HOW DO CHANGES IN THE NEIGHBORHOOD FOOD ENVIRONMENT INFLUENCE DIET AND BODY MASS INDEX OVER TIME? AN INNOVATIVE METHOD USING 20 YEARS OF SPATIAL, DIET, AND ANTHROPOMETRY DATA

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ABSTRACT

Andrea S Richardson: How do changes in the neighborhood food environment influence diet and body mass index over time? An innovative method using 20 years of spatial, diet, and anthropometry data
(Under the direction of Penny Gordon-Larsen)

Cross-sectional studies suggest neighborhood socioeconomic disadvantage is associated with obesogenic food environments. Yet, it is unknown how exposure to neighborhood socioeconomics (SES) patterning through adulthood corresponds to food environments that also change over time. Further, obesity reduction strategies often target neighborhood food resources, without considering separate pathways from multiple types of resources to body mass index (BMI), through diet, or how reverse causality plays a role.

We capitalized on a large Geographic Information Systems derived temporally and spatially linked to respondents (residential locations) in the large cardiovascular cohort study called Coronary Artery Risk Development in Young Adults (CARDIA). We estimated longitudinal pathways from neighborhood food resources to BMI and studied pathways from neighborhood fast food, sit-down restaurants, supermarkets and convenience stores to BMI, through diet behaviors. We approximated reverse causality with reverse pathways from period-specific diet behaviors to future neighborhood food resources.

Socioeconomically disadvantaged neighborhood residents had fewer sit-down restaurants, more convenience stores, and similar numbers of supermarkets in their neighborhoods than the advantaged residents. Neighborhood fast food and sit-down restaurants

were associated with higher BMI through the consumption of foods typically purchased from fast food restaurants (i.e., fast food-type diet). Fast food-type diet was consistently associated with higher BMI while consumption of the sit-down restaurant-type diet was associated with lower BMI. Including reverse pathways from time period specific diet behaviors to future food environment suggests that diet behaviors may act as a proxy for individual preferences/constraints associated with future neighborhood food stores and restaurants. Approximating reverse causality with reverse pathways from time period-specific diet behaviors to future neighborhood food resources, increased both the magnitude and strength of the associations between neighborhood restaurants and diet behaviors, but did not change the associations between neighborhood food stores and diet behaviors.

Neighborhood fast food and sit-down restaurants may play comparatively stronger roles than food stores in diet behaviors and BMI. Public health policies that address food environment disparities to improve diet and reduce obesity may need to focus on eating away-from-home behaviors and the types of restaurants (i.e., fast food versus sit-down) more than on food stores.

I dedicate this work to my men big and little: Tony, Jack and DJ Richardson who are the joys of my life. Throughout this process, Tony has supported me by picking up the slack when needed, deftly giving me perspective when I felt overextended, and always made me laugh. Every day Jack and DJ remind me of what is important in life and how fast the time flies by. My insightful and delightful sons can also always make me laugh and I thank them for sharing their mother with the doctoral program.

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PREFACE

I was happy in my career as a masters-level public health researcher. But throughout the years I grew more concerned about the obesity epidemic, especially for socioeconomically disadvantaged populations living in deprived communities. It seemed intuitive that if you lack resources and you are surrounded by fast foods with little access to healthy foods, then it would be very difficult to maintain a health diet. Thus, improving food environments should be a policy target to reduce obesity. While policies and initiatives currently exist there is a lack of evidence and obesity remains a major public health issue. I first worked with Penny Gordon-Larsen as an Applications Analyst, and began to tackle the challenges involved when analyzing associations between environmental characteristics and individual health behaviors or disease outcomes. I realized quickly that I needed a doctorate in Nutrition Epidemiology to successfully tackle obesity disparities in disadvantaged populations living in poor communities. This work is the culmination of my doctorate training and that has poised me to apply my skills to help reduce health disparities in obesity.

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LIST OF ABBREVIATIONS

BMI	Body Mass Index
CARDIA	Coronary Artery Risk Development in Young Adults
CFI	Comparative Fit Index
FPL	Federal Poverty Level
HS	High school
HU	Housing Unit
kg	kilogram
m	meter
SEM	Structural equation modeling
SES	Socioeconomic status
SD	Standard deviation
SSB	Sugar-sweetened beverage
RMSEA	Root mean square error approximation
TLI	Tucker-Lewis Index

CHAPTER I: INTRODUCTION

A. BACKGROUND

Obesity increased dramatically nationwide during the mid-1980's to 2006, with socioeconomically disadvantaged populations disproportionately affected.[1,2] Disparities in obesity have lead researchers to investigate the degree to which disadvantaged neighborhoods have poor food environments that may promote the over-consumption of unhealthy energy-dense foods.[3-6] The idea that policies could reduce health disparities by modifying features of the built environment lead to efforts that targeted food resources.[7-9] Despite the theoretical appeal of this approach, there remains a paucity of high-quality evidence supporting these activities. The largely cross-sectional evidence base about socioeconomic disparities in the food environment is mixed with both positive and negative findings.[10-13] Without rigorous scientific evidence it is unlikely that any efforts to reduce obesity by modifying food environments will be effective.

Shifts in neighborhood socioeconomics that co-occur with changes in the food environment may underlie existing equivocal evidence. In addition, most research focuses on a single part of the pathway, generally either the associations between food resources and diet behaviors or the association between food resources and body mass index (BMI). Yet, the extent to which changing food environments lead to dietary change and consequent reduction in obesity, through diet, is unknown. In addition, when estimating associations between neighborhood food stores and restaurants, with diet and BMI, reverse causality (individual diet preferences shaping residential neighborhood selection) is often ignored and could bias relevant pathways.

To address these limitations, we capitalized on a large and unique Geographic Information Systems (GIS) database of neighborhood features linked to Coronary Artery Risk Development in Young Adults (CARDIA) respondent residential locations. CARDIA is a longitudinal cohort study of 5,114 black and white young adults (aged 18-30 at baseline in 1985-86). We used two decades (1985-86 to 2005-06) of time-varying data on neighborhood-level food resources, U.S. Census data, individual-level detailed diet, anthropometric, and sociodemographic and behavior data.

First, we used latent class analysis to identify different longitudinal patterns of neighborhood SES indicators. The exposure to neighborhood SES over time is a latent construct that is not measured by any single demographic variable, rather it is a combination of neighborhood characteristics over time. By using this method we parsimoniously quantified SES using a number of these neighborhood characteristics and captured each participants 20-year exposure to neighborhood SES. Second, we built a structural equation model (SEM) to delineate the complex relationships between changes in neighborhood food environment and changes in diet and BMI. SEMs refer to modeling techniques that are equipped to handle <u>multiequation models</u>, multiple measures of concepts (e.g., latent constructs), and measurement error. We simultaneously estimated separate longitudinal pathways from neighborhood fast food restaurants, sit-down restaurants, supermarkets, and convenience stores to BMI *through* diet behaviors. While many studies examine only one type of food resource (e.g., supermarkets), our approach accounted for potentially different and simultaneous effects of different restaurants and food stores on diet behaviors and BMI across the whole of the food environment. Further, we investigated how these relationships differed by sex, race and neighborhood socioeconomics. Third, to approximate reverse causality, we explicitly investigated reverse pathways from predicted and time period-specific diet behaviors to future neighborhood food resources. The prospective, longitudinal design, exceptionally varied range of social, demographic, behavioral, and community exposure and anthropometric data allowed an outstanding opportunity to investigate how different types of neighborhood restaurants and food stores contribute to obesity disparities through diet across a major lifecycle period of risk for weight gain.

B. SPECIFIC AIMS

The overall goal of this research was to characterize how temporal changes in neighborhood food resources influence diet behaviors, and through this pathway influence weight gain in young adults followed over 20 years. Further, we examined whether these pathways varied by socioeconomic and sociodemographic factors, and studied the potential influence of reverse causality on our estimates from the food environment to BMI through diet behaviors. We achieved this goal through the following aims:

1) Identify longitudinal pathways from four types of neighborhood food resources (fast food restaurants, sit-down restaurants, supermarkets and convenience stores) to BMI through diet behaviors and test how the pathways vary by race, sex, and longitudinal neighborhood socioeconomic status (SES) patterns.

a. Using latent class analysis (LCA), classify individuals according to varying levels of 20-year exposure to dynamic neighborhood socioeconomic domains (e.g., occupation, poverty, education) and determine how the availability of the four types of neighborhood food resources differed by 20-year neighborhood SES patterning.

b. Develop a structural equation model to delineate the longitudinal pathways from each type of neighborhood food resource to BMI, specifically the indirect pathways to BMI through diet behaviors.

c. Test statistical interactions by individual-level sex, race, and the longitudinal neighborhood SES classes derived in Aim 1a to test how neighborhood food resources influence diet behaviors differently for males versus females, blacks versus whites, and for CARDIA participants living in neighborhoods in declining versus improving or stable SES.

2) Approximate reverse causality to observe how it might bias the associations observed in the Aim 1 analyses. We will test this by extending our models in Aim 1 to include the reverse pathways from predicted and time period-specific diet behaviors to future neighborhood food resources.

CHAPTER II: LITERATURE REVIEW

A. THE IMPORTANCE OF THE FOOD ENVIRONMENT AND DISPARITIES IN THE UNITED STATES

Obesity rates have increased drastically in the last few decades nationwide, yet socioeconomically disadvantaged populations are disproportionately affected.[1,2] Unequal food environments are related to neighborhood socioeconomic status (SES).[2,6] As such, neighborhood food resources have been linked to disparities in obesity and poor diet.[10-13] National and local efforts have targeted environmental food resources as a means to improve diet quality and physical activity in disadvantaged areas.[7-9] Yet, the obesity gap continues to widen.[14] Few longitudinal analyses have focused on diet as a proximal outcome to obesity or BMI, and these have yielded findings that suggest complex relationships. For example, supermarket availability bore no relation to prospective diet quality[15] perhaps because supermarkets sell healthy *and* unhealthy foods or current statistical modeling strategies do not account for dynamic changes in the environment or the multiple types of food resources from which individuals choose to patronize.

Increased consumption of foods away-from-home has paralleled the obesity epidemic[16] and the frequent consumption of quick-service convenience foods (e.g., burgers, fries, pizza, sodas, etc.) characterized by poor nutrient quality, high fat, salt and added sugars predicts higher body mass index,[17,18] weight gain,[19] and adverse cardiometabolic outcomes[20] in adults.

B. NEED FOR LONGITUDINAL STUDIES

Much of the findings from cross-sectional data are mixed[21-23] but in general there is evidence, albeit from weak designs that neighborhood food resources are associated with obesity, BMI, and some diet behaviors.[10-12] However, cross-sectional analyses of neighborhood health effects lack the ability to examine bi-directional relationships and are particularly vulnerable to selection bias. Individual personal preferences may drive neighborhood choice and may create spurious associations between neighborhood environment and obesity related behaviors.

C. CONSIDERATION FOR MUTLIPLE TYPES OF FOOD RESOURCES

Research has focused on “food deserts”, generally defined as areas with limited access to affordable fresh foods from supermarkets.[13,23-25] Subsequently, “food swamps”,[26,27] characterized as neighborhoods with disproportionate access to convenient, energy dense, nutrient poor foods sold by convenience stores and fast food restaurants, emerged as important dimensions of the food environment. Thus, attention to a variety of food resources, such as supermarkets, convenience stores, sit-down, and fast food restaurants is a more useful approach to examining neighborhood food access than considering only one type hypothesized to sell either healthy or unhealthy foods.[13,28,29]

Supermarkets and sit-down restaurants may promote a better diet because they can sell higher quality foods than fast food restaurants and convenience stores but they also sell large portions of processed, high fat and sugar foods. However, when we expect to see “food deserts” in dense urban low income and high minority neighborhoods, we do also observe areas with greater supermarket store availability than more affluent urban neighborhoods.[6] A better understanding of how the food landscape, comprised of different types of food stores and restaurants, influence the consumption of foods that promote or protect against weight gain is needed.

D. THE BLACK BOX

While research on the food environment, diet behaviors, and body weight has proliferated over the past several years, most of this research ignores the multiple pathways from environment to BMI through diet behaviors.[30-32] Thus, the bulk of the literature involves a black box step from the food environment to BMI and is largely mixed (see reviews [12,33]). In one of the few longitudinal studies, Block et al. [5] found no consistent association between neighborhood fast food and full-service restaurants with BMI in Framingham, MA adults. Yet, the Block et al. study did not address the pathway to BMI through diet and lacking predicted diet behaviors as a function of the food environment in their analysis may have confounded their findings.

E. NEIGHBORHOOD SES, SEX, AND RACE ARE OFTEN OVERLOOKED

In the few existing longitudinal analyses of neighborhood health effects on diet and BMI there is evidence that neighborhood features, including fast food availability, are differentially associated with obesity related behaviors by sex.[15,34,35] Neighborhood SES has been associated with an increased prevalence of the metabolic syndrome among women but not men in the Atherosclerosis Risk in Communities Study (ARIC).[36] This suggests women have different diet behaviors than men in response to features of the neighborhood that are related to SES, such as the availability of unhealthy and healthy foods from different stores and restaurants.

In cross-sectional analyses, allocation of neighborhood food resources depending on income has received the most focus, with some examination of differences according to race. For example, the influence of the neighborhood food environment on fruit and vegetable intake varied for race/ethnic subpopulations living in Detroit.[37] While neighborhood socioeconomic characteristics have been associated with modest increases in CVD mortality in white participants, this was not the case for African American participants in ARIC.[38] Similarly, inconsistent associations with neighborhood advantage were documented for serum cholesterol and disease prevalence in African-American men.[39] Carson et al. also observed a significant association between neighborhood SES and mean intima-media thickness among whites, but not blacks.[40] Evidence of substantial heterogeneity in black-white hypertension differences depending on geographic group was observed in MESA.[41] Lastly, among CARDIA participants, insulin resistance was inversely associated with increasing neighborhood SES in white men and women but this association was only observed among black participants who had high income and education.[42] Different relationships between the environment and cardiometabolic outcomes for white and African Americans may reflect race specific diet behaviors in response to neighborhood disadvantage and poor food availability that lead to increased BMI and adverse cardiometabolic consequences.

Consideration of neighborhood socioeconomic status in relation to disparities in the food environment yielded inconsistent results even in national samples.[29,43-45] This suggests that there may be unmeasured complex relationships between neighborhood SES and features of the food environment. Complex relationships between neighborhood SES and the food environment are difficult to capture. Neighborhood SES cannot be explicitly measured. Instead it is a latent construct comprised of multiple SES domains such as income and wealth, education, occupation, and housing. Multiple aspects of neighborhood SES may track together over time, such as poverty and unemployment. However, there may also be other aspects of neighborhood SES that drive commercial zoning policies or economic incentives for food retailers. For instance, supermarket owners may be more likely to locate in a low income neighborhood with vacant housing because the property taxes are lower than in a low income neighborhood with no vacant housing. [46] Our proposed longitudinal neighborhood SES classes captured the neighborhood sociodemographics race, poverty, education, unemployment, income, and real estate value that change across exam years.

F. REVERSE CAUSALITY

Neighborhoods, comprised by social, natural, and built environments, can be defined broadly as something that surrounds and influences populations and is a dynamic component of population health. Relationships between the individuals and the environment are bi-directional; people choose their surroundings and conversely, the environment affects people such that everyday lifestyle choices that impact health are made in the context and constraints of the environment. Evidence suggests the preference for neighborhood amenities guides residential location choice and can have a direct association with behavior. [47-52] In a cross-sectional survey, participants reporting access to public transit as a priority for residential location were almost 20 times more likely to use rail transit than those who did not cite this preference. [53] Furthermore, recent surveys suggest increasing preferences for traditionally designed communities (e.g., centrally located retail, alternative transportation infrastructure) among a nationally representative sample of US adults.[54] In addition there is evidence that desiring to live in an activity-friendly community is predicted by beliefs that an activity friendly community will support active transit.[55] There is substantial evidence that race and income are important factors in residential mobility, migration, and housing choice.[56-58] Residential location choice is complex and driven by more than dietary preferences. However, individual diet preferences and behaviors may be ***tied to unobserved characteristics*** (e.g., culture, health consciousness, and social ties) that determine an individuals' residential location. Not accounting for this influence <u>(individual</u>

to environment) will bias any paths we estimate in the other direction (environment to individual). Structural equation modeling (SEM) can model these simultaneous or bi-directional paths.

G. METHODS ARE LACKING

Longitudinal methods that employ fixed effects models may provide insight into residential selection bias because they obviate confounding by unmeasured time invariant aspects. But fixed effect models cannot address the confounding due to unmeasured *time varying* characteristics. Furthermore, estimation of direct effects from the broad environment to individual obesity or BMI will miss the necessary path through diet. The food resources in a neighborhood can only influence BMI through an effect on individual diet. SEM can account for the bi-directional relationship between diet and the food environment and estimate effects of latent (unmeasured) characteristics that *vary over time*.

H. SUMMARY

There are few longitudinal studies of the food environment, diet, and BMI and there are even fewer that use sophisticated modeling to address complex pathways from the environment to BMI through diet. The prospective, longitudinal design, exceptionally varied range of data allow an outstanding opportunity to characterize how different types of neighborhood restaurants and food stores contribute to obesity disparities through diet across a major lifecycle period of risk for weight gain. In sum, through the proposed analyses we characterized how temporal changes in neighborhood food resources influence diet behaviors, and through this pathway influenced weight gain in young adults followed over 20 years. Further, we examined whether socioeconomic and sociodemographic factors influence these pathways through mediation effects. Our work importantly provides an innovative method to approximate reverse causality and come one step closer towards understanding how individual effects on the food environment bias associations from the food environment to the individual. Our findings will inform policies and campaigns to improve the food environment for vulnerable populations.

CHAPTER III: METHODS

A. STUDY POPULATION AND DATA SOURCES

The Coronary Artery Risk Development in Young Adults (CARDIA) study is a longitudinal cohort with detailed diet, clinic, physical activity, environmental, and sociodemographic data collected for 5,114 white or black United States (U.S.) adults aged 18-30 years. Throughout 20 years of follow-up data derived from a geographic information system (GIS) was linked temporally and geographically to respondents residential locations at the time of each exam.

CARDIA

Respondents were recruited originally from 4 centers: Birmingham, AL; Chicago, IL; Minneapolis, MN; and Oakland, CA. Participants were selected in 1985-86 with approximately equal numbers by race, gender, education (high school or less versus more than high school), age (18-24 years versus 25-30 years) within each center, and followed over 25 years. The GIS is currently linked to exam years 0, 7, 10, 15, and 20. However, linking the GIS to year 25 data is underway and will be valuable in future research.

BODY MASS INDEX

At each examination, participants' weight was measured to the nearest 0.2 kg and height was measured to the nearest 0.5 centimeter. BMI is calculated as weight in kilograms divided by height in meters squared and measured at exam years 0, 7, 10, 15, and 20.

DIETARY ASSESSMENT

An interviewer-administered CARDIA Diet History [59] at exam years 0, 7, and 20 was used to assess diet. Interviewers asked open-ended questions about dietary consumption in the past month within 100 food categories that referenced 1609 separate food items. Nutrients and food groups were assigned by the University of Minnesota Nutrition Coordinating Center (NCC). We further combined NCC-assigned food groups into one of 13 food groups and 5 beverage groups [assessed as servings per day of constituent foods (Web Table 1)] shown to be associated with weight change per 4-year period in the Nurse's Health Study I and II, and the Health Professionals Follow-up Study [19] and cardiometabolic outcomes.[60] We also used survey data collected at exam years 0, 7, 10, 15, and 20 regarding the number of times per week respondents ate meals at fast food restaurants.[18] We categorized weekly fast food consumption and servings per day of consumed foods and into low, medium, or high consumption, either by year-specific tertiles or as non-consumers (0 servings per day) versus upper and lower distributions of consumers (≥1 serving per day), values defined in Web Table 2. We used year-specific tertiles to allow for temporal changes in diet behaviors.

We set reported diet behaviors and BMI to missing when participants had extreme energy intakes [61] [<800 or >8000 kcal/d for men (n=73 at year 0, n=60 at year 7, and n=25 at year 20); and <600 or >6000 kcal/d for women (n=53 at year 0, n=34 at year 7, and n=29 at year 20)] or when women were pregnant (n= 7 at year 0, n=62 at year 7, and n=6 at year 20).

GIS DATABASE

Our Obesity and Environment database is a unique and large GIS that links biologic, and behavior data to environment indicators over time. It provides tremendous opportunities to study multi-level determinants of obesity and inform policies with the goal to address inequalities in disadvantaged communities and reduce obesity disparities in vulnerable populations. It contains many community-level variables including counts of many types of food resources, roadway length, population density and sociodemographics that are linked temporally and spatially to CARDIA each participant's individual-level clinic, behavior, and anthropometric data.

B. ANALYTIC VARIABLES

NEIGHBORHOOD FOOD ENVIRONMENT

We obtained counts of chain fast-food restaurants (hereafter referred to as fast food restaurants), all other restaurants not classified as chain fast food (hereafter referred to as sit-down restaurants), supermarkets, and convenience stores from Dun and Bradstreet (D&B), a commercial dataset of U.S. business records using 8-digit Standard Industrial Classification (SIC) codes for years 7, 10, 15, and 20 and a combination of 4 digit SIC codes and matched business names at year 0 (Web Table 3). D&B includes many other food resources however, we focused on the types that were conceptually more stable drivers of diet behaviors, We used a 3-km Euclidean buffer around each respondent's residential location for restaurants [15,62] and an 8-km Euclidean buffer for food stores, [62,63] based on empirical evidence. Using StreetMap 2000 (v. 9.0) for years 7 (1993) and 10 (1996), StreetMap Pro 2005 (v. 5.2) for year 15 (2001), and StreetMap Pro 2010 (v. 7.2) for year 20, (Environmental Systems Research Institute; ESRI, www.esri.com: Redlands, CA), we calculated densities of restaurants and stores as counts per 10 km secondary roads (to connect smaller towns, subdivisions, and neighborhoods) and local roads (for local traffic, usually with a single lane of traffic in each direction), resulting in a measure of concentration of food resources along streets representing overall commercial activity.[64,65] We also included variables reflecting urbanicity and development as these relate directly to the food environment. Given that population density varies across roadway structure [66] and across rural versus urban areas;[67] population density and commercial development were independently associated with geographic food resource distribution and were not highly correlated in our data ρ=0.35. Therefore, we included population density (representing area-level development and population) and counts per roadway (representing commercial development) in our analyses.

AREA-LEVEL SOCIOECONOMIC INDICATORS

Neighborhood SES was derived at the U.S. census tract-level at all years; tract-level SES is more strongly associated with health outcomes as compared to block group-level SES.[68,69] Neighborhood SES is a latent construct comprising multiple SES domains and is an individual-level exposure; that is, people may experience temporal changes in neighborhood SES through residential movement or changes in their neighborhood. In addition, food environments may improve or worsen over time, and these dynamics may relate to neighborhood SES. We included multiple measures of socioeconomic disadvantage that reflect the domains of income, education, race, employment, and housing value from years 0, 7, 10, 15, and 20: % race white, % education <high school, % poverty (below 150% federal poverty level[70]), % unemployed, % professional/management occupation, median income, % vacant housing, aggregate housing value, % owner occupied, and median rent. We also used population density (census tract population per square km of land excluding water) as an indicator of area-level development.

INDIVIDUAL-LEVEL CONFOUNDERS

We characterized individual-level confounders using data from structured interview or self-administered questionnaire collected at each exam year. Time-invariant sociodemographic variables were sex, race (white/black), exam attendance, and center. Time-varying characteristics were maximum reported number of years of schooling completed by the exam year (continuous), and mean household income inflated to U.S. dollars at year 20 (2005-06) using the Consumer Price Index. Income was not collected in year 0, so we used the closest measurement (year 5) for year 0. At each exam, participants reported their engagement in 13 different categories of moderate and vigorous recreational sports, exercise, leisure, and occupational activities in the past 12 months and activity scores were calculated based on frequency and intensity of each activity. An overall measure of physical activity was calculated as the sum of the 13 distinct activity scores.[71]

CHAPTER IV: NEIGHBORHOOD SOCIOECONOMIC STATUS AND FOOD ENVIRONMENT: A 20-YEAR LONGITUDINAL LATENT CLASS ANALYSIS AMONG CARDIA PARTICIPANTS1

A. ABSTRACT

Cross-sectional studies suggest neighborhood socioeconomic (SES) disadvantage is associated with obesogenic food environments. Yet, it is unknown how exposure to neighborhood SES patterning through adulthood corresponds to food environments that also change over time. We used latent class analysis (LCA) to classify participants in the U.S.-based Coronary Artery Risk Development in Young Adults study [n=5,114 at baseline 1985-1986 to 2005-2006] according to their longitudinal neighborhood SES residency patterns (upward, downward, stable high and stable low). For most classes of residents, the availability of fast food and non-fast food restaurants and supermarkets and convenience stores increased ($p<0.001$). Yet, socioeconomically disadvantaged neighborhood residents had fewer fast food and non-fast food restaurants, more convenience stores, and the same number of supermarkets in their neighborhoods than the advantaged residents. In addition to targeting the pervasive fast food

[1] This chapter previously appeared as an article in the Journal of Health & Place and is in press. The original citation is as follows: Richardson AS, et al. Neighborhood socioeconomic status and food environment: A 20-year longitudinal latent class analysis among CARDIA participants. Health Place. 2014 Sep 29;30C:145-153. doi: 10.1016/j.healthplace.2014.08.011. [Epub ahead of print]

restaurant and convenient store retail growth, improving neighborhood restaurant options for disadvantaged residents may reduce food environment disparities.

B. INTRODUCTION

From the mid-1980's to the 2000's, obesity increased dramatically in developed countries, such as the U.S., U.K., New Zealand, and Canada[72] with socioeconomically disadvantaged populations disproportionately affected.[73,74] Disparities in obesity have lead researchers to investigate the degree to which disadvantaged neighborhoods have poor food environments that promote the over-consumption of unhealthy foods.[3-6] Identifying modifiable features of the food environment hypothesized to influence individual-level diet behaviors could lead to effective policies that will improve health in disadvantaged populations. However, the largely cross-sectional evidence base about socioeconomic disparities in the food environment is mixed with positive and negative findings.[10-13] Complexities resulting from temporal patterns in neighborhood modifications and residential mobility may underlie existing equivocal evidence.

Several large international obesity literature reviews recognize the need for comprehensive strategies and systems models[75,76] and attention to wider environmental and societal factors in efforts to reduce obesity disparities. Nonetheless, socioeconomically disadvantaged subpopulations in developed countries remain disproportionately affected by obesity.[77] Thus, there is growing interest by researchers in the U.S. and other developed countries on the role of socioeconomic factors in temporal declines in healthy food environments.[78-81] But findings are mixed and studies examining temporal patterns in food environments are sparse (see review[33]). There is a large gap in long-term, population-based research in racially diverse samples with detailed time-varying food environment data.

In particular, two major gaps in the literature limit our understanding of inequities in the food environment. First, how does exposure to socioeconomic aspect of neighborhoods change through the life course? Second, do patterns of change in the neighborhood SES environment also reflect changes in exposure to different types of food resources? Understanding the relationships between these two aspects of longitudinal neighborhood exposures may shed insight on how to effectively modify food environments for socioeconomically disadvantaged populations to improve diet and reduce obesity.

Complex relationships between neighborhood SES and the food environment are difficult to capture. Neighborhood SES cannot be explicitly measured. Instead it is a latent construct comprised of multiple SES domains such as income and wealth, education, occupation, and housing. Multiple aspects of neighborhood SES may track together over time, such as poverty and unemployment. However, there may also be other aspects of neighborhood SES that drive commercial zoning policies or economic incentives for food retailers. For instance, supermarket owners may be more likely to locate in a low income neighborhood with vacant housing because the property taxes are lower than in a low income neighborhood with no vacant housing.[46]

Another layer of complexity underlying relationships between neighborhood SES and the food environment is that, as individuals experience neighborhood SES changes over time, heterogeneities and similarities may develop within and across socioeconomic domains. For example, at the community-level vacant housing and the number of residents living in poverty may increase steadily in one neighborhood over time, while in another neighborhood, residents may attain higher levels of education but community-level household income may not increase until after graduates have entered the workforce. As an individual-level exposure, people may experience such neighborhood SES changes over time as they live within or move across neighborhoods. In addition, depending on neighborhood SES, food environments may improve or worsen over time. Therefore, a single snapshot in time may not capture patterns of socioeconomic characteristics that drive greater or reduced access to different types of food stores and restaurants.

To overcome these gaps in the literature, we capitalized on a geographic information system (GIS)-derived dataset in the United States (U.S.) spatially and temporally linked to Coronary Artery Risk Development in Young Adults (CARDIA) respondent residential locations at each of five exam years occurring over a 20-year period. We examined how individuals were exposed to different patterns of multiple neighborhood SES characteristics (e.g., occupation, poverty, and education) during young to middle adulthood using Latent Class Analysis (LCA). The result was a classification of CARDIA participants according to 20 years of their time-varying neighborhood SES characteristics. During a period when adult obesity increased rapidly in the U.S. we examined how neighborhood fast food restaurants, non-fast food restaurants, supermarkets, and convenience stores compared over time for adults across longitudinal neighborhood SES patterns. We hypothesized that participants with a 20-year history of living in socioeconomically disadvantaged neighborhoods were exposed to worse food environments (i.e., few supermarkets and more fast food restaurants) that deteriorated over time compared to those with a history of living in advantaged neighborhoods.

C. METHODS

DATA

CARDIA is a longitudinal cohort with detailed diet, physical activity, environmental, demographic and socioeconomic data collected for 5,114 white or black U.S. adults aged 18-30 years originally from 4 centers: Birmingham, AL; Chicago, IL; Minneapolis, MN; and Oakland, CA. Participants were selected in 1985-86 with approximately equal numbers by race, gender, education (high school or less versus more than high school), age (18-24 years versus 25-30 years) within each center, and followed over 5 exams during 1992-93 (Year 7), 1995-96 (Year 10), 2000-01 (Year 15), and 2005-06 (Year 20). Retention rates were 81%, 79% , 74% , and 72% , respectively, of the surviving cohort.

We used data from 5 exam years (0, 7, 10, 15, and 20) and a GIS-derived dataset of time-varying neighborhood-level food resources and U.S. Census data were spatially and temporally linked to CARDIA respondent residential locations at each exam year.

AREA-LEVEL INDICATORS

U.S. Census block groups were not available in the 1980 census data (year 0) so census tracts were used to define neighborhoods at all years. Census tract measures have been shown to identify health disparities as well as, if not better than, block groups.[68,69] The geographic area of U.S. Census tracts depends on population density, with an optimum size tract of 4,000 people, although census tracts range from 1,200 to 8,000 people.[82] At baseline, the catchment area of the four CARDIA centers comprised 799 Census tracts, by 2005-06 as individuals moved out of the original four field site cities, the catchment increased to include 2,800 tracts. We included multiple measures of socioeconomic disadvantage that addressed the domains of income, education, race, employment, and housing value (Table 1). Population density was calculated as tract population per square kilometer of land excluding water; it was not included in the LCA but was included as a covariate in multivariable models to adjust for area-level development.

NEIGHBORHOOD FOOD ENVIRONMENT

Counts of chain fast-food restaurants (hereafter referred to as fast food restaurants), all other restaurants not classified as chain fast food (hereafter referred to as non-fast food restaurants), supermarkets, and convenience stores were obtained from Dun and Bradstreet (D&B), a commercial dataset of U.S. business records. They were classified according to 8-digit Standard Industrial Classification (SIC) codes (Table 2) for years 7, 10, 15, and 20. Year 0 SIC codes were 4 digits; this limited the specificity of restaurant classification, so fast food restaurants were identified by matching business names with fast food restaurants at years 1991-1996 and by SIC code. Fast food restaurants, non-fast food restaurants, supermarket, and convenience stores were aggregated as counts within 3 kilometers (km) of each respondent's residential location (Euclidean buffer). The 3 km buffer was chosen to capture distances readily accessible by walking and driving to neighborhood diet-related resources as supported by several studies.[62,64,83] Food resource densities were derived as counts per 10 km secondary roadway (roads used to connect smaller towns, subdivisions, and neighborhoods) and local roadway (roads used for local traffic, usually with a single lane of traffic in each direction), resulting in a measure of concentration of food resources along streets representing overall commercial activity.[64,65] Roadway lengths were calculated from street networks extracted from StreetMap 2000 (v. 9.0) for years 7 (1993) and 10 (1996), from StreetMap Pro 2005 (v. 5.2) for year 15 (2001), and from StreetMap Pro 2010 (v. 7.2) for year 20. Street network source datasets were obtained from Environmental Systems Research Institute (ESRI, www.esri.com: Redlands, CA). We opted for the roadway-scaled measures rather than raw food resource counts because count measures can introduce spurious associations between neighborhood SES and food stores and restaurants. For example, low SES neighborhoods may have more convenience stores because they have more businesses in general, due to roadway structures and commercial development. Using raw counts would then reflect commercial development differences by neighborhood SES and thus might obscure disparities in the food environment by neighborhood SES. While we did not use network buffers, we addressed differences in food resources according to overall commercial activity by scaling counts by roadway length while holding Euclidean area constant across geographic areas varying in terrain and network distances. Thus, the resources relative to roadway lengths provides measures relative to road network, whereas the Euclidean buffers provide the salient geographic area of focus.

INDIVIDUAL-LEVEL CHARACTERISTICS

Individual-level sociodemographics were used to describe the study population throughout the study period. Sociodemographics were collected at each exam year by a structured interview or self-administered questionnaire. Sex, race (white/black), exam attendance, and center were time-invariant variables. Time-varying individual-level characteristics included working full-time (yes, no), marital status (married, not married), maximum reported number of years of schooling completed by the exam year (less than high school, high school, some college, college degree or above), and mean household income inflated to U.S. dollars at year 20 (2005-06) using the Consumer Price Index. Income was not collected in year 0, so the closest measurement (year 5) was used for year 0.

