CARDIA, 2000-2011

	Food Sufficiency: *Food sufficient in 2000–2001 and 2005–2006*	**Food Insufficient in 2000–2001 only:** *Food insufficient in 2000–2001, food sufficient in 2005–2006*	**Food Insufficient in 2005–2006 only:** *Food sufficient in 2000–2001, food insufficient in 2005–2006*	**Persistent Food Insufficiency:** *Food insufficient in 2000–2001 and 2005–2006*
BMI, kg/m^2				
IP weighted - Overall	Ref.	0.13 (-0.80, 1.12)	0.87 (-0.04, 1.80)	0.46 (-0.41, 1.31)
IP weighted - Males	Ref.	0.60 (-0.65, 2.05)	0.70 (-0.48, 1.95)	-0.27 (-1.32, 0.70)
IP weighted - Females	Ref.	-0.23 (-1.55, 1.12)	1.01 (-0.31, 2.31)	1.02 (-0.26, 2.29)
Waist circumference, cm				
IP weighted - Overall	Ref.	1.12 (-0.95, 3.34)	2.05 (0.06, 4.00)	1.39 (-0.70, 3.46)
IP weighted - Males	Ref.	2.53 (-0.64, 6.08)	0.82 (-2.59, 4.33)	-0.71 (-3.75, 2.23)
IP weighted - Females	Ref.	0.03 (-2.64, 2.72)	2.99 (0.64, 5.28)	3.01 (0.20, 5.77)
Systolic blood pressure, mmHg				
IP weighted - Overall	Ref.	2.02 (-0.55, 4.41)	1.80 (-0.57, 4.13)	0.25 (-2.71, 3.09)
IP weighted - Males	Ref.	3.01 (-0.51, 6.39)	0.31 (-2.03, 2.71)	1.92 (-3.26, 6.77)
IP weighted - Females	Ref.	1.26 (-2.28, 4.63)	2.96 (-0.75, 6.71)	-1.04 (-4.40, 2.17)
Diastolic blood pressure,				
IP weighted - Overall	Ref.	1.55 (-0.18, 3.30)	1.41 (-0.14, 2.92)	-0.11 (-2.33, 1.97)
IP weighted - Males	Ref.	2.16 (-0.31, 4.62)	-0.86 (-2.91, 1.29)	1.49 (-2.81, 5.35)
IP weighted - Females	Ref.	1.09 (-1.27, 3.40)	3.16 (0.96, 5.33)	-1.34 (-3.51, 0.78)

Supplementary Table 3.7 (Continued)

Total cholesterol, mg/dL				
IP weighted - Overall	Ref.	-1.15 (-6.66, 4.26)	-1.69 (-7.35, 4.15)	-1.83 (-7.86, 4.18)
IP weighted - Males	Ref.	-1.35 (-10.43, 7.39)	-5.25 (-14.21, 3.69)	-0.25 (-10.93, 10.28)
IP weighted - Females	Ref.	-1.01 (-8.16, 6.43)	1.05 (-6.50, 8.60)	-3.05 (-10.43, 4.04)
HDL cholesterol, mg/dL				
IP weighted - Overall	Ref.	0.23 (-2.85, 3.52)	-1.01 (-2.73, 0.78)	-3.39 (-5.78, -0.94)
IP weighted - Males	Ref.	-1.83 (-4.94, 1.33)	2.63 (0.22, 5.14)	-1.99 (-5.91, 2.01)
IP weighted - Females	Ref.	1.81 (-3.09, 7.18)	-3.81 (-6.25, -1.27)	-4.47 (-7.55, -1.40)
Fasting Sample (≥12 hours)				
Triglycerides, mg/dL				
IP weighted - Overall	Ref.	-4.17 (-15.82, 8.74)	3.30 (-6.28, 13.12)	-1.24 (-12.30, 11.13)
IP weighted - Males	Ref.	-1.79 (-21.73, 22.62)	-11.48 (-26.82, 4.60)	-11.48 (-26.82, 4.60)
IP weighted - Females	Ref.	-5.94 (-18.41, 7.51)	14.30 (1.35, 26.78)	2.67 (-8.73, 13.93)
LDL cholesterol, mg/dL				
IP weighted - Overall	Ref.	-0.57 (-6.57, 5.68)	2.91 (-3.50, 9.55)	-2.42 (-8.62, 3.79)
IP weighted - Males	Ref.	0.30 (-7.45, 8.81)	-0.25 (-10.15, 10.38)	-3.48 (-13.16, 6.49)
IP weighted - Females	Ref.	-1.22 (-9.80, 7.46)	5.26 (-3.62, 13.63)	-1.63 (-9.40, 6.09)
Fasting Sample (≥ 8 hours)				
Fasting plasma glucose, mg/dL				
IP weighted - Overall	Ref.	-3.53 (-6.92, -0.07)	1.07 (-3.58, 6.36)	3.08 (-2.69, 9.03)
IP weighted - Males	Ref.	-1.96 (-6.92, 3.39)	-3.29 (-8.78, 2.81)	5.21 (-4.35, 16.30)
IP weighted - Females	Ref.	-4.72 (-9.44, -0.18)	4.40 (-2.73, 12.61)	1.44 (-5.43, 8.93)

