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Does Where You Shop or Who You Are Predict What You Eat?: The Role of Stores and Individual Characteristics in Dietary Intake

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Abstract

Interventions to address diet, a modifiable risk factor for diabetes, cancer, and cardiovascular disease, have increasingly emphasized the influence of the physical environment on diet, while more traditional approaches have focused on individual characteristics. We examined environmental and individual influences on diet to understand the role of both. Household interviews were conducted in 2011 with 1,372 individuals randomly selected from two low-income, predominantly African American neighborhoods in Pittsburgh, PA. Participants reported their sociodemographic characteristics, food shopping behavior, and dietary intake. Both food shopping frequency at different types of food stores and sociodemographic characteristics showed significant associations with diet in adjusted regression models. More frequent shopping at convenience and neighborhood stores and being younger, male, without a college degree, and receiving SNAP benefits were associated with greater intake of sugar-sweetened beverages (SSBs), added sugars, and discretionary fats. Being older, male, and having a college degree were associated with greater intake of fruits and vegetables. However, while food shopping behavior and sociodemographic characteristics accounted for similar amounts of nonoverlapping variance in fruit and vegetable intake, food shopping behavior accounted for much less variance, and little unique variance, in SSBs, added sugars, and discretionary fats in models with sociodemographic characteristics. The current study reinforces the need for policies and interventions at both the environmental and individual levels to improve diet in food desert residents. Individual interventions to address food choices associated with certain sociodemographic characteristics might be particularly important for curbing intake of SSBs, added sugars, and discretionary fats.

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Conflict of Interest Statement

Conflicts of interest: None.

Keywords

diet; nutrition

Introduction

Diet is a modifiable risk factor for chronic conditions, including diabetes (Hu et al., 2001), cancer (Key et al., 2002), and cardiovascular disease (Hung et al., 2004), and has been identified as a major public health problem (Story et al., 2008). Questions of the role of the local food retail environment – and whether proximity to food selections that are healthy (i.e., fruits and vegetables) vs. unhealthy (i.e., high in added sugar, salt, or discretionary fats or calories) influences diet-- have dominated much of the research (Caspi et al., 2012; Larson and Story, 2009; Story et al., 2008) and served as a policy leverage point. A growing body of research has demonstrated that proximity to certain store *types* (e.g., convenience stores versus supermarkets) is associated with diet (Larson et al., 2009; Story et al., 2008). At the same time, residents of low-income communities are more likely to reside in "food deserts," where healthy food options are extremely limited (Larson et al., 2009; Story et al., 2008).

The immediate food environment has been posited to influence diet. Those who live closer to stores with healthy food options may buy and eat healthier food. Some research has documented an association between shopping at corner stores versus other types of stores (e.g., supermarkets) and purchasing foods high in fat and/or sugar (D'Angelo et al., 2011) and between shopping at a supermarket or specialty grocery store and fruit and vegetable (FV) intake (Zenk et al., 2005).

Alternatively, sociodemographic characteristics may influence where shoppers buy food, and shopping at stores that emphasize certain types of foods can encourage purchasing and consumption of those foods. Prior research suggests that higher income and educational attainment are associated with shopping at supermarkets (vs. other store types) and purchasing (D'Angelo et al., 2011; Zenk et al., 2005) and consumption of FV (Casagrande et al., 2007).

Research that has simultaneously examined the effects of shopping at different store types and shoppers' sociodemographic characteristics on diet has produced mixed findings. Some research suggests that shopping at supermarkets and specialty stores (vs. other store types) is associated with higher FV intake after controlling for age, income, and education (Zenk et al., 2005). In other research, the poorer dietary quality of residents of low-income, low-access (to food) areas relative to their socioeconomically advantaged peers has not been adequately explained by differences in the food retail channels where they shop; rather, demographic characteristics such as race, education, and income have evidenced a much stronger effect on diet (Rahkovsky and Snyder, 2015).

Disentangling the contributions of the food retail environment and sociodemographic characteristics to diet is critical to shaping nutrition policy. If shopping for food more frequently at stores that offer limited healthy food and more unhealthy food more strongly reduces dietary quality than sociodemographic characteristics, interventions should focus on promoting access to healthy food and de-emphasizing unhealthy food in the environment. However, if associations between food purchasing behavior and consumption are primarily due to individual characteristics, then interventions should focus on improving the food choices of individuals with sociodemographic characteristics associated with unhealthy diet. Alternatively, both environmental and individual influences may make significant, unique contributions to diet. This more complex scenario would suggest the merit of an ecological approach in which dietary interventions must address both individual and environmental influences to exert maximal impact.

