Is the focus on food deserts fruitless? Retail access and food purchases across the socioeconomic spectrum *

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July 28, 2015

Abstract

Despite an absence of causal evidence showing that limited access to healthy foods is to blame for unhealthful consumption, policies aimed at improving poor diets by improving access are ubiquitous. In this paper, we use novel data describing both the healthfulness of household food purchases and the retail landscapes facing consumers to measure the role that access plays in explaining why some people in the United States eat more nutritious foods than others. We first confirm that households with lower income and education purchase less healthful foods. We then measure the spatial variation in the average nutritional quality of available food products across local markets, revealing that healthy foods are less likely to be available in low-income neighborhoods. Though significant, spatial differences in access are small relative to the spatial differences in store sales and explain only a fraction of the variation that we observe in the nutritional content of household purchases. Systematic socioeconomic disparities in household purchases persist after access is equated: even in the same store, wealthier and more educated households purchase more healthful foods. Consistent with this result, we further find that the nutritional quality of household purchases responds very little to changes in their retail environment, especially among households with low levels of income and education. Together, our results indicate that even if spatial disparities in access are entirely resolved, over two-thirds of the existing socioeconomic disparities in consumption would remain.

*Prottoy Aman Akbar and Yue Cao provided us with outstanding research assistance. David Cuberes, Amanda Chuan, Janet Currie, Gilles Duranton, Ephriam Liebtag, Ilyana Kuziemko, Todd Sinai, Diane Whitmore Schanzenbach, Tom Vogl, and David Weinstein provided helpful comments. We thank participants in seminars at the 2014 Urban Economics Association Meeting, the 2015 American Economic Association Meeting, the 2015 NBER Summer Institute, NYU, Princeton, the Federal Trade Commission, Wharton, and the Economic Research Service at the USDA. Jessie Handbury would like to thank the Wharton Social Impact Initiative, the Research Sponsors' Program of the Wharton Zell-Lurie Real Estate Center, and the Economic Research Service at the USDA for generous financial support. The views expressed are those of the authors and should not be attributed to the Economic Research Service, the USDA, Nielsen, Gladson, or IRI. This paper was previously circulated under the title "What drives nutritional disparities? Retail access and food purchases across the socioeconomic spectrum," NBER Working Paper No. 21126, April 2015.

1 Introduction

While it is well known that there are large nutritional disparities across different socioeconomic groups in the United States, concrete evidence on why these disparities exist has been elusive. Poor diets could be attributed to any of three factors: limited access to healthy foods, higher prices of healthy foods, or preferences for unhealthy foods. Under the assumption that differential access plays an important role in explaining nutritional disparities, the Agricultural Act of 2014 appropriated $125 million in federal funds to be spent annually in each of the next five years to promote access to healthy foods in underserved communities (Aussenberg (2014)). Many state and local governments have also introduced programs to improve access by providing loans, grants, and tax credits to stimulate supermarket development and encourage existing retailers to offer healthier foods in food deserts (CDC (2011)).[1]

Despite the growing popularity of such programs, little is known about their potential for narrowing nutritional disparities. This paper seeks to fill this gap. In doing so, we make three key contributions to our understanding of socioeconomic disparities in nutrition and spatial disparities in access. First, we construct a dataset describing the nutritional quality of the food products purchased by households across the entire U.S. to provide the most thorough depiction of socioeconomic disparities in nutritional consumption to date.[2] Combining data on the spatial distribution of stores, availability of nutritious products, and relative prices of healthy-to-unhealthy foods, we then provide an equally comprehensive depiction of spatial disparities in access. Finally, in our main contribution, we use the detailed nature of our data to show that spatial disparities in access play a limited role in generating socioeconomic disparities in nutritional consumption. Our results indicate that improving access to healthy foods alone will do little to close the gap in the nutritional quality of grocery purchases across households with different levels of income and education. Even if spatial disparities in access were entirely resolved, over 70% of the existing socioeconomic disparities in nutritional consumption would remain.

Before quantifying the role that access plays in generating nutritional disparities, we must first measure the disparities themselves. Previous studies have documented disparities in nutritional consumption by focusing on purchases of a few products, such as fruits or vegetables, or in specific localities (see Bitler and Haider (2011) for a detailed survey of this work).[3] To obtain a more complete picture of the nutritional quality of household purchases, we combine consumption data from Nielsen with nutritional information from Gladson and IRI. The dataset we construct describes the full nutritional profiles of the grocery purchases made by an unbalanced panel of over 100,000 households across the U.S. in each month between 2006 and 2011. We calculate two complementary household-level indexes, an "expenditure score" and a "nutrient score," that represent the healthfulness of the product bundles purchased relative to USDA category-level expenditure recommendations and FDA recommendations for per calorie nutrient consumption, respectively.[4] An examination of these household-level nutritional indexes reveals significant disparities in the healthfulness of purchases across households with different levels of income and education. On average, households with above median income and education have scores that are 26-30% of

[1]Between 2004 and 2010, the Pennsylvania Fresh Food Financing Initiative provided $73.2 million in loans and $12.1 million in grants to stimulate supermarket development in food deserts in the state. In 2013, North Carolina House Bill 957 began granting tax credits to retailers who offer healthful foods in food deserts. In 2014, Maryland House Bill 451 provided $1 million in assistance to food deserts through loans and grants, and the New Jersey Food Access Initiative started a private-public partnership to attract supermarkets to underserved areas.

[2]We use "purchases" and "consumption" interchangeably. Differences in food waste, charitable giving, etc. that lead household purchases to systematically differ from household consumption are beyond the scope of this paper.

[3]While there is a large literature in economics on the relationship between socioeconomic status and various health behaviors (e.g. Cutler and Lleras-Muney (2010); Jones (1997)), grocery purchases are one health behavior which has received surprisingly little attention.

[4]Our expenditure score is an extension of the measure used by Volpe et al. (2013). Given the nutritional information we have from Gladson and IRI, however, we can go further than looking at expenditures on food group categories alone. Our nutrient score directly measures the healthfulness of the relative quantities of nutrients in the products purchased.

a standard deviation higher than the scores of households with below median income and education.

Next, we provide the most comprehensive picture to date of how access to healthy food varies across the U.S. and quantify the degree to which retail environments systematically differ by neighborhood demographics.[5] Using an annual, geo-coded census of over 200,000 food retailers for 2006 through 2011, we first corroborate previous work which finds that residents of wealthier and more educated neighborhoods have more food stores in their vicinity (Beaulac et al. (2009); Ver Ploeg et al. (2009)). Going beyond previous studies, we then use weekly store-level sales data from Nielsen to identify the products available and the prices at which these products are offered at over 30,000 retailers. We merge the store-level Nielsen data with nutritional information from Gladson and IRI to calculate three novel measures of access. The first two measures are analogous to the indexes used in the household-level analysis and reflect the healthfulness of the products available at stores. We find statistically significant correlations between observable market characteristics and the store-level healthfulness indexes, with stores in higher socioeconomic status (SES) neighborhoods offering more healthful products. These differences, however, are small relative to the differences in the healthfulness of store sales, the scores for which vary between four to six times more across neighborhoods than the availability scores.

Even if similar products are available across neighborhoods, healthful foods may be relatively less expensive, and in turn more accessible, in wealthier and more educated neighborhoods. Our final accessibility index looks at prices and reflects the relative markup over national prices for healthy versus unhealthy products at each store. An examination of this measure reveals that differential pricing is not to blame: healthful foods are, if anything, relatively *more* expensive than unhealthful foods in wealthier and more educated neighborhoods. Together, these results establish that retail environments differ more in the density of stores available to consumers than in either the nutritional quality of available products or the relative prices of products offered in these stores.[6]

The main goal of this paper is to quantify the role that the spatial disparities we document using the store-level data play in generating the consumption disparities that we observe using the household-level data. While there has long been agreement among researchers that both spatial disparities in access and socioeconomic disparities in nutritional consumption exist, up to this point the actual effects of access to healthy foods on food purchases have been heavily contested (Bitler and Haider (2011)).[7] Some studies find no relationship between store density and consumption (see, for example, Pearson et al. (2005) and Kyureghian et al. (2013)), while studies that do find a positive relationship infer the role of food environments from a cross-sectional correlation between local store density and food purchases in a single city or in a few neighborhoods (Rose and Richards (2004); Morland et al. (2002); Bodor et al. (2008); Sharkey et al. (2010)). Determining the direction of causality in this relationship is crucial in assessing the potential impact of policies that encourage the entry of new stores into food deserts on food purchases of households in these areas.

We present a simple model to highlight the identification challenge that we face in identifying the causal role of access. The model nests two mechanisms, one driven by demand and one driven by supply, each which can independently explain the socioeconomic disparities in access and consumption that we observe. The demand-side explanation relies on within-group preference externalities: In a monopolistically competitive retail industry, firms

[5] In what follows, we define a neighborhood as a census tract.

[6] Product presentation and freshness are other dimensions of access that may systematically vary across neighborhoods. While we do not have the qualitative data necessary to examine this directly, we will be able to control for *all* dimensions of access by comparing the purchases made by households shopping in the same store.

[7] There is also no consensus on the impact of a household's retail environment on obesity and other health problems. Anderson and Matsa (2011) find no effect of fast food entry on obesity, while Currie et al. (2010) find impacts for school children and pregnant women. Courtemanche and Carden (2011) find that Walmart entry increases local obesity rates, though non-causal results from Chen et al. (2010) and Volpe et al. (2013) suggest that the impact of store entry varies with neighborhood characteristics and the type of store entering.

will cater to the prevalent tastes in the local market. If high-SES households have stronger tastes for healthy foods, then it follows that more healthful food products will be available in high-SES neighborhoods. The supply-side explanation relies on two fairly general assumptions: (i) wholesale unit costs are increasing in product healthfulness but do not vary across location, and (ii) the marginal cost of retailing, specifically, the rental cost of shelf space, is increasing in the share of high-SES residents in a neighborhood but does not vary across products. These assumptions imply that firms in neighborhoods with a greater share of high-SES residents have a comparative advantage in the distribution of nutritious products. As a result, they will offer more healthful food products than stores in low-SES neighborhoods, even if high-SES and low-SES households have identical tastes. Since either the supply-side or the demand-side mechanism is sufficient to generate the observed correlation between consumption and access, this correlation alone is not sufficient to uncover the role that access plays in generating nutritional disparities separately from the role of demand-side factors.