Note: In this sensitivity analysis, we treat interim CVD events (i.e., myocardial infarction or stroke) as a time-varying confounder. Participants who had previously experienced an interim CVD event were excluded at baseline, while those who experienced an interim CVD event over follow-up were still included in analysis but were captured using an indicator variable for experiencing interim CVD events by 2005–2006. Thus, in this analysis, we allow for interim CVD events to be both a mediator and a confounder. Results do not meaningfully differ from primary analyses.

Supplementary Table 4.1: Analytic sample sizes, by food benefit category

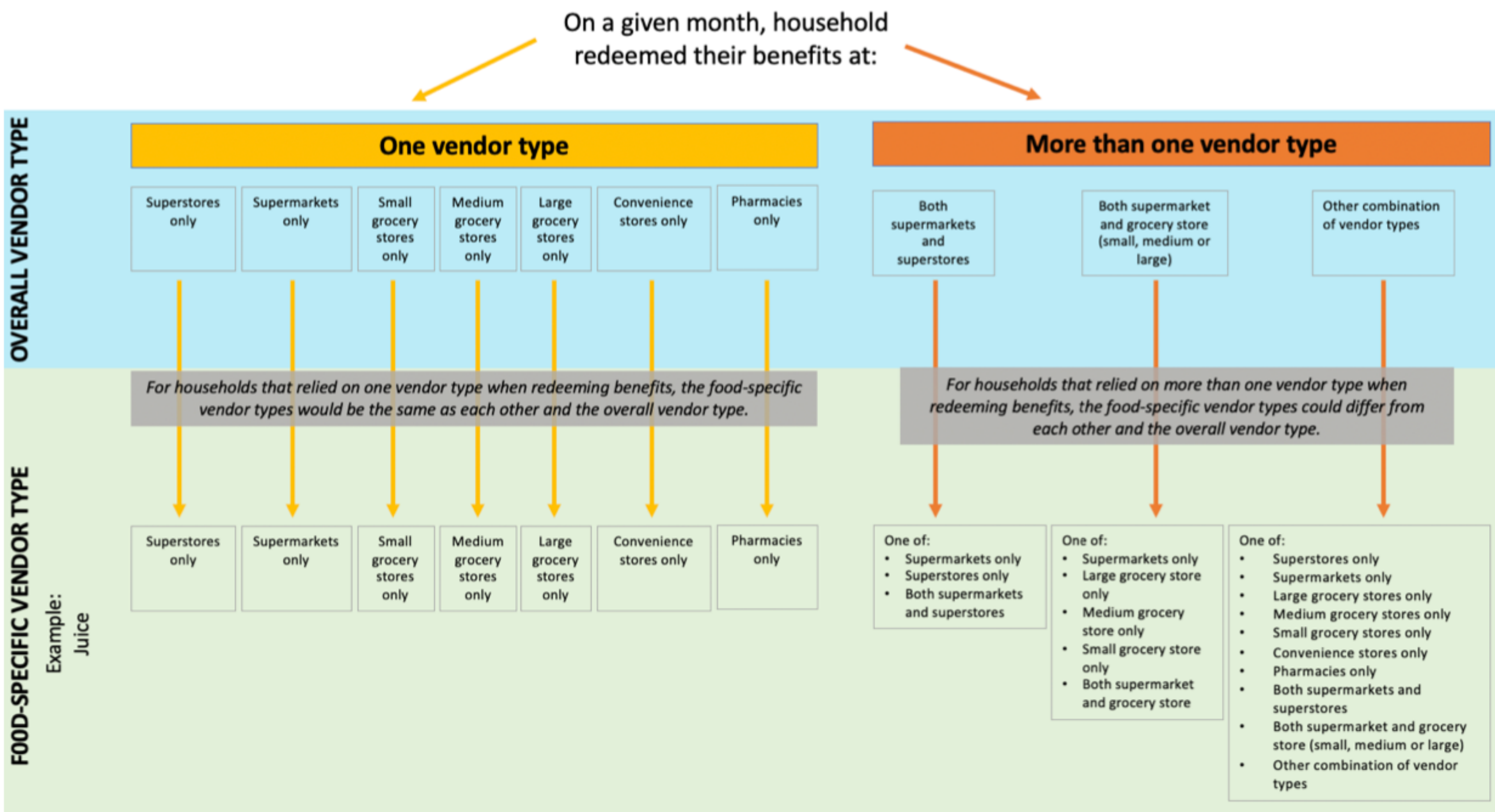
	Among households who redeemed at least some benefits from any food benefit category in a given month	
Food benefit category	**Number of household-months where household was issued food benefit[1]**	**Number of household-months where household redeemed at least some of food benefit[2]**
Breakfast cereal	3,777,125	2,953,917
Cheese/tofu	3,171,437	2,494,161
CVB	3,831,626	3,632,425
Eggs	3,696,990	3,241,312
Fish	176,378	115,852
Infant formula	1,131,086	1,107,018
Infant cereal	669,003	428,351
Infant F&V	672,483	546,847
Infant meats	59,757	25,862
Juice	3,756,431	3,175,437
Legumes/PB	3,777,208	2,751,563
Low fat milk	3,099,750	2,848,662
Whole grains	3,452,112	2,497,858
Whole milk	992,418	959,222
Yogurt	1,905,136	1,130,457