Prior work is limited in that it has mostly analyzed food shoppers within mutually exclusive categories of stores based on where they do most of their food shopping. However, individuals may buy food from multiple store types, and so assignment of individuals' shopping behavior to just one store type may yield miscalculated conclusions. Simultaneous examination of the effects of food shopping at multiple store types on diet is necessary to obtain a more comprehensive understanding of food shopping behavior.

The current study was designed to strengthen the evidence base by examining the unique, relative contributions of food shopping frequency at several store types and sociodemographic characteristics to diet of residents of two low-income, predominantly African American neighborhoods that are food deserts. In addition, we used a high-quality measure of diet, the 24-hour dietary recall. Building on a larger study of the dietary impact of adding a grocery store to one of the neighborhoods, we analyzed household interview data on sociodemographic characteristics, food shopping behavior, and diet and used food store audit data to describe the availability and prominence of healthy and unhealthy food in the local retail environment.

Methods

Design and Sample

The Pittsburgh Hill/Homewood Research on Eating, Shopping, and Health (PHRESH) is a 5-year quasi-experimental study of two predominantly African American, low-income "food deserts" in Pittsburgh, Pennsylvania, one of which was slated to acquire a new full-service supermarket (intervention neighborhood). These neighborhoods were sociodemographically and geographically matched to permit clearer attribution of differences observed at follow-up to the new supermarket. For both neighborhoods, 95% of residents were African American, and the mean self-reported annual household income was less than $15,000. Before the new supermarket opened, the closest supermarket was, on average, 1.73 miles (SD = 0.35) and 1.45 miles (SD = 0.35) from residents of the intervention and comparison neighborhoods, respectively.

PHRESH participants were recruited from a random sample of households drawn from a complete list of residential addresses in both neighborhoods generated by the Pittsburgh Neighborhood and Community Information System, with sampling in the intervention neighborhood stratified by distance to the planned supermarket. Trained data collectors went door-to-door to 4,002 sampled addresses, determined that 2,900 of these were not vacant, and reached a household member in 1,956 addresses. Of these members, 1,649 were over 18 and the primary household food shopper and therefore eligible to participate; 1,434 (87%) of eligible residents agreed to participate. After excluding 62 residents who provided incomplete or unusable data, the final sample comprised 1,372 households. Before the new supermarket opened, data collectors administered in-home interviews to each household's primary food shopper between May and December 2011 and audited food purchasing venues in the local retail environment. More details on study procedures are available in the main paper describing the quasi-experimental evaluation (Dubowitz et al., 2015). The study protocol was approved by the RAND Human Subjects Protection Committee.

Household Interviews

Household interviews assessed participants' sociodemographic and other characteristics. Annual household income was measured with a nine-category ordinal scale and recoded to the interval midpoint, and missing values were imputed with the software IVEW are in SAS macros. Adjusted income was the ratio of household income to household size. Body mass index (BMI) (or weight in kg/height in m^2) was calculated from interviewer-measured height to the nearest eighth inch using a carpenter's square (triangle) and an 8-foot folding wooden ruler marked in inches and weight to the nearest tenth of a pound using the SECA Robusta 813 digital scale (without shoes). We defined obesity as BMI of at least 30 (Centers for Disease Control and Prevention, 2016).

Diet was assessed with the automated self-administered 24 hour recall (ASA-24), once during the household interview and again seven to 10 days later by telephone (Subar et al., 2012). The ASA-24 estimates nutrients values based on the USDA's Food and Nutrient Database for Dietary Studies and the MyPyramid Equivalents Database. The ASA-24 has been shown to produce comparable dietary intake estimates relative to interviewer-administered 24 hour recalls in a racially/ethnically diverse sample of adults (Thompson et al., 2015). Moreover, web-based 24 hour recalls have been validated in black adults using the objective biomarker of the doubly-labeled water method for estimating total energy expenditure (Arab et al., 2011). For this study, we analyzed kilocalories of sugar-sweetened beverages (SSBs), teaspoons of added sugars, grams of discretionary (solid) fats (i.e., fats that are solid at room temperature, such as butter, lard, and shortening), and cups of FV. The ASA-24 automatically estimates all of these except for kilocalories of SSBs, which were estimated by 1) reviewing codes for beverages to create a subcategory for SSBs, and 2) using kilocalories calculated by the ASA-24 to compute kilocalories from SSBs for each person. Dietary indicators were computed as the average of both dietary recalls.