Our model motivates two complementary analyses that allow us to go beyond existing work and examine the direction of causality in the relationship between nutritional availability and nutritional consumption. Our first empirical strategy is cross-sectional and compares the disparities that exist across the entire U.S. to disparities that exist across households living in the same location or shopping in the same store. We expect disparities in consumption that are due to differential access to exist only between households living in different neighborhoods, so the disparities that we observe within a given retail environment provide an estimate of the disparities in consumption that would persist if spatial disparities in access were fully resolved. The difference between these within-location disparities and those that we observe in the full cross-section of households therefore provides an estimate of the proportion of existing nutritional disparities that can be removed by equating access across the entire U.S. If tastes only vary with income and education, this estimate will be exact. If tastes also vary with unobservable household characteristics, and households sort into residential and retail locations according to these tastes, then the observed within-location disparities will instead be a downward-biased estimate of the disparities that would persist if retail access were equalized nationwide. In this case, the difference between the within-location disparities and the disparities that we observe in the full cross-section will instead provide an upper bound on the maximum potential impact of access-improving polices.[8]

Our cross-sectional results indicate that equalizing retail access across the entire U.S. would resolve less than a third of the observed disparities in nutritional consumption. When we control for access by looking at households living in the same census tract, nutritional disparities between households that are above versus below the national medians for both income and education are reduced by 23-32%. It is possible, though, that households living in the same neighborhood still have differential access, either because they live in different locations within the neighborhood or because of differences in mobility. To eliminate differences in access entirely, we look at purchases made within a given store. The results from the within-store analysis mirror those from the within-location analysis: the socioeconomic gap in the healthfulness of food purchases is reduced by less than a quarter when we only compare purchases in the same store. In both the within-location and within-store analyses, the majority of the disparities that we observe between households across the entire U.S. persist when we control for access. Even if spatial

[8]Note that, even without unobserved heterogeneity in tastes, the within-location disparities only provide a lower bound (rather than a point estimate) for the role of demand in generating the *observed* disparities in consumption. By focusing on the purchase disparities between households shopping in the same retail environment, we completely shut down any supply-side mechanisms driving consumption disparities. In addition to this, however, we also shut down the "preference externalities" component of the demand-side mechanism; that is, the endogenous differences in access that are caused by spatial differences in demand. As such, within-location estimates will underestimate the role of demand. The model therefore also serves to demonstrate that the difference between the disparities we observe across the entire U.S. and the disparities that we observe within locations can be interpreted as an upper bound on the component of the existing disparities in purchases that can be explained by differences in retail environments that are not driven by differences in demand.

disparities in access are entirely resolved, at least 68% of the existing nutritional disparities would remain.

Policies that improve access in underserved areas will only be effective in resolving socioeconomic disparities in nutritional consumption insofar as they induce households with low levels of income and education to buy healthier foods. Our second empirical strategy leverages observed changes in retail environments over our sample period to directly measure how households in our data responded to changes in access in the past. While comparing the purchases of the same household over time removes any correlation between changes in access and time-invariant components of household demand, changes in access will likely be correlated with unobserved changes in household tastes. This endogeneity of changes in access to these unobserved taste shocks implies that the observed response of households "treated" with changes in access are an upper-bound for the expected response of underserved households more generally.

Previous studies measuring the effects of changes in retail landscapes on food purchases are local in scope, looking at either the entry of a single supermarket or an intervention to increase the availability of nutritious food products in a single urban food desert, and find modest effects (Wrigley et al. (2003); Cummins et al. (2005); Weatherspoon et al. (2013); Song et al. (2009); Cummins et al. (2014)). We demonstrate that these results hold more generally by showing that the elasticity of the healthfulness of household food purchases with respect to the density and nutritional quality of retailers in the household's vicinity is positive, but close to zero. Providing the typical low-SES household with access to the retail environment of the average high-SES neighborhood would only close the gap in nutritional consumption across these groups by 1-3%. Looking at changes in access driven by store entry alone, we again find very limited responses of the healthfulness of household purchases despite evidence that households are aware of new stores: an event study analysis shows that households change the mix of stores in which they shop when a new store is introduced, but there is no lasting impact on the nutritional quality of household purchases. These results again indicate that policies aimed at improving access to healthful foods will do little to resolve disparities in nutritional consumption.

Despite a large policy literature on the topic, the relationship between access and nutritional consumption has been largely ignored by economists. Methodologically, our paper is closest to a literature that uses the entry of fast food restaurants and large retailers, such as Walmart, to identify a causal relationship between retail environments and obesity (Currie et al. (2010); Anderson and Matsa (2011); Courtemanche and Carden (2011)). Our paper departs from these previous studies in two important dimensions. First, we are concerned not just with the relationship between access and nutritional consumption, but rather the interaction between access, nutritional consumption, and socioeconomic status.[9] This is important for evaluating the effectiveness of current policies, as recent efforts to improve access do so with the intent of reducing disparities in consumption across different socioeconomic groups. Second, we look directly at the mechanism, food purchases, by which we expect changes in retail environments to impact obesity, rather than obesity itself. While access may have a causal impact on obesity, it need not work through the hypothesized mechanism, and the mechanism is of greater concern from a policy perspective.

If disparities in retail access do not generate the consumption disparities that we observe, then something else is to blame. In the context of our model, differences in demand are generated by differences in tastes. There are, however, a range of other explanations for disparities in purchases, including differences in price sensitivities and

[9]Currie et al. (2010) examine differences by race and education. They find that the impact of fast food entry on weight gain is greatest among African American mothers and mothers with a high school education or less. In our time-series analysis, we find that wealthier and more educated households respond slightly more to improvements in access to healthful foods. This difference is consistent with the finding of Chen et al. (2010) and Volpe et al. (2013) that the impact of store entry depends on both neighborhood characteristics and the type of store entering.

budget constraints. For the purposes of this paper, we remain agnostic as to the reasons why we observe systematic differences in the healthfulness of purchases made by households either living in the same location or shopping in the same store. In future work, we aim to determine which factors are most important for explaining the large disparities that persist when we look at households in the same retail environment.

The paper proceeds as follows. In Section 2, we describe the datasets that we use. In Section 3.1, we present the indexes that we construct to measure the nutritional quality of household consumption baskets, and we document how these indexes vary across households with different levels of income and education. Section 3.2 introduces our measures of access to nutritious foods and documents disparities in access across markets with different observable characteristics. In Section 4.1, we provide the intuition behind a model that nests two mechanisms that can each generate the observed disparities in both purchases and access, and we demonstrate how the detailed nature of our data can be used to bound the role that access plays in generating consumption disparities. Section 4.2 implements our cross-sectional approach by looking at whether consumption disparities persist when we control for residential or retail location. Section 4.3 takes an alternative, time-series approach and examines whether we observe the healthfulness of household purchases responding to changes in local access. In Section 5, we provide a discussion of our results and conclude.

2 Data

We combine six datasets that together describe the nutritional quality of grocery purchases that households make, the food stores located in the neighborhoods where these households reside, the nutritional quality of the products offered in these stores, and the demographics of these neighborhoods. The first dataset is the Homescan data collected by the National Consumer Panel (NCP)[10] and provided by Nielsen. The Homescan data contains transaction-level purchase information for a representative panel of 114,286 households across the U.S. between 2006 and 2011. Households in the panel use a scanner provided by NCP to record all of their purchases at a wide variety of stores where food is sold.[11] After scanning the Universal Product Code (UPC) of each item purchased, the household records the date, store name, quantity purchased, and price. Households participate in the NCP panel on average for two years and eight months with the length of observed participation ranging from six months to the full period of analysis (2006 to 2011). In addition to household-level purchase activity, the Homescan data also includes yearly information on demographics and residential location for each household in the panel. We use the demographic data to measure two dimensions of socioeconomic status that are posited to impact a household's consumption decisions: income and education.[12,13]

While the Homescan data describes the stores in which panelists shop and the products that they purchase at these stores, it only provides a limited picture of the retail environments in which households are making their

[10]The National Consumer Panel is a joint venture between Nielsen and IRI.

[11]See Harding and Lovenheim (2014) for a detailed description of how households are recruited and encouraged to report purchases on a weekly basis.

[12]Households record whether their income falls into one of 16 categories, listed in Table A.1. We limit our analysis to households that have at least one household head working over 30 hours a week and report annual earnings of over $8,000. We assign households an income equal to the midpoint of their income category for each bounded category and an income of $260,000 for the "$200,000 and above" category. Where noted, we adjust the resulting household income for household size using the OECD equivalence scale. The first adult in the household receives a weight of 1, all other adults receive weights of 0.5, and each child receives a weight of 0.3 (http://www.oecd.org/eco/growth/OECD-Note-EquivalenceScales.pdf).

[13]Households record the household head's education in one of six categories: grade school, some high school, high school graduate, some college, college graduate, or post-college graduate. The distributions of household heads across these education categories by sex are recorded in Tables A.2 and A.3. Households in which either household head reports only a grade school education are excluded from our analysis. We assign each household head a number of years of education assuming that some high school corresponds to 10 years, some college corresponds to 14 years, and post college corresponds to 18 years. For households with two household heads, we use their average years of education.

purchase decisions. There are two problems with using the Homescan data to characterize retail environments: First, if no household in the Homescan sample shops at a given store, then we do not observe from the data that this store exists. Second, even if we do observe households shopping in a given store, we only observe the products that they actually purchase, not the full variety of products offered. Because of these limitations, we use two additional datasets, both maintained by Nielsen, to obtain a more comprehensive picture of the retail environments that households face. To see the full set of stores available to households, we use the Nielsen TDLinx data. The TDLinx data contains the names and geo-coded locations of nearly 200,000 food stores across the U.S.[14] To see the full set of food products available at a subset of these stores, we use the Nielsen Scantrack data provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business.[15] The Scantrack data contains weekly sales and quantities by UPC collected by point-of-sale systems in over 30,000 participating retailers across the U.S.[16] We use this data to calculate indexes that summarize both the nutritional quality and the relative prices of products offered by each store in the dataset.[17,18,19]

The Nielsen datasets do not contain nutritional information for the products purchased by Homescan panelists or sold by Scantrack stores. We obtain this information from Gladson and IRI. The Gladson Nutrition Database provides nutritional information for over 200,000 unique UPCs throughout the entire length of our sample. For 2008 onwards, we supplement the Gladson data with nutritional information from the IRI database of over 700,000 UPCs. Each database contains information on the quantity of macro-nutrients and vitamins per serving, serving size in weight, and the number of servings per container. Gladson and IRI collect this information directly from product labels.[20] We merge the Gladson and IRI data with the Homescan and Scantrack data to uncover the full nutritional profiles of products we observe being purchased by households and sold in stores.[21] In Sections 3.1 and 3.2, we describe how we use this information to measure the healthfulness of household grocery purchases and the healthfulness of products offered in stores, respectively.

The final dataset that we use contains tract-level demographics from the 2010 U.S. Census.[22] We use this information to measure the distribution of income and education in the neighborhoods in which Nielsen households reside and Nielsen stores are located.

[14]Stores are divided into five categories in the TDLinx data: grocery, convenience, drug, mass merchandise, and wholesale club.

[15]Information on availability and access to this data is available at http://research.ChicagoBooth.edu/nielsen.

[16]Stores are divided into four categories in the Scantrack data: grocery, convenience, drug, and mass merchandise.

[17]We assume that every product available in a store is sold to at least one customer each month.