[1]These analytic samples were used when generating results in Supplementary Table 4.3. Results for Figure 4.2 were further limited to household-months from 2019 only.

[2]These analytic samples were used when generating results in Supplementary Table 4.2. Results for Figure 4.1 were further limited to household-months from 2019 only.

Abbreviations: CVB=Cash Value Benefit, F&V= Fruit and Vegetable, PB = Peanut Butter, WIC = Special Supplemental Nutrition Program for Women, Infants and Children.

Supplementary Figure 4.1: Classification scheme illustrating how MA WIC households were classified as having overall vendor type and food-specific vendor types in a given month



Supplementary Table 4.2: Trends in the percentage of WIC households that redeemed food benefits at each food-specific vendor type[2] in a given month between 2015 and 2019, by benefit category

Benefit category	Food-Specific Vendor Type	2015	2016	2017	2018	2019	Δ per year[1]
Breakfast cereal	Superstore	7.0	7.2	7.4	7.8	8.0	0.3
	Supermarket	65.9	66.7	67.5	68.7	68.9	0.8
	Large grocery store	2.2	2.7	3.4	3.7	3.9	0.4
	Medium grocery store	6.4	6.6	6.6	6.4	6.9	0.1
	Small grocery store	13.8	12.4	11.5	10.1	9.2	-1.2
	Convenience Store	1.3	0.8	0.4	0.1	0.0	-0.4
	Supermarket & superstore	1.2	1.3	1.2	1.3	1.3	0.0
	Supermarket & grocery store	1.4	1.5	1.5	1.5	1.5	0.0
	Other combination of vendor types	0.7	0.7	0.5	0.4	0.4	-0.1
Bread & whole grains	Superstore	5.6	5.6	5.7	6.1	6.6	0.2
	Supermarket	64.7	65.9	67.2	68.8	68.4	1.1
	Large grocery store	2.2	2.6	3.4	3.6	4.0	0.5
	Medium grocery store	6.3	6.6	6.5	6.3	6.8	0.1
	Small grocery store	14.7	13.5	12.3	10.9	10.1	-1.2
	Convenience Store	1.6	1.0	0.5	0.1	0.0	-0.5
	Supermarket & superstore	1.7	1.6	1.5	1.5	1.5	0.0
	Supermarket & grocery store	2.3	2.2	2.1	2.1	2.0	-0.1
	Other combination of vendor types	1.1	1.0	0.8	0.6	0.5	-0.2
Cash Value Benefit (CVB) for fruits and vegetables	Superstore	6.0	5.7	5.6	6.0	6.4	0.1
	Supermarket	68.7	68.2	68.7	69.3	68.6	0.1
	Large grocery store	2.0	2.3	2.8	3.0	3.1	0.3
	Medium grocery store	5.8	5.7	5.5	5.3	5.6	-0.1
	Small grocery store	8.6	7.3	6.6	5.9	5.4	-0.8
	Convenience Store	0.5	0.3	0.1	0.0	0.0	-0.2
	Supermarket & superstore	3.5	4.2	4.3	4.3	4.6	0.2
	Supermarket & grocery store	3.5	4.6	4.7	4.7	4.9	0.3
	Other combination of vendor types	1.4	1.7	1.6	1.4	1.5	0.0
Cheese & tofu	Superstore	6.6	7.5	7.9	8.6	9.4	0.7
	Supermarket	66.8	67.9	68.8	69.8	69.4	0.8
	Large grocery store	2.5	2.8	3.5	3.7	3.8	0.4
	Medium grocery store	7.0	7.1	7.0	6.8	7.1	0.0
	Small grocery store	14.0	12.2	11.0	9.7	8.9	-1.3
	Convenience Store	1.6	0.9	0.4	0.1	0.0	-0.5
	Supermarket & superstore	0.6	0.6	0.6	0.6	0.6	0.0
	Supermarket & grocery store	0.6	0.6	0.6	0.5	0.5	0.0
	Other combination of vendor types	0.3	0.3	0.2	0.2	0.2	0.0