STATISTICAL ANALYSES

All descriptive analyses and multivariable models were performed using Stata 13.0 (StataCorp, College Station, TX).

Descriptive statistics. To describe the study population and their neighborhoods over exam years 0, 7, 10, 15, and 20, we calculated means and standard deviations (continuous variables) and percentiles (categorical variables) of individual-level sociodemographics. Medians and interquartile ranges were calculated for neighborhood-level characteristics.

Latent class analysis: derivation of longitudinal neighborhood SES classes. We performed LCA models with Mplus[84] to classify CARDIA respondents into longitudinal neighborhood SES latent classes according to Census demographics. All variables used in the LCA were transformed to year-specific standard normal deviates [(X- mean)/SD] (hereafter referred to as Z-scores) to facilitate convergence of the LCA models. The variables related to housing were transformed to Z-scores specific to CARDIA study center, to account for the large cost of living differences between centers. Residential mobility was not included in these analyses because our aim was to quantify exposure to patterns of neighborhood SES over time, regardless of mobility.

A two-class model was estimated first with maximum likelihood methods and then models were considered with additional classes. We used the following criteria determine the number of k latent classes for our final model: 1) the Bayesian Information Criteria (BIC) (model fit and parsimony across models whereby smaller values indicate better fit); 2) the interpretability of model solution with assessment of size and uniqueness of each class; and 3) Lo-Mendell-Rubin (LMR) p-value (k vs. $k - 1$ class). A significant LMR p-value indicates that the k-class solution is significantly different from the (k-1)-class solution, suggesting that k-class solution is preferred. Using these criteria, interpretability, and verifying model fit with BIC, we selected 4 SES classes.

Each individual was assigned to the single longitudinal neighborhood SES class for whom they had the highest posterior class membership probability. A minimum number of follow-up visits was not an inclusion criterion and on average respondents attended most follow-up visits (mean=3.98, SD=1.39). Class results are illustrated by plotting the mean Z-score for the component variables at each of the exam years. For greater detail, interquartile ranges were calculated for all components and food resource measures by class.

Relationship between longitudinal neighborhood SES classes with food environment measures. Next, we compared changes in neighborhood food resources over time experienced by participants across the four longitudinal neighborhood SES classes. Longitudinal multilevel random effects regression models estimated each neighborhood food resource density relative to roadway length separately as a function of SES class indicators (referent was class with largest sample size), exam year (continuous), interaction of class indicators by exam year, and a random effect for each participant. Population density [which can vary across roadway structure,[66] rural and urban areas[67] and commercial development were each independently associated with geographic food resource distribution and were not highly correlated in our data ρ=0.35. Therefore, we addressed population density (representing area-level development and population) and counts per roadway (representing commercial development) in our modeling. Time trends were statistically significant if the p-value of the estimated marginal year effect within class was less than 0.05. Linear contrasts (Stata's 'lincom' command) compared food resource densities relative to roadway length by year and for each class pair and marginal predictions estimated mean food resource densities relative to roadway length by class and year.

Food environment model results are presented as: 1) plots of the estimated mean densities relative to roadway length for each type of neighborhood restaurant and food store by class and year; 2) table of beta coefficients from the multivariable random effects models for each food resource; and 3) table of the linear contrasts by year and for each class pair.

D. RESULTS

Descriptive statistics. Across 20 years of CARDIA exams, participant educational attainment, income, and proportion married increased over time (Table 3). Overall, the neighborhoods in which CARDIA participants lived improved over time in terms of economic and social environment indicators (Table 4). Counts of neighborhood fast food restaurants and convenience stores increased, non-fast food restaurants decreased, and supermarkets remained fairly stable.

Latent class analysis. CARDIA participants were classified into four latent classes of longitudinal neighborhood SES based on BIC =610725 and LMR (p=0.04 for four vs. three classes compared to p=0.72 for five vs four classes classes): downwardly mobile neighborhood SES residents (n=1,014); stable low neighborhood SES residents (n=1,581); upwardly mobile neighborhood SES residents (n=665); and stable high neighborhood SES residents (n=1,854) (Figure 1). The average posterior probability within each class was > 0.97. In general, the LCA components that indicated neighborhood advantage (e.g., income, aggregate housing value) tracked together over time, as did the indicators of disadvantage (e.g., unemployment, vacancy). Medians and interquartile ranges of neighborhood SES and food resource measures are presented by longitudinal neighborhood SES class in Table 5.

Relationship between longitudinal neighborhood SES classes with food environment. The plotted mean food resource densities relative to roadway length and time trends are presented by class and year for restaurants (Figure 2) and food stores (Figure 3). In general, time trends in each type of food resource were similar for all residents regardless of their neighborhood SES class. Neighborhood densities of fast food restaurants, supermarkets, and convenience stores relative to roadway length increased over time for all classes of neighborhood SES residents. Neighborhood non-fast food restaurant density relative to roadway length increased over time for all residents except the upwardly mobile neighborhood SES residents, who experienced little change in neighborhood non-fast food restaurant density relative to roadway length over time.

Beta coefficients from the multivariable random effects models for each food resource are presented in Table 6. Linear contrasts for each class pair are presented by year and food resource in Table 7. In contrast to the time trends, fast food and non-fast food restaurant densities relative to roadway length varied markedly across classes of neighborhood SES residents, and the differences were stable over time. The participants belonging to the upwardly mobile and stable high neighborhood SES residential classes had more non-fast food restaurants in their neighborhoods at all observed years than those in the downwardly mobile or stable low SES neighborhood classes. Likewise, stable high neighborhood SES residents and upwardly mobile neighborhood SES residents consistently had more fast food restaurants in their neighborhoods than downwardly mobile and stable low SES neighborhood residents. In sum, advantaged neighborhood (stable high SES or upwardly mobile) residents consistently had more of both types of restaurants than the disadvantaged neighborhood (stable low SES or downwardly mobile) residents.

At most years, all residents had similar supermarket density relative to roadway length in their neighborhoods, regardless of their neighborhood SES resident class (Table 7). While neighborhood convenience store densities relative to roadway length were relatively similar for all residents in the mid-1980's over time, the downwardly mobile neighborhood SES residents had more convenience stores in their neighborhoods than all other classes of residents.

E. DISCUSSION

Using a unique set of data covering 20 years of residential histories and latent class analysis methods, we found that neighborhood restaurant and food store availability increased for all residents. Further, the more advantaged neighborhood SES residents had greater neighborhood restaurant availability and less convenience store availability at any given time.

Our approach addressed two gaps in the literature: 1) How does exposure to socioeconomic aspects of neighborhoods change through the life course? Indeed, we successfully classified CARDIA participants into four distinct patterns of longitudinal neighborhood SES: downwardly mobile neighborhood SES residents, stable low neighborhood SES residents, upwardly mobile neighborhood SES residents, or stable high neighborhood SES residents. 2) Are patterns of change in the neighborhood SES environment also associated with changes in exposure to different types of food resources? We found that blacks and whites who lived in neighborhoods of low or declining SES during young to middle adulthood, had consistently more convenience stores and fewer restaurant options over time than individuals living in socioeconomically advantaged neighborhoods.

During a period when obesity prevalence increased significantly in the U.S.,[1,85] neighborhood fast food restaurant, non-fast food restaurant, convenience store and supermarket availability also increased for most CARDIA participants. Such trends are consistent with national reports[86-89] and reflect macroeconomic shifts in the retail food industry.

Two decades of residential histories in our large sample reveal disparities in how such national trends in food retail were experienced for subpopulations with different longitudinal neighborhood SES patterns. At any given time, those consistently living in socioeconomically disadvantaged neighborhoods had lower neighborhood density of non-fast food restaurants relative to roadway length than those consistently living in socioeconomically advantaged neighborhoods. Socioeconomically advantaged neighborhood residents had more fast food *and* non-fast food restaurants in their neighborhoods; therefore, they had a greater variety of restaurant options to choose from than socioeconomically disadvantaged neighborhood residents.

However, non-fast food restaurants, as defined here, are a heterogeneous group of restaurants and do not necessarily represent restaurants that only sell healthy options.

Residential mobility could have resulted in more dramatic changes in food environment exposures for individuals who moved versus those who remained in the same residential location over the follow-up, if changes in food environment were greater among those who moved residences. In our data, only 378 (7%) participants stayed in the same residential location throughout the study period and the changes in neighborhood SES were actually larger in non-movers versus movers ($P<0.001$). Among the 378 non-movers, 50% were classified into one of the upwardly (7%) or downwardly (43%) mobile SES residency classes, compared to only 31% of the movers (13% upward; 18% downward). Changes in the food environment were similar for movers and non-movers, except that non-movers had greater temporal increases in numbers of non-fast food restaurants and convenience stores ($P<0.001$). Given that residential mobility did not predict greater changes in neighborhood SES or food environment it is unlikely that residential mobility biased our findings.

Our findings contradict prior research showing that low income and high minority population neighborhoods have more fast food and fewer full-service restaurants than socioeconomically advantaged neighborhoods.[90-92] However, our results concur with a large national study that found that predominantly black neighborhoods had fewer full-service and fast food restaurants than predominantly white neighborhoods.[93]

In our study, supermarket availability was similar for socioeconomically disadvantaged compared to advantaged neighborhood residents throughout most of two decades. At the same time, the most socioeconomically disadvantaged neighborhood residents had more convenient food shopping options than the other neighborhood SES class residents. These results contrast with the prevailing view that neighborhood disadvantage has been associated with reduced access to supermarkets/grocery stores. However, associations have varied by neighborhood racial composition.[6,90,94,95]

In addition to the cross-sectional design, most of the above studies were geographically limited or did not control for area-level development. Socioeconomically deprived neighborhoods in dense urban areas may have many fast food restaurants as a consequence of commercial development; thus, not accounting for such area-level development can create spurious associations between neighborhood disadvantage and disparities the food environment. In this study, respondents lived in mainly urban areas however, population density can vary across urban areas.[67] Population density and commercial development are correlated and independently associated with dietary behaviors.[96] We addressed commercial density by scaling food resource measures by roadway length and controlling for population density in regression models.

Our findings suggest that overall fast food industry growth may have a greater impact on diet behaviors among persons living in the most disadvantaged neighborhoods because they have less access to alternative away-from-home eating options. Greater total food outlet density has been inversely associated with BMI, perhaps because greater density typically offers a wider array of food options or lower prices so that residents can make healthier food purchases[97] despite rising fast food availability.[86] Conversely, lower BMI in areas with high food outlet density may reflect overall dietary preferences of the residents.[98] Alternatively, lower BMI and high food outlet density may both be consequences of living in a more privileged environment, without one causing the other.

At the same time fast food availability increased, neighborhood convenience store availability increased for all participants. Participants with a history of living in socioeconomically declining neighborhoods at most years had more convenience stores in their neighborhoods than the other residents. Psychological distress due to neighborhood deprivation and disorder has been identified as an important mechanism of poor diet.[99] Compared to people living in neighborhoods with low but stable SES, residents exposed to increasing signs of neighborhood decay may experience more stress. Therefore, the combination of experiencing greater neighborhood deprivation and greater access to convenient neighborhood food shopping options may be a potent promoter of poor diet.

Our study has some limitations. The electronic business record D&B data are widely used in other neighborhood environment research studies and are currently the only option for retrospective longitudinal studies spanning multiple decades. Yet these data are vulnerable to misclassification error including geospatial inaccuracy, missing data, and classification inaccuracy.[100-102] We were unable to retrospectively field validate the historical food environment data from Exam Years 0-15 but other studies provide field validation of the D&B data from 2009.[103-105] It is possible that increases in numbers of food resources over time could reflect temporal improvements in complete business listings. However, data on U.S. food industry trends confirm the nature and direction of the increase in food stores and restaurants that we observed.[86,88,106] Powell et al. conducted a ground-truthed study in Chicago and some surrounding suburban/rural Census tracts,[104] finding higher validity between D&B business listings and ground-truthed locations was higher in white versus predominantly black race Census tracts. Thus there may be more database inaccuracies in disadvantaged versus advantaged neighborhoods.[104] However, findings from two other validation studies set in

Chicago[100] and Baltimore,[105] suggest that neighborhood socioeconomics were not associated with disagreement between business lists and field observations. Powell's larger study[104] included non-urban tracts compared to the latter two studies that were set in urban areas. Other studies also suggest validity may be poor in rural compared to urban areas.[101,102,107-110] Nonetheless, CARDIA participants were recruited from four major U.S. cities and after 20 years, over 90% of them were still living either in or less than a mile away from an urban area. Therefore, differential misclassification in our data by urbanicity is not likely. Another limitation of all secondary business data sources is that lists capture only a snapshot and may not be updated frequently enough to capture new food retail outlets. However, our data are spatially and temporally matched to each exam year so we capture changes over time. In addition, we lacked data regarding the quality of the foods sold that might differ over time and by neighborhood SES. The decennial Census data, which are not precisely matched to exam year is another limitation. Despite these limitations we took advantage of a large and unique GIS that captured multiple types of neighborhood food resources, time-varying data on food environment characteristics and community-level sociodemographics for black and white men and women during their young to middle adulthood.

The period between 1985-2006 was a time of economic expansion in the U.S.(U.S. Department of State 2011). Yet, our findings suggest that neighborhood SES did not improve for all Americans, and in fact, declined for some. Over time, we observed an increase in numbers of all types of food resources, however these changes were different by neighborhood SES (despite increasing numbers of total food resources over time, there were consistently more convenience stores and fewer non-fast food restaurant options in disadvantaged neighborhoods). In the U.S., residential segregation persists perhaps due in part, to past and present discrimination and policies that are exacerbated by gentrification and suburbanization.[31] All of these factors could underlie the geographic distribution and changes over time in numbers of restaurants and convenience stores. Similar socioeconomic processes and patterning exist outside the U.S. such that the World Health Organization argued that urban development, housing and transport infrastructure are health determinants, and consequently, important health policy targets.[111] In our paper, we provide evidence that Americans exposed to socioeconomically worsening neighborhoods were additionally burdened by worsening food environments, potentially playing a role in widening health disparities over time.

CONCLUSION

From 1985 to 2006, when obesity prevalence significantly increased among U.S. adults, those living in socioeconomically disadvantaged neighborhoods had less variety in away-from-home eating options compared to those living in advantaged neighborhoods. All respondents had relatively similar numbers of supermarkets in their neighborhoods, whereas residents of socioeconomically disadvantaged neighborhoods had more convenience food shopping options than those in other neighborhood SES classes. As fast food restaurant and convenience store industries grow nationally, disadvantaged populations may be at higher risk than advantaged populations to buy the abundant cheap and convenient food retail options that are high in calories, fat, and sugar. Reducing convenience store and fast food restaurant access while increasing the variety of nutritious restaurant options may improve obesity related disparities in disadvantaged populations.

Table 1. Neighborhood-level socioeconomic indicators included as components of latent class analysis

Percent population race white
Percent population education < High School
Percent population <150% FPL
Median income per $10,000
Percent population professional/management occupation[c]
Percent population unemployed[c]
Median rent
Percent population owner-occupied HU
Percent vacant HU
Aggregate value HU[d] per $1,000,000

[a]U.S. Census-tract level data spatially and temporallly linked linked to respondent residential locations to CARDIA exam years (Year 0, 1980; Years 7 and 10, 1990; Year 15, 2000; Year 20, 2000)
[b]Among census tract population ages 16 years or older.
[c]Owner occupied housing units within census tract.
FPL: federal poverty level, HU: housing units

Table 2. Detailed food resource definitions based on 8-digit Standard Industrial Classification (SIC) codes

Food Resource Type	Description	SIC
Fast food chain	Fast-food restaurant, chain	58120307
	Pizzeria, chain	58120601
Non-fast food	Fast food restaurants and stands	58120300
	Box lunch stand	58120301
	Carry-out only (except pizza) restaurant	58120302
	Chili stand	58120303
	Coffee shop	58120304
	Delicatessen (eating places)	58120305
	Drive-in restaurant	58120306
	Fast-food restaurant, independent	58120308
	Food bars	58120309
	Grills (eating places)	58120310
	Hamburger stand	58120311
	Hot dog stand	58120312
	Sandwiches and submarines shop	58120313
	Snack bar	58120314
	Snack shop	58120315
	Pizza restaurants	58120600
	Pizzeria, independent	58120602
	Mexican Restaurants	58120112
	Seafood Restaurants: Includes sushi restaurants, oyster bars & seafood shacks:	58120114
		58120700
		58120701
		58120702
	Steak House & BBQ Restaurants:	58120800
		58120801
		58120802
	Chicken Restaurants	58129904
	Family-owned restaurant chain	58120501
	Family-owned restaurant, non-chain:	58120500
		58120502
Supermarkets	Supermarkets, chain	54110101
	Supermarkets, greater than 100,000 square feet (hypermarket)	54110103
	Supermarkets, independent	54110102
	Supermarkets, 55,000 - 65,000 square feet (superstore)	54110104
	Supermarkets, 66,000 - 99,000 square feet	54110105

Convenience Stores	Supermarkets	54110100
	Variety stores	53310000
	Convenience stores	54110200
	Convenience stores, chain	54110201
	Convenience stores, independent	54110202
	Gasoline service stations	55410000
	Gasoline service stations, nec	55419900
	Filling stations, gasoline	55419901

Table 3. Individual-level characteristics by year: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.

	Year 0	Year 7	Year 10	Year 15	Year 20
N	5114	4085	3949	3671	3549
Mean age	24.8 (0.05)	32.0 (0.06)	35.0 (0.06)	40.2 (0.06)	45.2 (0.06)
Female (%)	54.5	55.1	55.6	55.9	56.7
Race (%)					
Black	51.6	48.3	48.8	47.1	46.5
White	48.4	51.7	51.2	52.9	53.5
Education (%)					
< High School	8.2	4.4	4.2	3.5	3.2
High School	66.4	56.5	53.8	50	48.3
Some college	20.5	27.1	28.2	29.1	29.7
College degree	4.9	12	13.9	17.5	18.9
Married (%)	22.3	44.1	48.6	53.5	55.3
Working full time (%)	43.6	29.6	26.7	25.8	30.3
Mean income[a]	2.6 (0.03)	3.1 (0.04)	3.9 (0.04)	7.1 (0.08)	7.1 (0.08)

[a]Income per $10,000, deflated to year 20 and income was not queried at exam year 0 so response at year 5 is used as a proxy.

Table 4. Neighborhood-level characteristics [median (interquartile range)] across exam year: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.

	Year 0	Year 7	Year 10	Year 15	Year 20
Socioeconomics within Census tract[a]:					
Number of neighborhoods[b]	799	2508	3406	3460	3645
Percent population race white	60.4 (24.4,86.9)	59.4 (18.3,86.9)	74.5 (33.3,91.3)	60.5 (21.5,84.1)	64.9 (26.7,86.3)
Percent population education < high school	30.4 (18.4,43.4)	20.0 (10.1,34.9)	18.2 (9.6,31.2)	15.3 (7.4,26.0)	14.2 (7.2,25.1)
Percent population <150% FPL	28.9 (15.4,41.0)	23.4 (10.7,37.6)	17.4 (8.5,32.8)	17.1 (8.6,33.7)	15.3 (7.8,30.6)
Median income per $10,000	14.1 (10.7,18.2)	27.8 (20.6,37.9)	31.0 (22.5,41.8)	43.4 (32.0,59.4)	45.9 (33.7,61.9)
Percent population professional/management occupation[c]	22.3 (12.9,32.4)	26.1 (17.4,38.9)	27.2 (18.3,38.6)	33.8 (23.6,49.0)	34.6 (24.4,49.1)
Percent population unemployed[c]	6.8 (4.2,11.0)	5.6 (3.6,9.9)	4.7 (3.0,8.1)	3.2 (2.0,5.4)	3.0 (1.9,5.2)
Median rent	238 (213,270)	480 (401,595)	495 (401,620)	655 (547,819)	660 (547,827)
Percent population owner-occupied HU	44.5 (25.7,64.8)	50.6 (33.7,70.2)	61.7 (38.9,79.0)	65.1 (42.5,81.4)	68.1 (47.2,84.1)
Percent population vacant HU	5.7 (3.5,5.7)	6.9 (4.2,6.9)	5.9 (3.7,5.9)	4.1 (2.5,4.1)	4.1 (2.5,4.1)
Aggregate value HU[d] per $1,000,000	21 (10,39)	47 (20,104)	69 (30,134)	120 (51,249)	134 (59,264)
Counts of food resources within 3 km Euclidean buffer per 10km of local and secondary roadways[e]:					
Fast food restaurants	0.2 (0.1,0.2)	0.2 (0.1,0.3)	0.2 (0.1,0.3)	0.2 (0.1,0.3)	0.4 (0.2,0.6)
Non-fast food restaurants	2.8 (1.4,5.1)	3.4 (1.5,6.5)	2.4 (1.2,4.7)	2.7 (1.4,4.6)	2.9 (1.5,5.3)
Supermarkets	0.0 (0.0,0.1)	0.1 (0.1,0.2)	0.1 (0.0,0.1)	0.1 (0.0,0.1)	0.1 (0.1,0.2)
Convenience stores	0.7 (0.5,0.9)	1.1 (0.7,1.6)	0.8 (0.5,1.1)	0.8 (0.5,1.0)	0.9 (0.6,1.2)

[a]U.S. Census-tract level data spatially linked to respondent residential locations and temporally linked to CARDIA exam years (Year 0, 1980; Years 7 and 10, 1990; Year 15 and 20, 2000).
[b]Total number of census tracts.
[c]Among census tract population ages 16 years or older.
[d]Owner occupied Housing Units within census tract.
[e]Counts of Dunn & Bradstreet food resources within Euclidean 3km buffer per 10 km local and secondary roadways.
FPL: federal poverty level, HU: housing

Table 5. Neighborhood-level characteristics[a] [median (interquartile range)] by classes[b] of longitudinal neighborhood SES residents by exam year: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.

	Year 0	Year 7	Year 10	Year 15	Year 20
Downwardly mobile neighborhood SES residents, n=1,014					
Socioeconomic indicators within Census tract[a]:					
Percent population race white	9.8 (2.9, 33.1)	4.5 (1.3, 20.2)	6.4 (2.0, 24.5)	3.8 (1.3, 14.2)	7.1 (1.7, 25.2)
Percent population education < High School	45.5 (37.7, 51.7)	38.0 (31.6, 45.7)	38.7 (32.6, 46.1)	35.3 (28.2, 41.1)	32.4 (25.1, 39.7)
Percent population <150% FPL	42.9 (33.2, 33.1)	44.2 (34.4, 20.2)	44.3 (34.4, 24.5)	43.0 (36.8, 14.2)	41.0 (31.7, 25.2)
Median income per $10,000	11.2 (8.6, 14.1)	194 (14.4, 23.7)	18.6 (14.4, 23.3)	26.9 (20.9, 32.6)	28.1 (21.9, 35.8)
Percent population professional/management occupation[c]	11.6 (8.2, 16.1)	15.7 (10.2, 19.3)	15.2 (10.2, 19.1)	19.5 (15.1, 23.5)	20.5 (15.7, 26.0)
Percent population unemployed[c]	13.4 (9.4, 17.5)	11.8 (9.1, 15.3)	11.1 (8.9, 14.9)	7.8 (5.9, 10.2)	7.3 (4.8, 9.9)
Median rent	223.0 (167.0, 236.0)	423.0 (312.0, 479.0)	407.0 (322.0, 470.0)	541.5 (394.0, 630.0)	547.0 (413.0, 642.0)
Percent population owner-occupied HU	37.6 (23.0, 54.3)	38.9 (26.7, 53.8)	40.7 (28.7, 54.9)	44.6 (31.9, 56.3)	47.9 (33.3, 63.6)
Percent vacant HU	6.3 (5.3, 7.4)	10.1 (7.2, 14.5)	10.1 (7.3, 13.6)	8.7 (6.1, 12.0)	8.0 (5.1, 11.5)
Aggregate value HU[d] per $1,000,000	14.4 (8.7, 22.5)	21.7 (12.0, 38.6)	22.3 (12.7, 38.7)	39.1 (20.4, 59.3)	43.8 (22.1, 76.2)
Food resource densities (counts within 3 km Euclidean buffer per 10km of local and secondary roadways[e]):					
Fast food restaurants	0.2 (0.1, 0.2)	0.2 (0.2, 0.3)	0.3 (0.2, 04)	0.2 (0.2, 0.3)	0.4 (0.3, 0.6)
Non-fast food restaurants	2.8 (1.3, 3.8)	4.0 (1.4, 6.2)	3.4 (1.4, 5.2)	3.1 (1.5, 4.5)	3.7 (1.7, 6.1)
Supermarkets	0.0 (0.0, 01)	0.1 (0.1, 02)	0.1 (0.1, 0.1)	0.1 (0.1, 0.2)	0.2 (0.1, 0.3)
Convenience stores	0.7 (0.5, 1.0)	1.2 (0.8, 1.7)	1.0 (0.9, 1.2)	1.0 (0.8, 1.2)	1.2 (0.9, 1.5)
Stable low neighborhood SES residents, n=1,581					
Socioeconomic indicators within Census tract[a]:					
Percent population race white	43.5 (15.0, 71.5)	39.5 (13.1, 67.6)	61.2 (32.5, 83.0)	41.5 (21.1, 65.2)	52.2 (25.2, 74.2)
Percent population education < High School	35.6 (24.4, 45.5)	28.3 (18.9, 37.1)	23.6 (16.1, 30.9)	19.7 (14.3, 25.7)	18.2 (11.9, 25.2)
Percent population <150% FPL	32.7 (23.4, 43.0)	32.1 (22.6, 42.5)	24.1 (16.3, 33.1)	24.5 (16.5, 33.4)	21.2 (12.7, 31.1)
Median income per $10,000	11.2 (8.6, 14.2)	19.4 (14.4, 23.7)	18.7 (14.4, 23.3)	26.9 (20.9, 32.6)	28.1 (21.9, 35.8)
Percent population professional/management occupation[c]	17.3 (12.0, 27.0)	20.4 (15.8, 30.0)	23.0 (18.1, 31.3)	29.6 (23.0, 36.9)	30.2 (23.8, 37.9)
Percent population unemployed[c]	8.5 (5.9, 12.0)	7.6 (5.1, 10.9)	5.8 (4.2, 8.1)	4.1 (2.8, 5.5)	3.8 (2.5, 5.3)
Median rent	231.0 (207.0, 249.0)	443.0 (376.0, 528.0)	457.0 (385.0, 549.0)	618.0 (525.0, 709.0)	632.0 (532.0, 731.0)

Percent population owner-occupied HU	44.5 (28.7, 57.5)	44.0 (30.7, 61.3)	57.4 (38.3, 73.4)	59.4 (39.4, 75.0)	65.6 (45.7, 79.7)
Percent vacant HU	5.8 (4.3, 5.8)	7.9 (5.5, 7.9)	6.5 (4.5, 6.5)	4.8 (3.1, 4.8)	4.5 (2.9, 4.5)
Aggregate value HU[d] per $1,000,000	18.5 (10.4, 30.0)	33.8 (16.4, 63.7)	49.7 (26.2, 88.5)	83.0 (44.9, 150.0)	96.5 (54.1, 175.0)
Food resource densities (counts within 3 km Euclidean buffer per 10km of local and secondary roadways[e]):					
Fast food restaurants	0.1 (0.1, 0.2)	0.2 (0.1, 0.3)	0.2 (0.1, 0.3)	0.2 (0.2, 0.4)	0.4 (0.3, 0.6)
Non-fast food restaurants	2.5 (1.4, 4.4)	3.5 (1.5, 6.3)	2.6 (1.2, 4.6)	2.8 (1.4,5.0)	2.7 (1.4, 5.2)
Supermarkets	0.0 (0.0, 0.01)	0.1 (0.1, 0.1)	0.1 (0.0, 0.1)	0.1 (0.0, 0.1)	0.1 (0.1, 0.2)
Convenience stores	0.7 (0.5, 0.9)	1.1 (0.8, 1.5)	0.9 (0.7, 1.1)	0.8 (0.6, 1.1)	0.9 (0.7, 1.2)
			Upwardly mobile neighborhood SES residents, n=665		
Socioeconomic indicators within Census tract[a]:					
Percent population race white	87.9 (71.5, 94.7)	88.5 (78.1, 94.3)	92.1 (83.8, 95.9)	87.7 (77.0, 93.2)	88.1 (77.9, 93.6)
Percent population education < High School	21.8 (15.2, 30.8)	13.2 (8.0, 19.2)	12.8 (8.6, 18.2)	9.7 (6.0, 14.9)	10.0 (6.3, 15.2)
Percent population <150% FPL	12.6 (8.2, 26.7)	8.0 (5.5, 13.0)	4.5 (3.2, 7.1)	4.8 (3.4, 6.9)	4.7 (3.3, 6.9)
Median income per $10,000	19.8 (13.8, 25.5)	46.0 (37.8, 57.9)	57.4 (48.9, 68.3)	84.2 (72.1, 101.3)	84.3 (72.3, 101.3)
Percent population professional/management occupation[c]	36.8 (28.7, 52.8)	49.0 (38.0, 57.4)	48.7 (41.5, 56.0)	58.4 (52.4, 65.6)	58.0 (52.3, 64.8)
Percent population unemployed[c]	3.7 (2.5, 5.7)	2.9 (2.0, 4.1)	2.4 (1.7, 3.2)	1.6 (1.1, 2.1)	1.6 (1.1, 2.2)
Median rent	287.0 (237.0, 372.0)	685.0 (527.0, 809.0)	748.0 (600.0, 894.0)	1,037.5 (837.0, 1,361.0)	1,022.0 (818.0, 1,340.0)
Percent population owner-occupied HU	44.5 (25.8, 74.0)	63.0 (43.1, 83.0)	84.2 (70.1, 92.1)	85.5 (74.5, 93.2)	86.0 (74.6, 93.9)
Percent vacant HU	5.0 (2.6, 8.0)	5.0 (3.0, 9.5)	3.6 (2.4, 5.5)	2.6 (1.7, 4.0)	2.7 (1.8, 4.1)
Aggregate value HU[d] per $1,000,000	27.8 (8.6, 67.0)	113.0 (49.9, 235.0)	251.0 (151.0, 387.0)	473.0 (313.0, 757.0)	473.0 (313.0, 760.0)
Food resource densities (counts within 3 km Euclidean buffer per 10km of local and secondary roadways[e]):					
Fast food restaurants	0.2 (0.1, 0.3)	0.2 (0.1, 0.5)	0.2 (0.1, 0.3)	0.2 (0.1, 0.3)	0.3 (0.1, 0.5)
Non-fast food restaurants	3.9 (1.8, 14.4)	3.9 (1.6, 20.2)	2.0 (1.0, 4.0)	2.3 (1.3, 3.9)	2.7 (1.6, 4.5)
Supermarkets	0.0 (0.0, 0.1)	0.1 (0.0, 0.2)	0.1 (0.0, 0.1)	0.1 (0.0, 0.1)	0.1 (0.0, 0.2)
Convenience stores	0.8 (0.6, 1.0)	1.0 (0.6, 2.4)	0.5 (0.3, 0.8)	0.5 (0.3, 0.7)	0.6 (0.4, 0.8)
			Stable high neighborhood SES residents, n=1,854		
Socioeconomic indicators within Census tract[a]:					
Percent population race white	82.0 (57.5, 93.0)	82.5 (61.6, 92.7)	87.2 (73.7, 94.9)	80.0 (61.6, 89.3)	80.9 (62.9, 91.1)
Percent population education < High School	21.8 (15.2, 30.8)	13.2 (8.0, 19.2)	12.8 (8.6, 18.2)	9.7 (6.0, 14.9)	10.0 (6.3, 15.2)

Percent population <150% FPL	18.3 (11.2, 30.9)	13.0 (8.5, 20.7)	11.2 (7.4, 16.4)	10.9 (7.4, 16.0)	10.9 (7.1, 16.4)
Median income per $10,000	16.0 (13.3, 20.2)	34.7 (27.9, 42.7)	36.5 (31.0, 43.47.0)	51.9 (44.2, 62.1)	52.0 (43.8, 62.9)
Percent population professional/management occupation[c]	28.3 (21.1, 36.7)	32.9 (24.3, 43.7)	32.8 (25.0, 41.2)	41.6 (33.0, 51.1)	40.7 (32.1, 50.4)
Percent population unemployed[c]	5.1 (3.4, 7.0)	4.0 (2.8, 5.3)	3.7 (2.6, 4.7)	2.5 (1.7, 3.4)	2.5 (1.7, 3.4)
Median rent	252.0 (231.0, 293.0)	528.0 (438.0, 655.0)	535.0 (445.0, 658.0)	709.0 (604.0, 853.0)	698.0 (591.0, 848.0)
Percent population owner-occupied HU	50.2 (28.5, 73.7)	61.3 (38.3, 78.5)	70.3 (49.6, 83.5)	73.4 (54.2, 86.1)	75.7 (56.4, 86.9)
Percent vacant HU	0.1 (0.0, 0.1)	0.1 (0.0, 0.1)	0.1 (0.0, 0.1)	0.0 (0.0, 0.1)	0.0 (0.0, 0.1)
Aggregate value HU[d] per $1,000,000	28.1 (13.4, 56.8)	80.0 (38.8, 130.0)	96.0 (56.5, 153.)	181.0 (114.0, 281.0)	188.0 (116.0, 295.0)
Food resource densities (counts within 3 km Euclidean buffer per 10km of local and secondary roadways[e]):					
Fast food restaurants	0.1 (0.1, 0.2)	0.2 (0.1, 0.3)	0.2 (0.1, 0.3)	0.2 (0.1, 0.3)	0.4 (0.2, 0.6)
Non-fast food restaurants	2.8 (1.5, 5.4)	3.0 (1.5, 6.6)	2.2 (1.2, 4.3)	2.6 (1.4, 4.4)	2.8 (1.5, 4.9)
Supermarkets	0.7 (0.5, 1.0)	1.2 (0.8, 1.7)	1.0 (0.9, 1.2)	1.0 (0.8, 1.2)	1.2 (0.9, 1.5)
Convenience stores	0.7 (0.5, 0.9)	1.0 (0.7, 1.4)	0.7 (0.5, 0.9)	0.7 (0.4, 0.9)	0.8 (0.5, 1.1)

[a]U.S. Census-tract level data spatially and temporally linked to respondent residential locations to CARDIA exam years (Year 0, 1980; Years 7 and 10, 1990; Year 15, 2000; Year 20, 2000)
[b]Derived from latent class analysis using Mplus version 7[84] of Census tract-level data from exam years 0, 7, 10, 15, and 20: percent race white, percent education <HS, percent poverty (below 150% FPL), percent unemployed, percent professional/management occupation, median income, percent vacant housing, aggregate housing value, percent owner occupied, median rent. All measures were normalized to Z-scores and percent vacant housing, aggregate housing value, percent owner occupied, median rent were normalized by center.
[c]Among census tract population ages 16 years or older.
[d]Owner occupied housing units within census tract.
[e]Counts of Dunn & Bradstreet food resources within Euclidean 3km buffer per 10 km local and secondary roadways.
FPL: federal poverty level, HU: housing units

Table 6. Model estimates[a] of neighborhood food resources[b] predicted for classes[c] of neighborhood SES residents: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.