[18]Despite this detailed information on prices and product offerings, the Scantrack data covers a more limited range of retail outlets than the TDLinx data and only provides us with the county, not the precise geo-coded location, of each store. Where possible, we obtain the geo-coded location of the stores in the Scantrack data by matching them to the TDLinx data as follows: If there is only one observation for a given combination of store name and county in both datasets, then we assume that this is the same store. If there are multiple observations for a given store name-county pair, we match the stores based on a comparison of the households that we observe shopping at both the TDLinx and the Scantrack store on the same day.

[19]One concern with the Scantrack data is that participation of retailers may systematically vary across neighborhoods. As shown in Figure A.1, the average share of TDLinx stores appearing in the Scantrack sample is the same across tracts with different demographics.

[20]Product characteristics can change without a change in the product's UPC. When Gladson receives an updated version of a product that was already in the database, it revises the entry and includes a time stamp of when the change was made. We use a version of the database that includes a snapshot of the market as of July 30th each year. We assume that these product characteristics are relevant for that calendar year.

[21]These merges are not perfect. Only 45% of the UPCs in the Homescan data and 57% of the UPCs in the Scantrack data are in either the Gladson or the IRI nutrition database. We impute nutritional information for products not in the Gladson or IRI data using the average for UPCs in the same product module and product group with the same values for all other relevant characteristics, including brand, flavor, form, formula, style, and type.

[22]The Nielsen data identifies household locations using 2000 census tract definitions. We adjust demographics from the 2010 Census to reflect boundaries from 2000.

3 Stylized Facts

3.1 Socioeconomic Disparities in Nutritional Consumption

We begin by documenting the extent of disparities in nutritional consumption across households with different levels of income and education. We focus on the *quality* rather than the quantity of food a household purchases since the latter is affected by the extent to which a family eats at restaurants, and a propensity for eating out is likely related to household characteristics.[23] We measure the quality of household purchases using two complementary indexes, both of which are calculated at a monthly frequency for each household in our sample. The first index, which we refer to as the "expenditure score," measures the extent to which a household's grocery purchases deviate from the USDA Center for Nutrition Policy and Promotion (CNPP)'s dietary guidelines for recommended expenditure shares by food category. This index follows the measure used by Volpe et al. (2013). Given the nutritional information we have from Gladson and IRI, however, we can go further than looking at expenditures on food categories alone. We therefore also calculate a "nutrient score" that directly measures the healthfulness of the relative quantities of nutrients in the products purchased. The nutrient score measures the extent to which a household's purchases deviate from the FDA's recommendations for nutrients per calorie. Both indexes are based on inverse squared loss functions that penalize households for monthly purchases above (below) the recommended amounts in unhealthful (healthful) food categories or nutrients.[24]

The expenditure score for the grocery purchases recorded by household h in month t is defined as

$$Expenditure\ Score_{ht} = \left[\sum_{c \in C_{Healthful}} \left(sh_{cht} - sh_{ch}^{CNPP} \right)^2 |sh_{cht} < sh_{ch}^{CNPP} \right.$$
$$\left. + \sum_{c \in C_{Unhealthful}} \left(sh_{cht} - sh_{ch}^{CNPP} \right)^2 |sh_{cht} > sh_{ch}^{CNPP} \right]^{-1}$$

where c indexes CNPP food categories, sh_{cht} denotes the percent of household h's grocery expenditures in month t spent on products in category c, and sh_{ch}^{CNPP} is the category c expenditure share, also in percent units, that the CNPP recommends for a household with the same gender-age profile as household h.[25] We determine which CNPP food categories are healthful and unhealthful using the recommendations from the Quarterly Food-at-Home Price

[23]We are working with the USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) to measure socioeconomic disparities in the nutritional quality of food consumed away from home. While knowing how nutritional consumption at home and away from home are related is important for understanding the overall nature of nutritional disparities, this relationship is not critical for our focus here. Current policies that aim to reduce nutritional disparities by improving access primarily do so by targeting access to food for at-home consumption. The relationship between the nutritional quality of food consumed at home and away from home will therefore only be important when evaluating the effectiveness of these policies if households substitute between these means of consumption when retail access improves. However, we do not observe any evidence of this substitution: the quantity of calories purchased by households in our panel do not increase when access changes. This suggests that only the direct effect of retail access on purchases for at-home consumption needs to be considered.

[24]Neither index rewards households for purchases below (above) the recommended amounts in unhealthful (healthful) categories or nutrients. Our results are robust to the use of indexes which incorporate the degree of compliance.

[25]We use the recommended individual expenditure shares from the "liberal food plan" in Carlson et al. (2007) to construct recommended household expenditure shares. The recommended category c expenditure share for each household member i, denoted by sh_{ci}^{CNPP}, is determined by his/her age and gender profile. We assign weights to each household member following the OECD equivalence scale and calculate the food expenditure weights as $w_{adult} = \frac{\frac{1+(n_{adult}-1)\times 0.5}{n_{adult}}}{1+(n_{adult}-1)\times 0.5+n_{children}\times 0.3}$ and $w_{child} = \frac{0.3}{1+(n_{adult}-1)\times 0.5+n_{children}\times 0.3}$. The recommended category c expenditure share for household h is a weighted average of the recommended category c expenditure shares for each household member, i.e. $sh_{ch}^{CNPP} = \sum_i w_i sh_{ci}^{CNPP}$. Our results are robust to using the recommended individual expenditure shares from the thrifty, low-cost, or moderate-cost food plans instead of those from the liberal food plan.

Database (QFAHPD) indicators for which of 52 food groups are healthful and unhealthful.[26,27] The expenditure score penalizes households for having a higher-than-recommended expenditure share for healthful food categories ($c \in C_{Healthful}$) and for having a lower-than-recommended expenditure share for unhealthful categories ($c \in C_{Unhealthful}$).[28] We follow Volpe et al. (2013) and take the inverse of the squared loss function so that higher scores are indicative of healthfulness.[29]

Analogously, the nutrient score for the grocery purchases recorded by household h in month t is defined as

$$\begin{aligned} Nutrient\ Score_{ht} \quad = \quad & \Bigg[\sum_{j \in J_{Healthful}} \left(\frac{pc_{jht} - pc_j^{FDA}}{pc_j^{FDA}} \right)^2 | pc_{jht} < pc_j^{FDA} \\ & + \sum_{j \in J_{Unhealthful}} \left(\frac{pc_{jht} - pc_j^{FDA}}{pc_j^{FDA}} \right)^2 | pc_{jht} > pc_j^{FDA} \Bigg]^{-1} \end{aligned}$$

where j indexes nutrients, pc_{jht} denotes the amount of nutrient j per calorie in household h's grocery purchases in month t, and pc_j^{FDA} is the amount of nutrient j that the FDA recommends an individual consume per calorie as part of a 2,000 calorie diet.[30] The FDA indicates whether to consider its recommendation for a given nutrient as a lower bound or an upper bound. We assign the nutrients for which the FDA recommendation is an upper bound to the unhealthful category (total fat, saturated fat, trans fat, sodium, and cholesterol) and the nutrients for which the FDA recommendation is a lower bound to the healthful category (fiber, iron, calcium, Vitamin A, and Vitamin C).[31] The nutrient score penalizes households for purchasing less (more) than the recommended amount of healthful (unhealthful) nutrients per calorie.[32] To account for differences in the units in which nutrients are measured, we normalize the deviations of household nutrient purchases from the FDA's recommendations.[33]

The two scores consider the healthfulness of consumer purchases from two complementary perspectives, and each measure has its strengths and its weaknesses.[34] Since consumers choose foods rather than nutrients, the expenditure score is more closely related to consumer demand. Furthermore, expenditures on specific food groups, such as fruits and vegetables, are used by many other studies, and thus the expenditure score is more comparable to previous research.[35] Finally, the expenditure score takes into account other nutrients, such as zinc and potassium,

[26] We aggregate the 52 QFAHPD food groups to the 24 CNPP food categories using the correspondence created by Volpe and Okrent (2013). In doing so, we find that two CNPP food categories, cheese and meat, contain both healthful and unhealthful food groups. Since the vast majority of cheese and meat purchases are of UPCs that fall into the unhealthful QFAHPD food groups, we assume that the aggregate CNPP cheese and meat categories are unhealthful. All of our results are robust to assuming that these food categories are instead healthful.

[27] Refer to Table A.4 for the full list of healthful and unhealthful food categories that we use.

[28] As there are no clear guidelines for which food categories are most important for health, the index construction gives equal weight to all categories. For example, an underconsumption of whole fruits and an overconsumption of frozen or refrigerated entrees are treated the same.

[29] We exclude expenditure scores that are more than twice the distance between the 90th and 50th percentiles from our analysis (nearly 5% of household-month scores).

[30] These recommendations come from the FDA's instructions for how to make use of nutritional labels (http://www.fda.gov/Food/IngredientsPackagingLabeling/LabelingNutrition/ucm274593.htm, last accessed on December 4, 2014).

[31] Some of these nutrients are identified as "nutrients of concern" in the USDA's Nutritional Guidelines for Americans while others are not. We use all of the available recommended nutrients, regardless of whether they are nutrients of concern, as our goal is to assess the overall healthfulness of individual diets rather than larger public health concerns. The nutrient index highlights the choices that consumers make relative to the information and recommendations available to them at the time of purchase. It is likely that the included nutrients, such as Vitamins A and C (both listed as "nutrients of concern" in 2005 but dropped in 2010 in response to increased consumption), are correlated with "nutrients of concern" for which we do not have information, such as potassium.

[32] As with food categories, there are no clear guidelines for which nutrients are most important for health. Therefore, the index construction gives equal weight to all nutrients. For example, an underconsumption of fiber and an overconsumption of saturated fat are treated the same.

[33] As with the expenditure scores, we exclude nutrient scores that are more than twice the distance between the 90th and 50th percentiles from our analysis (nearly 5% of household-month scores).

[34] The household expenditure and nutrient scores are positively correlated (correlation coefficient of 0.19).

[35] The correlation between our expenditure score and expenditure shares on fruits and vegetables is 0.54.

which are not displayed on the nutritional facts panel and are therefore not included in the nutrient score. The nutrient score, on the other hand, distinguishes between products in the same food category, e.g. frozen fish fillets versus fish sticks, that will be missed by the expenditure score. The nutrient score is also not sensitive to systematic variations in the price of foods purchased by different socioeconomic groups. If, for example, low-income and high-income consumers purchase identical quantities of cheese, but high-income consumers purchase more expensive varieties, then for all else equal expenditure scores will differ by income. The nutrient score, on the other hand, will reflect that both groups have similar diets.[36]

We are interested in the extent to which the nutritional quality of household purchases varies systematically with household characteristics. In Table 1, we regress household expenditure and nutrient scores on household income, household education, and other demographics with year-month fixed effects.[37,38] We see that wealthier and more educated households purchase more healthful foods, measured using either the expenditure or the nutrient score. Although both effects are statistically significant, the standardized coefficients reported in columns (4) and (8) reveal that education explains more of the variation in the quality of household purchases than income. Nutritional disparities across households with different levels of education but the same level of income are 32-43% larger than disparities across income levels controlling for education.