Supplementary Table 4.2 (continued)

Benefit category	Food-Specific Vendor Type	2015	2016	2017	2018	2019	Δ per year[1]
Eggs	Superstore	6.9	6.5	6.8	7.5	8.3	0.3
	Supermarket	67.2	69.1	70.0	70.9	70.5	0.9
	Large grocery store	2.3	2.7	3.4	3.6	3.8	0.4
	Medium grocery store	6.5	6.7	6.7	6.6	6.9	0.1
	Small grocery store	13.6	12.3	11.2	9.8	8.9	-1.2
	Convenience Store	1.5	0.9	0.4	0.1	0.0	-0.5
	Supermarket & superstore	0.7	0.6	0.6	0.6	0.6	0.0
	Supermarket & grocery store	0.9	0.8	0.7	0.7	0.7	-0.1
	Other combination of vendor types	0.4	0.3	0.3	0.2	0.2	-0.1
Fish	Superstore	7.3	7.9	8.2	8.2	9.5	0.5
	Supermarket	77.5	76.5	76.9	77.9	76.9	0.0
	Large grocery store	2.6	3.3	3.6	4.0	4.2	0.4
	Medium grocery store	4.8	4.8	4.6	4.1	4.0	-0.2
	Small grocery store	5.5	5.7	5.3	4.6	4.0	-0.4
	Convenience Store	0.6	0.3	0.1	0.0	0.0	-0.2
	Supermarket & superstore	0.8	0.6	0.5	0.6	0.6	0.0
	Supermarket & grocery store	0.7	0.8	0.5	0.5	0.7	0.0
	Other combination of vendor types	0.2	0.2	0.2	0.1	0.1	0.0
Infant cereal	Superstore	9.0	11.7	10.5	12.9	16.8	1.6
	Supermarket	68.8	66.4	66.9	66.6	65.5	-0.7
	Large grocery store	1.9	2.5	3.0	3.2	2.9	0.3
	Medium grocery store	5.4	5.5	6.2	5.8	5.2	0.0
	Small grocery store	10.6	10.1	9.9	8.5	6.5	-0.9
	Convenience Store	1.2	0.6	0.4	0.1	0.0	-0.4
	Supermarket & superstore	1.3	1.5	1.4	1.5	1.7	0.1
	Supermarket & grocery store	1.1	1.1	1.2	1.1	1.0	0.0
	Other combination of vendor types	0.6	0.5	0.5	0.4	0.4	0.1
Infant formula	Superstore	8.6	10.5	12.2	12.8	13.8	1.3
	Supermarket	56.0	54.3	53.9	53.7	52.9	-0.7
	Large grocery store	1.6	1.9	2.1	2.3	2.4	0.2
	Medium grocery store	4.3	4.5	5.0	4.8	5.0	0.2
	Small grocery store	10.2	10.1	9.5	8.6	7.6	-0.6
	Convenience Store	3.0	3.1	3.4	3.2	3.2	-0.5
	Supermarket & superstore	3.0	3.1	3.4	3.2	3.2	0.1
	Supermarket & grocery store	2.1	2.1	1.9	1.8	1.6	-0.1
	Other combination of vendor types	6.3	6.1	5.5	5.3	5.3	-0.3

Supplementary Table 4.2 (continued)