Frequency of food shopping was assessed for each store type with a single question: "In general, when you buy food, how often do you go to…" followed by a list that included convenience stores, neighborhood stores, dollar stores, discount grocery stores, supercenters, wholesale clubs, full-service supermarkets, specialty grocery stores, and FV stores or farm stands. We classified stores based on definitions from the Food Marketing Institute (FMI) and the North American Industry Classification System (NAICS) and confirmed our classifications with our Community Advisory Board, comprised of key resident stakeholders in each neighborhood. Local examples were provided to clarify the definition of each store type. Response options ranged from *never* (1) to *often* (4).

Store Audits

We audited all 24 food stores in the study neighborhoods and 14 food venues outside both neighborhoods where residents reported doing major food shopping. We compiled a complete list of food stores in the neighborhoods from in-person neighborhood scans and feedback from data collectors, all of whom were study neighborhood residents, and the Community Advisory Board. We selected food venues outside the neighborhoods by examining the top ten responses to an interview question about the two stores where participants did their major food shopping and removing duplicate responses.

We used the Bridging the Gap Food Store Observation Form (BTG-FSOF) (Rimkus et al., 2013), because its reliability and validity have been demonstrated in past research, and it allows for more comprehensive assessment of food stores than other measures, assessing the availability, pricing, and marketing of healthy as well as unhealthy foods and beverages (Rimkus et al., 2013). We adapted the form for the setting and population of PHRESH based on feedback from our Community Advisory Board by, for example, including local examples of different store types (e.g., convenience stores) and some foods that are commonly eaten in African American populations (see Appendix).

We counted the availability of 22 FV that are commonly eaten in the U.S. general population (e.g., apples, broccoli) and specifically in African American populations (e.g., okra, greens), as well as nine unhealthy foods: family-size regular soda; individual size regular soda; regular, salted potato chips sold in a package size less than three ounces; regular, salted potato chips sold in a package size three ounces or greater; hot or spicy chips sold in a package size less than three ounces; hot or spicy chips sold in a package size of three ounces or greater; snack cakes; cookies; and chocolate bars/candy.

We also counted food displays (end aisle, special floor, and cash register). We documented the number of each type of display that promoted healthy foods, including FV or products with at least 50% whole grains, and unhealthy foods (i.e., SSBs, salty snacks, candy, or sweetened baked goods), and whether the view from the store's main entrance was dominated by healthy or unhealthy foods.

Statistical Analyses

First, we computed univariate descriptive statistics to characterize the household interview participants and the local food retail environment. Then we estimated multivariate ordinary least squares (OLS) regression models in which we regressed dietary outcomes on the frequency of food shopping at different store types and sociodemographic characteristics. We estimated three separate multivariate models for each outcome, two *partially adjusted* models and one *fully adjusted* model. In one set of partially adjusted models, we regressed each outcome on food shopping frequency at all store types. In the other partially adjusted models, we regressed each outcome on sociodemographic characteristics. The fully adjusted models included both food shopping frequency at all store types and sociodemographic characteristics as predictors. Before estimating models, we confirmed the basic assumptions of OLS regression, including normality of residuals. Analyses were conducted in SAS, version 9.4, of the SAS System for Windows.

Results

Descriptive Statistics

Study Participants—Table 1 displays the characteristics of study participants. As also indicated there, the vast majority (97%) of participants reported buying food at least occasionally at two or more store types. On average, full-service supermarkets were the most-frequently visited store, followed by supercenters and dollar stores. FV stores, discount grocery stores, wholesale clubs, convenience stores, and neighborhood stores were visited less frequently. Specialty grocery stores were visited least frequently.