One can see this graphically in Figure 1, which depicts the average expenditure and nutrient scores for households with income and education above and below the respective medians.[39] In addition to confirming that average scores vary more across education groups than across income groups, these bar charts also provide a way to interpret the magnitude of the variation in expenditure and nutrient scores by socioeconomic status. Comparing the high-income, high-education average with the low-income, low-education average, we see that the scores of households with above median income and education are on average 26-30% of a standard deviation higher than the scores of households with below median income and education.

Table 1: Household Characteristics and Nutritional Quality of Purchases

	Ln(Expenditure Score)				Ln(Nutrient Score)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Income)	0.0424***		0.0241***	0.0426***	0.146***		0.0893***	0.0636***
	(0.0013)		(0.0014)	(0.0024)	(0.0028)		(0.0030)	(0.0021)
Ln(Education)		0.247***	0.203***	0.0743***		0.798***	0.635***	0.0939***
		(0.0060)	(0.0065)	(0.0024)		(0.013)	(0.014)	(0.0021)
Observations	3,440,297	3,440,297	3,440,297	3,440,297	3,440,297	3,440,297	3,440,297	3,440,297
R^2	0.061	0.064	0.066	0.066	0.022	0.026	0.029	0.029
Standardized	No	No	No	Yes	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Observations are at the household-month level. Standard errors are clustered by household. All regressions include year-month fixed effects and controls for household demographics, including household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic.

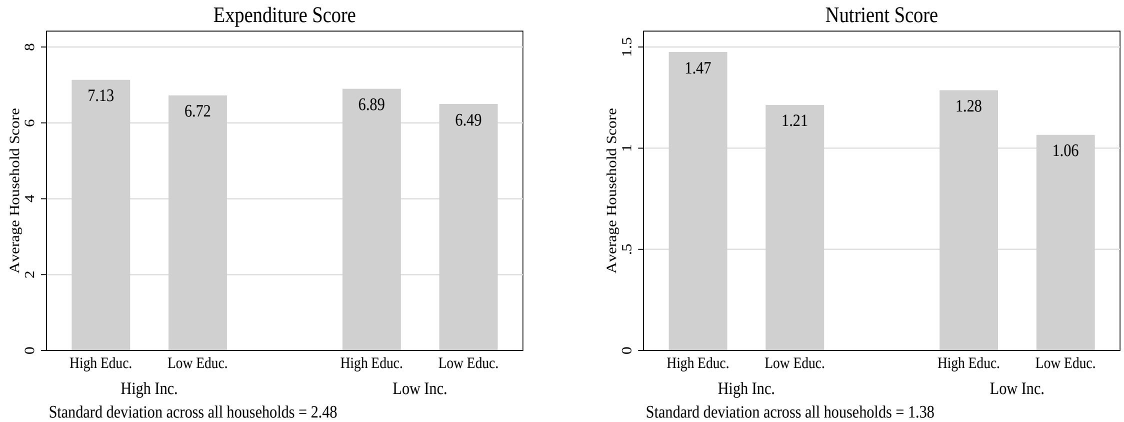
[36]To address the sensitivity of expenditure scores to prices, we recompute household food category expenditures using the average price per module instead of the actual price paid. Expenditure scores based on this alternative measure of expenditures are comparable to expenditure scores calculated using observed expenditures.

[37]All regressions include household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic. See Table A.6 for the full regression results.

[38]Refer to Tables A.7 – A.10 for regression results by individual food categories and nutrients. That is, we run the same regressions as in Table 1, but instead of the household nutrition indexes the dependent variable is either the difference between the household's expenditure share and the recommended expenditure share on a particular food category or the normalized deviation of the household's per-calorie consumption from the recommended per-calorie consumption of a particular nutrient.

[39]Refer to Figures A.2 and A.3 for average household expenditure and nutrient scores by income terciles and by education terciles, respectively.

Figure 1: Expenditure and Nutrient Scores Across Households



Notes: The figure above presents average household-level expenditure and nutrient scores across households with different socioeconomic profiles. Households are considered high income (HI) if their size-adjusted household income falls above the median level across all households ($39,221) and low income (LI) otherwise. Households are considered high education (HE) if the average years of education of their household head(s) falls above the median across all households (13.98 years) and low education (LE) otherwise. 33% of households are HI/HE, 17% are HI/LE, 17% are LI/HE, and 33% are LI/LE. These results are for January 2010; they are representative of the other months in the Homescan data.

3.2 Spatial Disparities in Access

We now turn to documenting disparities in access to healthy foods across neighborhoods with different income and education profiles. We characterize retail environments using indexes which reflect the number of stores consumers have access to, the healthfulness of the products available in these stores, and the prices of healthy, relative to unhealthy, products offered by these stores.

3.2.1 Store Concentration

We start by looking at simple concentration indexes that reflect the spatial distribution of retail food stores in and around each census tract in the U.S. The concentration indexes are kernel densities based on store locations from the TDLinx data. Let d_{sl} denote the distance between store s and the centroid of census tract l, and let S_t denote the universe of stores in our sample in time t. We define the concentration index for census tract l in time t as a Gaussian kernel with a bandwidth of 20km:[40]

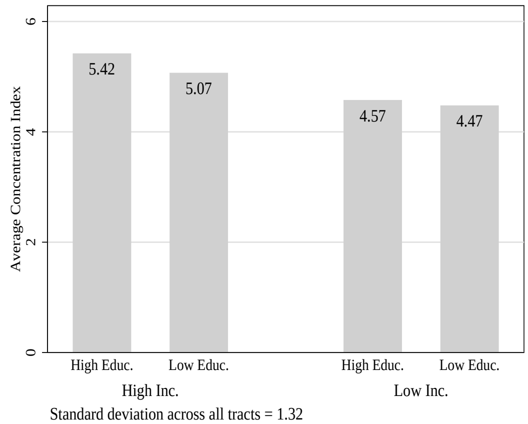
$$Concentration\ Index_{lt} = \sum_{s=1}^{S_t} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{d_{sl}}{20}\right)^2}$$

Figure 2 depicts how store concentration indexes vary with tract demographics from the 2010 Census.[41] We see that there is spatial correlation between income, education, and the concentration indexes: wealthier and more educated census tracts have a higher concentration of stores in their vicinity. These differences are large, with households in tracts with above versus below median income and education facing concentration indexes that are on average 73% of a standard deviation higher. In contrast to what we saw with the household scores in Section 3.1, concentration indexes vary more with neighborhood income than with neighborhood education. These patterns suggest that household education matters more for purchases whereas neighborhood income matters more for access.

[40]Our results are robust to the use of alternative bandwidths and kernel specifications.

[41]Refer to Figure A.4 for average concentration indexes by terciles of median income and by terciles of college-educated shares.

Figure 2: Store Concentration Indexes Across Census Tracts



Notes: The figure above presents average concentration indexes across census tracts with different socioeconomic compositions. Tracts are considered high income (HI) if their median household income falls above the median level across all tracts ($47,299) and low income (LI) otherwise. Tracts are considered high education (HE) if their share of college-educated residents falls above the median share across all tracts (22.5%) and low education (LE) otherwise. 46% of tracts are HI/HE, 10% are HI/LE, 10% are LI/HE, and 34% are LI/LE. These results are for 2010; they are representative of the other years in the TDLinx sample.

In Table 2, we regress tract-level concentration indexes on tract-level characteristics. Figure 2 is formalized in column (1): median income within a tract is positively associated with store concentration, whereas the share of college-educated households has a significantly negative, but comparatively negligible, association with store concentration. Columns (2) through (6) display the relationship between tract-level demographics and store type-specific concentration indexes. That is, the dependent variable is the concentration of a certain store type, such as grocery stores, instead of the concentration of all food stores. We see that the results in column (1) do not mask significant differences across store types: high-income neighborhoods have significantly more stores of *all* types than low-income neighborhoods.

Table 2: Neighborhood Characteristics and Store Concentration

	(1) All	(2) Grocery	(3) Convenience	(4) Drug	(5) Mass Merch.	(6) Club
Ln(Median Income)	0.343***	0.359***	0.339***	0.337***	0.208***	0.301***
	(0.0071)	(0.0070)	(0.0071)	(0.0071)	(0.0075)	(0.0073)
Ln(College-Educated Share)	-0.0196**	-0.00652	-0.0188**	-0.0153*	-0.0935***	-0.0647***
	(0.0071)	(0.0070)	(0.0071)	(0.0071)	(0.0074)	(0.0073)
Observations	44,530	44,530	44,530	44,530	44,528	44,507
R^2	0.105	0.122	0.103	0.103	0.021	0.062

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Observations are at the tract-year level. All variables are standardized. These results are for 2010; they are representative of the other years in the TDLinx sample.

3.2.2 Nutritional Availability

While kernel densities of the number of stores allow us to examine disparities in the spatial distribution of retailers, this measure ignores the fact that all stores are not equal. Importantly, stores may differ in the products they offer, even within store types. To account for spatial disparities in nutritional availability across neighborhoods, we use the Scantrack data to compute healthfulness indexes for each of the stores in the Scantrack panel that we are able to match to location information in the TDLinx data.

To summarize the nutritional content of the products offered in a given store in a given month, we use store-level variants of the expenditure and nutrient scores defined in Section 3.1 for households. The indexes reflect the category-level expenditure shares and per calorie nutrients that a representative household would purchase in store s in month t. The household is nationally representative in that they purchase *all* of the products available in a store such that their relative UPC-level expenditure shares for that store reflect the national average.[42] The expenditure score for store s in month t can be written as

$$Expenditure\ Score_{st} = \left[\sum_{c \in C_{Healthful}} \left(sh_{cst} - sh_{c\bar{h}}^{CNPP} \right)^2 | sh_{cst} < sh_{c\bar{h}}^{CNPP} \right. \\ \left. + \sum_{c \in C_{Unhealthful}} \left(sh_{cst} - sh_{c\bar{h}}^{CNPP} \right)^2 | sh_{cst} > sh_{c\bar{h}}^{CNPP} \right]^{-1}$$

where c again indexes CNPP food categories.[43] sh_{cst} is the representative household's predicted category c expenditure share in store s in month t, calculated as

$$sh_{cst} = \sum_{u \in U_{cst}} \left(\frac{v_{ut}}{\sum_{u \in U_{st}} v_{ut}} \right)$$

Here, U_{cst} is the set of CNPP-category c UPCs with positive sales in store s in month t, U_{st} is the set of all UPCs with positive sales in store s in month t, and v_{ut} is the total value of sales of UPC u across all stores in the national Scantrack sample in month t. We look at the distance of this representative household's category expenditure shares from the CNPP's recommended category expenditure shares for a "typical" household, consisting of a male of age 19-50, a female of age 19-50, one child of age 6-8, and one child of age 9-11. We denote the recommended expenditure share in category c for this modal household by $sh_{c\bar{h}}^{CNPP}$.[44]

Similarly, the nutrient score for store s in month t can be written as

$$Nutrient\ Score_{st} = \left[\sum_{j \in J_{Healthful}} \left(\frac{pc_{jst} - pc_j^{FDA}}{pc_j^{FDA}} \right)^2 | pc_{jst} < pc_j^{FDA} \right. \\ \left. + \sum_{j \in J_{Unhealthful}} \left(\frac{pc_{jst} - pc_j^{FDA}}{pc_j^{FDA}} \right)^2 | pc_{jst} > pc_j^{FDA} \right]^{-1}$$

where j again indexes nutrients, and pc_j^{FDA} is the FDA's recommendation for the per calorie consumption of nutrient j.[45] pc_{jst} is the per calorie amount of nutrient j that would be purchased by a representative household in

[42] Neither of the store-level indexes defined below use any information on actual store-level sales. We use national-sales weights rather than store-sales weights in order to capture the relative importance of products to a nationally representative consumer rather than a store-specific representative consumer. Indexes based on store-sales weights will be biased towards the tastes of the households visiting that store and, therefore, will mechanically be correlated with the demographics of the store's local community. By using national weights we are able to control for the relative importance of UPCs to the typical consumer without introducing this local bias.