	Fast food restaurants	Non-fast food restaurants	Supermarkets	Convenience stores
	Estimated beta (95% Confidence Interval)	Estimated beta (95% Confidence Interval)	Estimated beta (95% Confidence Interval)	Estimated beta (95% Confidence Interval)
Latent class 1: downwardly mobile	-0.02 (-0.03, -0.01)	-2.18 (-2.50, -1.86)	-0.002 (-0.009, 0.005)	-0.03 (-0.06, 0.00)
Latent class 2: upwardly mobile	-0.02 (-0.03, -0.01)	-1.39 (-1.67, -1.11)	0.003 (-0.003, 0.009)	0.02 (0.00, 0.05)
Latent class 3: stable low SES	0.04 (0.03, 0.06)	2.34 (1.97, 2.71)	-0.013 (-0.021, -0.005)	-0.04 (-0.7, -0.01)
Latent class 4: stable high SES	ref	ref	ref	ref
Year	0.01 (0.01, 0.01)	0.10 (0.08, 0.11)	0.006 (0.006, 0.006)	0.01 (0.01, 0.01)
Latent class 1 X year	0.000 (-0.001, 0.001)	0.03 (0.01, 0.05)	0.001 (0.000, 0.001)	0.01 (0.01, 0.02)
Latent class 2 X year	0.001 (0.000, 0.002)	0.03 (0.02, 0.05)	0.000 (0.000, 0.000)	0.004 (0.002, 0.01)
Latent class 3 X year	-0.005 (-0.006, -0.004)	-0.10 (-0.12, -0.08)	0.001 (0.000, 0.001)	-0.002 (-0.004, 0.00)

[a]Multivariable random effects regressions modeling each neighborhood food resource as function of class indicators (referent is stable high neighborhood SES residents) , exam year (continuous), interaction of class indicators by exam year, population density, and a random effect for each participant.
[b]Counts of Dunn & Bradstreet food resources within Euclidean 3km buffer per 10 km local and secondary roadways.
[c]Derived from latent class analysis using Mplus version 7[84] of Census tract-level data from exam years 0, 7, 10, 15, and 20: percent race white, percent education <HS, percent poverty (below 150% FPL), percent unemployed, percent professional/management occupation, median income, percent vacant housing, aggregate housing value, percent owner occupied, median rent.
Abbreviations: SES: socioeconomic status, CI: Confidence interval, FPL: federal poverty level, HU: housing units, HS: High School.

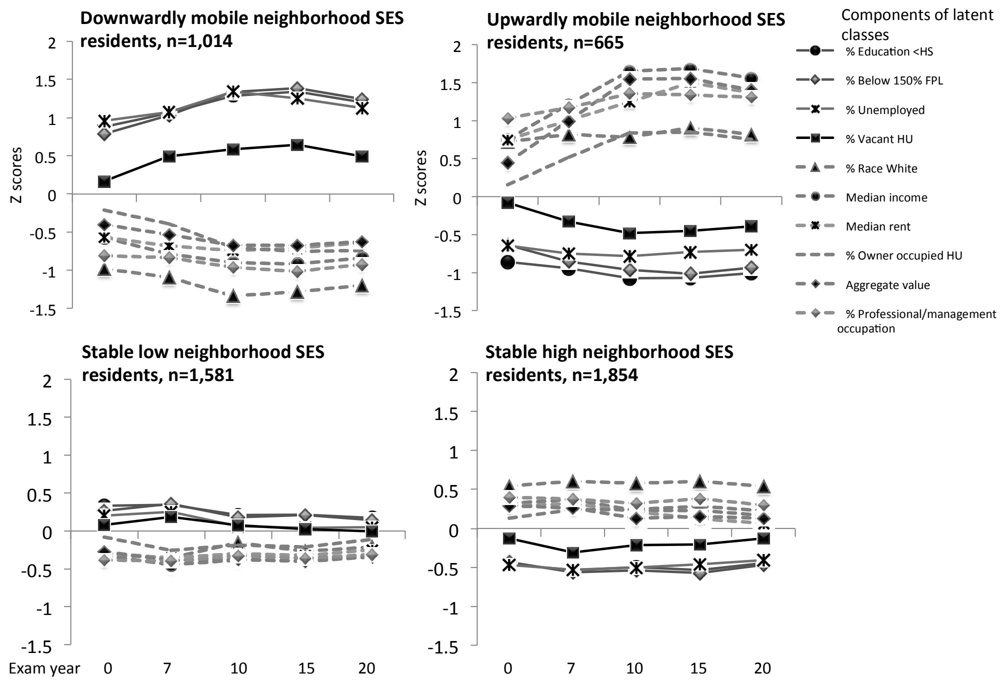
Table 7. Post-estimated[a] linear contrasts of neighborhood food resources[b] for classes[c] of longitudinal neighborhood SES residents at exam years 0, 7, 10, 15, and 20: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.

	Fast food restaurants		Non-fast food restaurants		Supermarkets		Convenience stores	
	Estimated beta (95% Confidence Interval)	P	Estimated beta (95% Confidence Interval)	P	Estimated beta (95% Confidence Interval)	P	Estimated beta (95% Confidence Interval)	P
Year 0								
Downwardly mobile vs. stable high SES	**-0.02 (-0.03, -0.01)**	**0.001**	**-2.18 (-2.50, -1.86)**	**0.000**	-0.002 (-0.009, 0.005)	0.596	-0.03 (-0.06, 0.00)	0.080
Downwardly mobile vs. upwardly mobile	**-0.06 (-0.08, -0.05)**	**0.000**	**-4.52 (-4.93, -4.11)**	**0.000**	**0.011 (0.002, 0.020)**	**0.015**	0.01 (-0.02, 0.05)	0.504
Stable low SES vs. stable high SES	**-0.02 (-0.03, -0.01)**	**0.000**	**-1.39 (-1.67, -1.11)**	**0.000**	0.003 (-0.003, 0.009)	0.267	0.02 (0.00, 0.05)	0.110
Downwardly mobile vs. stable low SES	0.00 (-0.01, 0.01)	0.800	**-0.79 (-1.12, -0.46)**	**0.000**	-0.005 (-0.012, 0.002)	0.145	**-0.05 (-0.08, -0.02)**	**0.002**
Upwardly mobile vs. stable low SES	**0.07 (0.05, 0.08)**	**0.000**	**3.73 (3.35, 4.10)**	**0.000**	**-0.016 (-0.024, -0.008)**	**0.000**	**-0.06 (-0.10, -0.03)**	**0.001**
Upwardly mobile vs. stable high SES	**0.04 (0.03, 0.06)**	**0.000**	**2.34 (1.97, 2.71)**	**0.000**	**-0.013 (-0.021, -0.005)**	**0.002**	**-0.04 (-0.07, -0.01)**	**0.025**
Year 7								
Downwardly mobile vs. stable high SES	**-0.02 (-0.03, -0.01)**	**0.000**	**-1.99 (-2.25, -1.73)**	**0.000**	0.003 (-0.002, 0.008)	0.259	**0.07 (0.05, 0.09)**	**0.000**
Downwardly mobile vs. upwardly mobile	**-0.03 (-0.04, -0.02)**	**0.000**	**-3.61 (-3.94, -3.28)**	**0.000**	**0.010 (0.003, 0.016)**	**0.005**	**0.12 (0.09, 0.15)**	**0.000**
Stable low SES vs. stable high SES	**-0.03 (-0.04, -0.02)**	**0.000**	**-1.15 (-1.38, -0.93)**	**0.000**	0.004 (-0.001, 0.008)	0.124	**0.05 (0.03, 0.07)**	**0.000**
Downwardly mobile vs. stable low SES	-0.01 (-0.01, 0.00)	0.297	**-0.83 (-1.10, -0.56)**	**0.000**	-0.001 (-0.006, 0.005)	0.835	0.02 (0.00, 0.04)	0.088
Upwardly mobile vs. stable low SES	**0.03 (0.01, 0.04)**	**0.000**	**2.78 (2.47, 3.09)**	**0.000**	**-0.010 (-0.017, -0.004)**	**0.001**	**-0.10 (-0.13, -0.08)**	**0.000**
Upwardly mobile vs. stable high SES	**0.01 (0.00, 0.02)**	**0.044**	**1.62 (1.32, 1.92)**	**0.000**	**-0.007 (-0.013, -0.001)**	**0.032**	**-0.05 (-0.08, -0.03)**	**0.000**
Year 10								
Downwardly mobile vs. stable high SES	**-0.02 (-0.03, -0.01)**	**0.000**	**-1.90 (-2.16, -1.65)**	**0.000**	**0.005 (0.000, 0.010)**	**0.047**	**0.11 (0.09, 0.13)**	**0.000**
Downwardly mobile vs. upwardly mobile	**-0.02 (-0.03, 0.00)**	**0.006**	**-3.22 (-3.54, -2.90)**	**0.000**	**0.009 (0.003, 0.016)**	**0.005**	**0.17 (0.14, 0.19)**	**0.000**
Stable low SES vs. stable high SES	**-0.01 (-0.02, 0.00)**	**0.004**	**-1.05 (-1.28, -0.83)**	**0.000**	0.004 (-0.001, 0.008)	0.099	**0.06 (0.04, 0.08)**	**0.000**
Downwardly mobile vs. stable low SES	-0.01 (-0.02, 0.00)	0.087	**-0.85 (-1.11, -0.59)**	**0.000**	0.001 (-0.004, 0.007)	0.593	**0.05 (0.03, 0.07)**	**0.000**

Upwardly mobile vs. stable low SES	0.01 (0.00, 0.02)	0.134	**2.37 (2.07, 2.67)**	**0.000**	**-0.008 (-0.014, -0.002)**	**0.011**	**-0.12 (-0.14, -0.10)**	**0.000**
Upwardly mobile vs. stable high SES	0.00 (-0.01, 0.01)	0.531	**1.32 (1.02, 1.61)**	**0.000**	-0.004 (-0.010, 0.002)	0.173	**-0.06 (-0.08, -0.04)**	**0.000**
Year 15								
Downwardly mobile vs. stable high SES	**-0.02 (-0.03, -0.01)**	**0.000**	**-1.76 (-2.03, -1.49)**	**0.000**	**0.009 (0.003, 0.014)**	**0.002**	**0.18 (0.15, 0.20)**	**0.000**
Downwardly mobile vs. upwardly mobile	0.01 (0.00, 0.02)	0.176	**-2.57 (-2.91, -2.23)**	**0.000**	**0.008 (0.001, 0.015)**	**0.019**	**0.25 (0.22, 0.27)**	**0.000**
Stable low SES vs. stable high SES	-0.01 (-0.01, 0.00)	0.182	**-0.89 (-1.12, -0.65)**	**0.000**	0.004 (-0.001, 0.009)	0.111	**0.08 (0.06, 0.10)**	**0.000**
Downwardly mobile vs. stable low SES	**-0.01 (-0.02, 0.00)**	**0.012**	**-0.88 (-1.15, -0.60)**	**0.000**	0.005 (-0.001, 0.010)	0.097	**0.10 (0.07, 0.12)**	**0.000**
Upwardly mobile vs. stable low SES	**-0.02 (-0.03, -0.01)**	**0.000**	**1.69 (1.38, 2.01)**	**0.000**	-0.004 (-0.010, 0.003)	0.271	**-0.15 (-0.18, -0.12)**	**0.000**
Upwardly mobile vs. stable high SES	**-0.03 (-0.04, -0.02)**	**0.000**	**0.81 (0.50, 1.12)**	**0.000**	0.000 (-0.006, 0.007)	0.934	**-0.07 (-0.10, -0.04)**	**0.000**
Year 20								
Downwardly mobile vs. stable high SES	**-0.02 (-0.03, -0.01)**	**0.003**	**-1.62 (-1.93, -1.31)**	**0.000**	**0.012 (0.006, 0.019)**	**0.000**	**0.24 (0.22, 0.27)**	**0.000**
Downwardly mobile vs. upwardly mobile	**0.03 (0.02, 0.05)**	**0.000**	**-1.92 (-2.32, -1.52)**	**0.000**	0.008 (-0.001, 0.016)	0.081	**0.32 (0.29, 0.36)**	**0.000**
Stable low SES vs. stable high SES	0.00 (-0.01, 0.01)	0.965	**-0.72 (-0.99, -0.45)**	**0.000**	0.004 (-0.002, 0.010)	0.171	**0.10 (0.08, 0.13)**	**0.000**
Downwardly mobile vs. stable low SES	**-0.02 (-0.03, -0.01)**	**0.005**	**-0.91 (-1.22, -0.59)**	**0.000**	**0.008 (0.001, 0.015)**	**0.020**	**0.14 (0.11, 0.17)**	**0.000**
Upwardly mobile vs. stable low SES	**-0.05 (-0.06, -0.04)**	**0.000**	**1.02 (0.65, 1.38)**	**0.000**	0.001 (-0.007, 0.008)	0.890	**-0.18 (-0.21, -0.15)**	**0.000**
Upwardly mobile vs. stable high SES	**-0.05 (-0.06, -0.04)**	**0.000**	0.30 (-0.06, 0.66)	0.103	0.005 (-0.003, 0.012)	0.239	**-0.08 (-0.11, -0.05)**	**0.000**

[a]Multivariable random effect regression modelling each neighborhood food resource as a function of class indicators (referent is stable high neighborhood SES residents), exam year (continuous), interaction of class indicators by exam year, and population density.
[b]Counts of Dunn & Bradstreet food resources within Euclidean 3km buffer per 10 km local and secondary roadways.
[c]Derived from latent class analysis using Mplus version 7[84] of Census tract-level data from exam years 0, 7, 10, 15, and 20: percent race white, percent education <HS, percent poverty (below 150% FPL), percent unemployed, percent professional/management occupation, median income, percent vacant housing, aggregate housing value, percent owner occupied, median rent.
Abbreviations: SES: socioeconomic status, CI: Confidence interval, FPL: federal poverty level, HU: housing units, HS: High School

Figure 1. Temporal changes in neighborhood SES characteristics[a], by 4 classes[b] of longitudinal neighborhood SES resident characteristics: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.

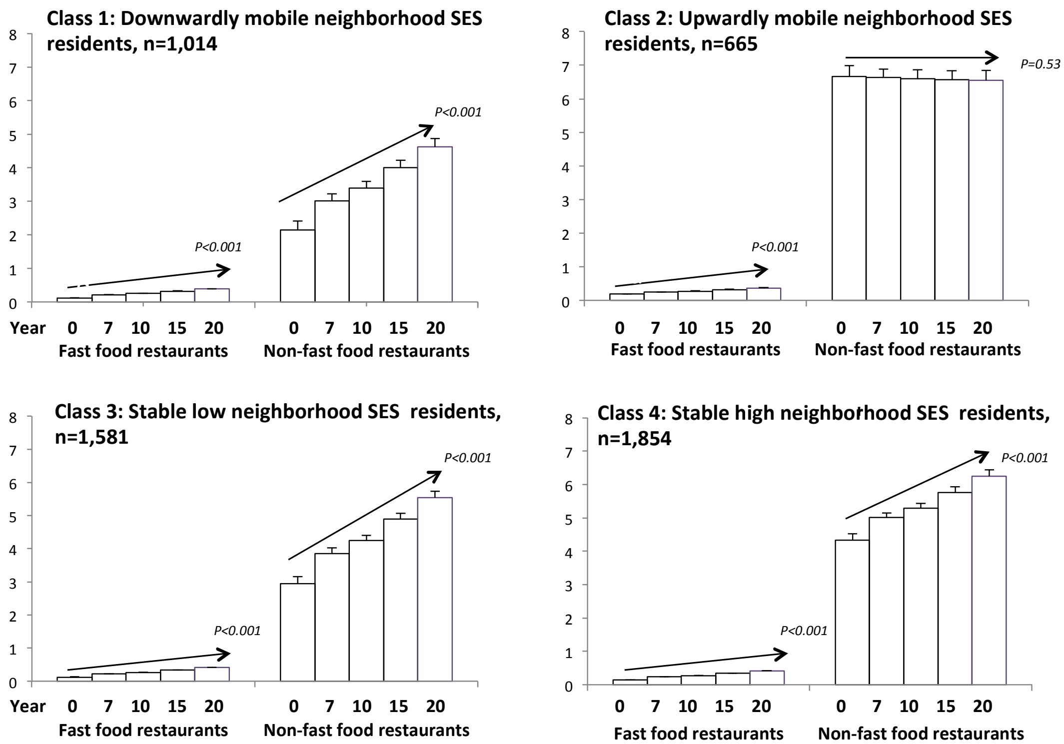


[a]U.S. Census-tract level data spatially and temporally linked to CARDIA exam years (Year 0, 1980; Years 7 and 10, 1990; Year 15 and Year 20, 2000); percent of education below HS is among persons aged 16 years and over, aggregate value is among owner-occupied HU

[b]Derived from latent class analysis using Mplus version 7[84] of Census tract-level data from exam years 0, 7, 10, 15, and 20: percent race white, percent education <HS, percent poverty (below 150% FPL), percent unemployed, percent professional/management occupation, median income, percent vacant housing, aggregate housing value, percent owner occupied, median rent. All measures were normalized to Z-scores and percent vacant housing units, aggregate housing value, percent owner occupied, median rent were normalized by center.

Abbreviations: SES: socioeconomic status, FPL: federal poverty level, HU: housing units, HS: High School.

Figure 2. Estimated mean densities[b] of neighborhood fast food and non-fast food restaurants[b] by 4 classes[c] of longitudinal neighborhood SES residents characteristics: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.

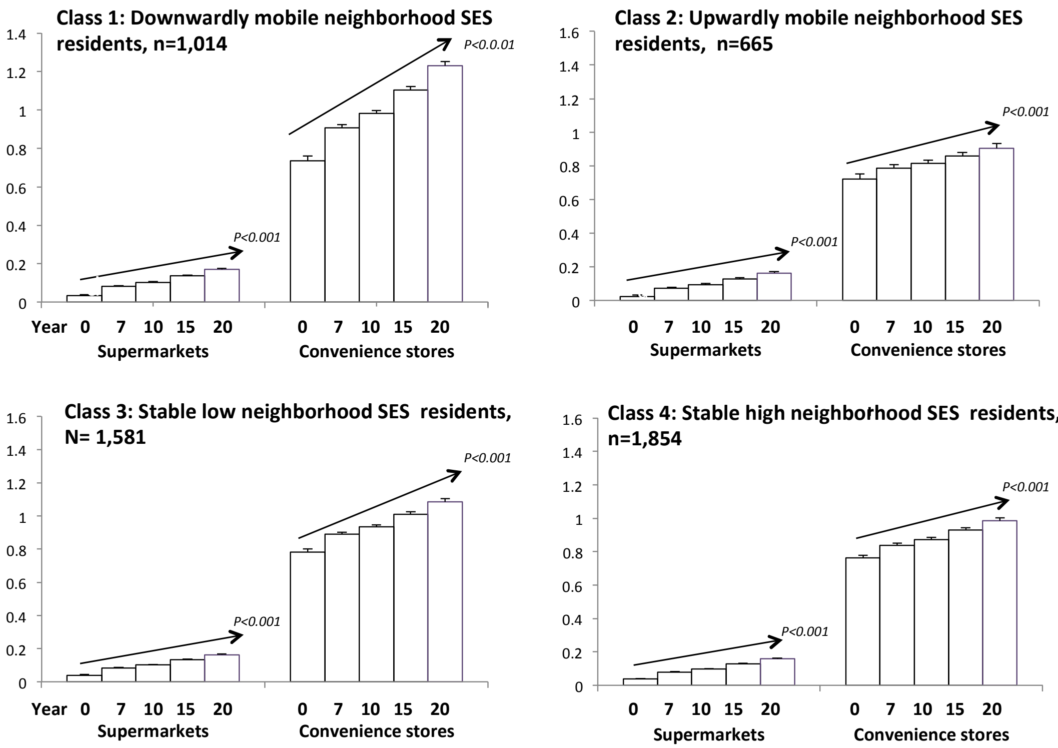


[a]Multivariable random effects regressions modeling each neighborhood food resource as function of class indicators (referent is stable high neighborhood SES residents), exam year (continuous), interaction of class indicators by exam year, population density, and a random effect for each participant. Time trends were derived from class-specific multivariable random effects regression models that included population density within tract, a random effect for each participant, and year.

[b]Counts of Dunn & Bradstreet food resources within Euclidean 3km buffer per 10 km local and secondary roadways.

[c]Derived from latent class analysis using Mplus version 7[84] of Census tract-level data from exam years 0, 7, 10, 15, and 20: percent race white, percent education <HS, percent poverty (below 150% FPL), percent unemployed, percent professional/management occupation, median income, percent vacant housing, aggregate housing value, percent owner occupied, median rent.

Figure 3. Estimated mean densities[a] of neighborhood supermarkets and convenience stores[b] by 4 classes[c] of longitudinal neighborhood SES residents characteristics: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.



[a]Derived from latent class analysis using Mplus version 7[84] of Census tract-level data from exam years 0, 7, 10, 15, and 20: percent race white, percent education <HS, percent poverty (below 150% FPL), percent unemployed, percent professional/management occupation, median income, percent vacant housing, aggregate housing value, percent owner occupied, median rent. Time trends were derived from class-specific multivariable random effects regression models that included population density within tract, a random effect for each participant, and year.
[b]Counts of Dunn & Bradstreet food resources within Euclidean 3km buffer per 10 km local and secondary roadways.
[c]Multivariable random effects regressions modeling each neighborhood food resource as function of class indicators (referent is stable high neighborhood SES residents) , exam year (continuous), interaction of class indicators by exam year, population density, and a random effect for each participant.

CHAPTER V: MULTIPLE PATHWAYS FROM THE NEIGHBORHOOD FOOD ENVIRONMENT TO INCREASED BODY MASS INDEX THROUGH DIET BEHAVIORS: A STRUCTURAL EQUATION-BASED ANALYSIS IN THE CARDIA STUDY

A. ABSTRACT

Obesity reduction strategies often target neighborhood food resources, without considering separate pathways from multiple types of resources to body mass index (BMI), through diet. We used data from Coronary Artery Risk Development in Young Adults participants (n=5,114) and structural equation modeling of longitudinal (1985-86 to 2005-06) pathways from neighborhood food resources to BMI. We studied pathways from neighborhood fast food restaurants, sit-down restaurants, supermarkets and convenience stores to BMI, through diet behaviors. We controlled for socioeconomic status (SES) and physical activity, and tested interaction by sex, race, and time-varying longitudinal neighborhood SES. Neighborhood fast food and sit-down restaurants were associated with consumption of foods typically purchased from fast food restaurants, such as potatoes/fries and sugar-sweetened beverages (i.e., fast food-type diet): greater numbers of fast food restaurants were associated with higher consumption of a fast-food type diet, and greater numbers of sit-down restaurants were negatively associated with a fast food-type diet. Fast food-type diet was consistently and positively associated with BMI. The pathways from food stores to BMI through diet were inconsistent in magnitude and

statistical significance. Availability of neighborhood fast food and sit-down restaurants may play comparatively stronger roles than food stores in shaping diet behaviors and BMI.

B. INTRODUCTION

National and local efforts have targeted neighborhood food resources to improve diet quality and reduce obesity in disadvantaged areas [7-9], without much evidence that this approach is effective. Furthermore, most research focuses on a single part of the pathway, either associations between food stores and restaurants with diet behaviors <u>or</u> with body mass index (BMI). Yet, the extent to which changing food environments lead to dietary change and consequent reduction in obesity, through diet, is unknown.

Evidence is largely based on cross-sectional studies that cannot link changes in neighborhood environments with changes in individual-level diet and body weight [22]. The few longitudinal studies [5,15,112] have generally examined associations between a single type of food resource with a single outcome, such as BMI, obesity, or a broad diet behavior (e.g., diet quality) [113]. Moreover, we posit that food stores and restaurants do not influence diet behaviors in isolation; rather, the availability of alternative food resources within the same neighborhood may also be important. Many studies overlook variation in relationships between neighborhood food stores and restaurants and obesity-related outcomes by sex [15,34,114-116], race [38,41,42,115,117], and neighborhood socioeconomic status (SES) [36,114,117]. The data and methodological limitations of current approaches that prevent modeling complex pathways that simultaneously account for multiple food store and restaurant options may help explain inconsistent findings in the literature on neighborhood environment and BMI [33].

Diet contributes to energy balance, influencing body weight so we hypothesized indirect pathways from neighborhood food stores and restaurants to obesity through diet behaviors. However, neighborhood resources may influence BMI through other pathways. For example, unmeasured features, such the aesthetics of natural and built environments can be related to food resources and can also influence physical activity[118] and consequently BMI. In the absence of complete information, this may yield confounding that is difficult to control. Modeling indirect pathways (through diet) and direct pathways (through other processes independent of diet) between neighborhood characteristics and BMI can begin to disentangle multiple neighborhood effects on behaviors and health outcomes. Yet, there is little pathway-based research to understand how different features of the food environment relate to obesity through dietary behaviors. Such analyses require simultaneous regression modeling via systems of equations [119].

We used a longitudinal structural equation model (SEM) in a large prospective cohort of adult black and white Americans over 20 years to estimate separate pathways from neighborhood food resources (fast food and sit-down restaurants, supermarkets and convenience stores) to BMI. We quantified indirect pathways from food resources to BMI, through consumption of specific foods typically acquired at each type of food resource. We hypothesized that the pathways from neighborhood restaurants and food stores to BMI would operate indirectly through the greater consumption of specific foods typically acquired from restaurants versus food stores. We also included direct pathways between food resources to BMI to capture neighborhood effects that occur through unmeasured factors that are independent of diet (e.g., aesthetics). We hypothesized that direct and indirect pathways vary by race, sex, and time-varying neighborhood SES.

C. METHODS

STUDY POPULATION

The Coronary Artery Risk Development in Young Adults (CARDIA) is a longitudinal cohort with detailed diet, clinic, physical activity, environmental, and sociodemographic data collected for 5,114 white or black United States (U.S.) adults aged 18-30 years originally from 4 centers: Birmingham, AL; Chicago, IL; Minneapolis, MN; and Oakland, CA. Participants were selected in 1985-86 with approximately equal numbers by race, gender, education (high school or less versus more than high school), age (18-24 years versus 25-30 years) within each center, and followed over 25 years. We used data from 5 exams during 1992-93 (Year 7), 1995-96 (Year 10), 2000-01 (Year 15), and 2005-06 (Year 20). Retention rates were 81%, 79%, 74%, and 72% (3,549), respectively, of the surviving cohort.

We used a geographic information system (GIS)-derived dataset of time-varying neighborhood-level food resources and U.S. Census data spatially and temporally linked to CARDIA respondent residential locations at each exam year. Study data were collected under protocols approved by Institutional Review Boards at each study center and the University of North Carolina at Chapel Hill.

BODY MASS INDEX

At each examination, participants' weight (nearest 0.2 kg) and height (nearest 0.5 centimeter) were measured and BMI (kg/m^2) calculated. We used years 0, 7, and 20 to correspond with the primary diet measures described below.

DIETARY ASSESSMENT

An interviewer-administered CARDIA Diet History [59] at exam years 0, 7, and 20 was used to assess diet. With a food-grouping system (University of Minnesota Nutrition Coordinating Center), we assigned foods (13 food groups and 5 beverage groups) [assessed as servings per day of constituent foods (Table 8)] associated with weight change per 4-year period [19] and cardiometabolic outcomes [60]. We also used survey data collected at exam years 0, 7, 10, 15, and 20 regarding the number of times per week respondents ate meals at fast food restaurants. [18] We categorized (low, medium, or high) weekly fast food consumption and servings per day of consumed foods, either by year-specific tertiles or as non-consumers (0 servings per day) versus upper and lower distributions of consumers (≥1 serving per day), values defined in Table 9. Year-specific tertiles allowed for temporal changes in diet behaviors.

We set reported diet behaviors and BMI to missing when participants had extreme energy intakes [61] [<800 or >8000 kcal/d for men (n=73 at year 0, n=60 at year 7, and n=25 at year 20); and <600 or >6000 kcal/d for women (n=53 at year 0, n=34 at year 7, and n=29 at year 20)] or when women were pregnant (n= 7 at year 0, n=62 at year 7, and n=6 at year 20).

NEIGHBORHOOD FOOD ENVIRONMENT

We obtained counts of chain fast-food restaurants (hereafter referred to as fast food restaurants), all other restaurants not classified as chain fast food (hereafter referred to as sit-down restaurants), supermarkets, and convenience stores from Dun and Bradstreet (D&B), using 8-digit Standard Industrial Classification (SIC) codes for years 7, 10, 15, and 20 and a combination of 4 digit SIC codes and matched business names at year 0 (Table 10). We used a 3-

km Euclidean buffer around each respondent's residential location for restaurants [15,62] and an 8-km Euclidean buffer for food stores [62,63], based on empirical evidence. Using StreetMap 2000 (v. 9.0) for years 7 (1993) and 10 (1996), from StreetMap Pro 2005 (v. 5.2) for year 15 (2001), and from StreetMap Pro 2010 (v. 7.2) for year 20, (Environmental Systems Research Institute; ESRI, www.esri.com: Redlands, CA), we calculated densities of restaurants and stores as counts per 10 km secondary (roads used to connect smaller towns, subdivisions, and neighborhoods) and local (roads used for local traffic, usually with a single lane of traffic in each direction) roadway, resulting in a measure of concentration of food resources along streets representing overall commercial activity [64,65].We included variables reflecting urbanicity and development as these relate directly to the food environment. Population density varies across roadway structure [66] and across rural versus urban areas [67]; population density and commercial development were independently associated with geographic food resource distribution and were not highly correlated in our data $\rho=0.35$. Therefore, we included population density (census tract population per square km of land excluding water) to represent area-level development and population, and counts per roadway (representing commercial development) in our analyses.

AREA-LEVEL SOCIOECONOMIC INDICATORS

Neighborhood SES was derived at the U.S. census tract-level at all years; tract-level SES is more strongly associated with health outcomes block group-level SES [68,69]. Neighborhood SES is a latent construct comprised of multiple SES domains and as an individual-level exposure; people may experience temporal changes in neighborhood SES through residential movement or changes around a given residential location. In addition, depending on neighborhood SES, food environments may improve or worsen over time. We used a composite variable from previous analyses [120] to characterize longitudinal neighborhood SES patterns, which we derived using data from years 0, 7, 10, 15, and 20: % race white, % education <high school, % poverty (below 150% federal poverty level [70]), % unemployed, % professional/management occupation, median income, % vacant housing, aggregate housing value, % owner occupied, and median rent. Our longitudinal neighborhood SES class variable characterized neighborhoods of downwardly or upwardly mobile neighborhood SES, or stable high or low neighborhood SES.

INDIVIDUAL-LEVEL CONFOUNDERS

We characterized individual-level socioedemographic and behavioral confounders using data from structured interview or self-administered questionnaire collected at each exam year. Time-invariant sociodemographic variables were sex, race (white/black), exam attendance, and center. Time-varying characteristics were maximum reported number of years of schooling completed by the exam year (continuous), and mean household income inflated to U.S. dollars at year 20 (2005-06) using the Consumer Price Index. Income was not collected in year 0, so we used the closest measurement (year 5) for year 0. At each exam, participants reported on 13 different categories of moderate and vigorous recreational sports, exercise, leisure, and occupational activities in the past 12 months and scores were calculated based on frequency and intensity of each activity. [71]

STATISTICAL ANALYSES

We performed descriptive analyses and multivariable models using Stata 13.0 (StataCorp, College Station, TX). We calculated means and standard deviations (continuous variables) and percentages (categorical variables) of individual-level characteristics at exam years 0, 7, 10, 15, and 20.

Structural equation modeling (SEM) is a pathway-based approach that can handle multi-equation models, and allows estimation among latent (unobserved) and observed variables of multiple estimated effects transmitted over combinations of paths. [121] SEMs are well suited to estimate a range of effects. [122] We used Mplus version 7.11[84] with maximum likelihood and missing values; statistical significance was set at $P<0.05$ (2-sided).

Latent factors used in structural equation modeling

Latent factors are underlying complex concepts that are not directly observed, but can be inferred mathematically from multiple observed variables. Thus, latent factors are useful to summarize a number of variables into a one meaningful factor. We constructed latent factors for diet behaviors and food environment.

Food environment. We created latent factors for each neighborhood food store and restaurant factors type (fast food restaurant, sit-down restaurant, supermarket and convenience stores) at each year using observed indicators: count per 10 km local and secondary roadway, within 8 km (food stores) or 3 km (restaurants) Euclidean buffer and the Z-score of population density.