Food Retail Environment—Nearly all store types emphasized unhealthy over healthy food (i.e., FV or products with at least 50% whole grains). Table 2 shows, for each store type, the percentage of stores for which the view from the main entrance was dominated by FV or unhealthy food, the average number of types of FV and unhealthy foods available across stores, and the average number of displays that promoted healthy and unhealthy food across stores. To streamline the presentation of results, we grouped store types into three categories based on their constituent stores' relative inventory and product placement of unhealthy vs. healthy food: *unhealthy*, which includes store types that strongly emphasized unhealthy over healthy food (i.e., had unhealthy food dominating the view from the store's main entrance, offered more types of unhealthy than healthy food, and had more displays promoting unhealthy than healthy food); *moderate*, which indicates slightly greater emphasis on unhealthy food but at least some emphasis on healthy food; and *healthy*, which connotes greater emphasis on healthy foods than the other two categories. Unhealthy store types included convenience stores, neighborhood stores, and dollar stores. Moderate store types included discount grocery stores, supercenters, and wholesale clubs, where, on average, many types of unhealthy food were available and more displays featured unhealthy than healthy food, and unhealthy food more frequently dominated the view from the main entrance. However, unlike the unhealthy category, the moderate store types also offered, on average, several types of FV. Healthy store types, which included full-service supermarkets, the specialty grocery store, and the FV store, featured, on average, numerous types and prominent displays of FV. However, even in the healthy store types (except for the FV store), unhealthy food was readily available and prominently displayed.

Multivariate Regression Models

As Table 3 shows, shopping more frequently at unhealthy and moderate food stores was associated with unhealthy diet: In partially and fully adjusted models, shopping more frequently at convenience stores was significantly associated with greater consumption of added sugars; buying food more often at neighborhood stores predicted significantly greater intake of SSBs and discretionary fats (e.g., butter); and buying food more often at supercenters was significantly associated with greater intake of discretionary fats. Conversely, shopping more often at specialty grocery stores and FV stores was significantly associated with greater FV consumption. In most of these cases, adjustment for sociodemographics slightly reduced associations between food shopping frequency and the outcome, though sociodemographics explained nearly half of the association between shopping at neighborhood stores and SSB consumption and none of the association between shopping at FV stores and FV consumption. Controlling for sociodemographics also reduced the coefficients for three store-type effects in the partially adjusted models to nonsignificance.

We also found evidence for the role of sociodemographics in diet. Specifically, being younger and male significantly predicted greater intake of SSBs, added sugars, and discretionary fats in partially and fully adjusted models. Being younger also predicted significantly lower FV intake, but being male predicted greater FV intake. Lacking a college degree was significantly associated with greater consumption of SSBs and discretionary fats and lower FV consumption. Receiving SNAP benefits was significantly associated with greater consumption of added sugars. In all cases, adjustment for food shopping frequency slightly reduced or did not change the associations between sociodemographics and the outcome.

Finally, we compared the relative associations of food shopping behavior and sociodemographics with diet. Sociodemographics accounted for about twice as much variance in unhealthy diet as store type (see Table 3 R^2s for partially adjusted models) and a small amount of unique additional variance compared to store type (R^2 increased by.01 from the models with only sociodemographics to the fully adjusted models). However, sociodemographics and store type contributed equally to FV intake in the partially adjusted models, and this variance was largely nonoverlapping. R^2 for the partially adjusted model of FV intake with only sociodemographics nearly doubled after adding store types in the fully adjusted model. Thus, although sociodemographics explained most of the explained variance in unhealthy diet, sociodemographics and store types contributed similarly to healthy diet.

Discussion

The current findings demonstrate the roles of both the food retail environment and individual characteristics in diet. Both food shopping behavior and sociodemographic characteristics significantly predicted intake of SSBs, added sugars, discretionary fats, and FV, and these associations were partially independent of one another. However, in models that included food shopping behavior and sociodemographic characteristics, the latter accounted for substantially more total variance in, and contributed more unique variance to, unhealthy diet. By contrast, both food shopping behavior and sociodemographic characteristics accounted for similar amounts of nonoverlapping variance in FV intake, indicating comparable contributions of the food retail environment and individual characteristics to healthy diet. Thus, while both environmental and individual influences warrant consideration in the design of nutrition policies and interventions, individual influences might be particularly important to address to curb unhealthy diet.