[43] Refer to Table A.4 for the full list of healthful and unhealthful food categories that we use.

[44] We exclude store expenditure scores that are more than twice the distance between the 90th and 50th percentiles from our analysis (less than 0.5% of store-month scores).

[45] Refer to Table A.5 for the full list of healthful and unhealthful nutrients that we use.

store s in month t, calculated as

$$pc_{jst} = \sum_{u \in U_{st}} \left[\left(\frac{v_{ut}}{\sum_{u \in U_{st}} v_{ut}} \right) pc_{ju} \right]$$

where pc_{ju} is the per calorie amount of nutrient j in UPC u.[46]

In Table 3, we regress these store nutritional availability indexes on store-specific, market-level variables.[47,48] Since the concentration indexes were at the tract level, we defined neighborhood socioeconomic characteristics by tract in Figure 2 and Table 2. Here, we treat space continuously and look at how the socioeconomic status of residents in the general vicinity of a store covaries with the nutritional quality of the products available in that store. We measure the average socioeconomic profile in the vicinity of a store using kernel densities of median household income and college-educated shares from the 2010 Census for census tracts surrounding the store.[49] Looking first to columns (1) and (4), we see that store nutrient scores covary with neighborhood demographics whereas store expenditure scores do not. Stores in wealthier and more educated neighborhoods tend to offer a range of products whose nutrient content, on the whole, better accords with the FDA recommendations. The range of products offered by stores in high-SES versus stores in low-SES neighborhoods, however, do not significantly differ in terms of their proximity to USDA recommendations for food category expenditures. This suggests that while stores stock a similarly balanced mix of products across food categories, the healthfulness of the products offered *within* these food categories varies systematically across neighborhoods.

In the subsequent columns we control for DMA (a Nielsen market definition of similar geographic scope as Metropolitan Statistical Areas) and store chain interacted with DMA. While income is positively associated with the nutrient scores of stores across DMAs, this association is greatly reduced when we control for store chain. This suggests that the main effect of income on nutritional availability comes through the particular retailers that locate in an area, rather than systematic differences in the types of products that a particular retailer offers. In nearly all specifications, the association between local education and the range of products offered in stores is more limited.

[46] As with the expenditure scores, we exclude store nutrient scores that are more than twice the distance between the 90th and 50th percentiles from our analysis (approximately 5% of store-month scores).

[47] The store expenditure and nutrient scores are positively correlated (correlation coefficient of 0.49).

[48] Refer to Tables A.7 – A.10 for regression results by food categories and nutrients. That is, we run the same regressions as in Table 3, but instead of the store availability indexes the dependent variable is either the difference between the nationally representative household's expenditure share and the recommended expenditure share on a particular food category or the normalized deviation of the nationally representative household's per-calorie consumption from the recommended per-calorie consumption of a particular nutrient.

[49] Letting L denote the set of census tracts, p_l the socioeconomic characteristic in census tract l in 2010, and d_{sl} the distance between store s and the centroid of census tract l, the relevant socioeconomic kernel density around store s is given by $\sum_{l=1}^{L} p_l w_{sl} / \sum_{l=1}^{L} w_{sl}$ where $w_{sl} = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{d_{sl}}{20}\right)^2}$. We use a Gaussian kernel with a bandwidth of 20km, although our results are robust to the use of alternative bandwidths and kernel specifications.

Table 3: Neighborhood Characteristics and Nutritional Quality of Product Offerings

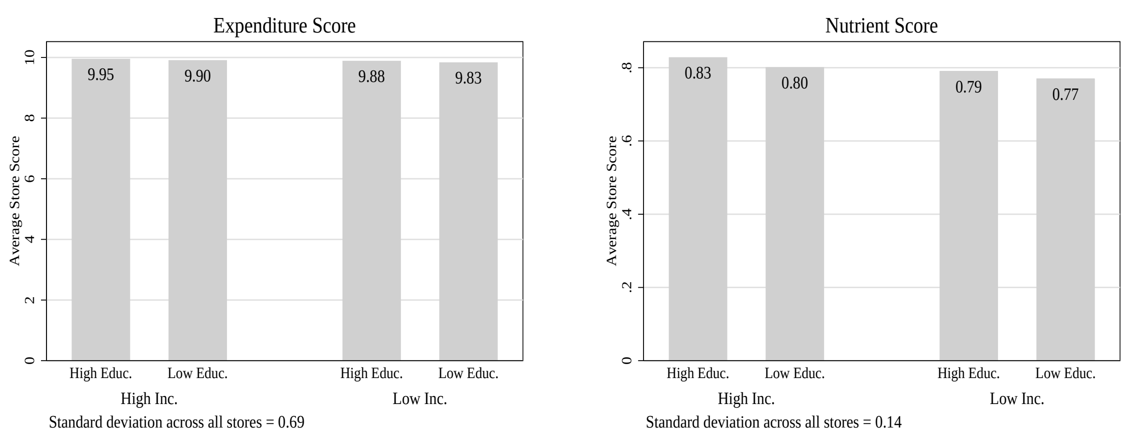
	Ln(Expenditure Score)			Ln(Nutrient Score)		
	(1)	(2)	(3)	(4)	(5)	(6)
Median Household Income Density	0.0171	0.161***	-0.00523	0.0874***	0.184***	0.0239***
	(0.0093)	(0.024)	(0.012)	(0.0083)	(0.019)	(0.0060)
College-Educated Share Density	0.00603	0.00435	0.0539***	0.0320***	-0.0461**	0.0319***
	(0.011)	(0.018)	(0.011)	(0.0084)	(0.014)	(0.0052)
Observations	1,239,023	1,239,023	1,239,023	1,239,021	1,239,021	1,239,021
R^2	0.092	0.200	0.707	0.152	0.203	0.803
FEs	None	DMA	DMAxCh	None	DMA	DMAxCh

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Notes: Observations are at the store-month level. Standard errors are clustered by store. All variables are standardized. All regressions include year-month fixed effects. DMA refers to designated market area, and DMAxCh is the interaction of DMA and store chain.

Figure 3 depicts how store expenditure and nutrient scores vary with tract demographics from the 2010 Census.[50] There appears to be almost no variation in the nutritional quality of product offerings across neighborhoods, especially when nutritional availability is measured using the expenditure score.[51] While these differences are more pronounced when compared to the standard deviation of scores across all stores, this is a mechanical artifact of the limited variation in healthfulness scores across stores. Recognizing that our store-level healthfulness scores are just household-level healthfulness scores for a nationally representative household, we can compare the difference in our representative household's average scores at stores in neighborhoods with different socioeconomic compositions to the standard deviation of healthfulness scores across all households. On average, the expenditure and nutrient scores of our nationally representative household in stores located in census tracts with above versus below median income and education are only 4% and 5% of a standard deviation higher, respectively.[52]

Figure 3: Expenditure and Nutrient Scores Across Stores: Available Products



Notes: The figure above presents average store-level expenditure and nutrient scores across census tracts with different socioeconomic compositions. Tracts are considered high income (HI) if their median household income falls above the median level across all tracts ($47,299) and low income (LI) otherwise. Tracts are considered high education (HE) if their share of college-educated residents falls above the median share across all tracts (22.5%) and low education (LE) otherwise. 54% of tracts are HI/HE, 7% are HI/LE, 11% are LI/HE, and 28% are LI/LE. These results are for January 2010; they are representative of the other months in the Scantrack sample.

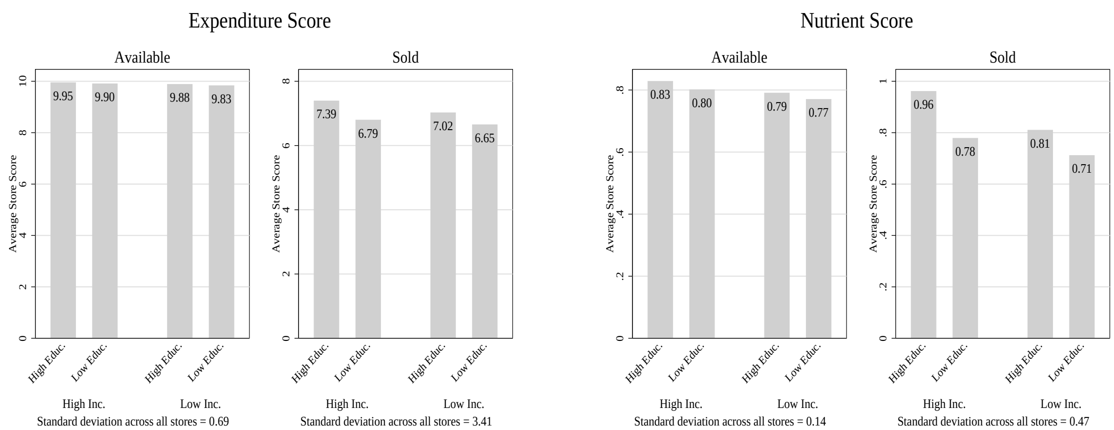
[50] Refer to Figures A.5 and A.6 for average store expenditure and nutrient scores by terciles of median income and by terciles of college-educated shares, respectively.

[51] The differences in expenditure scores are more pronounced when we look across store type instead of store location. Looking to Figure A.7, we see that food stores have higher expenditure scores than convenience stores, for example.

[52] We see similar results at the neighborhood level. Using kernel densities of the expenditure and nutrient scores of stores surrounding each census tract centroid, we find very little variation in expenditure scores and only a small amount of variation in nutrient scores across neighborhoods with different demographics.