Diet behaviors. We created four latent diet factors for each year (fast food restaurant-type diet; sit-down restaurant-type diet, supermarket-type diet, and convenience store-type diet) using intake categories of foods we considered, *a priori*, to be acquired at each type of establishment (e.g., fries from fast food restaurants, fruits from supermarkets). We hypothesized that food groups reflected the types of foods commonly offered at each specific type of store or restaurant

[123-126] and that the restaurants and food stores would be associated with the consumption of these food as shown in Figure 4. Our approach differs from standard approaches focusing on classifying establishments on the basis of selling “healthy” [127] or “unhealthy” [81] foods, given that identical foods can be acquired from a range of stores and restaurants.

Structural equation modeling

We constructed a single SEM to examine pathways from neighborhood food stores and restaurants to BMI, including direct and indirect pathways through diet behaviors.

Figure 5 presents our conceptual model of the longitudinal direct and indirect pathways of the food environment (neighborhood food stores and restaurants), BMI and diet, temporally related by auto-regression (linear association between time-lagged variables). The auto-correlation explicitly addresses the well-recognized tracking of health status and behaviors over time. We hypothesized that tracking between the years closest in time is more relevant than across the full 20-year period so we only included auto-regression between variables from years 0 to 7 and years 7 to 20. We hypothesized that the associations between the food environment, diet, and BMI operate concurrently so we did not include pathways from the food environment to outcomes at later exams, except through tracking of the food environment over time. We also assumed that the food environment impacts diet, which in turn, impacts BMI and that the indirect effect of the food environment on BMI operates solely through diet. We allowed for direct effects of the food environment on BMI because there may be unmeasured factors in the food environment that influence BMI. For example, a neighborhood with many food resources may be perceived as aesthetically displeasing because it lacks natural spaces and parks. Then residents may limit their outdoor physical activity,[118] increasing their risk of unwanted weight gain. We assumed that all relationships were linear and that there was no interaction between food environments and diet behavior.

We considered several types of confounding variables (Figure 6). We addressed confounding of associations between: (1) food environment and diet; (2) diet and BMI; and (3) food environment and BMI after excluding diet-BMI confounders that were likely affected by the food environment. [66,128-130] We addressed confounding of food environment-diet, diet-BMI, and food environment-BMI associations after excluding diet-BMI confounders that were likely affected by the food environment. [66,128-130] We controlled for the following confounders: time-varying education and income (food environment-diet); baseline age, race, sex and time-varying education, and income (diet and BMI); time-varying education, and income, center, the longitudinal neighborhood SES class, and physical activity (food environment-BMI). Since physical activity may be influenced [131,132] by the food environment and there may be unmeasured factors related to where a person lives as well as how physically active they are (e.g., preferences), we controlled for physical activity along the exposure-outcome pathway. We also modeled associations between covariates to account for dependencies between covariates. Time-varying physical activity was associated with baseline age, race, sex and current education and income while longitudinal neighborhood SES was associated with race, sex, baseline age, education, and income.

Our main interest is in the indirect pathways from the food environment to BMI through diet, as presented in detail in Figure 7. We hypothesized that stores and restaurants each sell a variety of healthy and unhealthy foods, and dietary choices are theoretically made in the context of the full dietary offerings in the neighborhood (away-from-home eating involving a choice set of restaurants and in-home eating involving a choice set of food stores), rather than in isolation.

Thus, we accounted for restaurant and food store options (separately) by including pathways from: fast food and sit-down restaurants to each of the fast food and sit-down restaurant diet factors; and supermarkets and convenience stores to each of the supermarket and convenience store diet factors.

Model fit. We defined good model fit as Root Mean Square Error of Approximation (RMSEA) <0.06 [133], and Comparative Fit Index (CFI) [134] and Tucker-Lewis Index (TLI) [135] values approaching 1.0.

Interactions. We assessed differential associations between neighborhood food resources and sex [15,34,35,37], individual-level race/ethnicity [38-42], and neighborhood SES [37,74,136]. We estimated two multi-group models (by sex, and by race): a model with freely estimated parameters for the pathways from the neighborhood food resource to diet and the pathways from the diet behaviors to BMI; and a nested model with constrained parameters to equalize associations across groups. We used a likelihood ratio test to compare the constrained versus the freed model, using no statistically significant difference ($P<0.05$) to indicate that parameters were similar between groups.

Sensitivity analyses. There is less evidence about the salient buffer size to examine restaurants versus food stores, so we compared model fit for our models (restaurants within 3 km) to 1 km and 8 km buffer sizes.

Because our models were limited to years 0, 7, and 20 because diet histories were not collected at years 10 and 15, we assessed the impact of analyzing three versus five exam years of diet behavior measures. We compared model fit and patterns of association to an identical model with fast food data at only years 0, 7, and 20.

D. RESULTS

Descriptive statistics. Mean BMI, income and years of schooling increased across 20 years of CARDIA exams, while physical activity and fast food consumption decreased over time (Table 11). Counts of neighborhood fast food and sit-down restaurants and convenience stores increased, and supermarkets remained fairly stable over 20 years (Table 12). The majority of participants were classified by either high or low neighborhood SES stability versus upward and downward mobility.

Structural equation modeling. Model 1 (Table 13) fit was adequate, however after co-varying error terms, model fit improved in Model 2, which we retained as our final SEM.

The standardized latent diet factor loadings reflected the degree to which multiple diet behaviors correlated with unique latent diet factors that we hypothesized would reflect the foods and beverages typically available at different restaurants and food stores (Table 14)

Throughout the 20-year study period, indirect pathways between fast food and sit-down restaurants suggest statistically significant associations with BMI, through diet behaviors (P<0.05). Although derived simultaneously in the same model, we present the standardized beta coefficients (interpreted as the change in one standard deviation of the outcome per standard deviation change in the exposure) for restaurants in Figures 8a and for food stores in Figures 8b. For parsimony, we present the direct pathway findings separately in Table 15. There were only two statistically significant direct associations between the food environment and BMI: at baseline both fast food restaurants and sit-down restaurants were positively associated directly with BMI. We do not present the autoregressive effects, but all were positive and statistically significant (*P*<0.001), indicating tracking of exposures and outcomes over time.

Pathways from fast food restaurants to BMI and sit-down restaurants to BMI operated indirectly through a fast food-type diet. Greater numbers of neighborhood fast food restaurants were indirectly associated with BMI through greater consumption (year 0: β=0.27, *P*<0.001, year 7: β=0.08, *P*=0.04), while greater numbers of sit-down restaurants were indirectly associated with BMI through lower consumption (year 0: β=-0.39, *P*<0.001, year 7: β=-0.10, *P*=0.004, year 20: β=-0.07, *P*=0.02) of foods typically purchased from fast food restaurants. Consumption of a fast food-type diet was statistically significantly associated with higher BMI (year 0: β=0.36, *P*=0.001, year 7: β=0.10 *P*<0.001, year 20: β=0.21 *P*<0.001). Indirect pathways from supermarkets and convenience stores to BMI, through diet behaviors were inconsistent.

Interactions. The tests for interactions by race (*P*=1.00), sex (*P*=1.00), and longitudinal neighborhood SES residency pattern (*P*=1.00) were not statistically significant.

Sensitivity Analyses. We tested Model 1 relative to two additional models (Table 14). Given lack of evidence for appropriate buffer sizes for restaurants, we compared our original 3-km buffer (Model 1) to an 8-km buffer (Model 3), which had worse fit, and a to a 1-km buffer (Model 4), which had similar model fit to Model 1.

We assessed the impact of three versus five exam years of diet behavior measures and found that the patterns of association were similar in the model using weekly fast food consumption measured at years 0, 7, and 20, compared to the identical model with fast food data at all exam years (Figures 9a and b).

E. DISCUSSION

Using pathway-based SEM and a unique environmental- and individual-level data spanning two decades, we provide evidence that changing the neighborhood availability of certain types of food resources could lead to dietary changes that could potentially reduce obesity. Findings suggest that pathways from neighborhood restaurants to BMI operate through higher consumption of an *a priori* fast food-type diet that was consistently associated with higher BMI. Living near fast food restaurants was associated with greater consumption of a fast food-type diet, while living near sit-down restaurants was associated with lower consumption of a fast food-type diet. We found no statistically significant direct or indirect pathways from neighborhood supermarkets and convenience stores to BMI through diet behaviors. Nor did we find evidence that estimated effects varied by race, sex, and longitudinal neighborhood SES.

During the 20-year study period, U.S. obesity rates increased, [1] as did numbers of neighborhood restaurants and food stores [86-89,106] and expenditures on away-from-home foods. [137] In this context, our findings suggest neighborhood fast food and sit-down restaurants seem to have comparatively stronger associations with diet behaviors and BMI, whereas supermarkets and convenience stores seem to have less consistent associations with diet behaviors and BMI.

While research on the food environment, diet behaviors, and body weight has proliferated over the past several years, most is cross-sectional and ignores the multiple pathways from environment to BMI through diet behaviors. [30-32] Thus, the bulk of the literature involves a black box step from environment to BMI and is largely mixed [see reviews [12,33]]. In one of the few longitudinal studies, Block et al. [5] found no consistent association between neighborhood fast food and full-service restaurants with BMI in Framingham adults. Yet, the Block et al. study did not address the pathway to BMI through diet.

We found very few statistically significant direct pathways from the food environment to BMI. Thus, our model suggests that previous studies with statistically significant associations between the food environment and BMI [30,138] may have been biased because they did not account for diet. In our model, greater numbers of fast food and sit-down restaurants were directly associated with higher BMI independent of diet, only at baseline (in young adulthood). This suggests that while no strong direct relationship exists between the food environment and BMI in later exam periods, there may be features associated with the food environment in early adulthood that influence BMI but not diet (e.g., aesthetics). Our study adds to the literature by using longitudinal data to model complex pathways, and our analysis simultaneously accounted for multiple food environment options and diet behaviors.

Previously, we used longitudinal CARDIA data to examine fast food restaurant and supermarket availability in separate models in which each model did not account for the wider availability of other food resources. [15] To overcome this limitation, we accounted for pathways from different types of restaurants (fast food versus sit-down restaurants) and food stores (supermarket versus convenience stores) to hypothesized restaurant and food store-type diet behaviors. While fast food and sit-down restaurants were statistically associated with obesity-related behaviors, we found stronger and more consistent associations for sit-down than fast food restaurants perhaps because there were relatively greater numbers of sit-down restaurants. Among 48,482 adult (aged 18+ years) NYC community health survey respondents, greater total food outlet density was inversely associated with BMI. [97] Our findings suggest that that even in neighborhoods with fast food restaurants, increasing sit-down restaurant options could potentially be associated with a decrease in BMI through reduced consumption of foods typically purchased from fast food restaurants.

We found no statistically significant pathways from food stores to BMI through diet. It is possible that the rise in new food and beverage products from the mid-1990s through 2010 [e.g., candy and snacks] [119] mitigated healthy dietary intake hypothesized to be associated with greater availability of supermarkets. Indeed, weaker associations between food stores compared to restaurants and healthy versus unhealthy diet behaviors may relate to a mix of unhealthy *and* healthy food options sold at supermarkets and convenience stores, as has been seen in other studies. [124,131,139,140]

Inconsistent findings in the literature might relate to patterning by neighborhood- [6,38,40,41,90,94,95,120,127] or individual-level SES. [15] However, none of these studies accounted for complex pathways from neighborhood food resources to BMI through diet behaviors. We found no evidence for variation in pathways by sex, individual-level race/ethnicity, or neighborhood SES. Our latent class variable categorized individual-level exposures to neighborhood SES over time and revealed food environment disparities [convenience stores and fewer non-fast food restaurant options in disadvantaged neighborhoods]. [120] However, our findings suggest the indirect effect of neighborhood food stores and restaurants on BMI is the same, regardless of neighborhood SES. How people interact with their environments, what and where they choose to purchase and consume food is complex. Pathway-based modeling is a step towards disentangling which features of the food environment should be modified to influence diet behaviors and improve health outcomes. Traditional regression models of a single exposure and a single outcome cannot capture these complexities.

Our study has limitations. Electronic business record data (e.g., D&B), are widely used in research and are currently the only option for retrospective longitudinal studies. Yet, these data are vulnerable to misclassification error including geospatial inaccuracy, missing data, and classification inaccuracy. [100,101] Powell et al. conducted a ground-truthed study in Chicago and some surrounding suburban/rural Census tracts, finding higher validity (D&B business listings compared to ground-truthed food store and restaurant locations) in white versus predominantly black race Census tracts and in higher compared to lower- and middle income tracts. [104] In contrast, other validation studies suggest no association between socioeconomics and agreement between business lists and field observations. [100,105] These findings might relate to differences by urbanicity, as the Powell et al. study [104] included non-urban tracts whereas the other studies suggest comparatively poor validity in rural compared to urban areas. [101,102,107-110] The CARDIA study recruited participants from four major U.S. cities and after 20 years, over 90% of them were still living either in or less than a mile away from an urban area. Therefore, differential misclassification in our data by urbanicity is not likely.

While we lacked diet record data from exam years 10 and 15, our sensitivity testing comparing models with three versus five exam years of fast food data indicated similar patterns of association between restaurants and BMI through diet behaviors. Dietary recall from a diet history has limitations that may bias reported diet behaviors. However, more rigorous methods to capture diet such as multiple 24-hour recalls are not feasible in such a large population based study. The tradeoff is that we had repeated measures of diet from three exam periods spanning 20 years during a period of considerable weight gain for the participants (mean increase of 17 kg in blacks and 12 kg in whites). [141] In addition, we lacked data on quality of foods sold at each establishment.

We did not know the specific stores and restaurants the participants frequented. Moreover, sit-down restaurants, as defined here, are a heterogeneous group of restaurants and do not necessarily represent restaurants that only sell healthy options. Lastly, residential location choice is complex and driven by more than dietary preferences. However, individual diet preferences and behaviors may be ***tied to unobserved characteristics*** (e.g., health consciousness) that determine an individuals' residential location. Not accounting for this influence (individual to environment) will bias any paths we estimate in the other direction (environment to individual), which requires a model of substantial complexity and should be a topic for future research.

We assumed our estimates were not confounded by unmeasured factors, but to our knowledge, sensitivity methods to address unmeasured bias [112] have not been adapted for longitudinal SEMs. Thus, unmeasured confounding could bias our estimates away from or towards the null.

Despite these limitations we used a large and unique GIS capturing multiple types of neighborhood food resources, spatial characteristics and demographics, with detailed diet and anthropometric data. We modeled latent factors and hypothesized causal relationships with longitudinal data from a large cohort during early- to late-adulthood. We combined multiple diet behaviors into latent factors that we hypothesized would be associated with each type of neighborhood food store or restaurant option. We included separate direct and indirect effects of neighborhood food stores and restaurants on BMI, and mediation by hypothesized diet behaviors. In addition, we accounted for other available restaurant (fast food versus sit-down) and food store (supermarkets versus convenience stores) options.

CONCLUSION

The food environment consists of a variety of food stores and restaurants that can influence consumption of a variety of foods. When we considered multiple direct and indirect pathways from a fast food and sit-down restaurants, supermarkets, and convenience stores to BMI, through diet behaviors, we found that neighborhood fast food and sit-down restaurants may play a comparatively greater role than food stores in diet behaviors and BMI.

Table 8. Specific Foods[a] and Beverages[a] Included in Each Food Group[b] to Model Latent factors for Hypothesized Diet Behaviors.

Food group	Foods
Beef	Beef
Butter	Butter
Cheese	Cheese (reduced- low-, whole-fat)
Chips	Snack chips, vegetable-based savory snack
Diet drinks	Artificially sweetened: fruit drinks, soft drinks, water, tea
Fried chicken/seafood	Fried: chicken, shellfish, fish
Fruit	Citrus fruit, non-citrus fruit, fried fruits, fruit-based savory snacks
Fruit juice	Citrus fruit juice, non-fruit juice
Low-fat milk	Low-fat milk
Nuts	Nuts, nut butter
Potatoes	White potatoes, fried potatoes
Processed meat	Cold cuts, meat snack, cured pork
Refined grains	Refined grain: flours, and dry mixes, crackers, bread/rolls, pasta, cereals, snack bars
SSB	Sweetened: fruit drinks, soft drinks, water, tea
Sweets	Candy, frosting or glaze, sugar, syrup, honey, jam, jelly, preserves, cakes, cookies, cobblers, pies, pastries, Danish, doughnuts, desserts, frozen desserts, pudding
Unprocessed red meat	Veal, lamb, pork
Vegetables	Dark green, deep yellow, and other vegetables, avocado, and tomato, vegetable juice, fried vegetables
Whole grains	Whole grain grains, flours, and dry mixes, crackers, bread/rolls, pasta, cereals,
Whole milk	Whole milk
Yogurt	Yogurt

SSB: Sugar-sweetened beverages
[a]Diet was assessed using an interviewer-administered CARDIA Diet History [59] Interviewers asked open-ended questions about dietary consumption in the past month within 100 food categories that referenced 1609 separate food items.
[b]Using a food-grouping system modified from the University of Minnesota Nutrition Coordinating Center we assigned foods into one of 13 food groups and 5 beverage groups.

Table 9. Reported Diet Behaviors (Range) Classified Into Low, Medium, and High Categories Across Exam Year: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114.

	Year 0		Year 7		Year 20	
	Range	Category	Range	Category	Range	Category
Fast food consumption per week						
	0.0 - 0.5	L	0.0 - 0.1	L	0.0 - 0.1	L
	0.7 - 1.8	M	0.1 - 0.4	M	0.1 - 0.4	M
	2.0 - 21.0	H	0.4 - 5.9	H	0.4 - 5.9	H
Reported consumption of foods within food group (servings per day)						
Beef	0.0 - 1.1	L	0.0 - 0.3	L	0.0 - 0.2	L
	1.1 - 2.4	M	0.5 - 1.8	M	0.5 - 1.6	M
	2.4 - 40.1	H	2.0 - 24.0	H	1.8 - 25.0	H
Butter	0.0 - 2.2	L	0.0 - 0.0	L	0.0 - 0.0	L
	2.2 - 4.8	M	0.0 - 0.4	M	0.0 - 0.4	M
	4.8 - 53.6	H	0.4 - 19.2	H	0.4 - 8.6	H
Cheese	0.0 - 0.4	L	0.0 - 0.8	L	0.0 - 0.6	L
	0.4 - 0.8	M	0.9 - 2.0	M	0.6 - 1.3	M
	0.8 - 6.3	H	2.0 - 34.5	H	1.3 - 12.3	H
Artificially sweetened drinks	0.0 - 0.0	L	0.0 - 0.3	L	0.0 - 0.2	L
	0.0 - 0.3	M	0.4 - 0.8	M	0.2 - 0.5	M
	0.3 - 182.1	H	0.8 - 13.1	H	0.5 - 13.5	H
Fried chicken/seafood	0.0 - 0.0	L	0.0 - 0.1	L	0.0 - 0.1	L
	0.0 - 0.1	M	0.1 - 0.7	M	0.1 - 0.6	M
	0.1 - 17.3	H	0.7 - 17.2	H	0.6 - 26.1	H
Fruit	0.0 - 0.5	L	0.0 - 0.0	L	0.0 - 0.0	L
	0.6 - 1.4	M	0.0 - 0.1	M	0.0 - 0.3	M
	1.4 - 16.2	H	0.1 - 16.2	H	0.3 - 22.5	H
Fruit juice	0.0 - 0.7	L	0.0 - 0.0	L	0.0 - 0.0	L
	0.7 - 2.0	M	0.0 - 0.1	M	0.0 - 0.2	M
	2.0 - 36.1	H	0.1 - 8.0	H	0.2 - 7.0	H

Low-fat milk	0.0 - 0.1	L	0.0 - 0.5	L	0.0 - 0.4	L
	0.1 - 0.6	M	0.5 - 1.5	M	0.4 - 1.3	M
	0.6 - 36.0	H	1.5 - 14.9	H	1.4 - 15.5	H
Nuts	0.0 - 0.1	L	0.0 - 0.4	L	0.0 - 0.2	L
	0.1 - 0.6	M	0.4 - 1.4	M	0.2 - 1.0	M
	0.6 - 21.2	H	1.4 - 47.9	H	1.0 - 16.5	H
Potato chips	0.0 - 0.1	L	0.0 - 0.4	L	0.0 - 0.3	L
	0.1 - 0.3	M	0.4 - 0.8	M	0.3 - 0.7	M
	0.3 - 12.0	H	0.8 - 8.0	H	0.7 - 10.1	H
Potatoes/fries	0.0 - 0.3	L	0.0 - 0.7	L	0.0 - 0.7	L
	0.3 - 0.8	M	0.7 - 1.7	M	0.7 - 1.8	M
	0.8 - 14.3	H	1.7 - 19.6	H	1.8 - 31.8	H
Processed meat	0.0 - 0.4	L	0.0 - 1.6	L	0.0 - 0.8	L
	0.5 - 1.3	M	1.6 - 3.8	M	0.8 - 2.1	M
	1.3 - 47.0	H	3.8 - 35.1	H	2.1 - 59.0	H
Refined grains	0.0 - 2.6	L	0.1 - 2.0	L	0.0 - 2.1	L
	2.6 - 4.9	M	2.0 - 3.8	M	2.1 - 3.8	M
	4.9 - 23.4	H	3.8 - 39.7	H	3.8 - 44.0	H
SSB	0.0 - 0.4	L	0.0 - 0.0	L	0.0 - 0.0	L
	0.4 - 1.6	M	0.0 - 0.9	M	0.0 - 1.0	M
	1.6 - 21.9	H	0.9 - 16.4	H	1.0 - 29.1	H
Sweets	0.0 - 1.4	L	0.0 - 0.3	L	0.0 - 0.1	L
	1.4 - 3.2	M	0.3 - 1.5	M	0.1 - 0.8	M
	3.2 - 30.5	H	1.5 - 24.3	H	0.8 - 16.9	H
Unprocessed red meat	0.0 - 0.1	L	0.0 - 0.0	L	0.0 - 0.1	L
	0.1 - 0.5	M	0.0 - 0.5	M	0.2 - 0.9	M
	0.5 - 14.8	H	0.5 - 24.0	H	0.9 - 25.5	H
Vegetables	0.0 - 1.6	L	0.0 - 3.3	L	0.0 - 2.1	L
	1.6 - 3.1	M	3.3 - 5.6	M	2.1 - 3.8	M
	3.1 - 33.8	H	5.6 - 30.9	H	3.9 - 29.3	H
Whole grains	0.0 - 0.3	L	0.0 - 1.5	L	0.0 - 1.1	L

	0.3 - 1.2	M	1.5 - 3.1	M	1.1 - 2.7	M
	1.3 - 13.0	H	3.1 - 35.3	H	2.7 - 73.6	H
Whole milk	0.0 - 0.0	L	0.0 - 0.1	L	0.0 - 0.1	L
	0.0 - 1.0	M	0.1 - 0.4	M	0.1 - 0.3	M
	1.0 - 16.1	H	0.4 - 14.5	H	0.3 - 30.1	H
Yogurt	0.0 - 0.0	L	0.0 - 0.4	L	0.0 - 0.5	L
	0.0 - 0.1	M	0.4 - 1.1	M	0.5 - 1.1	M
	0.1 - 3.9	H	1.1 - 24.7	H	1.2 - 12.5	H

SSB: Sugar sweetened beverages, L: low, M: medium, H: high

Table 10. Detailed Food Store and Restaurant Types Based on 8-digit Standard Industrial Classification (SIC) Codes

Food Resource Type	Description	SIC
Fast food chain restaurant	Fast-food restaurant, chain	58120307
	Pizzeria, chain	58120601
Sit-down restaurant	Fast food restaurants and stands	58120300
	Box lunch stand	58120301
	Carry-out only (except pizza) restaurant	58120302
	Chili stand	58120303
	Coffee shop	58120304
	Delicatessen (eating places)	58120305
	Drive-in restaurant	58120306
	Fast-food restaurant, independent	58120308
	Food bars	58120309
	Grills (eating places)	58120310
	Hamburger stand	58120311
	Hot dog stand	58120312
	Sandwiches and submarines shop	58120313
	Snack bar	58120314
	Snack shop	58120315
	Pizza restaurants	58120600
	Pizzeria, independent	58120602
	Mexican Restaurants	58120112
	Seafood Restaurants: Includes sushi restaurants, oyster bars & seafood shacks:	58120114
		58120700
		58120701
		58120702
	Steak House & BBQ Restaurants:	58120800
		58120801
		58120802
	Chicken Restaurants	58129904
	Family-owned restaurant chain	58120501
	Family-owned restaurant, non-chain:	58120500
		58120502
Supermarkets	Supermarkets, chain	54110101
	Supermarkets, greater than 100,000 square feet (hypermarket)	54110103
	Supermarkets, independent	54110102
	Supermarkets, 55,000 - 65,000 square feet (superstore)	54110104
	Supermarkets, 66,000 - 99,000 square feet	54110105

	Supermarkets	54110100
Convenience Stores	Variety stores	53310000
	Convenience stores	54110200
	Convenience stores, chain	54110201
	Convenience stores, independent	54110202
	Gasoline service stations	55410000
	Gasoline service stations, nec	55419900
	Filling stations, gasoline	55419901

Figure 4. Diet Behaviors Hypothesized to be Associated with Neighborhood Food Resources

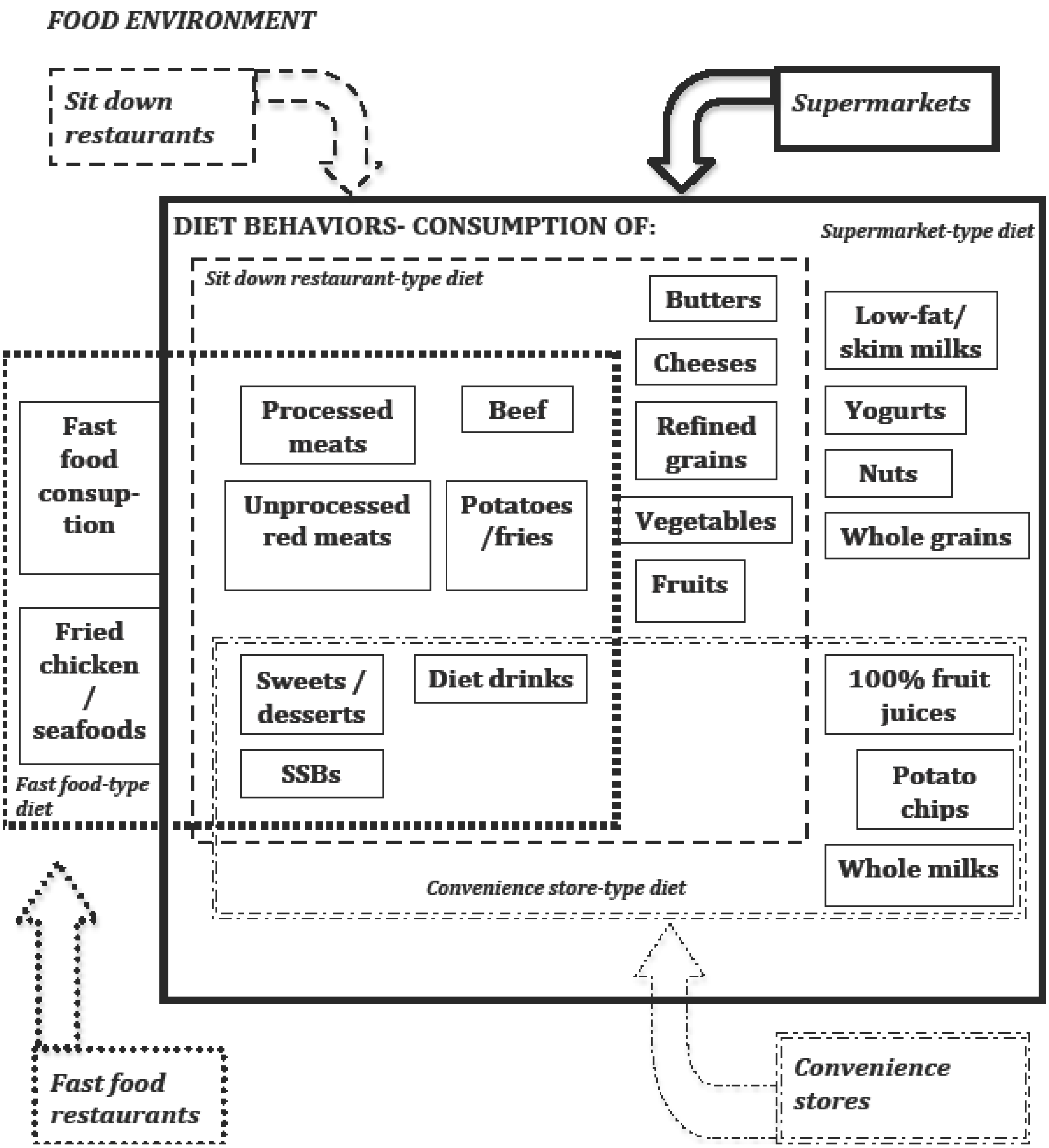
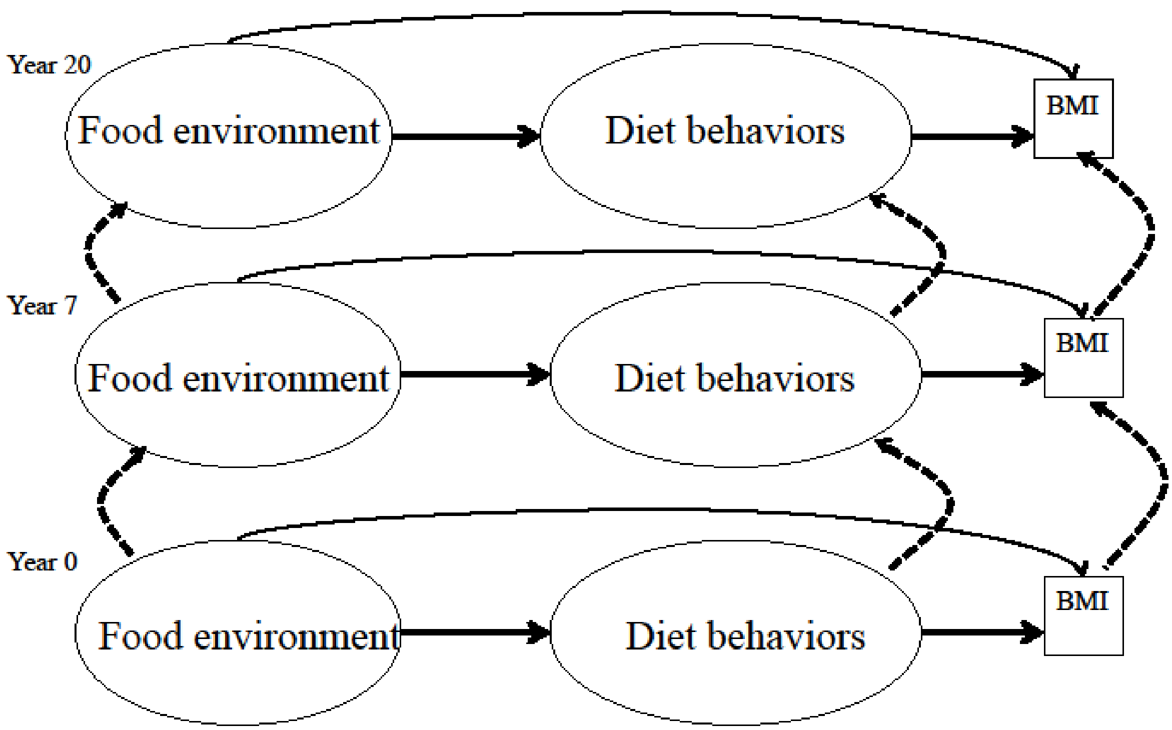
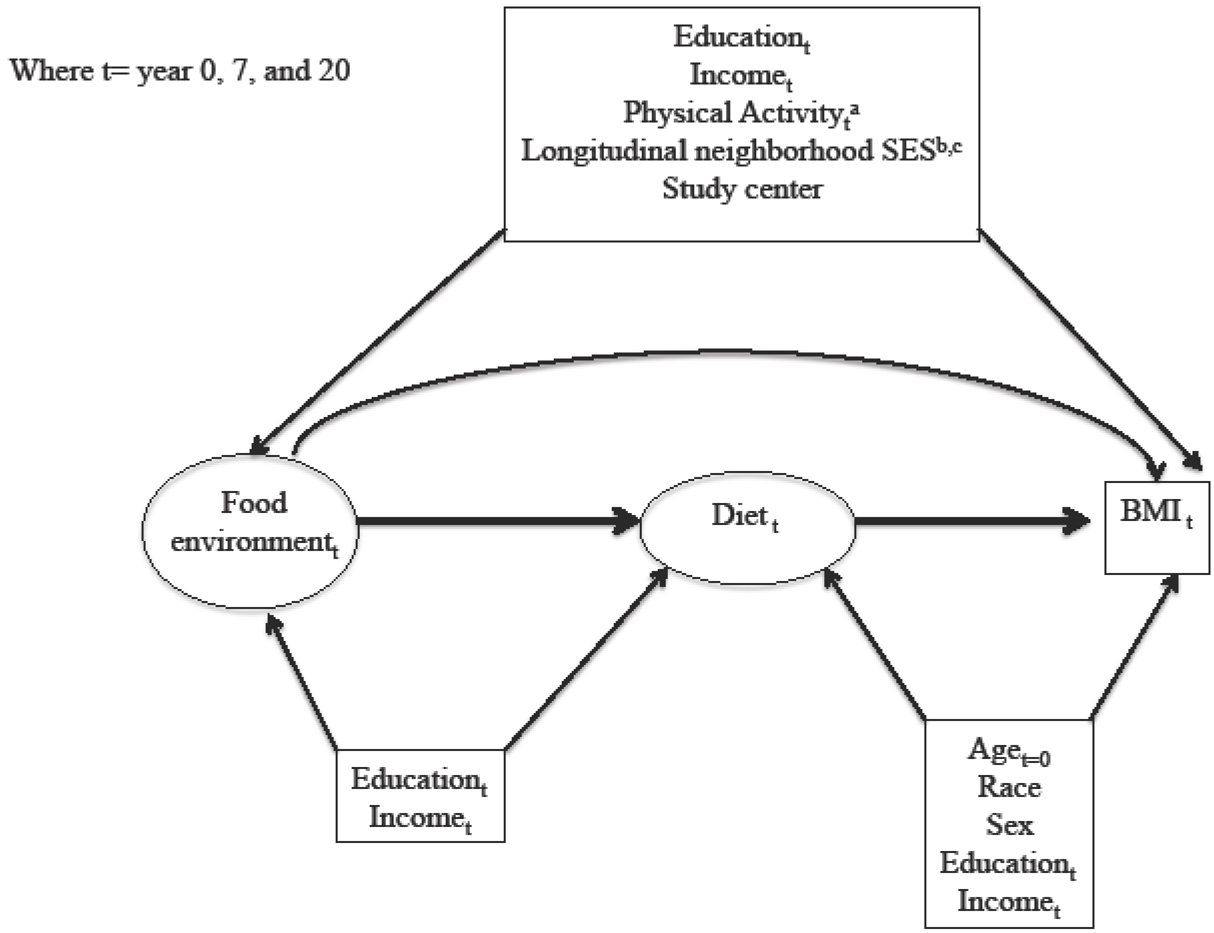


Figure 5. Conceptual Model of Temporal Associations Among Direct Pathways from Neighborhood food Environment to BMI, and Indirect Pathways from Neighborhood Food Environment to BMI Through Diet



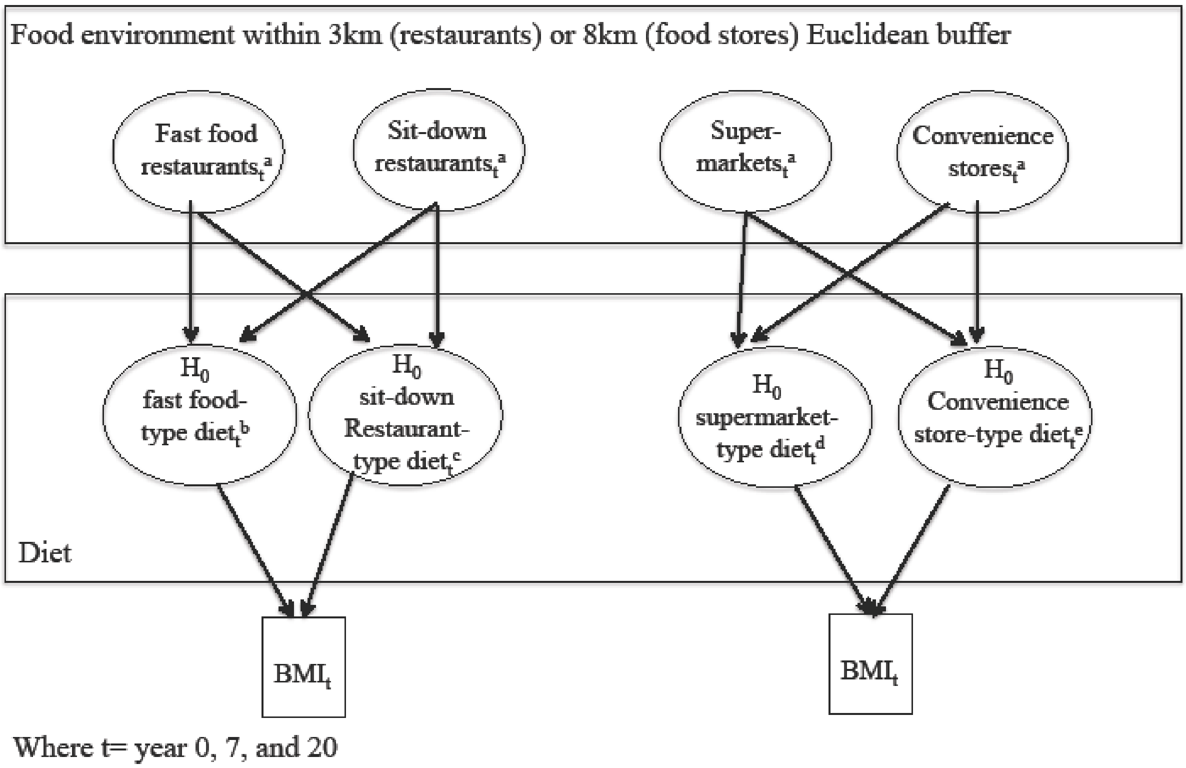
BMI: Body mass index
Figure legend. Ovals represent latent (unobserved) variables and rectangles represent observed variables. Solid arrows represent causal relationships and dashed lines represent auto-regression (linear associations between time-lagged variables).