This study adds to the growing body of evidence suggesting that shopping at corner stores and convenience stores is associated with unhealthy diet (D’Angelo et al., 2011; Larson et al., 2009). We found that shopping at convenience and neighborhood stores was associated with unhealthy diet after adjusting for sociodemographic characteristics and food shopping frequency at all other store types. However, contrary to other studies documenting nutritional benefits associated with shopping at supermarkets (D'Angelo et al., 2011; Zenk et al., 2005), we failed to find associations between food shopping frequency at supermarkets and diet. This might be explained by the high frequency of food shopping at supermarkets, which restricted variation in this variable and may have impeded the detection of significant associations with other variables.

At the same time, this study augments an accumulating body of evidence highlighting the role of sociodemographic characteristics in diet, particularly consumption of unhealthy beverages and foods such as SSBs, added sugars, and discretionary fats. Our findings that educational attainment and receipt of SNAP benefits robustly predict diet converge with recent findings showing that sociodemographic characteristics, namely socioeconomic status indicators (education, income), better explain variation in diet than where people buy food (Rahkovsky and Snyder, 2015).

At the food environment level, there are multiple potential avenues of intervention. Changing the environment by adding a full-service supermarket facilitates access to unhealthy as well as healthy foods and has not been shown to directly produce the expected benefits on diet (Cummins et al., 2014; Dubowitz et al., 2015; Elbel et al., 2015a; Elbel et al., 2015b). Thus, policies and interventions that curb unhealthy diet and increase healthy diet are needed. For example, SSB taxes in Mexico and Berkeley, California have been found to reduce SSB purchases (Batis et al., 2016) and consumption (Falbe et al., 2016). Given that most residents shopped at multiple store types, and our finding that store type contributed limited unique variance to unhealthy diet, care must be taken to ensure that policies cut across store types, rather than focusing on a single store type (e.g., convenience stores). Store-level interventions may need to focus more on healthy diet. Other research suggests that in-store marketing strategies and pricing can be leveraged to emphasize healthy foods and de-emphasize unhealthy foods (Cohen et al., 2015; Ghosh-Dastidar et al., 2014).

However, as our study demonstrates, some associations between food shopping behavior and diet were explained by sociodemographic characteristics, thus indicating that intervening at the individual level might also help to improve nutrition in this population. Being younger and male were consistently associated with greater intake of SSBs, added sugars, and discretionary fats. This suggests a need for alternative methods to improve the diet of individuals with these characteristics. For example, these individuals may benefit from targeted interventions designed to modify dietary choices. Such interventions may be particularly critical for curbing unhealthy diet given our findings that sociodemographic characteristics accounted for more variance, and more unique variance, in unhealthy diet than food shopping behavior. More research is needed to understand why certain subgroups are more inclined to consume unhealthy food.

Study strengths and limitations

The study's primary strengths include the analysis of a broad array of food store types, the use of audit data to describe the food retail environment, and the use of a high-quality measure of dietary intake.

The study also has some limitations. First, the study's correlational design precludes causal inferences. Nonetheless, this design allowed us to determine that some of the associations between frequency of food shopping at a particular store type and diet are better explained by individual characteristics. Measuring predictors on the individual and environmental levels enhanced our understanding of the relative importance of both levels to diet. Second, we did not examine the dietary influences of food sources other than stores (e.g., restaurants). However, in a separate analysis of food receipts collected from members of the same cohort, we found that food stores accounted for the great majority (92.6%) of total food and beverage expenditures (Vaughan et al., 2016). Third, we examined only sociodemographic characteristics and food shopping behavior as predictors of diet, which has a broader array of determinants. Additional influences on diet identified in previous research include self-efficacy (Steptoe et al., 2004), social support (Greaves et al., 2011; Steptoe et al., 2004), and positive outcome expectancies for healthy diet (Steptoe et al., 2004), as well as the taste of food, cost, and limited dietary knowledge (James, 2004). Our exclusion of these influences likely accounts for the relatively small amounts of variance in dietary indicators explained in our models. Finally, another limitation is that some store types in the audit were represented by one store that may not conform to the prototypical store in that category. Thus, our findings may not be representative of some store types.

Conclusion

The current study reinforces the need for policies and interventions at the environmental and individual levels to improve diet in food desert residents. However, individual interventions to address dietary choices associated with certain sociodemographic characteristics might be particularly important for curbing unhealthy diet.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Abbreviations

FV	fruits and vegetables
SNAP	Supplemental Nutrition Assistance Program
SSB	sugar-sweetened beverages

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Highlights

- Both environmental and individual influences were significantly associated with diet.
- Individual factors explained more unique variance in unhealthy diet than environmental.
- Policies are needed at the environmental and individual levels to improve diet.
- Individual interventions might be particularly important for curbing unhealthy diet.