An alternative way to assess the magnitude of the disparities in the healthfulness of products available in stores is to compare them with the disparities in the healthfulness of store sales. Recall that the availability indexes were computed using national-sales weights so as not to reflect local demand. We measure the healthfulness of store sales by computing analogous indexes where we instead use actual store-sales weights. In Figure 4, we see that the differences in the healthfulness of products sold across neighborhoods with different demographics are much more pronounced than the differences in the healthfulness of the products available. Though differences in the healthfulness of products offered across neighborhoods are limited, the differences in the healthfulness of products sold mirror the patterns we observed using the household-level data in Section 3.1. The gaps between the expenditure and nutrient scores reflecting what is sold in stores in neighborhoods with above versus below income and education are more than four times as large as the gaps in the expenditure and nutrient scores for what is available in stores in these neighborhoods.

Figure 4: Expenditure and Nutrient Scores Across Census Stores: Available versus Sold



Notes: The figure above presents average store-level expenditure and nutrient scores, computed using either store-sales or national-sales weights, across census tracts with different socioeconomic compositions. Tracts are considered high income (HI) if their median household income falls above the median level across all tracts ($47,299) and low income (LI) otherwise. Tracts are considered high education (HE) if their share of college-educated residents falls above the median share across all tracts (22.5%) and low education (LE) otherwise. 54% of tracts are HI/HE, 7% are HI/LE, 11% are LI/HE, and 28% are LI/LE. In each subfigure ("Expenditure Score", "Nutrient Score"), the plot on the left ("Available") replicates the availability indexes presented in Figure 3 above, while the plots on the right ("Sold") reflect store-level scores calculated using the observed sales in each store. These results are for January 2010; they are representative of the other months in the Scantrack sample.

Given the disconnect between the nutritional quality of products available and the nutritional quality of products actually sold across neighborhoods, it is unlikely that differences in product availability drive the observed differences in sales. This is confirmed in Table 4, where we see that stores in wealthier and more educated neighborhoods sell more healthful bundles of products, *even* controlling for the availability of products. In fact, adding the availability control has almost no impact on the association between store-sales-weighted expenditure scores and neighborhood characteristics. This is not surprising given the small amount of variation we observed in the national-sales-weighted expenditure scores in Figure 3 and Table 3 above. In general, these results suggest that nutritional disparities in the products sold across stores cannot be explained by any constraint imposed by differences in the availability of nutritious food products alone.

Table 4: Neighborhood Characteristics and Nutritional Quality of Store Sales

	Ln(Expenditure Score, Store Weights)		Ln(Nutrient Score, Store Weights)	
	(1)	(2)	(3)	(4)
Median Household Income Density	0.115***	0.104***	0.108***	0.0317***
	(0.011)	(0.0080)	(0.0096)	(0.0044)
College-Educated Share Density	-0.112***	-0.116***	-0.0198*	-0.0478***
	(0.011)	(0.0081)	(0.0100)	(0.0046)
Ln(Relevant Score, National Weights)		0.643***		0.876***
		(0.020)		(0.0032)
Observations	1,239,023	1,239,023	1,239,022	1,239,021
R^2	0.024	0.359	0.044	0.650

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Observations are at the store-month level. Standard errors are clustered by store. All variables are standardized. All regressions include year-month fixed effects. In columns (1) and (2), the relevant score is the expenditure score; in columns (3) and (4), the relevant score is the nutrient score.

3.2.3 Relative Prices

There are other dimensions of access, such as prices and store amenities, that may also influence household purchases. Even though a product is on the shelf in a low-SES neighborhood, the product may be prohibitively expensive or offered in an unkept section of the store such that the item is not truly "accessible" to households in that neighborhood.

The Scantrack data includes the prices offered to consumers, allowing us to examine the role of differential pricing directly. One commonly cited hypothesis for why low-income consumers eat less healthy foods is that unhealthy calories are less expensive than healthy calories.[53] Since low-income consumers face tighter budget constraints and food is a necessity good, they will allocate more of their expenditure towards cheaper, less healthful foods than high-income consumers. While relative prices may be a key driver of nutritional disparities in general, they are only relevant for this paper insofar as the pricing practices of the stores in low-SES neighborhoods lead low-SES households to purchase *even more* unhealthy foods than they would if they had access to the prices offered by stores in high-SES neighborhoods. If store pricing is to blame for the relative unhealthfulness of sales in stores in low-SES neighborhoods, it must be the case that either (a) these stores charge higher prices for all food products, limiting their customers' consumption possibilities and forcing them to allocate even more of their expenditure towards cheaper products than they would otherwise, or (b) these stores charge relatively more than stores in high-SES neighborhoods for healthful versus unhealthful food products. We explore these hypotheses by looking at the spatial distribution of prices for all food products, as well as the distribution of the prices offered for healthy relative to unhealthy foods.

We first study whether stores in low-SES neighborhoods charge higher prices across all food products. We define the aggregate price index for store s in month t as

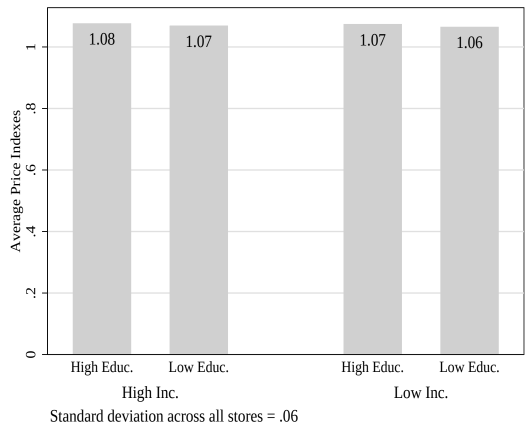
$$P_{st} = \prod_{u \in U_{st}} \left(\frac{p_{ust}}{p_{ut}} \right)^{\frac{v_{ut}}{\sum_{u \in U_{st}} v_{ut}}}$$

[53]We see this to be the case in the Nielsen data. In the majority of product groups, we observe that the national average price per calorie of products in CNPP healthful food categories is, on average, higher than the national average price per calorie of products in the CNPP unhealthful food categories.

where p_{ust} is the sales-weighted average price of UPC u in store s in month t, p_{ut} is the sales-weighted average price of UPC u across all stores in the Scantrack sample in month t, and U_{st} denotes the full set of UPCs sold in store s in month t. This price index summarizes how the average price of each UPC that the store offers compares to the national average price for the UPC.

Figure 5 shows how these aggregate price indexes vary with tract demographics from the 2010 Census.[54] Not surprisingly, we see that prices are relatively higher in census tracts with higher levels of income and education. This suggests that low-income households facing tight budget constraints would be even more constrained in their purchases if they shopped in high-SES neighborhoods than they are shopping in low-SES neighborhoods.

Figure 5: Aggregate Price Indexes Across Census Tracts



Notes: The figure above presents average store-level price indexes across tracts with different socioeconomic compositions. Tracts are considered high income (HI) if their median household income falls above the median level across all tracts ($47,299) and low income (LI) otherwise. Tracts are considered high education (HE) if their share of college-educated residents falls above the median share across all tracts (22.5%) and low education (LE) otherwise. 54% of tracts are HI/HE, 7% are HI/LE, 11% are LI/HE, and 28% are LI/LE. These results are for January 2010; they are representative of the other months in the Scantrack sample.

Even if stores in low-SES neighborhoods offer lower prices in aggregate, they may still incentivize their customers to purchase more unhealthy foods than they would if they lived in a high-SES neighborhood by charging relatively higher prices for healthy food products than for unhealthy food products. To explore this hypothesis, we use store-level price indexes for healthful and unhealthful products to measure the spatial distribution of the cost of healthy and unhealthy eating. For each store, the healthful (unhealthful) price index summarizes how the average price of each healthful (unhealthful) UPC that the store offers compares to the national average price for that UPC. The price index of healthful products offered in store s in month t is defined as

$$P_{st}^{Healthful} = \prod_{u \in U_{st}^{Healthful}} \left(\frac{p_{ust}}{p_{ut}} \right)^{\frac{v_{ut}}{\sum_{u \in U_{st}^{Healthful}} v_{ut}}}$$

where $U_{st}^{Healthful}$ is the set of all UPCs sold in store s in month t that are classified in a healthful CNPP food category. Analogously, the price index of unhealthful products offered in store s in month t is given by

$$P_{st}^{Unhealthful} = \prod_{u \in U_{st}^{Unhealthful}} \left(\frac{p_{ust}}{p_{ut}} \right)^{\frac{v_{ut}}{\sum_{u \in U_{st}^{Unhealthful}} v_{ut}}}$$

where $U_{st}^{Unhealthful}$ is the set of all UPCs sold in store s in month t that are classified in an unhealthful CNPP

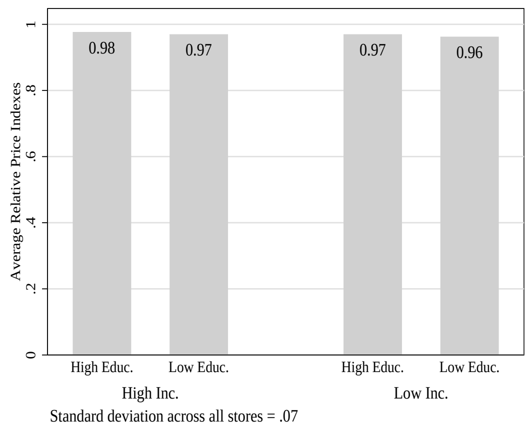
[54]Refer to Table A.8 for aggregate price indexes by terciles of median income and terciles of college-educated shares.

food category.

As our focus is on the accessibility of healthful versus unhealthful foods, we consider the ratio of a store's healthful-to-unhealthful price indexes, i.e $\frac{P_{st}^{Healthful}}{P_{st}^{Unhealthful}}$. This ratio, which we refer to as the "relative price index" and denote by $P_{st}^{Relative}$, compares a store's average markup over national prices for the healthful products it offers to its average markup over national prices for the unhealthful products it offers. A store with a higher relative price index charges relatively more than average for its healthful versus its unhealthful products than a store with a lower relative price index. If differences in relative pricing are to blame for the consumption disparities that we observe, relative price indexes should be higher for stores in neighborhoods with lower levels of income and education.

Figure 6 shows how relative price indexes vary with tract demographics from the 2010 Census.[55] Perhaps strikingly, we see very little variation in relative price indexes across neighborhoods. If anything, relative price indexes are higher in census tracts with higher levels of income and education. Based on these price patterns alone, we would expect the sales of stores in low-SES neighborhoods to be more, as opposed to less, healthful than the sales of stores in neighborhoods with wealthier and more educated residents.

Figure 6: Relative Price Indexes Across Census Tracts



Notes: The figure above presents average store-level relative price indexes across tracts with different socioeconomic compositions. Tracts are considered high income (HI) if their median household income falls above the median level across all tracts ($47,299) and low income (LI) otherwise. Tracts are considered high education (HE) if their share of college-educated residents falls above the median share across all tracts (22.5%) and low education (LE) otherwise. 54% of tracts are HI/HE, 7% are HI/LE, 11% are LI/HE, and 28% are LI/LE. These results are for January 2010; they are representative of the other months in the Scantrack sample.