Figure 6. Conceptual Model of Confounding Among the Direct Associations Between Neighborhood Food and BMI, and Indirect Relationships Through Diet



BMI: Body mass index, SES: socioeconomics
Figure legend. Ovals represent latent (unobserved) variables and rectangles represent observed variables.
[a]Time-varying physical activity was associated with baseline age, race, sex and current education and income.
[b]Derived from latent class analysis using Mplus version 7.11[84] of Census tract-level data from exam years 0, 7, 10, 15, and 20: % race white, % education <high school, % poverty (below 150% federal poverty level), % unemployed, % professional/management occupation, median income, % vacant housing, aggregate housing value, % owner occupied, median rent[120].
[c]Longitudinal neighborhood SES was associated with race, sex, baseline age, education, and income.

Figure 7. Conceptual Model of Indirect Pathways from Neighborhood Restaurants and Food Stores to BMI Mediated Through Hypothesized Diet Behaviors



BMI: Body mass index

Figure legend. Ovals represent latent (unobserved) factors and rectangles represent observed variables. Solid arrows represent causal relationships.

[a] Latent food environment factors indicated by: count of the food resources within 3km (restaurants) or 8km (food stores) Euclidean buffer per 10km local/secondary roadway and population density Z-scores from U.S. Census-tract level data spatially linked to respondent residential locations and temporally linked to CARDIA exam years (Year 0, 1980; Years 7 and 10, 1990; Year 15 and 20, 2000).

[b]Latent fast food-type diet indicated by: fast food consumption per week and servings per day of fried chicken/seafood, processed meats, unprocessed meats, beef, potatoes/fries, sweets/desserts, sugar-sweetened beverages, and diet drinks.

[c]Latent sit-down restaurant-type diet indicated by: servings per day of processed meats, unprocessed meats, beef, potatoes/fries, sweets/desserts, sugar-sweetened beverages, diet drinks, butter, cheeses, refined grains, vegetables, and fruits.

[d]Latent supermarket-type diet indicated by: servings per day of processed meats, unprocessed meats, beef, potatoes/fries, sweets/desserts, sugar-sweetened beverages, diet drinks, butter, cheeses, refined grains, vegetables, fruits, low-fat/skim milks, whole milks, yogurts, nuts, whole grains, 100% fruit juices, and potato chips.

[e]Latent convenience store-type diet indicated by: servings per day of sweets/desserts, sugar-sweetened beverages, diet drinks, whole milks, 00% fruit juices, and potato chips.

Table 11. Individual-level Characteristics by Exam year: Coronary Artery Risk Development in Young Adults (CARDIA), 1985/1986 to 2005/2006, n=5,114

	Year 0	Year 7	Year 10	Year 15	Year 20
N	5114	4085	3949	3671	3549
White race, %	51.6	48.3	48.8	47.1	46.5
Male sex, %	45.5	44.9	44.4	44.1	43.3
BMI (kg/m^2), mean (SD)	24.5 (0.1)	26.7 (0.1)	27.5 (0.1)	28.7 (0.1)	29.4 (0.1)
Education[a], mean (SD) y	13.8 (0.0)	14.7 (0.0)	14.9 (0.0)	15.2 (0.0)	15.4 (0.0)
Income[b], mean (SD) per $10,000	6.3 (0.1)[a]	5.3 (0.1)	5.6 (0.1)	7.2 (0.1)	8.0 (0.1)
Physical activity index[c], mean (SD)	420 (4.2)	338 (4.3)	331 (4.4)	347 (4.7)	336 (4.6)
Frequency of fast food consumption, mean (SD) times/wk	2.0 (0.0)	1.9 (0.0)	1.7 (0.0)	1.8 (0.0)	1.7 (0.0)

BMI: Body mass index, SD: Standard deviation.
[a]Highest year of education reported from Year 0 through year 20.
[b]Income per $10,000, inflated to year 20 and income was not queried at exam year 0 so closest measure at year 5 is used as a proxy.
[c]Physical activity scores were calculated in exercise units based on frequency and intensity of each activity[71].

Table 12. Neighborhood-level Characteristics Across Exam Year: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.

	Year 0	Year 7	Year 10	Year 15	Year 20
Number of neighborhoods[a]	799	2508	3406	3460	3645
Counts of food resources[b] within 3km (restaurants) or 8km (food stores) Euclidean respondent residential buffer per 10km of local and secondary roadways [median (interquartile range)] :					
Fast food restaurants	0.2 (0.1,0.2)	0.2 (0.1,0.3)	0.2 (0.1,0.3)	0.2 (0.1,0.3)	0.4 (0.2,0.6)
Sit-down restaurants	2.8 (1.4,5.1)	3.4 (1.5,6.5)	2.4 (1.2,4.7)	2.7 (1.4,4.6)	2.9 (1.5,5.3)
Supermarkets	0.0 (0.0,0.1)	0.1 (0.1,0.2)	0.1 (0.0,0.1)	0.1 (0.1,0.1)	0.1 (0.1,0.2)
Convenience stores	0.6 (0.5,0.7)	1.0 (0.7,1.2)	0.8 (0.6,0.9)	0.7 (0.6,0.8)	0.8 (0.6,1.0)
Longitudinal neighborhood SES residency pattern[c] [% of participants]					
Downwardly mobile neighborhood SES	19.8	17.7	18.0	17.1	17.2
Stable low neighborhood SES	30.9	30.0	29.9	29.6	28.5
Upwardly mobile neighborhood SES	13.0	13.9	14.1	14.8	15.2
Stable high neighborhood SES	36.3	38.3	38.0	38.6	39.1

[a]Total number of census tracts.

[b]Dunn & Bradstreet food resources.

[c]Derived from latent class analysis using Mplus version 7.11[84] of Census tract-level data from exam years 0, 7, 10, 15, and 20: % race white, % education <high school, % poverty (below 150% federal poverty level), % unemployed, % professional/management occupation, median income, % vacant housing, aggregate housing value, % owner occupied, median rent[120].

Table 13. Model Fit Estimates From Structural Equation Models Examining the Pathways From Neighborhood Restaurants to BMI Through Hypothesized Diet Behaviors: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114.

	CFI	TLI	RMSEA
Model 1	0.58	0.55	0.06
Model 2	0.82	0.80	0.04
Model 3	0.55	0.51	0.06

RMSEA: Root Mean Square Error of Approximation, CFI: Comparative Fit Index, TLI: Tucker-Lewis Index

Model 1: initial SEM tested as hypothesized in Figures 2a and b with restaurants aggregated within 3 km Euclidean buffer.

Model 2: Model 1 + allowing the error terms to co-vary across and within the repeated neighborhood food resource, diet, BMI, education, income, and latent factors.

Model 2: Model 1 using counts of restaurants within 8 km Euclidean respondent residential buffer.

Model 3: Model 1 using counts of restaurants within 1 km Euclidean respondent residential buffer.

Figure 8a. Standardized Estimates From Structural Equation Models Examining the Indirect Pathways From Neighborhood Restaurants to BMI Mediated by Hypothesized Diet Behaviors: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114

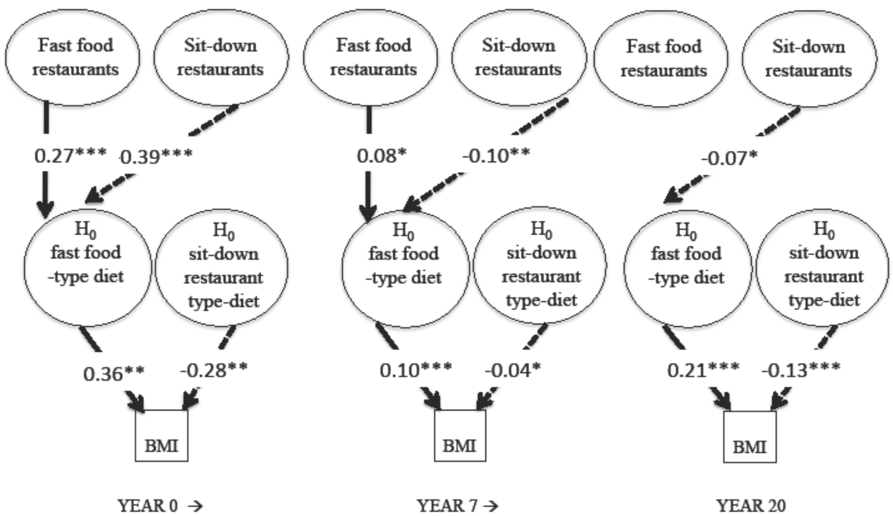


Figure 8b. Standardized Estimates From Structural Equation Models Examining the Indirect Pathways From Neighborhood Food Stores to BMI Mediated by Hypothesized Diet Behaviors: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114.

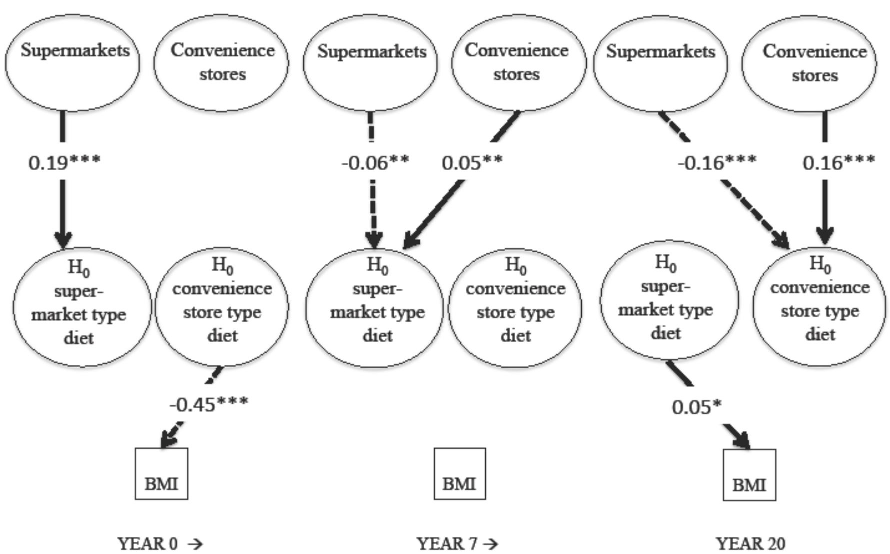


Figure legend. Ovals represent latent (unobserved) variables and rectangles represent observed variables. The time varying and invariant covariates omitted from the figure for clarity were: longitudinal neighborhood SES residency pattern, center, age at year 0, race, and sex individual-level education, income, and physical activity. Arrows represent estimated associations. Further omitted for clarity were: direct pathways, non-statistically significant associations ($P \geq 0.05$), indicators of latent variables, arrows for co-varying error terms, and the autoregressive pathways for the latent neighborhood food resource availabilities, the diet behaviors, and the BMI measures. Model estimated with Mplus version 7.11[84]

*$P<0.05$, **$P<0.01$, ***$P<0.001$

Table 14. Standardized factor loadings from structural equation measurement models[a] for latent neighborhood food resource and diet behavior variables: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.

Latent factors	Indicators	Factor loadings, λ (p-value)					
		Year 0		Year 7		Year 20	
Neighborhood:		λ	*P*-value	λ	*P* -value	λ	*P* -value
fast food restaurant availability	Count of fast food restaurants within 3 km Euclidean buffer per 10km of local and secondary roadways[b,c]	1.00	---	1.00	---	1.00	---
	Population density[d]	0.12	0.000	0.17	0.000	-0.09	0.000
non-fast food restaurant availability	Count of non-fast food restaurants within 3 km Euclidean buffer per 10km of local and secondary roadways[b,c]	1.00	---	1.00	---	1.00	---
	Population density[c]	0.38	0.000	0.36	0.000	0.53	0.000
supermarket availability	Count of supermarkets within 3 km Euclidean buffer per 10km of local and secondary roadways[b,c]	1.00	---	1.00	---	1.00	---
	Population density[d]	-0.05	0.000	0.11	0.000	0.37	0.000
convenience store availability	Count of convenience stores within 3 km Euclidean buffer per 10km of local and secondary roadways[b,c]	1.00	---	1.00	---	1.00	---
	Population density[d]	0.40	0.000	0.34	0.000	0.19	0.000
Hypothesized diet behaviors associated with: fast food restaurants	Fast food consumption per week*	0.42	0.000	0.59	0.000	0.61	0.000
	Potatoes/fries	0.25	0.000	0.10	0.854	0.10	0.005
	Processed meats	0.19	0.000	0.14	0.000	0.05	0.235
	Beef	0.13	0.003	0.11	0.000	-0.06	0.137
	Fried chicken/seafood	0.08	0.001	0.51	0.000	0.47	0.000

	Sweets/desserts	0.20	0.000	0.04	0.172	0.04	0.234
	SSB	0.26	0.000	0.13	0.000	0.09	0.000
	Diet drinks	0.20	0.000	0.14	0.000	0.23	0.000
Sit-down restaurants	Refined grains*	0.79	0.000	0.75	0.000	0.72	0.000
	Processed meats	0.51	0.000	0.51	0.000	0.55	0.000
	Potatoes/fries	0.47	0.000	0.49	0.000	0.46	0.000
	Beef	0.67	0.000	0.66	0.000	0.69	0.000
	Unprocessed red meat (pork/veal/lamb)	0.53	0.000	0.51	0.000	0.43	0.000
	Sweets/desserts	0.18	0.000	0.29	0.000	0.19	0.000
	SSB	0.09	0.017	0.12	0.000	0.09	0.006
	Diet drinks	-0.03	0.460	0.02	0.585	-0.07	0.068
	Cheese	0.46	0.000	0.43	0.000	0.37	0.000
	Vegetables	0.33	0.000	0.24	0.000	0.06	0.013
	Fruit	0.15	0.000	0.02	0.243	-0.06	0.000
	Butter	0.67	0.000	0.58	0.000	0.46	0.000
Supermarkets	Cheese*	0.56	0.000	0.44	0.000	0.45	0.000
	Refined grains	0.26	0.000	0.31	0.000	0.24	0.000
	Potato chips	0.19	0.002	0.23	0.000	0.18	0.000
	Potatoes/fries	0.29	0.000	0.26	0.000	0.17	0.000
	Processed meats	0.07	0.024	0.10	0.000	0.12	0.000
	Unprocessed red meat (pork/veal/lamb)	0.07	0.011	0.05	0.045	0.10	0.000
	Beef	0.24	0.000	0.14	0.000	0.20	0.000
	Sweets/desserts	0.36	0.000	0.34	0.000	0.29	0.000
	SSB	-0.03	0.606	0.03	0.650	0.06	0.567
	Diet drinks	0.23	0.001	0.25	0.000	0.19	0.035
	Vegetables	0.69	0.000	0.64	0.000	0.58	0.000

	Fruit	0.45	0.000	0.46	0.000	0.41	0.000
	Butter	0.26	0.000	0.20	0.000	0.26	0.000
	Juice	0.50	0.000	0.43	0.000	0.41	0.000
	Nuts	0.35	0.000	0.27	0.000	0.41	0.000
	Whole grains	0.38	0.000	0.43	0.000	0.39	0.000
	Yogurt	0.49	0.000	0.43	0.000	0.39	0.000
	Low-fat milk	0.35	0.000	0.34	0.000	0.30	0.000
	Whole milk	0.06	0.508	-0.05	0.494	0.06	0.146
Convenience stores	Whole milk*	0.50	0.000	0.38	0.000	0.20	0.000
	Sweets/desserts	0.34	0.000	0.24	0.000	0.25	0.000
	SSB	0.24	0.000	0.36	0.000	0.52	0.000
	Diet drinks	-0.39	0.000	-0.40	0.000	-0.48	0.000
	Juice	0.50	0.000	0.38	0.000	0.57	0.000
	Potato chips	0.50	0.000	0.20	0.000	0.18	0.000

*Referent indicator

[a]Derived from structural equation modeling using Mplus version 7.11[84]

[b]Counts of Dunn & Bradstreet food resources.

[c]Residual variances were set to zero to facilitate convergence.

[d]Population density Z-scores from U.S. Census-tract level data spatially linked to respondent residential locations and temporally linked to CARDIA exam years (Year 0, 1980; Years 7, 1990; Year 15 and 20, 2000).

Table 15. Standardized Estimates From Structural Equation Models[a] Examining the Direct Pathways From Neighborhood Food Resources to BMI: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114.

		β	*P*-value
Year 0			
BMI on:	Fast food restaurants[b]	0.13	0.002
	Sit-down restaurants[b]	0.12	0.03
	Supermarkets[b]	0.09	0.19
	Convenience stores[b]	0.01	0.56
Year 7			
BMI on:	Fast food restaurants[b]	0.02	0.31
	Sit-down restaurants[b]	0.00	0.93
	Supermarkets[b]	0.01	0.61
	Convenience stores[b]	-0.02	0.06
Year2 0			
BMI on:	Fast food restaurants[b]	-0.01	0.61
	Sit-down restaurants[b]	0.02	0.26
	Supermarkets[b]	0.02	0.22
	Convenience stores[b]	-0.03	0.1

BMI: Body mass index

[a]Derived from structural equation modeling using Mplus version 7.11

[b]Latent factors modeled with by: counts of Dunn & Bradstreet food resources within Euclidean 3km buffer per 10 km local and secondary roadways and population density (U.S. Census-tract level data spatially linked to respondent residential locations and temporally linked to CARDIA exam years (Year 0, 1980; Year7, 1990; and 20, 2000).

Figure 9a. Standardized Estimates From Sensitivity Structural Equation Models Examining the Indirect Pathways From Neighborhood Restaurants to BMI Mediated by Hypothesized Diet Behaviors, Using Fast Food Consumption at Exam Years 0, 7,10, 15, and 20: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114.

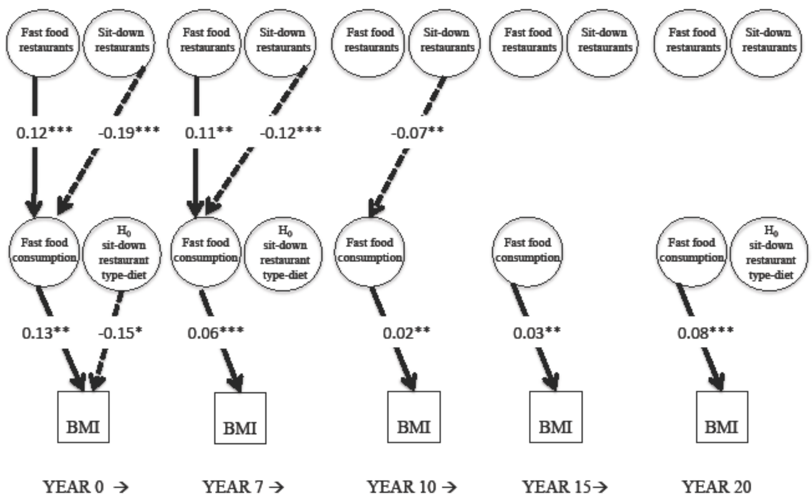
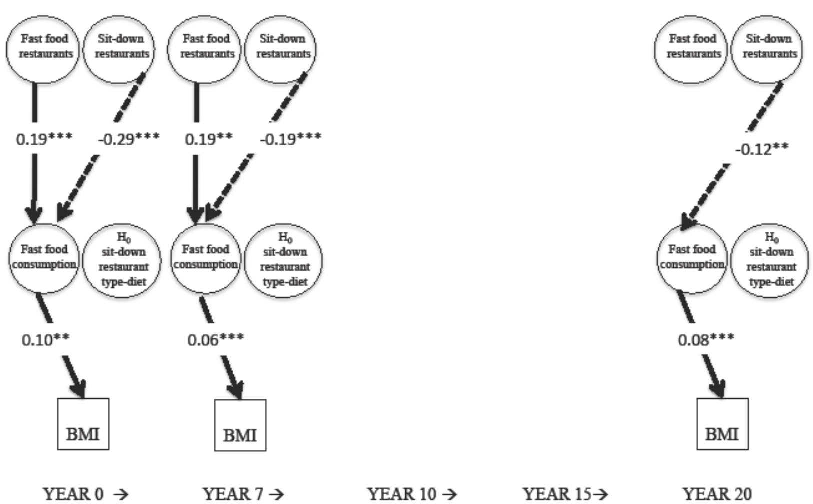


Figure 9b. Standardized Estimates From Sensitivity Structural Equation Models Examining the Indirect Pathways From Neighborhood Restaurants to BMI Mediated by Hypothesized Diet Behaviors, Using Fast Food Consumption at Exam Years 0, 7,10, 15, and 20: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114.



BMI: Body mass index

[a] Comparative Fit Index =0.71, Tucker-Lewis Index=0.68, and Root Mean Square Error of Approximation =0.05.
[b] Comparative Fit Index =0.70, Tucker-Lewis Index=0.67, and Root Mean Square Error of Approximation =0.05.

Figure legend. Ovals represent latent (unobserved) variables and rectangles represent observed variables. The time varying and invariant covariates omitted from the figure for clarity were: longitudinal neighborhood SES residency

pattern, center, age at year 0, race, and sex individual-level education, income, and physical activity. Arrows represent estimated associations. Further omitted for clarity were: non-statistically significant associations ($P \geq 0.025$), indicators of latent variables, arrows for co-varying error terms, and the autoregressive pathways for the latent neighborhood food resource availabilities, the diet behaviors, and the BMI measures (e.g., BMI at year 20 is regressed on BMI at year 7 and BMI at year 7 is regressed on BMI at year 0). The auto-regressive pathways connect the pathways at years 7 and 20 to the pathway at year 0 which includes the time-invariant covariates. Thus, pathways at years 7 and 20 also account for the time-invariant covariates. Model estimated with Mplus version 7.11[84]
*P<0.05, **P<0.01, ***P<0.001

CHAPTER VI: HOW MUCH DOES REVERSE CAUSALITY BIAS ASSOCIATIONS BETWEEN THE FOOD ENVIRONMENT, DIET, AND BODY MASS INDEX? A STRUCTURAL EQUATION-BASED METHOD USING 20 YEARS OF NEIGHBORHOOD, DIET, AND ANTHROPOMETRY DATA FROM THE CARDIA STUDY

A. ABSTRACT

Obesity reduction strategies commonly target neighborhood food resources without considering reverse causality. When estimating associations between neighborhood food stores and restaurants, with diet and body mass index (BMI), reverse causality (individual diet preferences shaping residential neighborhood selection) is often ignored and could bias relevant pathways. We used longitudinal data from participants enrolled in the Coronary Artery Risk Development in Young Adults (n=5,114; 1985-86 to 2005-06) and structural equation modeling to examine) pathways from neighborhood fast food and sit-down restaurants, supermarkets and convenience stores to BMI, through diet behaviors hypothesized to be more commonly associated with each of the neighborhood food store and restaurant types. We controlled for socioeconomic status and physical activity. We explicitly investigated reverse pathways finding statistically significant associations between period-specific diet behaviors and future neighborhood food resources ($p<0.05$). Findings were similar in models with and without reverse pathways, suggesting both neighborhood fast food and sit-down restaurants were associated with higher BMI through the consumption foods typically purchased from fast food restaurants (i.e., fast food-type diet) ($p<0.05$). However, after adjusting for reverse pathways, we found evidence

in early adulthood, that neighborhood fast food and sit-down restaurants *also* associated with lower BMI through the consumption of a sit-down restaurant-type diet ($p<0.05$). Attention to reverse pathways from diet behaviors to food environment, suggests that there are individual preferences/constraints related to diet that are associated with future neighborhood food stores and restaurants. Accounting for reverse causality, with reverse pathways from period-specific diet behaviors to future neighborhood food resources, increased magnitude and strength of the associations between neighborhood restaurants and diet behaviors, but did not change the associations between neighborhood food stores and diet behaviors.

B. INTRODUCTION

Obesity rates in the U.S. have increased drastically over the last few decades, with socioeconomically disadvantaged populations disproportionately affected.[1] National and local efforts have targeted neighborhood food resources as a means to improve diet quality in disadvantaged areas.[7-9] Yet, findings from studies that examine how features of the food environment or neighborhood relate to individual-level diet and obesity are mixed. Furthermore, reverse causality bias remains largely unaddressed.[10] Thus, the inability to control for unmeasured characteristics (e.g., attitudes and preferences) that relate to where people choose to live as well as related health outcomes remain fundamentally unaddressed in the neighborhood literature on food environments and weight-related outcomes. However, evidence is increasing suggesting that preferences for specific neighborhood amenities guide residential location choice and can have an association with behavior.[47-52] Thus, health conscious individuals may choose to consume healthier diets and they may also select neighborhoods that support or encourage healthy diets, thus creating spurious positive associations between neighborhood food stores and restaurants with higher diet quality. A further complication is that higher quality food environments may be more likely to be situated in higher SES neighborhoods.

Thus, it is imperative that studies address this source of reverse causality (the influence of diet behaviors of given individuals on the types of food stores and restaurants found in their neighborhoods). Furthermore, examining these associations with longitudinal data to understand the sequence of diet and neighborhood choices can inform understanding of the direction of these associations. Even better, statistical methods that can estimate complex and bidirectional relationships between neighborhood environments, behaviors, and health outcomes can provide important insights into these complexities.

Structural equation modeling (SEM) is a pathway-based approach that can handle multiequation and bi-directional models and allow quantification and testing of hypothesized relationships among latent (unobserved) and observed variables. SEMs are well-suited to estimate a broad range of effects [122] and multiple estimated effects transmitted over combinations of paths. [121]

We used a longitudinal SEM in a large prospective cohort of adult black and white Americans over 20 years to estimate pathways from neighborhood fast food and sit-down restaurants, supermarkets and convenience stores to BMI (directly) and indirectly through diet behaviors, as well allow for their reverse pathways. First, we quantified the indirect pathways from food resources to BMI, through the consumption of specific foods typically acquired at each type of food resource. We hypothesized that the estimated pathways from neighborhood restaurants and food stores to BMI would operate indirectly through the consumption of specific foods typically acquired from restaurants versus food stores. We included direct pathways between food resources to BMI designed to capture neighborhood effects that occur through unmeasured factors that are independent of diet, such as the aesthetics. For example, the aesthetics of natural and built environments can be related to food resources and can influence physical activity[118] and consequently BMI. Second, we added reverse pathways from period-specific diet behaviors to future neighborhood food resources to compare patterns of association in the models with and without reverse pathways.

C. METHODS

STUDY POPULATION

The Coronary Artery Risk Development in Young Adults (CARDIA) is a longitudinal cohort with detailed diet, clinic, physical activity, environmental, demographic, and socioeconomic data collected for 5,114 white or black United States (U.S.) adults aged 18-30 years originally from 4 centers: Birmingham, AL; Chicago, IL; Minneapolis, MN; and Oakland, CA. Participants were selected in 1985-86 with approximately equal numbers by race, gender, education (high school or less versus more than high school), age (18-24 years versus 25-30 years) within each center, and followed over 5 exams during 1992-93 (Year 7), 1995-96 (Year 10), 2000-01 (Year 15), and 2005-06 (Year 20). Retention rates were 81%, 79%, 74%, and 72% (3,549), respectively, of the surviving cohort.

We used data from a geographic information system (GIS)-derived dataset of time-varying neighborhood-level food resources and U.S. Census data that were spatially and temporally linked to CARDIA respondent residential locations at each exam year. Study data were collected under protocols approved by Institutional Review Boards at each study center and the University of North Carolina at Chapel Hill.

BODY MASS INDEX

At each examination, participants' weight was measured to the nearest 0.2 kg and height was measured to the nearest 0.5 centimeter. BMI is calculated as weight in kilograms divided by height in meters squared and measured at exam years 0, 7, 10, 15, and 20. We examined years 0,7, and 20 to correspond with the primary diet measures described below.

DIETARY ASSESSMENT

An interviewer-administered CARDIA Diet History[59] at exam years 0, 7, and 20 was used to assess diet. Interviewers asked open-ended questions about dietary consumption in the past month within 100 food categories that referenced 1609 separate food items. We modified a food-grouping system devised by the University of Minnesota Nutrition Coordinating Center, whereby we assigned foods into one of 13 food groups and 5 beverage groups [assessed as servings per day of constituent foods (Table 16)] shown to be associated with weight change per 4-year period in the Nurse's Health Study I and II, and the Health Professionals Follow-up Study[19] and cardiometabolic outcomes.[60] We also used survey data collected at exam years 0, 7, 10, 15, and 20 regarding the number of times per week respondents ate meals at fast food restaurants.[18] We categorized weekly fast food restaurant visits and servings per day of consumed foods and into low, medium, or high consumption, either by year-specific tertiles or as non-consumers (0 servings per day) versus upper and lower distributions of consumers (≥1 serving per day), values defined in Table 17. We used year-specific tertiles to allow for temporal changes in diet behaviors.

We set reported diet behaviors and BMI to missing when participants had either extreme caloric intakes:[61] kcal per day <800 or >8000 for men (n=73 at year 0, n=60 at year 7, and n=25 at year 20); and kcal per day <600 or >6000 for women (n=53 at year 0, n=34 at year 7, and n=29 at year 20) and for pregnant women (n= 7 at year 0, n=62 at year 7, and n=6 at year 20).