Table 1

Characteristics of Primary Household Food Shoppers Residing in a Food Desert in Pittsburgh, 2011 (N = 1,372)

Characteristic	N or Mean (SD)	%
Demographics		
Age (years)	53.7(17.6)	
Female gender	1,016	74.0
Non-Hispanic black race/ethnicity	1,234	90.5
Household composition		
Married or living with partner	254	18.6
At least one child under 18 residing in household	371	27.0
Lives alone	723	52.7
Socioeconomic status		
Annual per capita household income in USD	13.4(13.1)[a]	
College degree	210	15.3
Access to vehicle	782	57.2
SNAP[b] benefits recipient in household	686	50.0
Obesity and food shopping behavior		
Obese (Body Mass Index > 30)	633	46.6
Does food shopping at two or more stores at least occasionally	43	96.9
Frequency of food shopping at different store types[c]		
Full-service supermarkets	3.6(0.7)	
Supercenters	2.5(1.1)	
Dollar stores	2.5(1.1)	
Fruit and vegetable store	2.1(1.1)	
Discount grocery stores	2.1(1.1)	
Wholesale clubs	1.9(1.0)	
Convenience stores	1.8(1.0)	
Neighborhood stores	1.8(1.0)	
Specialty grocery store	1.5(0.9)	

[a]Reported in 1,000s.

[b]SNAP = Supplemental Nutrition Assistance Program.

[c]Frequency of food shopping at different types of stores was rated on a scale that ranged from 1 (never) to 4 (often).

Table 2

Characteristics of Audited Stores in Food Deserts in Pittsburgh by Store Type, 2011

Store type	Number of stores audited	Food that dominates the view from store's main entrance (%)		Average number of types of food available M(SD)		Average number of displays that promote type of food M(SD)	
		FV[a,b]	Unhealthy Food[c]	FV[a,d],d	Unhealthy food[e]	Healthy food[f]	Unhealthy food[g]
Unhealthy							
Convenience store	4	0	100	0	7.5(1.3)	0	6.0(3.7)
Neighborhood store	18	0	94.4	0.22(0.65)	7.5(1.4)	0	5.8(6.7)
Dollar store[h]	1	0	0	0	9.0	0	9.0
Moderate							
Discount grocery store	2	50	50	15.0(0)	6.0(1.4)	5.0(2.8)	13.0(12.7)
Supercenter	2	0	100	20.0(0)	9.0(0)	10.0(2.8)	90.0(1.4)
Wholesale club[h]	1	0	0	15.0	4.0	5.0	12.0
Healthy							
Full-service supermarket	8	63	37	20.8(1.3)	8.3(0.71)	16.1(9.7)	42.3(7.2)
Specialty grocery store[h]	1	0	100	20.0	6.0	21.0	16.0
Fruit and vegetable store/farm stand[h]	1	100	0	17.0	0	0	0

[a] FV = fruits and vegetables.

[b] This column contains the percentage of stores of each type in which FV dominated the view from the main entrance. The denominator for these percentages varies by store type and is the number of stores shown for the store type in the column "Number of stores audited".

[c] This column contains the percentage of stores of each type in which unhealthy food dominated the view from the main entrance. The denominator for these percentages varies by store type and is the number of stores shown for the store type in the column "Number of stores audited".

[d] This column contains the average (mean) numbers and standard deviations of types of FV available in stores of each type. Possible scores on this indicator ranged from 0 to 22.

[e] This column contains the average (mean) numbers and standard deviations of types of unhealthy food available in stores of each type. Possible scores on this indicator ranged from 0 to 9.

[f] Healthy food, as defined with respect to the types of food promoted in different displays, includes products with at least 50% whole grains in addition to fruits and vegetables. This column contains the average (mean) numbers and standard deviations of displays that promoted healthy food.

[g] This column contains the average (mean) numbers and standard deviations of displays that promoted unhealthy food.

[h] Because there was only one store of this type, no standard deviation could be computed for the average numbers of types of fruits and vegetables and unhealthy food or for the average numbers of displays that promote healthy food and unhealthy food.