Benefit category	Food-Specific Vendor Type	2015	2016	2017	2018	2019	Δ per year[1]
Infant fruits & vegetables	Superstore	8.7	10.4	10.8	11.8	13.4	1.1
	Supermarket	65.3	63.2	62.8	62.6	62.2	-0.7
	Large grocery store	1.6	2.2	2.5	2.7	2.6	0.3
	Medium grocery store	4.6	4.6	4.9	4.9	4.7	0.1
	Small grocery store	8.0	7.8	7.1	6.6	5.2	-0.6
	Convenience Store	0.9	0.5	0.2	0.0	0.0	-0.3
	Supermarket & superstore	5.2	5.4	5.7	5.9	6.8	0.3
	Supermarket & grocery store	3.6	3.9	4.1	3.9	3.6	0.0
	Other combination of vendor types	2.1	2.0	1.9	1.6	1.5	-0.2
Infant meats	Superstore	7.7	9.6	9.3	9.9	11.4	0.7
	Supermarket	76.5	73.2	74.4	74.0	73.0	-0.6
	Large grocery store	1.2	2.3	2.6	2.8	3.1	0.4
	Medium grocery store	3.7	3.0	3.2	2.7	2.3	-0.3
	Small grocery store	3.4	3.6	3.4	3.7	2.9	0.0
	Convenience Store	0.4	0.2	0.1	0.0	0.0	-0.1
	Supermarket & superstore	4.5	5.0	5.0	5.1	5.7	0.2
	Supermarket & grocery store	1.8	2.4	1.6	1.4	1.2	-0.2
	Other combination of vendor types	0.7	0.7	0.5	0.4	0.4	-0.1
Juice	Superstore	6.5	6.9	7.3	8.0	8.6	0.5
	Supermarket	65.1	66.1	67.0	68.0	67.7	0.8
	Large grocery store	2.2	2.6	3.2	3.5	3.7	0.4
	Medium grocery store	6.3	6.5	6.6	6.5	6.9	0.1
	Small grocery store	13.9	12.7	11.6	10.2	9.4	-1.2
	Convenience Store	1.4	0.9	0.4	0.1	0.0	-0.5
	Supermarket & superstore	1.3	1.3	1.2	1.3	1.3	0.0
	Supermarket & grocery store	2.1	2.0	1.9	1.9	1.8	-0.1
	Other combination of vendor types	1.1	0.9	0.7	0.6	0.5	-0.2
Legumes & peanut butter	Superstore	6.1	6.4	6.7	7.2	7.6	0.4
	Supermarket	67.8	69.0	69.8	71.0	70.6	0.8
	Large grocery store	2.4	2.8	3.5	3.8	4.0	0.4
	Medium grocery store	6.6	6.9	6.8	6.5	7.0	0.0
	Small grocery store	14.1	12.4	11.2	9.9	9.1	-1.3
	Convenience Store	1.2	0.7	0.3	0.1	0.0	-0.4
	Supermarket & superstore	0.5	0.5	0.5	0.6	0.6	0.0
	Supermarket & grocery store	0.9	0.9	0.9	0.9	0.9	0.0
	Other combination of vendor types	0.4	0.3	0.3	0.2	0.2	0.0

Supplementary Table 4.2 (continued)

Benefit category	Food-Specific Vendor Type	2015	2016	2017	2018	2019	Δ per year[1]
Low fat milk	Superstore	4.1	4.3	4.5	4.9	5.4	0.3
	Supermarket	57.5	58.2	59.6	61.2	61.3	1.1
	Large grocery store	1.7	2.0	2.5	2.8	3.0	0.3
	Medium grocery store	4.8	5.0	5.0	4.9	5.3	0.1
	Small grocery store	12.5	11.1	10.0	8.7	7.9	-1.2
	Convenience Store	1.2	0.8	0.5	0.1	0.0	-0.4
	Supermarket & superstore	5.6	5.8	6.0	6.2	6.3	0.2
	Supermarket & grocery store	7.8	8.2	8.2	8.1	8.1	0.1
	Other combination of vendor types	4.8	4.5	3.9	3.0	2.7	-0.6
Whole milk	Superstore	4.2	4.2	4.6	5.2	5.8	0.4
	Supermarket	56.8	56.6	57.5	58.9	58.7	0.6
	Large grocery store	1.5	1.9	2.5	2.5	2.9	0.4
	Medium grocery store	4.4	4.4	4.4	4.6	4.9	0.1
	Small grocery store	10.7	9.8	8.9	7.8	7.3	1.0
	Convenience Store	1.3	0.9	0.4	0.1	0.0	-0.4
	Supermarket & superstore	6.7	7.1	7.5	7.8	7.9	0.3
	Supermarket & grocery store	8.6	9.5	9.4	9.4	9.1	0.1
	Other combination of vendor types	5.8	5.6	4.8	3.7	3.3	-0.7
Yogurt	Superstore	7.9	8.6	8.7	9.2	9.8	0.4
	Supermarket	83.5	79.3	78.3	77.7	77.3	-1.1
	Large grocery store	3.0	3.2	3.8	4.3	4.3	0.4
	Medium grocery store	4.2	5.5	5.0	4.7	4.7	-0.1
	Small grocery store	1.0	2.8	3.7	3.5	3.1	0.4
	Convenience Store	0.0	0.0	0.0	0.0	0.0	0.0
	Supermarket & superstore	0.3	0.4	0.4	0.4	0.5	0.0
	Supermarket & grocery store	0.1	0.2	0.2	0.2	0.3	0.0
	Other combination of vendor types	0.0	0.0	0.0	0.0	0.0	0.0