NEIGHBORHOOD FOOD ENVIRONMENT

We obtained counts of chain fast-food restaurants (hereafter referred to as fast food restaurants), all other restaurants not classified as chain fast food (hereafter referred to as sit-down restaurants), supermarkets, convenience stores from Dun and Bradstreet (D&B), a commercial dataset of U.S. business records using 8-digit Standard Industrial Classification (SIC) codes for years 7, 10, 15, and 20 and a combination of 4 digit SIC codes and matched business names at year 0 (Table 18). We used a 3 kilometer (km) Euclidean buffer around each respondent's residential location for restaurants[15,62] and an 8 kilometer (km) Euclidean buffer for food stores,[62,63] based on empirical evidence. Using StreetMap 2000 (v. 9.0) for years 7 (1993) and 10 (1996), from StreetMap Pro 2005 (v. 5.2) for year 15 (2001), and from StreetMap Pro 2010 (v. 7.2) for year 20, (Environmental Systems Research Institute; ESRI, www.esri.com: Redlands, CA), we calculated densities of restaurants and stores as counts per 10 km secondary (roads used to connect smaller towns, subdivisions, and neighborhoods) and local (roads used for local traffic, usually with a single lane of traffic in each direction) roadway, resulting in a measure of concentration of food resources along streets representing overall commercial activity.[64,65] We also included variables reflecting urbanicity and development as these relate directly to the food environment. Given that population density varies across roadway structure[66] and across rural versus urban areas;[67] population density and commercial development were independently associated with geographic food resource distribution and were not highly correlated in our data ρ=0.35. Therefore, we included population density (representing area-level development and population) and counts per roadway (representing commercial development) in our analyses.

AREA-LEVEL SOCIOECONOMIC INDICATORS

Neighborhood SES was derived at the U.S. census tract-level at all years; tract-level SES is more strongly associated with health outcomes block group-level SES.[68,69] We conceived of neighborhood SES as a latent construct comprised of multiple SES domains and as an individual-level exposure; that is, people may experience temporal changes in neighborhood SES through residential movement or changes around a given residential location. In addition, depending on neighborhood SES, food environments may improve or worsen over time. We used an SES composite variable that we have used in other analyses [120] to characterize temporal patterns of neighborhood SES, which we derived using data from years 0, 7, 10, 15, and 20: % race white, % education <high school, % poverty (below 150% federal poverty level[70]), % unemployed, % professional/management occupation, median income, % vacant housing, aggregate housing value, % owner occupied, median rent. Our longitudinal neighborhood SES class variable characterized neighborhoods of downwardly or upwardly mobile neighborhood SES, or stable high or low neighborhood SES. We also used population density (census tract population per square kilometer of land excluding water) as an indicator of area-level development.

INDIVIDUAL-LEVEL CONFOUNDERS

We characterized individual-level confounders using data from structured interview or self-administered questionnaire collected at each exam year. Time-invariant sociodemographic variables were sex, race (white/black), exam attendance, and center. Time-varying characteristics were maximum reported number of years of schooling completed by the exam year (continuous), and mean household income inflated to U.S. dollars at year 20 (2005-06) using the Consumer Price Index. Income was not collected in year 0, so we used the closest measurement (year 5) for year 0. At each exam, participants reported on 13 different categories of moderate and vigorous recreational sports, exercise, leisure, and occupational activities in the past 12 months and scores were calculated based on frequency and intensity of each activity.[71]

STATISTICAL ANALYSES

We performed all descriptive analyses and multivariable models using Stata 13.0 (StataCorp, College Station, TX). Descriptive statistics included calculation of means and standard deviations (continuous variables) and percentages (categorical variables) of individual-level characteristics at exam years 0, 7, 10, 15, and 20.

Latent factors used in structural equation modeling

Latent factors are underlying complex concepts that are not directly observed, but can be inferred mathematically from multiple observed variables. Thus, estimating latent factors is a useful way of summarizing a number of variables into a one meaningful factor.

We constructed latent factors for diet behaviors and food environment.

Food environment. We created latent factors for each neighborhood food store and restaurant factors type (fast food restaurant, sit-down restaurant, supermarket and convenience stores) at each year using observed indicators: count per 10km local and secondary roadway within 8km (food stores) or 3km (restaurants) Euclidean buffer and the Z-score of population density.

Diet behaviors. We hypothesized that certain food groups reflected the types of foods commonly offered at each specific type of store or restaurant[123-126] and that the restaurants and food stores would be associated with the consumption of these foods, as shown in separate boxes in Figure 10. We created four latent diet behavior factors for each year (fast food restaurant-type diet; sit-down restaurant-type diet, supermarket-type diet, and convenience store-type diet) using intake categories of foods we considered, *a priori*, to be acquired at each type of establishment. Specifically, we made the following *a priori* assignments: foods typically acquired from **fast food restaurants** include fast foods (e.g., processed meats, fried chicken/seafood, and fries)**;** consumption of foods from **sit-down restaurants** consisted of meats, fruits, vegetables, cheeses, whole grain food, and some fast foods; consumption of foods from **convenience stores** included snack-type foods/beverages; consumption of foods from **supermarkets** included foods/beverages from all groups except fried chicken/seafood, which we hypothesized would be typically consumed as prepared food at restaurants. Our approach differs from standard approaches that classify establishments on the basis of selling "healthy"[127] or "unhealthy"[81] foods. Rather, our approach allowed for the fact that identical foods can be acquired from a range of stores and restaurants.

Structural equation modeling

First, we constructed a <u>single</u> causal framework using simultaneous regression models to examine pathways from neighborhood food stores and restaurants to BMI, including direct and indirect pathways through diet behaviors. Second, we added reverse pathways from current diet behaviors to the following period's neighborhood food stores and restaurants. We used Mplus version 7.11[84] with maximum likelihood and missing values; statistical significance was set at $P<0.05$ (2-sided).

Figure 11 presents our conceptual model of reverse pathways in the context of the longitudinal direct and indirect pathways of the food environment (neighborhood food stores and restaurants), BMI and diet, with linear association between time-lagged variables or auto-regression (e.g., current BMI influences future BMI). The auto-correlation explicitly addresses the well-recognized tracking of health status and behaviors over time. We hypothesized that tracking between the years closest in time is more relevant than across the full 20-year period so we only included auto-regression between variables from years 0 to 7 and years 7 to 20. We hypothesized that the associations between the food environment, diet, and BMI operate concurrently so we did not include pathways from the food environment to outcomes at later exams, except through tracking of the food environment over time. We also assumed that the food environment impacts diet, which in turn, impacts BMI and that the indirect effect of the food environment on BMI operates solely through diet. We allowed for direct effects of the food environment on BMI because there may be unmeasured factors in the food environment that influence BMI. For example, a neighborhood with many food resources may be perceived as aesthetically displeasing because it lacks natural spaces and parks. Then residents may limit their outdoor physical activity,[118] increasing their risk of unwanted weight gain.

We assumed that all relationships were linear and that there was no interaction between food environments and diet behavior. We designed the analysis to examine how the indirect pathways from the food environment to BMI through diet, changed when we included reverse pathways from period-specific diet behaviors to future food environments.

Our research question relates to the relationship between the food environment, diet behaviors, and BMI (Figure 12). In addition, we considered several types of confounding variables. Race and sex are time-invariant variables that we consider to influence only individual-level variables, diet and BMI. We addressed confounding of food environment-diet, diet-BMI, and food environment-BMI associations after excluding diet-BMI confounders that were likely affected by the food environment:[66,128-130] time-varying education and income (food environment-diet); baseline age, race, sex and time-varying education, and income (diet and BMI); time-varying education, and income, center, the longitudinal neighborhood SES class, and physical activity (food environment-BMI). Since access to diverse destinations may promote physical activity and physical activity may contribute to better weight regulation,[142] we controlled for physical activity along the food environment (exposure)- BMI (outcome) pathway. We also modeled associations between covariates to account for dependencies between covariates. For example, individual sociodemographics play a role in physical activity (e.g., young adults are on average more physically active than older adults). Thus, we modeled time-varying physical activity as a function of baseline age, race, sex and current education and income. In addition, we modeled longitudinal neighborhood SES as a function of race, sex, baseline age, education, and income.

Figure 13 presents the indirect pathways in more detail where we hypothesized that stores and restaurants sell a variety of healthy and unhealthy foods. Furthermore, dietary choices are theoretically made in the context of the full dietary offerings in the neighborhood, rather than in relation to a single store or restaurant. Thus, we accounted for restaurant and food store options by including pathways from: fast food and sit-down restaurants to each of the fast food and sit-down restaurant diet factors; and supermarkets and convenience stores to each of the supermarket and convenience store diet factors. Finally, since we hypothesized that choices to consume foods purchased in stores versus at restaurants involve distinct decisions and processes, thus we conducted separate models for food stores and restaurants.

Model fit. We defined good model fit as Root Mean Square Error of Approximation (RMSEA) <0.06[133], and Comparative Fit Index (CFI)[134] and Tucker-Lewis Index (TLI)[135] values approaching 1.0.

D. RESULTS

Descriptive statistics. Mean BMI, income and years of schooling increased across 20 years of CARDIA exams, while physical activity and fast food restaurant visits decreased over time (Table 19). Counts of neighborhood fast food restaurants, sit-down restaurants and convenience stores increased, and supermarkets remained fairly stable over 20 years (Table 20). The majority of participants were classified by either high or low neighborhood SES stability versus upward and downward neighborhood SES mobility.

Structural equation modeling. Model fit was similar between the two models without (CFI=0.82, TLI=0.80, RMSEA=0.04) and with (CFI=0.80, TLI=0.78, RMSEA=0.04) the reverse pathways.

We present the standardized beta coefficients (interpreted as the change in one standard deviation of the outcome per standard deviation change in the exposure) in separate models for restaurants (Figure 14a) and food stores (Figures 15a) using the model without reverse pathways (Figures 14b and 15b show the models that include the reverse pathways). In the model without reverse pathways, the estimates suggest statistically significant and consistent associations between fast food and sit-down restaurants indirectly with BMI, through diet behaviors ($P<0.05$) (Figure 14a). Both fast food restaurants and sit-down restaurants operated indirectly on BMI through a fast food-type diet. Greater numbers of neighborhood fast food restaurants were indirectly associated with BMI through greater consumption (year 0: $\beta=0.27$, $P<0.001$, year 7: $\beta=0.08$, $P=0.04$), while greater numbers of sit-down restaurants were indirectly associated with BMI through lower consumption (year 0: $\beta=-0.39$, $P<0.001$, year 7: $\beta=-0.10$, $P=0.004$, year 20: $\beta=-0.07$, $P=0.02$) of foods typically purchased from fast food restaurants. Consuming a fast food-type diet was statistically significantly associated with higher BMI (year 0: $\beta=0.36$, $P=0.001$, year 7: $\beta=0.10$ $P<0.001$, year 20: $\beta=0.21$ $P<0.001$). In contrast, consuming a sit-down restaurant-type diet was statistically significantly associated with lower BMI (year 0: $\beta=-0.28$, $P=0.005$, year 7: $\beta=-0.04$, $P=0.02$, year 20: $\beta=-0.13$, $P<0.001$). When we included the reverse pathways (period-specific diet behaviors to future food environments), we observed negative associations along the reverse pathways from the consumption of fast food-type and sit-down restaurant-type diets at baseline (early-adulthood) with future neighborhood fast food restaurants and sit-down restaurants (Figure 14b). However, in later adulthood there were no statistically significant associations between diet behaviors and future neighborhood restaurants. In the model without reverse pathways, the pathways from food stores to BMI through diet were inconsistent in magnitude and statistical significance (Figure 15a). After accounting for the reverse pathways, we observed negative and positive associations between current diet behaviors and future neighborhood food stores (Figure 15b).

The patterns of association along the pathways from food environment indirectly to BMI through diet were very similar in both models. However, there were some notable differences. In the model with reverse pathways, fast food and sit-down restaurants were statistically significantly associated with lower BMI through the consumption of a sit-down restaurant type diet. A greater number of neighborhood fast food restaurants was indirectly associated with higher BMI through lower consumption of a sit-down restaurant-type diet (year 0: $\beta=-0.06$, $p<0.05$), while greater numbers of sit-down restaurants were indirectly associated with lower BMI through higher consumption of a sit-down restaurant-type diet (year 0: $\beta=0.09$, $p<0.001$). Consuming a sit-down restaurant-type diet was negatively associated with and BMI only in early adulthood. There were no statistically significant indirect pathways from food stores to BMI thorough diet, regardless of whether or not the model included reverse pathways.

E. DISCUSSION

Using pathway-based SEM and a unique set of environmental, clinic, and behavior data spanning two decades, we modeled pathways from neighborhood food stores and restaurants to BMI through diet behaviors as well as reverse pathways from period-specific diet behaviors to future neighborhood food stores and restaurants. We found evidence of reverse causality in these associations. Our findings suggest that current individual-level diet behaviors and preferences may underlie future residential location choice on the basis of neighborhood restaurant and food store amenities.

During the 20-year period covered by our study, U.S. obesity rates increased,[1] as did numbers of neighborhood restaurants and food stores[86-89,106] and expenditures on away-from-home foods.[137] Our model addressed reverse causality in the context of pathways from neighborhood food resources operating indirectly on BMI through diet behaviors. After adjusting for reverse pathways (from period-specific diet behaviors to future neighborhood food resources), we found evidence that fast food and sit-down restaurants influenced BMI of young adults through the consumption of a fast food-type diet as well as a sit-down restaurant-type diet ($p<0.05$). Accounting for reverse causality with reverse pathways, strengthened associations between neighborhood restaurants and diet behaviors in magnitude and statistical significance, but it did not change the nature of the associations between neighborhood food stores and diet behaviors.

While research on the food environment, diet behaviors, and body weight has proliferated over the past several years, most of this research is cross-sectional, involves crude associations, and ignores reverse causality.[33] We modeled reverse causality with reverse pathways, representing one aspect of individual-level preferences for residential location. It may be that people do not choose their neighborhoods based on the food resources, however, it may be that the food environment comes as a package with other environmental amenities that factor into residential choice (i.e., fast food restaurants are not typically placed in higher end neighborhoods). Therefore, individual diet preferences may be ***tied to unobservable or unmeasured characteristics*** (e.g., culture, health consciousness, and social ties) that determine an individuals' residential location. Using SEM and reverse pathways from current diet behaviors to future neighborhood restaurants, allowed us to observe indirect pathways from neighborhood restaurants to BMI operating through the consumption of a sit-down restaurant-type diet that were unobserved in the model without the reverse pathways. Although, controlling for reverse pathways did not elucidate any statistically significant pathways from food stores to BMI through diet.

Life course milestones, such as new employment or starting a family, are time-varying exposures and can be important determinants of where people choose to live. CARDIA participants were followed from 1985-86 in early to mid/late adulthood when they were making some of their first choices, independent of parents/caregivers, about where to live. Perhaps the negative associations we observed between baseline diet behaviors and future food environments reflect individual-level constraints (e.g., finances) versus preferences that shaped decisions about where to live. For example, the participants who preferred to consume foods typically offered at restaurants in early adulthood may have chosen in the future to live neighborhoods with few restaurants because they couldn't afford to live in neighborhoods with many restaurants. Indeed, the positive associations, between diet behaviors in mid/late-adulthood and future neighborhood food stores, may reflect how participants' financial resources increased in later adulthood, which made it easier for them to exert personal preferences in residential location choices.

Our analysis suffers from some limitations. We were unable to follow the participant's from childhood to construct a complete history of their residential neighborhood food environments, diet behaviors, and BMI. However, the twenty-year study period captured the participant's adulthood (ages 18-30 to 38-50 years) when they made life-changing choices about family, employment, and lifestyles. Another limitation is that electronic business record data, such as D&B, are widely used in research studies and are currently the only option for retrospective longitudinal studies. Yet these data are vulnerable to misclassification error including geospatial inaccuracy, missing data, and classification inaccuracy.[100,101] Powell et al. conducted a ground-truthed study in Chicago and some surrounding suburban/rural Census tracts, finding higher validity (D&B business listings compared to ground-truthed food store and restaurant locations) in white versus predominantly black race Census tracts and in higher compared to lower- and middle income tracts.[104] In contrast, other validation studies suggest no association between socioeconomics and agreement between business lists and field observations.[100,105] These findings might relate to differences by urbanicity, as the Powell et al.

study[104] included non-urban tracts whereas the other studies[100,105] were set in urban areas. Other studies suggest comparatively poor validity in rural compared to urban areas.[101,102,107-110] The CARDIA study recruited participants from four major U.S. cities and after 20 years, over 90% of them were still living either in or less than a mile away from an urban area. Therefore, differential misclassification in our data by urbanicity is not likely.

We also did not know the specific stores and restaurants the participants frequented nor the quality of foods sold at each establishment. Moreover, sit-down restaurants, as defined here, are a heterogeneous group of restaurants and do not necessarily represent restaurants that only sell healthy options.

We assumed our estimates were not confounded by unmeasured factors, but to our knowledge, sensitivity methods to address unmeasured bias[112] have not been adapted for longitudinal SEMs. Thus, unmeasured confounding could bias our estimates away from or towards the null. Further, residential location choice is complex and driven by more than dietary preferences. Our study did not explicitly model residential choice or account for residential selection bias, thus there may be residual confounding in our estimates due to unmeasured characteristics that influence neighborhood choice.

Despite these limitations we used a large and unique GIS capturing multiple types of neighborhood food resources, spatial characteristics and demographics, with detailed diet and anthropometric data. We modeled reverse pathways and provide evidence of reverse causality in the context of food environments influence on diet and BMI. We used latent factors to test hypothesized causal relationships with longitudinal data from a large diverse cohort during mid- to late-adulthood. We combined multiple diet behaviors into latent factors that we hypothesized would be associated with each type of neighborhood food store or restaurant option. We included separate direct and indirect pathways from neighborhood food stores and restaurants to BMI, through hypothesized diet behaviors. Lastly, we accounted for other available restaurant (fast food versus sit-down) and food store (supermarkets versus convenience stores) options.

CONCLUSION

The food environment consists of a variety of food stores and restaurants that can influence dietary intake of a variety of foods. When we considered reverse causality in the context of multiple direct and indirect pathways from multiple types of restaurants and food stores to BMI through diet behaviors, we found evidence that diet preferences may underlie neighborhood choice based on restaurants and food stores. Failure to account for reverse pathways can minimize the ability to detect associations between restaurants (not food stores) and diet behaviors.

Table 16. Specific Foods[a] and Beverages[a] Included in Each Food Group[b] to Model Latent factors for Hypothesized Diet Behaviors.

Food group	Foods
Beef	Beef
Butter	Butter
Cheese	Cheese (reduced- low-, whole-fat)
Chips	Snack chips, vegetable-based savory snack
Diet drinks	Artificially sweetened: fruit drinks, soft drinks, water, tea
Fried chicken/seafood	Fried: chicken, shellfish, fish
Fruit	Citrus fruit, non-citrus fruit, fried fruits, fruit-based savory snacks
Fruit juice	Citrus fruit juice, non-fruit juice
Low-fat milk	Low-fat milk
Nuts	Nuts, nut butter
Potatoes	White potatoes, fried potatoes
Processed meat	Cold cuts, meat snack, cured pork
Refined grains	Refined grain: flours, and dry mixes, crackers, bread/rolls, pasta, cereals, snack bars
SSB	Sweetened: fruit drinks, soft drinks, water, tea
Sweets	Candy, frosting or glaze, sugar, syrup, honey, jam, jelly, preserves, cakes, cookies, cobblers, pies, pastries, Danish, doughnuts, desserts, frozen desserts, pudding
Unprocessed red meat	Veal, lamb, pork
Vegetables	Dark green, deep yellow, and other vegetables, avocado, and tomato, vegetable juice, fried vegetables
Whole grains	Whole grain grains, flours, and dry mixes, crackers, bread/rolls, pasta, cereals,
Whole milk	Whole milk
Yogurt	Yogurt

SSB: Sugar-sweetened beverages

[a]Diet was assessed using an interviewer-administered CARDIA Diet History[59] Interviewers asked open-ended questions about dietary consumption in the past month within 100 food categories that referenced 1609 separate food items.

[b]Using a food-grouping system modified from the University of Minnesota Nutrition Coordinating Center we assigned foods into one of 13 food groups and 5 beverage groups

.

Table 17. Reported Diet Behaviors (Range) Classified Into Low, Medium, and High Categories Across Exam Year: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114.

	Year 0		Year 7		Year 20	
	Range	Category	Range	Category	Range	Category
Fast food consumption per week						
	0.0 - 0.5	L	0.0 - 0.1	L	0.0 - 0.1	L
	0.7 - 1.8	M	0.1 - 0.4	M	0.1 - 0.4	M
	2.0 - 21.0	H	0.4 - 5.9	H	0.4 - 5.9	H
Reported consumption of foods within food group (servings per day)						
Beef	0.0 - 1.1	L	0.0 - 0.3	L	0.0 - 0.2	L
	1.1 - 2.4	M	0.5 - 1.8	M	0.5 - 1.6	M
	2.4 - 40.1	H	2.0 - 24.0	H	1.8 - 25.0	H
Butter	0.0 - 2.2	L	0.0 - 0.0	L	0.0 - 0.0	L
	2.2 - 4.8	M	0.0 - 0.4	M	0.0 - 0.4	M
	4.8 - 53.6	H	0.4 - 19.2	H	0.4 - 8.6	H
Cheese	0.0 - 0.4	L	0.0 - 0.8	L	0.0 - 0.6	L
	0.4 - 0.8	M	0.9 - 2.0	M	0.6 - 1.3	M
	0.8 - 6.3	H	2.0 - 34.5	H	1.3 - 12.3	H
Artificially sweetened drinks	0.0 - 0.0	L	0.0 - 0.3	L	0.0 - 0.2	L
	0.0 - 0.3	M	0.4 - 0.8	M	0.2 - 0.5	M
	0.3 - 182.1	H	0.8 - 13.1	H	0.5 - 13.5	H
Fried chicken/seafood	0.0 - 0.0	L	0.0 - 0.1	L	0.0 - 0.1	L
	0.0 - 0.1	M	0.1 - 0.7	M	0.1 - 0.6	M
	0.1 - 17.3	H	0.7 - 17.2	H	0.6 - 26.1	H
Fruit	0.0 - 0.5	L	0.0 - 0.0	L	0.0 - 0.0	L
	0.6 - 1.4	M	0.0 - 0.1	M	0.0 - 0.3	M
	1.4 - 16.2	H	0.1 - 16.2	H	0.3 - 22.5	H
Fruit juice	0.0 - 0.7	L	0.0 - 0.0	L	0.0 - 0.0	L
	0.7 - 2.0	M	0.0 - 0.1	M	0.0 - 0.2	M
	2.0 - 36.1	H	0.1 - 8.0	H	0.2 - 7.0	H
Low-fat milk	0.0 - 0.1	L	0.0 - 0.5	L	0.0 - 0.4	L

	0.1 - 0.6	M	0.5 - 1.5	M	0.4 - 1.3	M
	0.6 - 36.0	H	1.5 - 14.9	H	1.4 - 15.5	H
Nuts	0.0 - 0.1	L	0.0 - 0.4	L	0.0 - 0.2	L
	0.1 - 0.6	M	0.4 - 1.4	M	0.2 - 1.0	M
	0.6 - 21.2	H	1.4 - 47.9	H	1.0 - 16.5	H
Potato chips	0.0 - 0.1	L	0.0 - 0.4	L	0.0 - 0.3	L
	0.1 - 0.3	M	0.4 - 0.8	M	0.3 - 0.7	M
	0.3 - 12.0	H	0.8 - 8.0	H	0.7 - 10.1	H
Potatoes/fries	0.0 - 0.3	L	0.0 - 0.7	L	0.0 - 0.7	L
	0.3 - 0.8	M	0.7 - 1.7	M	0.7 - 1.8	M
	0.8 - 14.3	H	1.7 - 19.6	H	1.8 - 31.8	H
Processed meat	0.0 - 0.4	L	0.0 - 1.6	L	0.0 - 0.8	L
	0.5 - 1.3	M	1.6 - 3.8	M	0.8 - 2.1	M
	1.3 - 47.0	H	3.8 - 35.1	H	2.1 - 59.0	H
Refined grains	0.0 - 2.6	L	0.1 - 2.0	L	0.0 - 2.1	L
	2.6 - 4.9	M	2.0 - 3.8	M	2.1 - 3.8	M
	4.9 - 23.4	H	3.8 - 39.7	H	3.8 - 44.0	H
SSB	0.0 - 0.4	L	0.0 - 0.0	L	0.0 - 0.0	L
	0.4 - 1.6	M	0.0 - 0.9	M	0.0 - 1.0	M
	1.6 - 21.9	H	0.9 - 16.4	H	1.0 - 29.1	H
Sweets	0.0 - 1.4	L	0.0 - 0.3	L	0.0 - 0.1	L
	1.4 - 3.2	M	0.3 - 1.5	M	0.1 - 0.8	M
	3.2 - 30.5	H	1.5 - 24.3	H	0.8 - 16.9	H
Unprocessed red meat	0.0 - 0.1	L	0.0 - 0.0	L	0.0 - 0.1	L
	0.1 - 0.5	M	0.0 - 0.5	M	0.2 - 0.9	M
	0.5 - 14.8	H	0.5 - 24.0	H	0.9 - 25.5	H
Vegetables	0.0 - 1.6	L	0.0 - 3.3	L	0.0 - 2.1	L
	1.6 - 3.1	M	3.3 - 5.6	M	2.1 - 3.8	M
	3.1 - 33.8	H	5.6 - 30.9	H	3.9 - 29.3	H
Whole grains	0.0 - 0.3	L	0.0 - 1.5	L	0.0 - 1.1	L
	0.3 - 1.2	M	1.5 - 3.1	M	1.1 - 2.7	M

	1.3	-	13.0	H	3.1	-	35.3	H	2.7	-	73.6	H
Whole milk	0.0	-	0.0	L	0.0	-	0.1	L	0.0	-	0.1	L
	0.0	-	1.0	M	0.1	-	0.4	M	0.1	-	0.3	M
	1.0	-	16.1	H	0.4	-	14.5	H	0.3	-	30.1	H
Yogurt	0.0	-	0.0	L	0.0	-	0.4	L	0.0	-	0.5	L
	0.0	-	0.1	M	0.4	-	1.1	M	0.5	-	1.1	M
	0.1	-	3.9	H	1.1	-	24.7	H	1.2	-	12.5	H

SSB: Sugar sweetened beverages, L: low, M: medium, H: high

Table 18. Detailed Food Store and Restaurant Types Based on 8-digit Standard Industrial Classification (SIC) Codes

Food Resource Type	Description	SIC
Fast food chain restaurant	Fast-food restaurant, chain	58120307
	Pizzeria, chain	58120601
Sit-down restaurant	Fast food restaurants and stands	58120300
	Box lunch stand	58120301
	Carry-out only (except pizza) restaurant	58120302
	Chili stand	58120303
	Coffee shop	58120304
	Delicatessen (eating places)	58120305
	Drive-in restaurant	58120306
	Fast-food restaurant, independent	58120308
	Food bars	58120309
	Grills (eating places)	58120310
	Hamburger stand	58120311
	Hot dog stand	58120312
	Sandwiches and submarines shop	58120313
	Snack bar	58120314
	Snack shop	58120315
	Pizza restaurants	58120600
	Pizzeria, independent	58120602
	Mexican Restaurants	58120112
	Seafood Restaurants: Includes sushi restaurants, oyster bars & seafood shacks:	58120114
		58120700
		58120701
		58120702
	Steak House & BBQ Restaurants:	58120800
		58120801
		58120802
	Chicken Restaurants	58129904
	Family-owned restaurant chain	58120501
	Family-owned restaurant, non-chain:	58120500
		58120502
Supermarkets	Supermarkets, chain	54110101
	Supermarkets, greater than 100,000 square feet (hypermarket)	54110103
	Supermarkets, independent	54110102
	Supermarkets, 55,000 - 65,000 square feet (superstore)	54110104
	Supermarkets, 66,000 - 99,000 square feet	54110105

	Supermarkets	54110100
Convenience Stores	Variety stores	53310000
	Convenience stores	54110200
	Convenience stores, chain	54110201
	Convenience stores, independent	54110202
	Gasoline service stations	55410000
	Gasoline service stations, nec	55419900
	Filling stations, gasoline	55419901

Figure 10. Diet Behaviors Hypothesized to be Associated with Neighborhood Food Resources

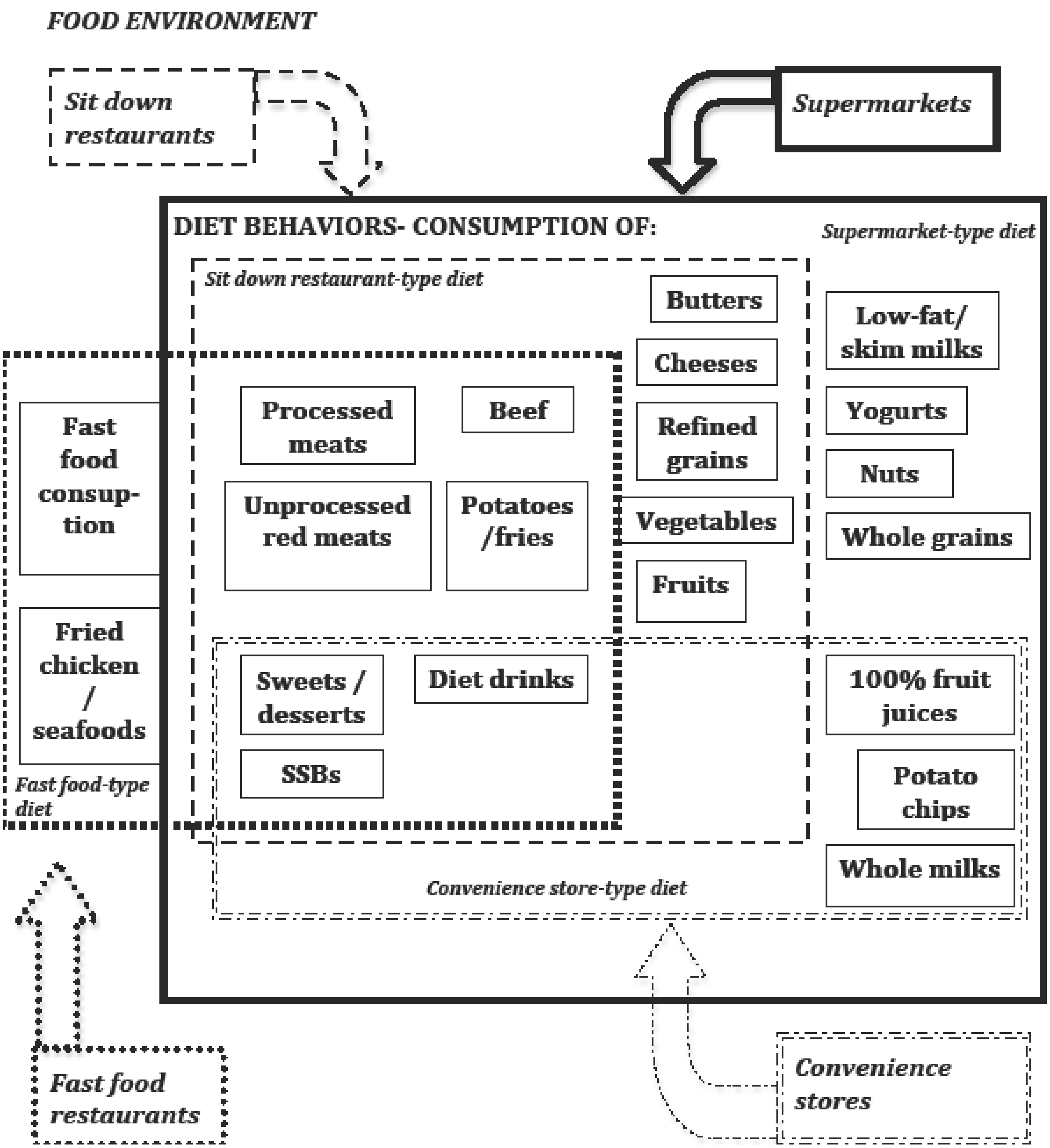
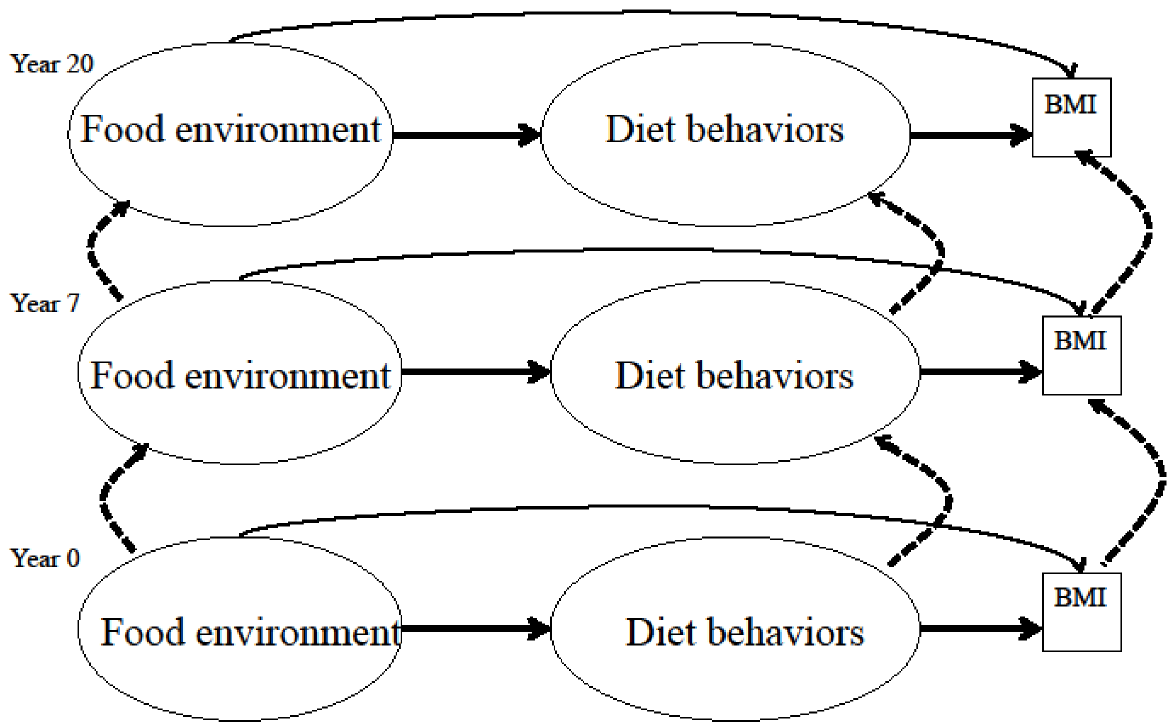
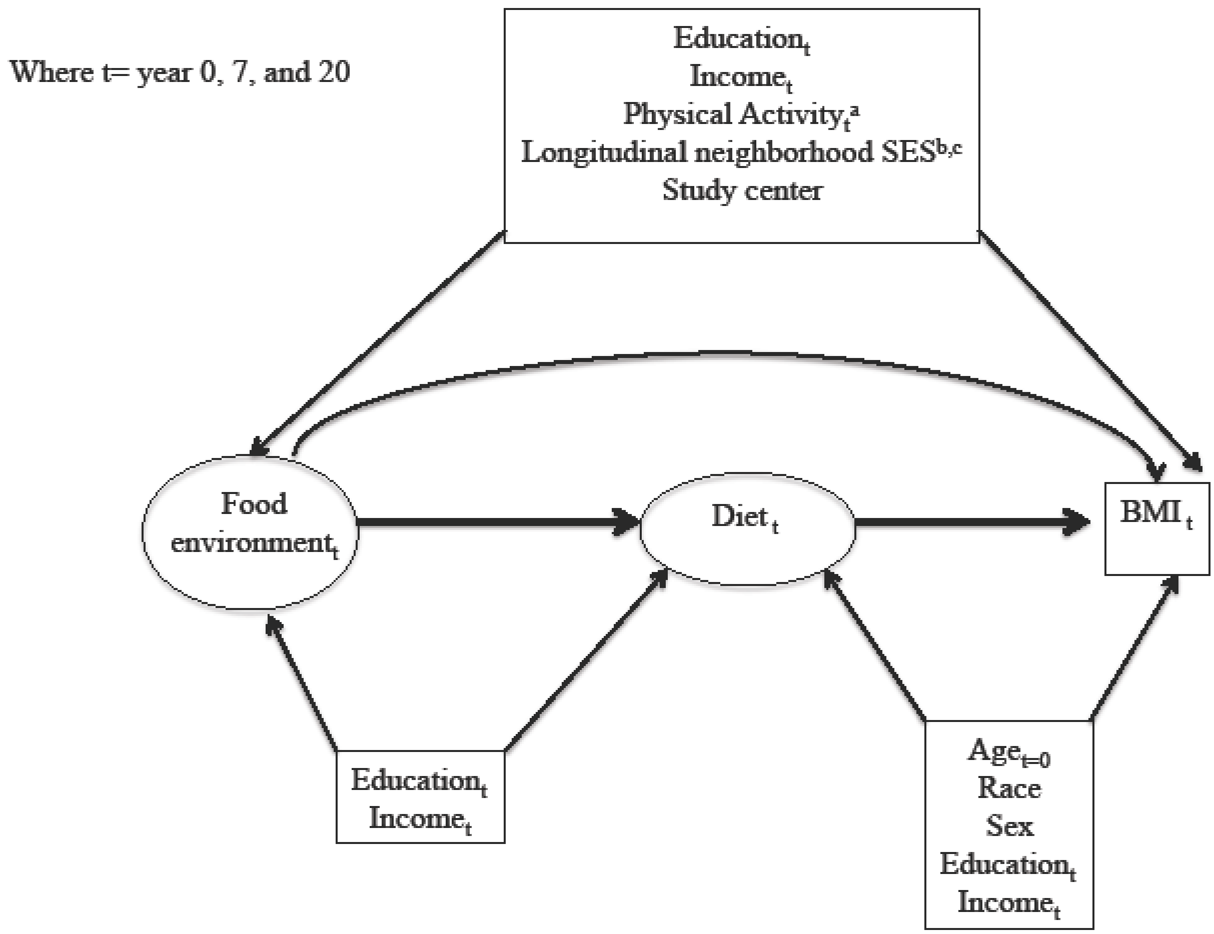


Figure 11. Conceptual Model of Temporal Associations Among Direct Pathways from Neighborhood food Environment to BMI, and Indirect Pathways from Neighborhood Food Environment to BMI Through Diet



BMI: Body mass index
Figure legend. Ovals represent latent (unobserved) variables and rectangles represent observed variables. Solid arrows represent causal relationships, long dashed arrows represent reverse pathways, and short dashed arrows represent auto-regression (linear associations between time-lagged variables).