Table 3

Multivariate Regression Models Predicting Dietary Intake from Frequency of Food Shopping at Different Types of Stores and Sociodemographics Among Primary Household Food Shoppers, Pittsburgh, 2011 (N = 1,372)

Model Predictors	SSBs (kcals)		Added sugars (tsp.)		Discretionary fats (g)		Fruits and vegetables (c.)	
	Partially Adjusted Model[a]	Fully Adjusted Model[b]	Partially Adjusted Model[a]	Fully Adjusted Model[b]	Partially Adjusted Model[a]	Fully Adjusted Model[b]	Partially Adjusted Model[a]	Fully Adjusted Model[b]
Store type								
Unhealthy								
Convenience store	8.28	4.45	1.01**	0.79*	0.92	0.21	−0.02	−0.02
Neighborhood store	17.87*	9.85*	1.12**	0.61†	2.85***	1.75*	0.03	0.05
Dollar store	−1.60	−1.88	0.15	0.16	0.40	0.81	−0.06	−0.03
Moderate								
Discount grocery store	6.15	4.28	0.12	0.05	0.41	0.29	0.08†	0.08*
Supercenter	8.34*	3.31	0.64*	0.48	1.68*	1.50*	−0.06	−0.03
Wholesale club	−0.40	0.42	−0.31	−0.06	−0.35	0.20	0.04	0.07
Healthy								
Full-service supermarket	2.63	3.85	0.53	0.66	0.61	1.19	0.004	0.02
Specialty grocery store	−7.82	−5.63	−0.34	−0.26	−1.33	−1.66*	0.24***	0.20***
Fruit and vegetable store	−5.63	−1.29	−0.15	0.10	−1.01	−0.11	0.10*	0.10*
Model R^2	0.04***	--	0.03***	--	0.03***	--	0.04***	--
Sociodemographic characteristics								
Demographics								
Age	−1.58***	−1.36***	−0.07***	−0.05*	−0.23***	−0.18***	0.01*	0.01*
Male	27.51**	25.97**	3.43***	3.40***	13.55***	13.84***	0.47***	0.48***
Socioeconomic status								
Annual household income	−0.18	−0.12	−0.001	0.01	0.01	0.02	0.01†	0.005
College degree	−27.55*	−23.32*	−1.11	−0.86	−5.00*	−3.91*	0.37**	0.30*
Access to vehicle	7.96	8.49	0.11	0.12	−0.36	−0.34	0.14	0.05
SNAP benefits	16.81*	13.22	2.07**	1.75*	0.49	−0.34	0.10	0.10
Household composition								
Married or living with partner	−11.29	−11.81	−1.14	−1.21	−1.12	−1.11	−0.12	−0.19

Model Predictors	SSBs (kcals)		Added sugars (tsp.)		Discretionary fats (g)		Fruits and vegetables (c.)	
	Partially Adjusted Model[a]	Fully Adjusted Model[b]	Partially Adjusted Model[a]	Fully Adjusted Model[b]	Partially Adjusted Model[a]	Fully Adjusted Model[b]	Partially Adjusted Model[a]	Fully Adjusted Model[b]
Any children under 18	12.27	12.49	1.88†	1.91	3.49	3.33	0.23	0.25
Number of residents	2.52	1.33	−0.20	−0.30	−0.91	−1.15	−0.07	−0.09†
Model R^2	0.08***	0.09***	0.05***	0.06***	0.08***	0.09***	0.04***	0.07***

Notes. SSBs = sugar-sweetened beverages. kcals = kilocalories. tsp. = teaspoons. g = grams. c. = cups. SNAP = Supplemental Nutrition Assistance Program. Annual household income is per capita. Regression coefficients are unstandardized and therefore represent the amount of change in the outcome in raw units for a one unit change in the predictor. For example, controlling for all predictors in the fully adjusted model, participants who had a college degree reported consuming 23.32 fewer kcals of SSBs over a 24-hour period than participants without a college degree.

[a]Partially adjusted multivariate models in the first half of the table include all store types as predictors and do not include sociodemographic characteristics. Partially adjusted multivariate models in the second half of the table include all sociodemographic characteristics as predictors and do not include store types.

[b]The fully adjusted multivariate model includes all store types and sociodemographic characteristics shown in the table as predictors.

† p < 10.

* p <.05.

** p <.01.

*** p <.001.