[1]Δ per year refers to the estimated annual percentage point change. This was estimated using a logistic regression model where the outcome variable was a binary indicator (yes/no) for whether or not a household redeemed at a given vendor type and the only predictor variable was a continuous year term. After fitting the model, Stata's margins dydx command was used to predict the average percentage point change per year. For example, the percentage of households that relied only on superstores in a given month when redeeming breakfast cereal increased by about 0.3 percentage points per year between 2015–2019.

Notes: Percentages are calculated only among households that redeemed at least some benefits for that benefit category that month. Sample interpretation: On a given month in 2019, 68% of the households that redeemed any of their juice benefit did so at supermarkets. Due to small sample sizes, households that redeemed any benefits from commissaries were excluded from this analysis.

Supplementary Table 4.3: Average percent redemption of each food benefit category in a given month between 2015 and 2019, by overall vendor type

Benefit category	Overall vendor type	2015	2016	2017	2018	2019	Δ per year[1]
Breakfast cereal	Superstore	61.5	59.8	55.7	54.6	53.1	-2.2
	Supermarket	70.3	68.4	65.2	63.9	63.7	-1.9
	Large grocery store	74.7	73.5	74.7	74.5	72.6	-0.3
	Medium grocery store	75.2	74.7	71.6	69.8	69.4	-1.7
	Small grocery store	77.7	75.8	74.6	73.1	74.0	-1.2
	Supermarket & superstore	72.3	70.7	67.1	66.3	65.4	-1.9
	Supermarket & grocery store	77.0	75.6	73.1	72.2	72.2	-1.4
	Other combination of vendor types	70.7	69.6	67.2	66.3	66.2	-1.3
Bread & whole grains	Superstore	55.1	50.3	49.4	46.9	46.4	-2.1
	Supermarket	66.7	65.3	63.2	62.1	60.6	-1.5
	Large grocery store	70.4	67.7	69.1	69.6	69.6	0.0
	Medium grocery store	70.9	71.0	68.0	64.1	63.6	-2.2
	Small grocery store	73.4	71.6	70.2	68.4	68.3	-1.5
	Supermarket & superstore	70.1	67.9	65.5	65.0	63.7	-1.6
	Supermarket & grocery store	74.3	72.7	70.5	69.4	68.4	-1.5
	Other combination of vendor types	70.7	69.0	66.8	65.6	64.7	-1.6
Cash Value Benefit (CVB) for fruits and vegetables	Superstore	74.8	74.5	72.7	73.8	73.7	-0.3
	Supermarket	88.4	88.9	89.0	89.4	89.9	0.3
	Large grocery store	86.1	86.6	87.6	87.9	88.4	0.6
	Medium grocery store	82.7	83.9	83.7	83.1	83.9	0.2
	Small grocery store	76.0	76.2	76.9	77.0	78.5	0.5
	Supermarket & superstore	91.6	91.8	91.6	92.0	92.6	0.2
	Supermarket & grocery store	90.8	91.8	92.1	92.7	93.4	0.6
	Other combination of vendor types	85.1	86.3	86.7	87.3	88.2	0.7
Cheese & tofu	Superstore	62.3	65.6	65.1	65.9	65.6	0.7
	Supermarket	76.4	76.8	75.5	74.9	73.9	-0.7
	Large grocery store	80.3	78.8	80.0	78.5	77.7	-0.5
	Medium grocery store	82.3	81.7	79.6	77.8	77.2	-1.4
	Small grocery store	81.9	80.2	79.6	78.3	78.8	-0.9
	Supermarket & superstore	80.4	81.7	80.8	80.6	80.3	-0.1
	Supermarket & grocery store	83.8	83.7	82.7	82.1	82.1	-0.5
	Other combination of vendor types	79.2	79.6	78.5	77.7	77.6	-0.5