The manner in which healthful products are presented, including their shelf space and department cleanliness, may also make these products relatively less attractive in certain stores (see, for example, Zenk et al. (2011)). We do not have the qualitative data required to assess whether these differences can help explain socioeconomic differences in store sales. In our analysis below we use fixed effects to control for *all* differences in access across neighborhoods and even across stores in order to obtain an upper bound on the role that these factors jointly play in explaining socioeconomic differences in household purchases.

4 Role of Access in Explaining Consumption Disparities

We have demonstrated that there are large socioeconomic disparities in the nutritional content of household grocery purchases as well as significant, yet more limited, spatial disparities in access to healthy foods. The direction of

[55] Refer to Table A.8 for relative price indexes by terciles of median income and terciles of college-educated shares.

causality here is undetermined. It is plausible that the disparities in nutritional consumption are due entirely to the fact that lower income and less educated households have access to different products than higher income and more educated households (that is, any systematic variation in the content of grocery purchases would disappear if all households lived in the same location). It is also plausible that these spatial disparities are due to households sorting into locations where they have access to the food products they prefer to purchase or, more likely, that households sort into locations based on factors correlated with their tastes for grocery products (e.g. housing prices, proximity to employment opportunities, schools, etc.) and spatial disparities in product availability arise because stores cater to local demand. In reality, there are likely feedback effects between household demand and retail access.

In Section 4.1, we introduce a simple theoretical framework in which local tastes and retail costs both influence the spatial distribution of retail food products. This framework demonstrates the challenge that the previous literature has faced in identifying the causal link between access and the nutritional quality of household purchases. It also suggests two ways in which we can use the detailed nature of our data to overcome this challenge. In Sections 4.2 and 4.3, we apply each of these approaches to empirically bound the impact that improving access can have on socioeconomic disparities in the healthfulness of household purchases.

4.1 Theoretical Framework

Consider an economy with many locations populated by an equal number of immobile households. Households can be of either high or low SES, with locations differing in the proportion of their population from each socioeconomic group. Two types of food inputs, healthful and unhealthful, are freely traded between locations on a wholesale market. Healthful foods take more labor to produce than unhealthful foods, so they sell at a higher wholesale price. Retailers in each location pay a fixed cost to operate and produce a mix of differentiated healthful and unhealthful food products. Only healthful (unhealthful) food inputs can be converted into healthful (unhealthful) food products. The production of a single unit of a differentiated food product requires a single unit of the relevant freely-traded input plus a single unit of shelf space.[56] For simplicity, we assume that households are immobile and can only shop at retail stores in their location.[57] Retail is monopolistically competitive, so the number of healthful and unhealthful food products a store produces will depend on the demand for each type of product in the retailer's location.

In Appendix B, we demonstrate two mechanisms through which a correlation between the spatial distribution of healthful foods and the spatial distribution of socioeconomic classes can emerge. First, we allow for high-SES individuals to have a stronger taste for healthful food products than low-SES individuals.[58] Assuming that there are fixed costs in the distribution of differentiated food products, these heterogeneous tastes and the spatial sorting of households by demographics will result in firms in high-SES neighborhoods offering more healthful

[56]Note that one could alternatively assume that healthful and unhealthful food products are produced from the same freely-traded input but using different technologies, where healthful food products require more units of the input than unhealthful food products, reflecting the fact that they may have a higher probability of spoilage and require more marketing.

[57]This assumption is innocuous for the purpose of distinguishing the role access plays in determining household's grocery purchases. In general, household mobility would be relevant in considering counterfactuals, since households may migrate across locations in response to changes in economic activity and retailers would, in turn, respond by further changing their product offerings to suit the new spatial distribution of demand. The counterfactual scenario that we explore is instead one in which access is equalized across space. In this case, household mobility will be irrelevant, as any responses of retailers to changing local demographics would be offset by further policy interventions to equalize access.

[58]To keep the model tractable, we abstract from other reasons why households of different socioeconomic characteristics but with the same choice set might purchase different products. For example, we assume that all households have the spending ability and, more importantly, can purchase products in continuous quantities. In doing so, we rule out the possibility that low-SES households may purchase fewer healthful food products because they are, in general, available only in discrete quantities at high prices and, therefore, do not fit within a more constrained budget. To the extent that these factors generate differences in demand across socioeconomic groups facing the same choice set, they can be considered complementary to the heterogeneous taste mechanism that we use here.

food products than firms in low-SES neighborhoods. The second mechanism works through supply, rather than demand. The assumption that the wholesale cost of the healthful food input is higher than the wholesale cost of the unhealthful food input, along with the assumed fixed shelf-space requirement, implies a complementarity between the healthfulness of the food products a retailer sells and the rental cost of shelf space in the market where they are located. If we further assume that retail rents are increasing in the neighborhood's share of high-SES residents, firms in high-SES locations will have a comparative advantage in the production of healthy food.

The theory delivers three key results. First, it confirms that the socioeconomic disparities in the availability and purchases of healthful food products that we observe are overdetermined. Each mechanism alone is sufficient to generate both the disparities in the healthfulness of food purchases across households and the disparities in the healthfulness of food availability across neighborhoods documented in Sections 3.1 and 3.2, respectively.

Second, the theory identifies an important distinction between the two mechanisms. Conditional on household location, the correlation between the healthfulness of household food purchases and SES is due solely to systematic differences in tastes across households. That is, if spatial disparities in nutritional consumption are entirely due to access, the model predicts that socioeconomic disparities in nutritional consumption will disappear when we focus our attention on households in the same location. Therefore, the difference between within-location disparities and the disparities that we observe in the full cross-section of households can be interpreted as the role that access, as opposed to tastes, plays in explaining socioeconomic disparities in nutritional consumption. That is, if retail environments were equalized across locations, we could not expect the resulting nutritional gap between high-SES and low-SES households to be any less than the estimated disparity between high-SES and low-SES households who currently have access to the same retail environment. In anything, the resulting gap will actually be greater than our estimates suggest because differences in retail environments themselves may be driven by unobservable differences in tastes. If households are sorted across locations according to unobservable tastes, then the differences in the purchases of the selected sample of high-SES and low-SES households that we observe in the same location will be lower, on average, than the differences that would persist between high-SES and low-SES households were retail access equalized nationwide.

Finally, in a simple extension to the model, we build on this intuition to demonstrate that the observed responses of household purchases to changes in their retail environments can be interpreted as an upper bound for the true elasticity of purchases to changes in access holding tastes fixed. Unobserved changes in tastes will, on average, be correlated with the observed changes in retail access, biasing our estimated elasticity upwards from its true value.

4.2 Cross-Sectional Approach

4.2.1 Controlling for Location

In the analysis that follows, we control for access to see whether the nutritional disparities remain. In columns (1) and (4) of Table 5, we replicate the regression analysis from columns (4) and (8) of Table 1 for the sample of households with non-missing county and census tract information. In subsequent columns, we add controls for household location, using either county or census tract fixed effects. In order to reduce noise, we use expenditure weights in all specifications. Looking first to the results for the nutrient score, we see that the association between income and healthfulness is reduced by approximately one third when we control for county fixed effects and again by another third when we control for census tract fixed effects. The relationship between education and the nutrient score, however, is more persistent: the coefficient on education remains surprisingly stable regardless of the access controls included. The results are quantitatively more pronounced for the nutrient score, although the results are

qualitatively similar for both indexes. Differential access explains between one third to one half of the nutritional disparities across different income groups but only 10% of the disparities across different education groups.

Table 5: Household Characteristics and Nutritional Quality of Purchases: Controlling for Location

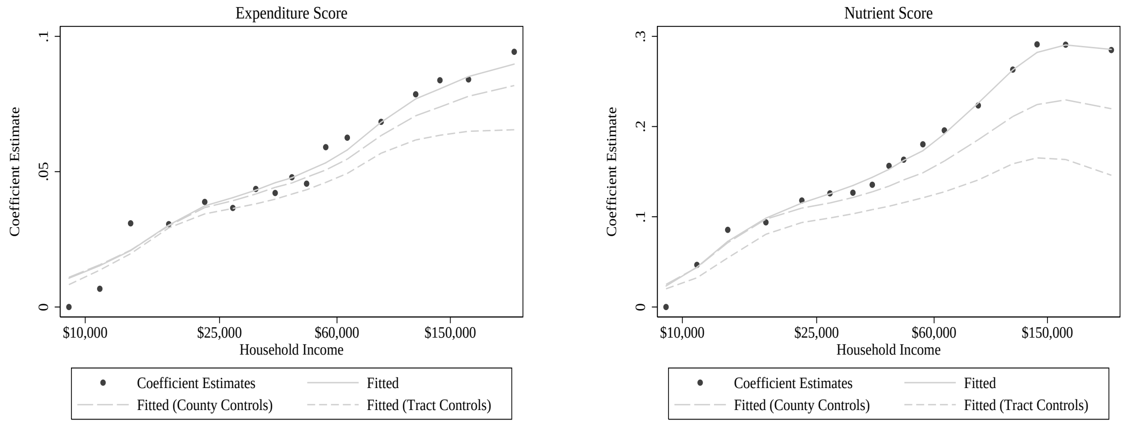
	Ln(Expenditure Score)			Ln(Nutrient Score)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Income)	0.0470***	0.0406***	0.0324***	0.0646***	0.0454***	0.0291***
	(0.0029)	(0.0029)	(0.0028)	(0.0026)	(0.0026)	(0.0026)
Ln(Education)	0.0810***	0.0773***	0.0672***	0.102***	0.0999***	0.0891***
	(0.0028)	(0.0028)	(0.0029)	(0.0026)	(0.0025)	(0.0027)
Observations	3,270,799	3,270,799	3,270,799	3,270,799	3,270,799	3,270,799
R^2	0.069	0.090	0.282	0.031	0.054	0.201
Location Controls	None	County	Tract	None	County	Tract

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Observations are at the household-month level. Standard errors are clustered by household. All variables are standardized. All regressions include year-month fixed effects and controls for household demographics, including household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic. All regressions include expenditure weights.