Figure 6. Conceptual Model of Confounding Among the Direct Associations BetweenNeighborhood Food and BMI, and Indirect Relationships Through Diet



BMI: Body mass index, SES: socioeconomics

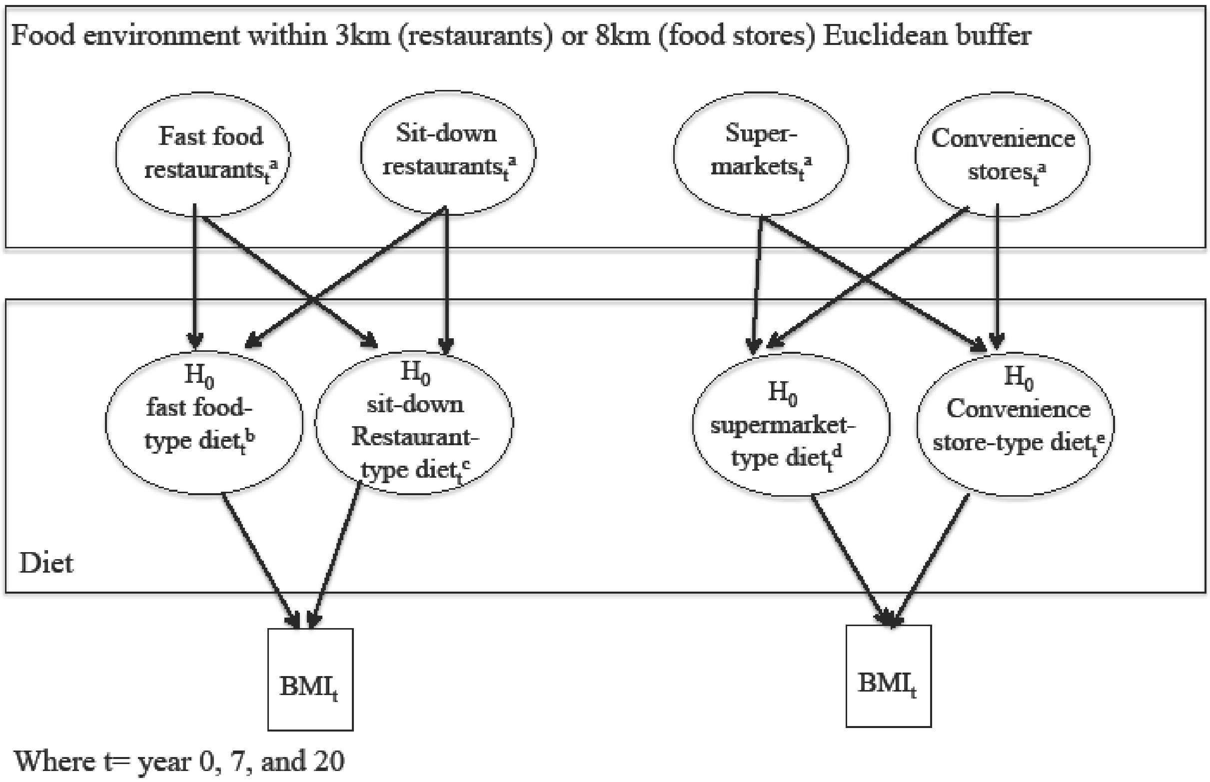
Figure legend. Ovals represent latent (unobserved) variables and rectangles represent observed variables.

[a]Time-varying physical activity was associated with baseline age, race, sex and current education and income.

[b]Derived from latent class analysis[120] using Mplus version 7.11.[84]

[c]Longitudinal neighborhood SES was associated with race, sex, baseline age, education, and income.

Figure 13. Conceptual Model of Indirect Pathways from Neighborhood Restaurants and Food Stores to BMI Mediated Through Hypothesized Diet Behaviors



BMI: Body mass index

Figure legend. Ovals represent latent (unobserved) factors and rectangles represent observed variables. Solid arrows represent causal relationships. Dashed arrows represent reverse arrows from diet behaviors at time t to neighborhood food resources at time t+1, where t=0, 7, and 20.

[a] Latent food environment factors indicated by: count of the food resources within 3km (restaurants) or 8km (food stores) Euclidean buffer per 10km local/secondary roadway and population density Z-scores from U.S. Census-tract level data spatially linked to respondent residential locations and temporally linked to CARDIA exam years (Year 0, 1980; Years 7 and 10, 1990; Year 15 and 20, 2000).

[b]Latent fast food-type diet indicated by: fast food consumption per week and servings per day of fried chicken/seafood, processed meats, unprocessed meats, beef, potatoes/fries, sweets/desserts, sugar-sweetened beverages, and diet drinks.

[c]Latent sit-down restaurant-type diet indicated by: servings per day of processed meats, unprocessed meats, beef, potatoes/fries, sweets/desserts, sugar-sweetened beverages, diet drinks, butter, cheeses, refined grains, vegetables, and fruits.

[d]Latent supermarket-type diet indicated by: servings per day of processed meats, unprocessed meats, beef, potatoes/fries, sweets/desserts, sugar-sweetened beverages, diet drinks, butter, cheeses, refined grains, vegetables, fruits, low-fat/skim milks, whole milks, yogurts, nuts, whole grains, 100% fruit juices, and potato chips.

[e]Latent convenience store-type diet indicated by: servings per day of sweets/desserts, sugar-sweetened beverages, diet drinks, whole milks, 00% fruit juices, and potato chips.

Table 19. Individual-level Characteristics by Exam year: Coronary Artery Risk Development in Young Adults (CARDIA),1985/1986 to 2005/2006, n=5,114

	Year 0	Year 7	Year 10	Year 15	Year 20
N	5114	4085	3949	3671	3549
White race, %	51.6	48.3	48.8	47.1	46.5
Male sex, %	45.5	44.9	44.4	44.1	43.3
BMI (kg/m^2), mean (SD)	24.5 (0.1)	26.7 (0.1)	27.5 (0.1)	28.7 (0.1)	29.4 (0.1)
Education[a], mean (SD) y	13.8 (0.0)	14.7 (0.0)	14.9 (0.0)	15.2 (0.0)	15.4 (0.0)
Income[b], mean (SD) per $10,000	6.3 (0.1)[a]	5.3 (0.1)	5.6 (0.1)	7.2 (0.1)	8.0 (0.1)
Physical activity index[d], mean (SD)	420 (4.2)	338 (4.3)	331 (4.4)	347 (4.7)	336 (4.6)
Frequency of fast food consumption, mean (SD) times/wk	2.0 (0.0)	1.9 (0.0)	1.7 (0.0)	1.8 (0.0)	1.7 (0.0)

BMI: Body mass index, SD: Standard deviation.

[a]Highest year of education reported from Year 0 through year 20.

[b]Income per $10,000, inflated to year 20 and income was not queried at exam year 0 so closest measure at year 5 is used as a proxy.

[c]Among those who attended exam.

[d]Physical activity scores were calculated in exercise units based on frequency and intensity of each activity[71].

Table 20. Neighborhood-level Characteristics Across Exam Year: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006.

	Year 0	Year 7	Year 10	Year 15	Year 20
Number of neighborhoods[a]	799	2508	3406	3460	3645
Counts of food resources[b] within 3km (restaurants) or 8km (food stores) Euclidean respondent residential buffer per 10km of local and secondary roadways [median (interquartile range)] :					
Fast food restaurants	0.2 (0.1,0.2)	0.2 (0.1,0.3)	0.2 (0.1,0.3)	0.2 (0.1,0.3)	0.4 (0.2,0.6)
Sit-down restaurants	2.8 (1.4,5.1)	3.4 (1.5,6.5)	2.4 (1.2,4.7)	2.7 (1.4,4.6)	2.9 (1.5,5.3)
Supermarkets	0.0 (0.0,0.1)	0.1 (0.1,0.2)	0.1 (0.0,0.1)	0.1 (0.1,0.1)	0.1 (0.1,0.2)
Convenience stores	0.6 (0.5,0.7)	1.0 (0.7,1.2)	0.8 (0.6,0.9)	0.7 (0.6,0.8)	0.8 (0.6,1.0)
Longitudinal neighborhood SES residency pattern[c] [% of participants]					
Downwardly mobile neighborhood SES	19.8	17.7	18.0	17.1	17.2
Stable low neighborhood SES	30.9	30.0	29.9	29.6	28.5
Upwardly mobile neighborhood SES	13.0	13.9	14.1	14.8	15.2
Stable high neighborhood SES	36.3	38.3	38.0	38.6	39.1

[a]Total number of census tracts.

[b]Dunn & Bradstreet food resources.

[c]Derived from latent class analysis using Mplus version 7.11[84] of Census tract-level data from exam years 0, 7, 10, 15, and 20: % race white, % education <high school, % poverty (below 150% federal poverty level), % unemployed, % professional/management occupation, median income, % vacant housing, aggregate housing value, % owner occupied, median rent[120].

Figure 14a. Standardized Beta Estimates From Structural Equation Models Examining the Indirect Pathways From Neighborhood Restaurants to BMI Mediated by Hypothesized Diet Behaviors Without Reverse Pathways: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114

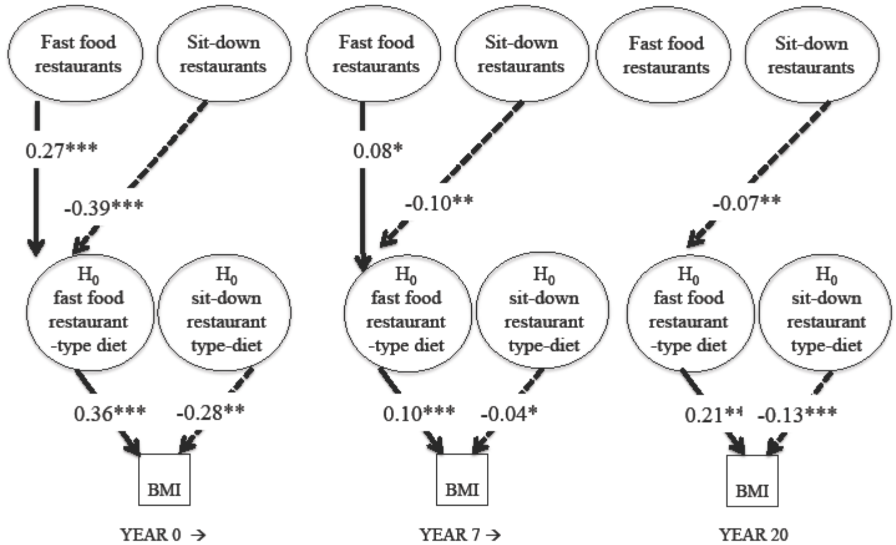


Figure 14b. Standardized Beta Estimates From Structural Equation Models Examining the Indirect Pathways From Neighborhood Restaurants to BMI Mediated by Hypothesized Diet Behaviors With Reverse Pathways: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114

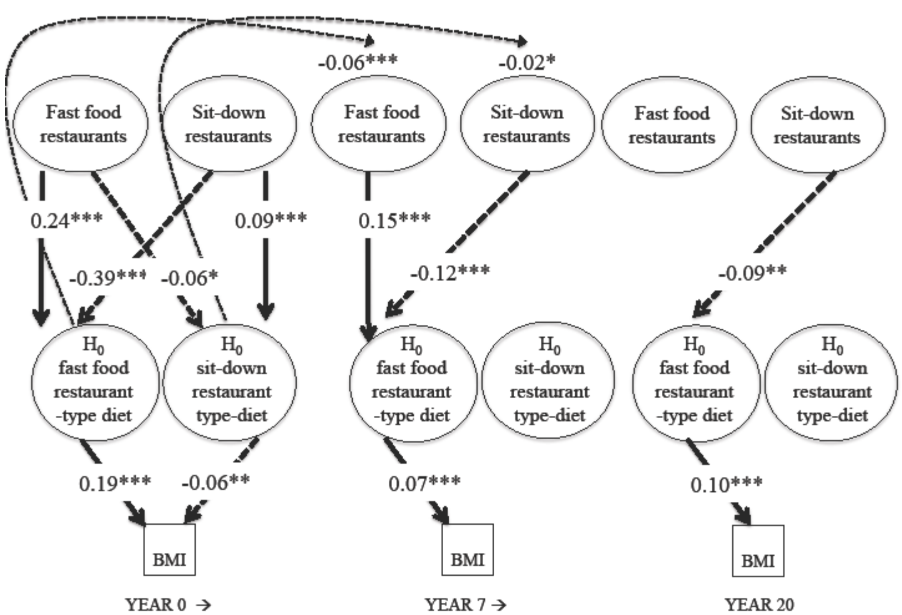


Figure legend. Ovals represent latent (unobserved) variables and rectangles represent observed variables. The time varying and invariant covariates omitted from the figure for clarity were: longitudinal neighborhood SES residency pattern, center, age at year 0, race, and sex individual-level education, income, and physical activity. Arrows represent estimated associations. Further omitted for clarity were: direct pathways, non-statistically significant associations ($P \geq 0.05$), indicators of latent variables, and the autoregressive pathways for the latent neighborhood food resource availabilities, the diet behaviors, and the BMI measures. Model estimated with Mplus version 7.11[84]

**P*<0.05, ***P*<0.01, ****P*<0.001

Figure 15a. Standardized Beta Estimates From Structural Equation Models Examining the Indirect Pathways From Neighborhood Food Stores to BMI Mediated by Hypothesized Diet BehaviorsWithout Reverse Pathways: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114

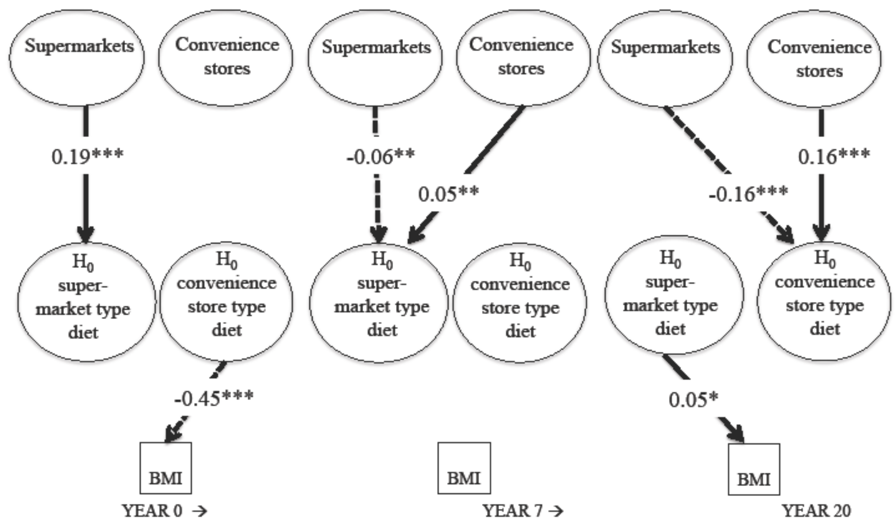


Figure 15b. Standardized Beta Estimates From Structural Equation Models Examining the Indirect Pathways From Neighborhood Food Stores to BMI Mediated by Hypothesized Diet Behaviors With Reverse Pathways: the Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-2006, n=5,114

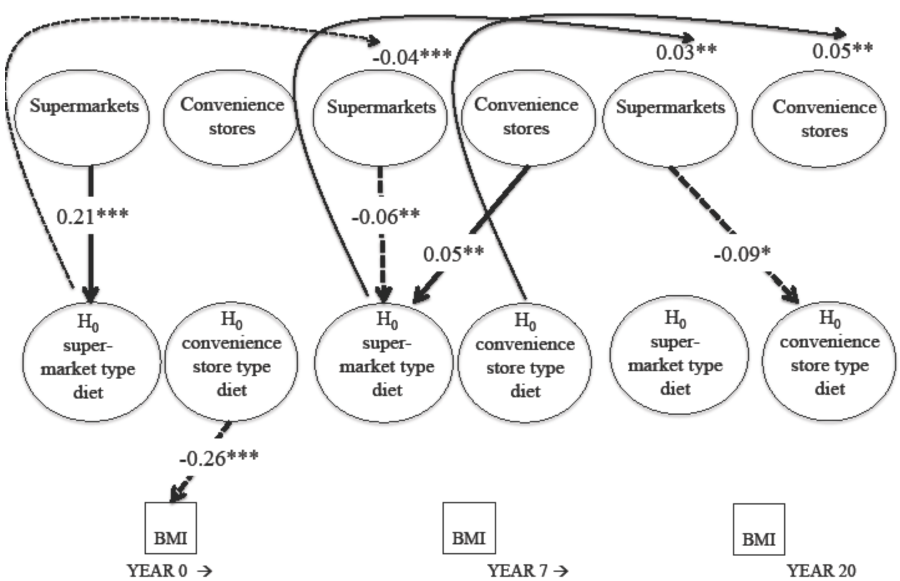


Figure legend. Ovals represent latent (unobserved) variables and rectangles represent observed variables. The time varying and invariant covariates omitted from the figure for clarity were: longitudinal neighborhood SES residency pattern, center, age at year 0, race, and sex individual-level education, income, and physical activity. Arrows represent estimated associations. Further omitted for clarity were: direct pathways, non-statistically significant associations ($P \geq 0.05$), indicators of latent variables, and the autoregressive pathways for the latent neighborhood food resource availabilities, the diet behaviors, and the BMI measures. Model estimated with Mplus version 7.11[84]

*$P<0.05$, **$P<0.01$, ***$P<0.001$

CHAPTER VII: SYNTHESIS

A. OVERVIEW OF FINDINGS

Our research utilizes a longitudinal approach and statistical methods to model complex relationships between neighborhood-level socioeconomics, restaurants, and food stores and individual-level diet behaviors and BMI using latent classes and structural equation modeling to estimate hypothesized causal relationships. We addressed the following specific aims: 1a) classify individuals according to varying levels of 20-year exposure across dynamic neighborhood socioeconomic domains to determine how neighborhood food resources differed by longitudinal neighborhood SES residency patterning; 1b) estimate simultaneously the separate direct and indirect pathways from fast food restaurants, sit-down restaurants, supermarkets, and conveniences stores to BMI through diet behaviors; 1c) test statistical interactions to examine how associations between neighborhood food resources and BMI, through diet behaviors might differ by sex, race, and longitudinal neighborhood SES; 2) evaluate how our findings may be biased by "reverse causality" using reverse pathways from diet behaviors to neighborhood food resources. We hypothesized that changes in neighborhood food environments would be worse (i.e., increasing fast food restaurants and decreasing supermarkets) for those exposed to two decades of chronic socioeconomic disadvantage than those living in more advantaged neighborhoods. We hypothesized that living in neighborhoods with increasing numbers of restaurants and convenience stores along with decreasing numbers of supermarkets would be associated with weight gain, and that these associations would differ by sex and race, and would be stronger and increase over time in areas of socioeconomic decline. We also hypothesized that we could approximate reverse causality using time period specific diet behaviors, albeit predicted from the food environment, as proxies of individual preferences/constraints that underlie future food environments. Further, we hypothesized that reverse causality would bias our pathways findings from restaurants and food stores to BMI through diet behaviors. We briefly summarize our findings and provide a synthesis of our overall research, and discuss the impact of our work on policy and public health in the "Public Health Significance" section.

NEIGHBORHOOD SOCIOECONOMIC STATUS AND FOOD ENVIRONMENT: A 20-YEAR LONGITUDINAL LATENT CLASS ANALYSIS AMONG CARDIA PARTICIPANTS

Disparities in obesity by socioeconomic status spurred investigations into the degree to which disadvantaged neighborhoods have poor food environments that promote the over-consumption of unhealthy energy-dense foods.[3-6] Identifying modifiable features of the food environment hypothesized to influence individual-level diet behaviors could lead to effective policies that will improve food environment disparities and health in disadvantaged populations. Obesity remains a major public health burden globally for socioeconomically disadvantaged subpopulations living in socioeconomically deprived neighborhoods with food environment disparities.[77] But findings are mixed and most studies have been cross-sectional in nature and work that examines temporal patterns in food environments are sparse [see review[33]]. The present research addresses this critical gap in the literature by using data from a longitudinal, population-based and racially diverse sample with detailed time-varying food environment data linked to sociodemographic, behavior, and weight data. Ultimately, we seek to delineate the pathways from the neighborhood food environment (restaurants and food stores) to BMI through impacts on dietary behaviors. These findings will enable us, as a society to make informed decisions about modifying the food environment, particularly in socioeconomically vulnerable populations. But, first it is imperative to understand the role neighborhood SES plays in food environment disparities that might underlie how socioeconomically disadvantaged populations living in poor communities are disproportionately burdened with obesity.[143] Thus, our goal was to use longitudinal data to examine how 20-year longitudinal patterns of neighborhood SES associated with temporal changes in the food environment. Once we quantified longitudinal neighborhood SES patterns, our aim was to use a pathway-based approach to delineate the separate pathways from fast food sit-down restaurants, supermarkets and convenience stores to BMI through diet behaviors, while accounting for interactions by race, sex, and neighborhood SES patterning. In addition, we aimed to explore how reverse causality may bias our findings by approximating reverse causality using reverse pathways from dietary behaviors (or their correlates) to neighborhood food resources, such as through differential residential selection.

Our study contributes to the literature by being one of the first to examine how longitudinal neighborhood SES patterning in the U.S. relates to disparities in dynamic food environments. We found that CARDIA participants were exposed to very different patterns of neighborhood SES during 20 years of their residential histories (downwardly mobile, upwardly mobile, stable low SES, and stable high SES). Over a temporal period of drastically increasing obesity prevalence in the U.S, we were able to examine how changes in the food environment considered obesogenic (e.g., increasing numbers of fast food restaurants) may have related to declining neighborhood SES. Further, our latent neighborhood SES class variable allowed us to test if pathways from restaurants and food stores to BMI varied by neighborhood SES patterns. Our findings in CARDIA participants suggest that despite economic growth in the U.S. (1985-86 to 2005-06), neighborhood SES did not improve for all white and black adults. In fact, it declined for some. Consistent with our hypothesis, socioeconomically disadvantaged neighborhood CARDIA residents had increasingly more convenience stores in their neighborhoods than the advantaged neighborhood residents. Counter to our hypothesis, we found that socioeconomically disadvantaged neighborhood CARDIA residents had fewer fast food and sit-down restaurants food restaurants and the same number of supermarkets in their neighborhoods than the residents living in socioeconomically advantaged neighborhoods. Despite common assumptions, we found that sparse access to supermarkets in socioeconomically deprived neighborhood did not appear to underlie obesity disparities. If living near restaurants and convenience stores contributes to diet behaviors that lead to weight gain in socioeconomically disadvantaged populations then we need to correct these disparities to reduce obesity.

MULTIPLE PATHWAYS FROM THE NEIGHBORHOOD FOOD ENVIRONMENT TO INCREASED BODY MASS INDEX THROUGH DIET BEHAVIORS: A STRUCTURAL-EQUATION BASED ANALYSIS IN THE CARDIA STUDY

Despite significant efforts to improve food environments with policies and initiatives,[7-9,89,144] there is little compelling evidence that these approaches improve diet and reduce obesity. The need to reduce obesity is clear. During the CARDIA study period (1985-86 to 2005-06), obesity prevalence increased in the U.S. and by 2008, 32% of American adults were obese.[85] If the prevalence had remained at 15% (Healthy People 2010 target) the medical savings attributable to obesity would have been 1.9 trillion.[145] Yet, forecasts suggest that if current trends continue, 51% of the population will be obese by 2030.[145] Obesity is a risk factor for multiple cardiometabolic outcomes,[146] including cardiovascular disease in adults[147] and children.[148] Ultimately, obesity increases morbidity and mortality risk, and decreases life expectancy.[147,149-152] Features of neighborhood socioeconomic disadvantage (e.g., low-income) have been associated with disparities in the food environment and obesity, although the relationships are not clear.[10-12] Inconsistent findings suggest that there are complex relationships between changes in neighborhood socioeconomics and changes in the quality of the neighborhood restaurants and food stores over time.

While research on the food environment, diet behaviors, and body weight has proliferated over the past several years, most of this research is cross-sectional and ignores the multiple pathways from environment to BMI through diet behaviors.[30-32] Further, most research focuses on a single part of the pathway, either associations between food resources and diet behaviors or associations between food resources and body mass index (BMI). Also, most studies test associations among one type of food resource with one outcome. Thus, there is a black box step, whereby it's unknown how different types of food resources simultaneously influence BMI through different diet behaviors.. Our research contributes substantive and methodological innovations to the literature. We used latent class analysis to quantify 20 years of neighborhood SES residential patterns. We used a pathway-based modeling approach that is only recently gaining interest in public health research[32,153,154] to address the complex longitudinal relationships between neighborhood SES, restaurants, food stores, dietary behaviors, and BMI. Specifically, we simultaneously examined the longitudinal pathways from multiple types of neighborhood food resources to BMI through multiple behaviors we hypothesized would be associated with each type of resource. We also continued our examination of these relationships while simultaneously accounting for potential effect modifiers, confounding variables, and approximating reverse causality with regard to predicted and time period-specific diet behaviors having the potential to impact future food resources. We combined 20 years of time-varying measures of multiple types of neighborhood food resources and diet behaviors into latent factors, which allowed us to identify how changing certain types of neighborhood food resources could lead to dietary changes that could potentially impact obesity.

Our results suggest that pathways from neighborhood fast food and sit-down restaurants to BMI operate through higher consumption of an *a priori* fast food-type diet (e.g., sugar sweetened beverages and fries) that, during early- to mid- adulthood, was associated with higher BMI. Consistent with our hypothesis, living near fast food restaurants was associated with greater consumption of a fast food-type diet, however we did not expect the findings that living near sit-down restaurants was associated with lower consumption of a fast food-type diet. When we approximated reverse causality, we found pathways in early-adulthood, operating from both fast food and sit-down restaurants to lower BMI through the consumption of a sit-down-type diet (e.g., refined grains, beef). While we did hypothesize that reverse causality could bias our pathway findings from the food environment to BMI through diet, we did not expect that it would only bias associations for restaurants and not food stores. The evidence for restaurants influencing weight gain through the consumption of a sit-down-type diet is particularly concerning because when we classified participants according 20 year residential histories, we found that residents who, throughout 20 years, consistently lived in socioeconomically disadvantaged neighborhoods had fewer neighborhood sit-down restaurants than those who lived in the socioeconomically advantaged neighborhoods over time. Thus, being exposed to worsening SES during 20 years, when obesity prevalence increased rapidly in the U.S.,[1] was associated at each exam year with living in neighborhoods that we found to be positively associated with obesity. Counter to our hypothesis, we found no statistically significant direct or indirect pathways from neighborhood supermarkets and convenience stores to BMI (either directly or through diet behaviors), even though during 1985-86 to 2005-06 the most socioeconomically deprived neighborhoods (compared to socioeconomically advantaged neighborhoods) consistently had greater numbers of convenience stores. Throughout the 20 year study period, not only were the numbers of supermarkets similar across all neighborhoods, the lack of statistically significant pathways from supermarkets to BMI suggests that the number of supermarkets in a neighborhood, whether it is a high or low SES neighborhood, does not significantly determine diet behaviors and BMI. This may be either because participants relied on eating away-from-home more than on home-prepared meals or the significant increase in food and beverages offered at supermarkets[119] (e.g., candy, snacks) mitigated the healthy diet behaviors we hypothesized would be associated with supermarkets. Also counter to our hypothesis, we did not find evidence that estimated pathways from four types of neighborhood food resources to BMI through diet behaviors varied by race, sex, and longitudinal neighborhood SES.

HOW MUCH DOES REVERSE CAUSALITY BIAS ASSOCIATIONS BETWEEN THE FOOD ENVIRONMENT, DIET, AND BODY MASS INDEX?: A STRUCTURAL-EQUATION BASED ANALYSIS USING 20 YEARS OF NEIGHBORHOOD, DIET, AND ANTHROPOMETRY FROM THE CARDIA STUDY

National and local efforts have targeted neighborhood food resources as a means to improve diet quality in disadvantaged areas.[7-9] Yet, findings from studies that examine how features of the food environment or neighborhood relate to individual-level diet and obesity are mixed. Furthermore, reverse causality bias remains largely unaddressed.[10] When health conscious individuals choose to consume healthier diets and if they also select neighborhoods that support or encourage healthy diets, this can create spurious positive associations between neighborhood food stores and restaurants with higher diet quality. Thus, it was our goal to approximate the source of reverse causality that comes from the influence of diet behaviors of given individuals on the types of food stores and restaurants found in their neighborhoods).

Much of the findings from the neighborhood health effects literature are cross-sectional and lack the ability to examine bi-directional relationships and are particularly vulnerable to reverse causality. Longitudinal methods that employ fixed effects models may provide insight into reverse causality because they obviate confounding by unmeasured time invariant aspects. But fixed effect models cannot address the confounding due to unmeasured *time varying* characteristics. This is a problem, because when we are exploring how the neighborhood food environment influences individual-level diet and downstream weight gain, if individual preferences/constraints related to diet are also associated with features of the neighborhood food environments then reverse causality may create spurious associations. Our research contributes to the field by approximating reverse causality with longitudinal data to establish a temporal sequence between time varying measures of time period-specific diet behaviors (predicted from the food environment) with future neighborhood food environments. By controlling for the associations between predicted and time period-specific dietary preferences and future neighborhood food environments, we were able to estimate how 20 years of changes in the numbers of neighborhood restaurants and food stores influence weight gain through diet behaviors with less of the bias from individual period-specific diet preferences influencing future food environments.