Supplementary Table 4.3 (continued)

Benefit category	Overall vendor type	2015	2016	2017	2018	2019	Δ per year[1]
Eggs	Superstore	78.2	69.9	69.4	71.6	72.9	-1.0
	Supermarket	87.5	86.1	85.2	85.6	84.9	-0.6
	Large grocery store	90.2	89.1	88.8	89.7	88.5	-0.3
	Medium grocery store	89.7	88.0	86.6	86.8	86.2	-0.9
	Small grocery store	89.2	87.1	86.2	85.7	86.1	-0.9
	Supermarket & superstore	89.1	86.6	86.1	87.3	87.1	-0.4
	Supermarket & grocery store	92.7	91.6	90.8	91.2	90.8	-0.5
	Other combination of vendor types	89.5	87.7	87.0	87.5	87.1	-0.6
Fish	Superstore	51.9	55.9	52.7	48.1	52.6	-0.8
	Supermarket	62.7	60.6	58.4	57.3	58.0	-1.4
	Large grocery store	69.0	59.9	58.7	59.6	60.0	-1.8
	Medium grocery store	69.7	66.9	58.0	60.9	57.3	-3.3
	Small grocery store	64.7	59.8	59.3	57.2	55.8	-2.1
	Supermarket & superstore	69.5	67.9	64.5	65.8	65.7	-1.1
	Supermarket & grocery store	71.8	70.3	66.8	67.1	68.3	-1.2
	Other combination of vendor types	69.5	70.6	67.5	70.0	66.9	-0.5
Infant cereal	Superstore	49.5	56.5	43.6	51.0	61.8	1.7
	Supermarket	61.3	60.6	55.9	58.5	61.9	-0.3
	Large grocery store	63.6	60.8	62.7	61.9	67.2	0.7
	Medium grocery store	66.1	65.1	62.0	64.3	62.2	-0.9
	Small grocery store	65.1	62.5	59.1	59.7	61.0	-1.4
	Supermarket & superstore	62.5	64.8	59.5	63.7	67.9	0.8
	Supermarket & grocery store	67.8	67.1	64.5	66.5	66.9	-0.3
	Other combination of vendor types	60.0	60.5	56.1	60.3	63.2	0.4
Infant formula	Superstore	96.0	96.1	96.4	96.4	96.1	0.1
	Supermarket	96.5	95.9	95.7	95.6	95.3	-0.3
	Large grocery store	95.4	94.5	94.4	94.7	94.7	-0.1
	Medium grocery store	96.8	96.0	96.3	96.1	95.9	-0.2
	Small grocery store	97.1	96.6	96.4	96.5	96.2	-0.2
	Supermarket & superstore	97.8	97.6	97.5	97.5	97.6	0.0
	Supermarket & grocery store	97.7	97.2	97.4	97.4	97.3	-0.1
	Other combination of vendor types	98.0	98.0	98.1	98.2	98.4	-0.1

Supplementary Table 4.3 (continued)

Benefit category	Overall vendor type	2015	2016	2017	2018	2019	Δ per year[1]
Infant fruits & vegetables	Superstore	66.5	69.3	65.0	65.1	67.1	-0.4
	Supermarket	71.2	69.4	68.3	67.0	67.6	-1.0
	Large grocery store	74.5	71.2	75.7	74.6	74.8	0.5
	Medium grocery store	72.3	70.8	70.4	69.0	70.1	-0.7
	Small grocery store	68.0	66.5	64.3	64.6	63.1	-1.2
	Supermarket & superstore	77.1	77.3	76.3	75.9	76.5	-0.3
	Supermarket & grocery store	77.9	77.3	77.2	76.4	75.8	-0.5
	Other combination of vendor types	72.3	72.3	72.2	72.4	72.6	-0.1
Infant meat	Superstore	27.6	33.4	25.1	22.2	26.5	-1.6
	Supermarket	30.9	29.2	27.5	23.9	27.2	-1.5
	Large grocery store	24.1	24.6	29.2	26.7	33.9	2.0
	Medium grocery store	33.9	29.3	23.1	20.3	22.4	-3.6
	Small grocery store	38.1	35.4	34.8	39.5	32.0	-0.5
	Supermarket & superstore	38.6	38.7	36.1	34.5	37.6	-0.7
	Supermarket & grocery store	35.7	35.2	30.5	30.5	29.3	-1.8
	Other combination of vendor types	37.8	37.6	36.1	35.3	31.1	-1.4
Juice	Superstore	73.0	72.8	70.6	71.7	71.6	-0.4
	Supermarket	79.9	79.9	78.2	77.6	76.6	-0.9
	Large grocery store	84.9	84.2	85.5	85.1	84.1	0.0
	Medium grocery store	84.6	84.9	83.9	82.7	82.9	-0.6
	Small grocery store	84.1	84.0	82.8	81.6	82.1	-0.7
	Supermarket & superstore	84.9	85.1	83.9	83.9	83.4	-0.4
	Supermarket & grocery store	86.7	86.8	85.4	85.1	85.0	-0.5
	Other combination of vendor types	84.1	84.6	83.1	82.7	82.5	-0.5
Legumes & peanut butter	Superstore	54.7	54.5	53.3	53.2	53.0	-0.5
	Supermarket	70.3	69.6	68.1	67.4	67.2	-0.9
	Large grocery store	74.5	72.7	74.3	74.6	73.7	0.1
	Medium grocery store	73.8	73.4	71.5	68.7	69.9	-1.3
	Small grocery store	75.0	73.0	71.9	70.9	72.0	-1.0
	Supermarket & superstore	69.6	69.7	68.7	68.6	69.1	-0.2
	Supermarket & grocery store	76.0	75.7	74.8	74.5	75.5	-0.3
	Other combination of vendor types	68.5	68.7	68.3	67.8	68.6	-0.1

Supplementary Table 4.3 (continued)

Benefit category	Overall vendor type	2015	2016	2017	2018	2019	Δ per year[1]
Low fat milk	Superstore	63.4	63.4	60.0	58.3	57.5	-1.7
	Supermarket	74.3	74.4	72.1	70.9	70.3	-1.2
	Large grocery store	78.8	79.1	78.2	78.7	79.5	0.1
	Medium grocery store	77.9	78.3	76.0	74.2	74.1	-1.1
	Small grocery store	82.3	81.4	79.2	77.9	78.3	-1.3
	Supermarket & superstore	78.3	79.0	77.2	76.2	75.4	-0.8
	Supermarket & grocery store	84.2	84.5	82.9	82.2	82.3	-0.7
	Other combination of vendor types	79.7	80.3	78.3	76.0	75.6	-1.2
Whole milk	Superstore	72.7	73.5	74.6	72.1	72.2	-0.2
	Supermarket	83.0	83.0	81.7	81.3	81.2	-0.5
	Large grocery store	86.8	87.8	87.8	87.6	87.9	0.2
	Medium grocery store	86.3	86.3	84.3	83.2	83.0	-1.0
	Small grocery store	87.4	87.3	86.2	85.1	85.6	-0.6
	Supermarket & superstore	86.6	87.9	87.4	86.9	87.3	0.0
	Supermarket & grocery store	90.7	91.2	90.3	90.4	90.2	-0.2
	Other combination of vendor types	89.7	90.1	89.4	89.0	88.6	-0.3
Yogurt	Superstore	42.9	49.3	48.5	49.6	51.3	1.3
	Supermarket	56.0	61.0	60.5	59.7	62.4	0.8
	Large grocery store	57.8	65.1	66.4	66.9	68.1	1.7
	Medium grocery store	38.3	54.6	51.4	51.4	51.1	1.1
	Small grocery store	5.5	21.5	33.3	35.1	33.8	6.9
	Supermarket & superstore	58.9	64.0	63.2	63.2	65.5	0.9
	Supermarket & grocery store	53.7	59.8	61.0	60.5	62.8	1.5
	Other combination of vendor types	46.1	53.1	53.5	53.5	56.3	1.7

[1]Δ per year refers to the annual percentage point change. This was estimated using a linear regression model where the outcome variable was a continuous variable for average percent redemption and the only predictor variable was a continuous year term. The coefficient of the continuous year term can be interpreted as the estimated annual percentage point change in the average percent redemption. For example, the average percent redemption of breakfast cereal among households that relied only on superstores in a given month decreased by about 2.2 percentage points per year between 2015–2019.

Notes: Due to small sample sizes, this analysis excluded households that exclusively redeemed benefits from pharmacies and convenience stores, as well as households that redeemed any benefits from commissaries.