Our research is unique because we modeled reverse pathways across time-varying exposures and outcomes and provided evidence that predicted and time period specific diet behaviors may approximate reverse causality in the context of pathways from multiple types of food environments to BMI through diet. Our findings support our hypothesis that predicted and time period-specific diet behaviors may be used as proxies of individual preferences/constraints that are associated with future neighborhood food stores and restaurants. Approximating reverse causality, with reverse pathways from time period-specific diet behaviors predicted (from the current food environment) to future neighborhood food resources, increased both the magnitude and strength of the associations between neighborhood restaurants and diet behaviors, but did not change the associations between neighborhood food stores and diet behaviors. We hypothesized that reverse causality could bias our pathway findings from restaurants and food stores to BMI through diet behaviors but the only evidence of bias appeared to exist only for the restaurant-diet behavior associations. Failure to account for reverse pathways can minimize the ability to detect associations between restaurants (not food stores) and diet behaviors.

B. PUBLIC HEALTH SIGNIFICANCE

Obesity remains a major public health burden in the U.S. with a third of adults obese.[1] Worldwide the prevalence of obesity has doubled since 1980.[155] Despite efforts to reduce obesity in the U.S., the Institute of Medicine describes obesity as one of the greatest public health challenges of the 21st century.[156] It's projected that by year 2030, there will be 65 million more obese adults in the USA and 11 million more obese adults in the United Kingdom (U.K.), and consequently an additional 6 to 8.5 million cases of diabetes, 5.6–7.3 million incident cardiovascular diseases, more than half a million new cancers, and 26 to 55 million quality-adjusted life years lost in the U.S. and U.K.[157] In parallel with the obesity epidemic in the U.S., the food environment changed with increased numbers of food resources, while dietary behaviors changed from foods eaten at-home to eaten away-from-home.[16] The foods eaten away-from-home are often characterized by poor nutrient quality, high fat, salt and added sugars. And the frequent consumption of such quick-service convenience foods (e.g., pizza, sodas) predicts higher BMI,[17,18] weight gain,[19] and adverse cardiometabolic outcomes.[20] Similar dietary changes occurred in low to mid-income countries where shifts in technology, increased away-from-home eating, and increased consumption of processed foods contributed to the global obesity pandemic.[158] At the same time, food environments are changing quickly in developing countries, with increasing numbers of restaurants <u>and</u> food stores[86-88,106] that promote the intake of processed, lower-quality foods[158,159] Thus, throughout the world people are increasingly exposed to more places to eat poor quality foods. The role the food environment plays in obesity is not just an American issue, it's a global public health issue.

Most of what we know about the role of the food environment on obesity comes from small cross-sectional studies restricted to a single food resource and obesity related outcome, which precludes our ability to identify changes in the types food resources that influence diet and obesity. In our research we found results that confirmed our hypothesis whereby fast food restaurants impacting weight gain through diet behaviors. We found that as total restaurants increased in number, fast food restaurants were associated with higher BMI through increased consumption of fast food type diet and reduced consumption of foods typically offered at sit-down restaurants. However, we hypothesized that sit-down restaurants would also be associated with weight gain through diet behaviors because eating-away-from home at any restaurant has been associated with higher BMI.[160-162] Our findings did not confirm this hypothesis. Sit-down restaurants were indirectly associated with lower BMI through fast food and sit-down restaurant –type diet behaviors. While sit-down restaurants offer some of the same foods and beverages as fast food restaurants they do typically offer a wider variety of foods. It may be that simply having non-fast food type options is enough to offset or reduce the consumption of fast foods that are typically very energy dense and nutrient poor (e.g., fried bologna and Velveta cheese biscuit). These findings are especially concerning because, compared to the socioeconomically advantaged neighborhoods, we observed a consistent 20-year lack of sit-down restaurants in the socioeconomically disadvantaged neighborhoods. This disparity in sit-down restaurants by neighborhood SES could underlie growing obesity disparities in socioeconomically vulnerable populations. If so, improving sit-down versus fast food restaurant options socioeconomically disadvantaged neighborhoods will be critical to food environment equality. On the other hand, neighborhoods with greater numbers of sit-down restaurants may also have other unmeasured characteristics (e.g., culture) that underlie unmeasured diet behaviors (e.g., high fiber intake) that limit weight gain. Future research disentangling intractable confounding across food environments, diet, and BMI is still needed.

During early- to late-adulthood (1985-86 to 2005-06), the CARDIA participants living in the most socioeconomically deprived neighborhoods had the same number of supermarkets as all other participants, yet they also had more convenience stores. Counter to our hypothesis, food stores did not appear to play a role in diet behaviors and BMI throughout CARDIA participants' adulthood, regardless of whether the participants lived in high or low SES neighborhoods. This work contradicts the assumptions many policies and initiatives are built on, that having more supermarkets and fewer convenience stores in neighborhoods, will improve diet and reduce obesity. If restaurants contribute more to obesity than food stores then policies and initiatives may need to shift their focus to effectively reduce obesity by decreasing the number of neighborhood fast food restaurants and increasing the number of sit-down restaurants. While supermarkets may be an important source of quality foods to nearby residents, many current policies and initiatives may be missing that fast food and sit-down restaurant might contribute, more than food stores, to diet behaviors and consequent weight gain. Thus community-level policies might be more effective reducing obesity if they shift their focus from increasing the numbers of supermarkets to decreasing the consumption of fast food-type diet by decreasing fast food restaurant numbers and increasing affordable sit-down restaurant options that offer non-fast food type foods, especially in deprived communities. Ultimately, the goal should be to deter people from consuming fast foods and policies can do this by reducing the number of fast food restaurants at the same time increasing affordable sit-down restaurant options and promoting preparing non-processed convenient foods at home.

OUR RESEARCH PROVIDES EVIDENCE THAT NEIGHBORHOOD SOCIOECONOMIC HISTORIES RELATE TO DISPARITIES IN THE FOOD ENVIRONMENT

Our findings suggest during a time of economic growth in the U.S.[163] neighborhood SES did not improve for all Americans, and in fact, it declined for some. In our paper, we provide evidence that Americans exposed to socioeconomically worsening neighborhoods were additionally burdened by worsening food environments during rapid obesity increases in the U.S.[1], potentially playing a role in widening health disparities over time. This is important because improving features of the food environment in deprived neighborhoods could improve diet behaviors and reduce obesity in the populations who are most burdened with obesity. This research contributes to the literature by characterizing 20-year changes in food resources according to patterns of neighborhood SES (downwardly mobile, upwardly mobile, stable high, and stable low). Further, it allowed us to find that longitudinal and separate pathways from fast food and sit-down restaurants, supermarkets and convenience stores to BMI through diet behaviors did not differ over 20 years for those exposed to varying levels of neighborhood SES. This work also allowed us to control for longitudinal neighborhood SES patterning when we approximated reverse causality with reverse pathways from predicted and time period-specific diet behaviors to future neighborhood food environments. Our observation that during 1985-86 to 2005-06, socioeconomically deprived neighborhoods had fewer sit-down restaurants than socioeconomically advantaged neighborhoods suggests that increasing the numbers of affordable sit-down restaurants could alleviate obesity disparities in socioeconomically disadvantaged populations. Greater numbers of sit-down restaurants might reduce weight gain by increasing consumption of a variety foods typically found at sit-down restaurants and by, more importantly, decreasing the consumption of a fast food type diet, regardless of how many supermarkets or convenience stores are in the neighborhood.

Understanding the combined influence of worsening neighborhood SES and food environments in obesity, and particularly among socioeconomically disadvantaged populations, is key to public health interventions and policies. Current policies and initiatives often target increasing supermarket availability in low-SES neighborhoods[8,144] but our findings suggest that this may not be necessary because the numbers of supermarkets were similar throughout two decades of residential histories, regardless of neighborhood SES. If greater numbers of convenience stores and lack of non-fast food restaurant options contributes to obesity in low-SES communities, policy efforts need to targeting increasing affordable sit-down restaurant options that offer non-fast foods and decreasing convenience stores may be more successful strategies. Such policies would impact the most the disadvantaged populations who are disproportionately burdened with obesity. Considering how fast food restaurant and convenience store numbers are rising,[86,87] policies focused on restaurants and convenience stores (not supermarkets) are necessary to improve worsening food environment disparities that could increase the national obesity prevalence.

THE FOOD ENVIRONMENT INFLUENCES WEIGHT GAIN THROUGH DIET

The black box represents the lack of evidence about how different food stores and restaurants simultaneously influence diet multiple behaviors that lead to weight gain. Quantifying changing food environments with multiple types of resources and changing diet behaviors according to the intake of many foods and beverages is very difficult. We used a unique and large racially diverse prospective cohort with GIS-derived data and sophisticated modeling to examine longitudinal pathways from fast food and sit-down restaurants, supermarkets and convenience stores to BMI through diet behaviors we hypothesized would be associated with each resource. Our results suggest that neighborhood fast food and sit-down restaurants were associated with consumption of foods typically purchased from fast food restaurants, such as potatoes/fries and sugar-sweetened beverages (i.e., fast food-type diet) and the fast food-type diet was consistently obesogenic. As we expected, greater numbers of fast food restaurants were associated with higher consumption of a fast-food type diet. But counter to our hypothesis greater numbers of sit-down restaurants were negatively associated with a fast food-type diet. In contrast to restaurant findings, the pathways from food stores to BMI through diet were inconsistent in magnitude and statistical significance. Availability of neighborhood fast food and sit-down restaurants may play comparatively stronger roles than food stores in shaping diet behaviors and BMI.

Disentangling the pathways from changing food environments to weight gain through diet behaviors has important implications for policy and public health interventions. Our findings suggest that policies aimed at both increasing sit-down restaurant options as alternatives to fast food and reducing the number of fast food restaurant options might reduce the consumption of a fast food-type diet that could in turn reduce obesity. Further, our findings suggest that fast food and sit-down restaurants influence diet and BMI similarly for whether they live in high or low SES neighborhoods. So policies and interventions may be more effective if they reduce the numbers of neighborhood fast food restaurants and increase sit-down restaurants options. And interventions may need to address why and where people choose to consume fast food. However, our research also shows that socioeconomically disadvantaged neighborhoods throughout 20 years, consistently had even fewer sit-down restaurant options so policies will need to focus on increasing options especially in deprived neighborhoods to address disparities in the food environment that could underlie obesity disparities.

Sit-down, also referred to as 'full service restaurants', are heterogeneous and offer a mix of healthy and unhealthy options. Indeed, consuming foods from full service restaurants was associated with increased energy intake and poor dietary intakes.[143] We did not model reported foods consumed at sit-down restaurants, instead we included in our sit-down restaurant-type diet all the options we hypothesized were frequently available at sit-down restaurants. So the protective effects we observed of sit-down restaurants on consuming less of a fast food-type diet; and from the sit-down restaurant-type diet onto lower BMI, likely reflect the healthy diet behaviors (e.g., fruit and vegetables) we included in our modeling. Or sit-down restaurants and the sit-down restaurant-type diet may reflect unmeasured features of the neighborhood (e.g., culture) or diet behaviors that we did not include in our model. Using SEM in our approach contributes to the field because we were able to combine multiple diet behaviors into a latent diet behavior variables that we hypothesized would be associated with each type of neighborhood food resource (fast food and sit-down restaurants and supermarkets and convenience stores). Further, using SEM allowed us to estimate a causal framework with separate longitudinal pathways that we hypothesized operated simultaneously from the neighborhood fast food and sit-down restaurants, supermarkets, and convenience stores to BMI through multiple diet behaviors. We present one causal model but there may be other valid causal models. Our findings shed light on the mechanism of how the food environment influences diet and BMI but they do not definitively clarify the underlying relationships between diet behaviors, restaurants and food stores.

Reducing away-from-home eating would be another approach to reduce people's intake of fast foods. Given the increases in away-from-home eating,[16] interventions aimed at increasing at-home cooking could reduce the consumption of a fast food-type diet. However, there are plenty of processed and nutrient poor foods available in food stores that can be prepared at home. Indeed, our research shows that living near supermarkets did not reduce BMI through improved diet behaviors perhaps because participants eat away-from-home than at home or because of the items they choose to purchase, prepare, and consume at home. Therefore, effective policies and interventions would need to improve both the quality of foods available and people's ability to make healthier purchasing choices within restaurants *and* food stores.

During the 20 year period (1985-86 to 2005-06) when the obesity epidemic was growing in the U.S.,[1] socioeconomically disadvantaged neighborhoods had the same numbers of supermarkets as advantaged neighborhoods. Furthermore, supermarkets did not appear to play a strong role in diet and BMI. Together, these findings have important policy implications. For example, "food deserts" defined as populated areas with little or no food retail provision[164] were one of the first neighborhood characteristics that researchers associated in low-SES areas with obesity disparities. Accordingly, some of the first policies targeted "food deserts", such as the Food Poverty (Eradication) Bill in the United Kingdom,[165] focusing on the addition of supermarkets and grocery stores into low-SES neighborhoods as a means to improve access to high quality foods. However, the effectiveness of interventions to improve physical access supermarkets and reduce in low-SES neighborhoods is still unclear.[78] However, our findings suggest that these policies need to shift the focus to restaurants since the most consistent pathways from the food environment were from both fast food and sit-down restaurants to BMI through diet.

Although, we found increased numbers of convenience stores in socioeconomically disadvantaged (versus advantaged) neighborhoods, over the 20-year study period, convenience stores did not appear to contribute to adult weight gain through diet behaviors or any other pathway. Our study participants were adults so we cannot address how convenience stores might relate to higher BMI through poor diet behaviors in children.[166] It is possible that exposure to greater numbers of convenience stores in low-SES neighborhoods than in high-SES neighborhoods plays a role in childhood obesity disparities. Proximity to convenience stores was positively associated with: sugar sweetened beverage intake, BMI Z-score, and percentage body fat in 349 Minnesotan adolescents; and with low Healthy Eating Index scores in 810 Canadian adolescents.[167] Future research is needed to understand how convenience stores may be disproportionately located in socioeconomically deprived neighborhoods and how they may play a role in childhood obesity and diet disparities.

EVIDENCE FOR REVERSE CAUSALITY

The inability to control for reverse causality where unmeasured characteristics (e.g., attitudes and preferences) relate to both where people choose to live and the health outcome of interest, is a major gap in the neighborhood health effects literature. Many studies ignore reverse causality because of data and methodological limitations. Our aim was to use a complex longitudinal SEM to approximate reverse causality using pathways from time period-specific diet behaviors, albeit predicted from food environments, to future neighborhood food environments. Reported diet behaviors and predictions from the food environment may be useful as proxies for individual preferences/constraints that are associated with future neighborhood food stores and restaurants. Approximating reverse causality, with reverse pathways from predicted and time period-specific diet behaviors to future neighborhood food resources, increased both the magnitude and strength of the associations between neighborhood restaurants and diet behaviors, but did not change the associations between neighborhood food stores and diet behaviors.

The public health policy implication of our findings is that the literature on food environment and obesity may be missing information about pathways and under estimating effects between restaurants with diet behaviors that could reduce obesity. To gain a better understanding of the complexity of different types of food environments and how people interact with them, it's imperative to account for reverse causality. Although, it may be less important for neighborhood food stores than for restaurants since it did not help clarify pathways from food stores to BMI through diet behaviors. Modifying the types of restaurants available in neighborhoods could shift adults' diet behaviors from a fast food-type diet to consuming more foods typically offered at sit-down restaurants and thereby reduce BMI in early-adulthood. Given that early adulthood is a high risk period for later weight gain,[168] interventions and policies that modify the neighborhood food environment could affect all residents, yet the interventions might have longer lasting impact on unwanted weight gain for young adult populations.

C. STRENGTHS AND LIMITATIONS

LIMITATIONS

Since the CARDIA study was not originally designed to study how the built environment relates to obesity some of our measures are not perfectly well suited to answer our research questions.

Study Period

We were unable to follow the participant's from childhood to construct a complete history of their residential neighborhood food environments, diet behaviors, and BMI. Thus, we cannot examine how residential mobility impacts our findings. We did not explicitly model residential mobility because we were interested in the changing neighborhood SES and food environment, regardless of residential mobility. So we had a mix of neighborhood food environments changing around participants who did not move and changes that occurred when participants moved into new neighborhoods. To adequately incorporate recursive iterative modeling strategies that would capture individual choice and environment influences on behaviors would require many more years of observation beginning in childhood. Individual choices about where to live and what to eat are often informed by experiences in childhood and parental influences. So to pull apart the neighborhood influence from individual tendencies would require an understanding of parental behaviors and childhood residential neighborhoods. Given that we lack any information about the participants early life experiences our findings could be biased either away from or towards the null. However, the twenty-year study period captured the participant's adulthood (ages 18-30 to 38-50 years) when they made life-changing choices about family, employment, and lifestyles.

Linking the individual behaviors to the neighborhood restaurants and food stores

We also did not know the specific stores and restaurants the participants frequented nor what they purchased and consumed, nor the quality of foods sold at each establishment. Further, our model assumes that the 3km and 8km Euclidean buffers reflect the salient food environments that influence behavior. There are food resources throughout the environment and there could be other geographic locations (e.g., commuting routes or work location) where people choose to purchase and consume food. While we did not know how much time the CARDIA participants spent in their neighborhoods, the majority of the Census tract residents (aged 16 years and over and not working from home) spent less than 30 minutes travelling to work (65% at years 0 and 7, and 61% at year 20). Thus, we can infer that the CARDIA participants spent a significant amount of time throughout the study period exposed to their neighborhood food environments.

Despite the many geographic areas outside residential neighborhoods where people are exposed to restaurants and food stores, decisions about where to purchase and consume food are informed by what people see within their neighborhood environment. For example, if someone prefers supermarkets outside their neighborhood compared to those within their neighborhood, they may choose to travel further to shop for food. So, even if participants didn't use the food resources within their neighborhoods, their choices were determined, in part, by the food resources they saw within their neighborhood. Our findings shed light on changing diet behaviors and weight gain in the context of changing food environments that is one piece of how people interact with and respond to dynamic food environments throughout their adulthood.

Defining the food environment

Electronic business record data, such as D&B, are widely used in research studies and are currently the only option for retrospective longitudinal studies. Yet these data are vulnerable to misclassification error including geospatial inaccuracy, missing data, and classification inaccuracy.[100,101]

Ground-truthed (i.e., direct observation) studies suggest validity may be higher in in white versus predominantly black race Census tracts[104] and that database inaccuracies may be higher in disadvantaged versus advantaged neighborhoods but there are no clear patterns of discrepancy.[100,105,169,170] We derived our longitudinal neighborhood SES class from many domains of neighborhood SES and may be less vulnerable to any systematic error due a single or few demographic characteristics.

Data source may also influence accuracy (e.g., InfoUSA, D&B).[100-104,169,171-173] D&B is a commonly used commercial data vendor and food outlet businesses register with D&B to obtain a tax identification number and are assigned an industry classification code based on the primary commercial activity. In contrast, InfoUSA and Reference USA are commercial vendors who collect their business lists from public sources and have had greater sensitivity than D&B but approximately the same positive predictive value.[101,103,104] Thus, D&B is less able to identify existing businesses than the InfoUSA and Reference USA vendors, however correct classification of the among the D&B business lists is comparable to the other vendors. While recent ground-truthing of 274 randomly selected Chicago area Census tracts suggest D&B correctly classified food outlets and had higher classification match rate than InfoUSA for supermarkets and grocery stores, but InfoUSA had higher classification match rate for convenience stores.[102] Fleischhacker et al. found that D&B had lower validity measures for general merchandise stores, restaurants, convenience stores, and specialty markets and shops in seven NC State Designated Tribal Statistical Areas than Reference USA and local health departments.[101] But grocery stores had near perfect sensitivity. If our D&B food resource data have poor sensitivity then there may be more food resources in the neighborhood that we are missing in our data and could bias our associations to the null as long as the misclassification is equal for all types of food outlets. Missing neighborhood food resources that influence diet behaviors could attenuate our findings.

Facility type may also influence accuracy in electronic business record databases.[100,101,103,104,107,172,174] Powell et al. assessed validity for 5 food outlet classifications (supermarkets, grocery stores, convenience stores, full-service restaurants and fast food restaurants) in urban Chicago and surrounding 46 suburban and 61 rural Census tracts and found that 52% of food store establishments observed on the ground were listed in the D&B.[104] Overall concordance was lowest for specialty restaurants and highest for fast food restaurants (range of 26.7–58.6%). We did not target specialized eating or food store establishments in this proposal and D&B validity measures for chain fast food restaurants, full service restaurants, grocery/supermarkets have been better than specialty food stores and restaurants.[103,104]

With respect to urbanicity, the CARDIA participants were initially recruited from four major U.S. cities and most resided in urban areas and this might reduce our vulnerability to differential misclassification by urbanicity at baseline. However, by exam year 15 participants had moved into 48 states with such that the mean population density decreased from 4,555 per km^2 at baseline to 1760 per km^2 at year 15.[116] Some studies suggest validity may be poor in rural compared to urban areas[101,102,107-110] but this finding is not consistent across studies.[104,107,169] In 1 urban and 7 rural South Carolina counties a field audit identified significantly more outlets than D&B.[103] Sensitivity was moderate (55%) and positive predictive value was good (78%) but the validity of the restaurant data decreased with decreasing urbanicity. While more than 80% of the food stores and restaurants combined were accurately geocoded to Census tract, only 29-39% were correctly assigned a location within 100m which could imply our food resource count data for the geographically similar suburban/rural areas may not be accurately aggregated within 100m of participants' residences. However, we used 3km and 8km buffers that may be less sensitive to such error than smaller buffer sizes. Differential misclassification of our food resource data by urbanicity could bias our analyses in any direction.

Another limitation of all secondary business data sources is that these lists that capture only a snapshot may not be updated frequent enough to capture new food retail outlets. However, our data are temporally matched to each exam year so we do not have to rely on a single view of the neighborhood food resources and we can capture changes over time.

Timing and Census data

Timing is a limitation of decennial Census data that are not temporally matched to exam years. Rather Census data were approximately time-matched to each examination period (CARDIA year, Census: Year 0, 1980; Years 7 and 10, 1990; Year 15, 2000; Year 20, 2000). This issue is most relevant for the periods when participants do not move between the exam years and we are relying on the same Census data (period 1: years 7 and 10; period 2: years 15 and 20). For example, a participant who does not move between exam years 7 and 10 will have the exact same neighborhood demographics from the 1990 Census for both exam years. There were 1,601 participants who did not move between exam years 7 and 10 (31%) and there were 3,432 (67%) who did not move between exam years 15 and 20. Among participants who do move, we do not know the precise between-exam move date but we do know the location at each exam date. Therefore, we cannot determine the exact time exposed to neighborhood environments in between exams. In addition, we do not know how much time participants spend in their neighborhood nor do we have spatial data from other areas, such as neighborhoods surrounding work locations.

Loss to follow-up

Losing participants in a cohort study is a common limitation in all longitudinal studies, especially one spanning multiple decades. A majority of the recruited participants were examined at each of the follow-up examinations. Over 20 years and 5 exams [1992-93 (Year 7), 1995-96 (Year 10), 2000-01 (Year 15), and 2005-06 (Year 20)] used in these analyses, the retention rates are excellent: 81%, 79%, 74%, and 72% (3,549), respectively, of the surviving cohort.

Residential Selection Bias

Our study did not explicitly model residential choice or account for residential selection bias. Thus, there may be residual confounding in our estimates due to unmeasured characteristics that influence neighborhood choice. Residential selection is very complex and driven by many factors that change throughout the life course (e.g., schools, marriage, jobs). To adequately account for it requires a wide breadth of longitudinal data and more sophisticated statistical approaches, such as a structural modeling approach for the joint estimation of associations that accounts for endogenous choices. Specifically, we would need to collect data covering a larger duration that begins during childhood or even birth and ends in later adulthood to incorporate residential mobility and recursive iterative statistical modeling.

Individual variation

In our study we estimated predicted diet behaviors as a function of neighborhood food resources. Thus, some individual variation is lost and we cannot explicitly model individual-level preferences or constraints. This limits the generalizability of our results to individuals versus populations.

STRENGTHS

Despite these limitations there are notable strengths to both our data and our analytic approach.

CARDIA is an ideal data source to evaluate the dynamic influence of the environment on individual behavior and health.

First, the CARDIA study is a large diverse cohort study with equal sampling by sex, race, education, and age is a significant strength of this research. CARDIA was created to study the development of clinical and sub-clinical cardiovascular disease. Thus, objectively measured anthropometry, physical activity, and sociodemographics were collected at each exam. CARDIA participants were followed from young adulthood to middle age capturing important life milestones such as marriage and children that influence physical activity and diet. CARDIA participants gained on average 17.9 kg among blacks and 12.5 kg among whites[141] over 20 years and dietary quality score increased from 64.1 ± 13.0 at year 0 to 71.1 ± 12.6 at year 20.[61] These data are ideal to examine the reciprocal relationships between different types of neighborhood restaurants and food stores and individual diet spanning 20 years, in the context of neighborhood SES while accounting for important changes of individual level SES and life course (e.g., education, employment, marriage, and children). <u>In addition, the sampling design allowed us to compare differences by CARDIA participant race and sex.</u>

Detailed diet history data collected at three exams is another significant strength of this work. Other large cohort studies often rely on less detailed food frequency questionnaires (FFQ) that are best suited for ranking individuals rather than quantifying amounts of foods/beverages consumed. For example, the American Cancer Society uses a 152 item modified Willett FFQ[175] that captures fewer foods and beverages than the referenced 1609 separate food items from the CARDIA diet history.[59] In addition, the open-ended questions and food-grouping system devised by the University of Minnesota Nutrition Coordinating Center, allowed the number of foods to increase over the 20 years while maintaining a consistent assessment method.

Obesity and Environment database

Our Obesity and Environment database is a unique and large GIS that links biologic and behavior data to the environment over time. It provided us with a tremendous opportunity to study the complex pathways from the neighborhood food environment to individual-level diet and BMI. Because it contains many community-level variables we were able to combine multiple features in our modeling latent neighborhood SES classes and latent food resource factors. Incorporating multiple measures into analyses captures the complexity of neighborhood environments that studies relying on single measures (e.g., distance to nearest outlet) miss. Further, the temporal and geographical link between the GIS to CARDIA participants allowed us to associate time varying features of the neighborhood with changes in the participant's behaviors, sociodemographics, and anthropometry throughout a period in the U.S., when obesity prevalence increased drastically. This rare database is a significant strength of this work.

Methodology

This research contributes two methodological innovations. First, latent class analysis is a sophisticated approach to quantify underlying relationships that are not explicitly measured.[176] Using this modeling technique we classified individuals according to a 20-year exposure to time-varying levels of neighborhood sociodemographics based on a combination of neighborhood characteristics rather than any single demographic, therefore better quantifying neighborhood

SES. Then we investigated disparities worsened or improved for participants depending on their exposure to different patterns of neighborhood SES.

Second, SEM is a flexible modeling approach which allows bi-directional path analysis, simultaneous testing of multiple relationships among unobserved characteristics, and allows for non-informative missing data. The food environment and diet are not simply measured and sophisticated statistical models are required to represent complex concepts. Using SEM, we captured multiple types of neighborhood resources into separate factors and to combine multiple diet behaviors into separate factors. Food stores and restaurants are very heterogeneous and offer many items that could be called healthy and unhealthy. Individuals eat a variety of foods and beverages that could also be called healthy (nutrient dense) and unhealthy (nutrient poor). Using SEM allowed us to combine multiple diet behaviors into latent factors that we hypothesized would be associated with each type of neighborhood food store or restaurant option. We simultaneously accounted for alternative restaurant (fast food versus sit-down) and food store (supermarkets versus convenience stores) options. SEM also allowed us to test our causal framework to provide evidence beyond the black box that indeed the food environment does influence weight gain through its influence on diet. Lastly we were able to use this complex SEM to address a piece of reverse causality sand how when we don't account for it this biases the associations.

D. FUTURE DIRECTIONS

While our research contributes substantive and methodological innovations to the field there are still gaps in our understanding about the role of the food environment on diet and obesity. We need to better understand where people shop for food, what they purchase, what they consume, and why. Food stores and restaurants offer a wide variety of foods and beverages and the quality of what is offered are not well characterized. Audit studies that characterize the quality of items available within restaurants and stores (e.g., Nutrition Environment Survey)[123,140,177] are improving how outlets can be classified regarding the healthiness of their inventory. In addition, access to scanned purchasing data (e.g., Nielsen Homescan Panel) is a valuable tool to objectively capture changes in purchasing behavior.[178] However, the pathway that connects the individuals to the exact point of purchase and later food consumption is lacking. Future research should link individuals in real time and space with the food resources they visit, what they purchase and then consume. Further, information about triggers and decisions about underlying diet behaviors could inform more tailored polices rather than focusing on numbers of different types of food stores and restaurants with a given geographic area. As new technologies and applications develop, future studies may capture the complete path in real time exposures, behaviors and outcomes.

Pathways from the food environment to BMI through diet could differ by age because younger versus older participants may have been exposed to different types of neighborhood food environments due to the circumstances of their life course (e.g., college). The CARDIA study design recruited participants at baseline so there would be equal sample sizes by ages 18-24 years and 25 to 30 years. In a sensitivity analysis, we took advantage of the age-based sampling and ran a multi-group analysis by age group (18-24 years versus 25 to 30 years). While the pathways findings were not statistically significantly different by age group there were some differences. The associations between restaurants and diet behaviors appeared to be stronger in both magnitude and significance at baseline for the younger than the older participants. The associations between the convenience stores and diet were stronger in both magnitude and significance at year 20 for the older than the younger group. Future research should explore how people differ in responses to food environments throughout the life course because there may be windows of time when people are more particularly vulnerable to "obesogenic" food environments to improve targeted food environment interventions.

Despite the uniqueness of this large racially diverse and prospective cohort, we lacked participants from other minority race/ethnicities that comprise a significant and growing proportion of the nation's demographics.[179] Further certain race subgroups, such as Hispanics are experiencing faster increases in obesity than non-Hispanic whites.[180] Thus, future research should explore pathways from the food environment to BMI through diet in more ethnically diverse populations that better represent the U.S. demographics. In addition, how pathways from neighborhood food environments to BMI through diet operate in rural areas is relatively unknown and warrants future research.

Food taxation and pricing policies can also influence diet behavior, therefore we need to understand how the food environment influences behaviors in the context of food and agriculture polices. New or changing policies offer researchers opportunities to take advantage of natural experiments to assess pre and post effects. Although more refined analyses might integrate legislative processes with epidemiological cohort data to establish timing of exposures and outcomes.

We hypothesized that visiting a restaurant versus food shopping in a food store are distinct processes but his may not be true. Perhaps decisions about which restaurant to visit can be swayed by nearby food stores and similarly some may decide, for example, to forego food shopping to eat dinner at a restaurant. In addition there is overlap among the diet behaviors we hypothesized would be associated with restaurants and food stores. In a sensitivity analysis, we included the pathways from each type of food resource to each of the latent diet behaviors. Compared to our main findings, the associations between restaurants and diet behaviors were attenuated. Greater numbers of neighborhood fast food restaurants were only associated with greater consumption at year 0 (β=0.23, *P*<0.001), while greater numbers of sit-down restaurants were associated with lower consumption (year 0: β=-0.27, *P*<0.001; year 7: β=-0.17, *P*<0.001) of foods typically purchased from fast food restaurants. At the same time, greater numbers of supermarkets were associated with lower consumption of the fast food (year 0: β=-0.21, *P*<0.001) and sit-down (year 0: β=-0.14, *P*<0.001; year 20: β=-0.09, *P*<0.001) restaurant-type diets. Conversely, greater numbers of convenience stores were associated with greater consumption of both the fast food (year 0: β=0.08, *P*=0.005) and sit-down (year 0: β=0.09, *P*<0.001; year 7: β=0.07, *P*=0.001) restaurant-type diets. Compared to our main findings for food stores, the pathways remained inconsistent when we included pathways from alternative neighborhood restaurants to influence consuming foods typically offered in food stores. However, greater numbers of fast food restaurants were associated with lower consumption of the supermarket-type diet (year 0: β=-0.25, *P*=0.001). Living near sit-down restaurants was associated with greater consumption of the supermarket-type diet (year 0: β=0.19, *P*=0.001) and lower consumption of the convenience store-type diet (year 0: β=-0.11, *P*<0.001). Future research should explore how diet behaviors associate with alternative restaurants and food stores.

There is limited information about what people actually consume at fast food versus sit-down restaurants and from purchases made at different types food stores. So, there may be other approaches to model diet behaviors that might be more meaningful to individuals. Further, dietary patterns, such as the Dietary Approach to Stop Hypertension diet, may better encompass the consumption of foods we did not include in our model but that are influenced by the food environment and contribute to weight gain (e.g., alcohol).

E. CONCLUSION

In conclusion, this research provides new longitudinal evidence that changes in the food environment influence weight gain through changes in diet behaviors. As numbers of restaurants and food stores increase globally, policymakers should consider reducing the numbers of fast food restaurants and increasing the numbers of sit-down restaurants in order to promote dietary changes that might prevent weight gain. Living in neighborhoods with more sit-down restaurants can increase the consumption of the variety of non-fast foods (e.g., fruits and vegetables) typically offered at sit-down restaurants, But more importantly, increasing numbers of sit-down restaurants can decrease the consumption of a fast food-type diet. Thus, policies may need to especially target the consistent 20-year lack of sit-down restaurants, as alternatives to fast food restaurants in the socioeconomically disadvantaged neighborhoods. Throughout 20 years of adulthood, residents living in the most socioeconomically deprived neighborhoods consistently had the same number of supermarkets, and more convenience stores in their neighborhoods than other residents, yet food stores did not appear to play a role in diet and BMI, regardless of whether the residents lived in high or low SES neighborhoods. If restaurants contribute more to obesity than food stores then policies and initiatives might be more effective if they shift their focus on food stores to restaurants and away-from-home eating behaviors.

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