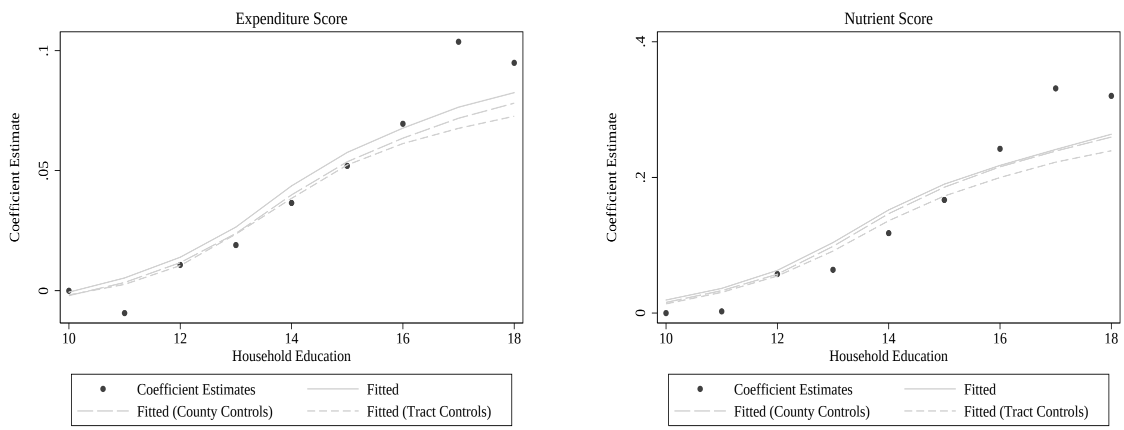
These results are visually depicted in Figures 7 and 8. The figures display the coefficients on income and education when the same analysis as shown in Table 5 is replicated using income and education dummies instead of levels. The dots in Figure 7 are the coefficient estimates on income dummies in the specification without household location controls plotted against the relevant income levels. The solid line depicts the smoothed kernel of these estimates. The dashed lines reflect the smoothed kernels of the coefficient estimates on income dummies in the specification with county or census tract controls. We see that for both the expenditure and the nutrient score, adding location controls dampens the association between income and nutritional quality. As before, the impact of location controls on the relationship between income and the healthfulness of household purchases is more pronounced when healthfulness is measured using the nutrient score. Looking to Figure 8, we see that the relationship between education and each measure of nutritional quality is more persistent: for both the expenditure and the nutrient score, the addition of county or census tract fixed effects does little to reduce the association between education and the healthfulness of household purchases.

Figure 7: Income Effects with Geographic Controls



Notes: The above plots depict how the association between income and the nutritional quality of household purchases changes when we control for access using location fixed effects. The dots in each plot are the coefficient estimates on income dummies from an expenditure-weighted regression of log household-month scores on income dummies, log education, other household demographics, and month-year fixed effects. The solid line depicts the smoothed kernel of these estimates. The dashed lines reflect the smoothed kernels of the coefficients on income dummies from the same regression with the addition of either county or census tract fixed effects.

Figure 8: Education Effects with Geographic Controls

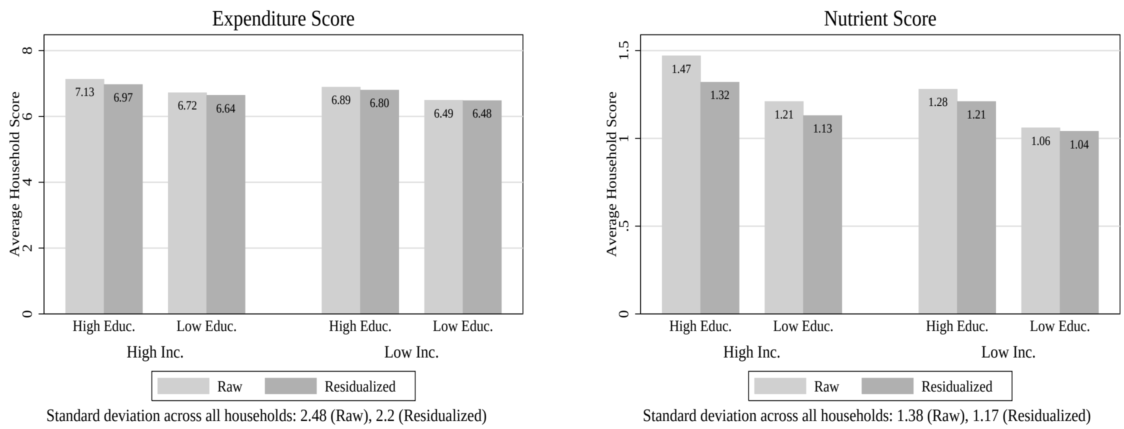


Notes: The above plots depict how the association between education and the nutritional quality of household purchases changes when we control for access using location fixed effects. The dots in each plot are the coefficient estimates on education dummies from an expenditure-weighted regression of log household-month scores on education dummies, log income, other household demographics, and month-year fixed effects. The solid line depicts the smoothed kernel of these estimates. The dashed lines reflect the smoothed kernels of the coefficients on education dummies from the same regression with the addition of either county or census tract fixed effects.

In Section 3.1, we saw that the disparities across education groups are larger than those across income groups. The fact that education disparities are also more persistent than income disparities within location suggests that much of the overall disparities between households remain intact within locations, even though up to half of the income disparities are resolved when controlling for access. We test whether this is the case by residualizing household expenditure and nutrient scores from tract fixed effects estimated in regressions that are similar to those depicted in columns (3) and (6) of Table 5. Instead of controlling for the continuous values of income and education, however, we control for income and education by including dummies for above-median income, above-median education, and the interaction between the two. Figure 9 depicts the average residuals for households in different income and education groups. Comparing these residualized averages to the averages of the unadjusted expenditure and nutrient scores originally presented in Figure 1, we see that the gap between the expenditure and

nutrient scores of households that are above versus below median income and education are only 23% and 32% lower, respectively, when we control for household location.

Figure 9: Residualized Expenditure and Nutrient Scores Across Households



Notes: The figure above presents average raw and residualized household-level expenditure and nutrient scores across households with different socioeconomic profiles. Residualized scores are obtained by subtracting census tract fixed effects estimated in regressions of the log scores against demographic controls, including interacted income and education group fixed effects, month fixed effects, and census tract dummies. Households are considered high income (HI) if their size-adjusted household income falls above the median level across all households ($39,221) and low income (LI) otherwise. Households are considered high education (HE) if the average years of education of their household head(s) falls above the median across all households (13.98 years) and low education (LE) otherwise. 33% of households are HI/HE, 17% are HI/LE, 17% are LI/HE, and 33% are LI/LE. These results are for January 2010; they are representative of the other months in the Homescan data.

4.2.2 Controlling for Store

One concern with the within-location analysis presented in Section 4.2.1 is that households living in the same neighborhood may still have differential access. Even within a census tract, distance to retail outlets varies depending on the location of the household, and factors such as car ownership or proximity to public transportation may yield differences in the ability of households to travel to stores. We now turn to a within-store analysis that controls for these factors. Specifically, we study how the nutritional quality of purchases varies with the characteristics of households shopping in the same store.

To characterize the disparities that exist within stores, we first calculate expenditure and nutrient scores for the purchases that households make in specific stores in each month. We then regress these household-store scores against household demographics, time fixed effects, and various levels of store controls.[59] In Table 6 we see that the healthfulness of household-store purchases are increasing in both income and education. When we control for access by looking within stores of the same type (i.e., grocery, drug, mass merchandise, or convenience) the association between the nutrient score and income falls slightly, but not by a statistically significant margin. Looking to the expenditure score, we see that the association between the nutritional quality of household purchases and income actually increases when we control for store type.

[59]To control for systematic differences across socioeconomic groups in the types of shopping trips that households make to specific stores, we use expenditure share weights in all specifications.

Table 6: Household Characteristics and Nutritional Quality of Purchases: Controlling for Store

	Ln(Expenditure Score)				Ln(Nutrient Score)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Income)	0.0200***	0.0238***	0.0222***	0.0207***	0.0459***	0.0449***	0.0335***	0.0280***
	(0.0022)	(0.0018)	(0.0018)	(0.0016)	(0.0026)	(0.0025)	(0.0025)	(0.0022)
Ln(Education)	0.0268***	0.0260***	0.0244***	0.0236***	0.0572***	0.0565***	0.0541***	0.0520***
	(0.0022)	(0.0018)	(0.0018)	(0.0016)	(0.0026)	(0.0025)	(0.0024)	(0.0022)
Observations	4,224,012	4,224,012	4,224,012	4,224,012	4,224,012	4,224,012	4,224,012	4,224,012
R^2	0.024	0.301	0.313	0.377	0.020	0.103	0.116	0.161
Store Controls	None	Channel	Parent	Store	None	Channel	Parent	Store

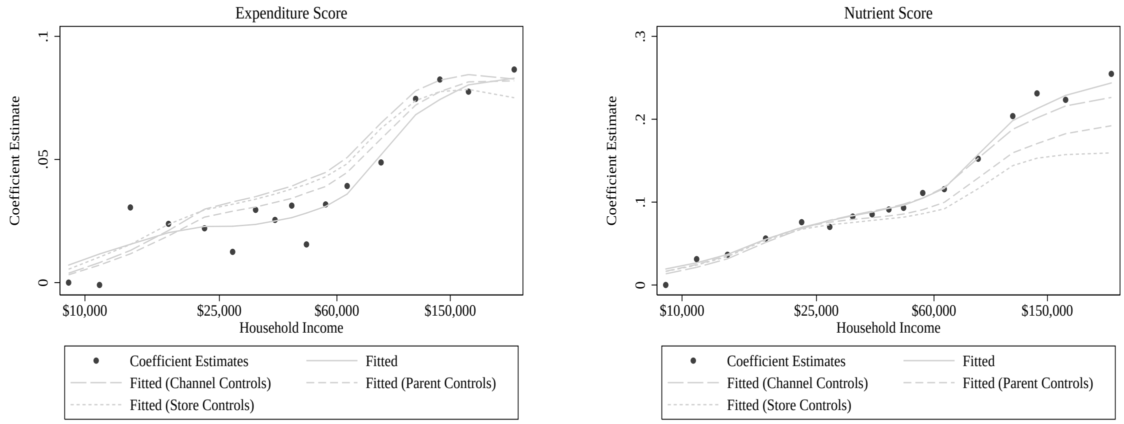
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Observations are at the household-store-month level. Standard errors are clustered by household. All variables are standardized. All regressions include year-month fixed effects and controls for household demographics, including household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic. Observations are weighted by the share of household-month expenditures that the household-store-month observation constitutes.

In Section 3.2, we saw that the store-level nutrient scores vary even across stores in the same chain. Therefore, to hold a household's shopping environment fixed, we need to control for the exact store in which the household is shopping. When we include store fixed effects, the association between household expenditure scores and income increases slightly, but not by a statistically significant margin, over the coefficient estimated in the specification without fixed effects. The association between household nutrient scores and income, however, is reduced by about 50%. This indicates that at least half of the observed disparity between the store-specific shopping bundles purchased by households with different levels of income can be explained by tastes. We stress that the remaining component could be explained by either tastes or access: households may shop at different stores either because they are more accessible or because they offer products better suited to their tastes. Access plays a smaller role in explaining the relationship between nutritional quality and household education: moving from columns (1) to (4) and from columns (5) to (8), we see that the associations between household expenditure and nutrient scores and household education each only fall by around 10%.

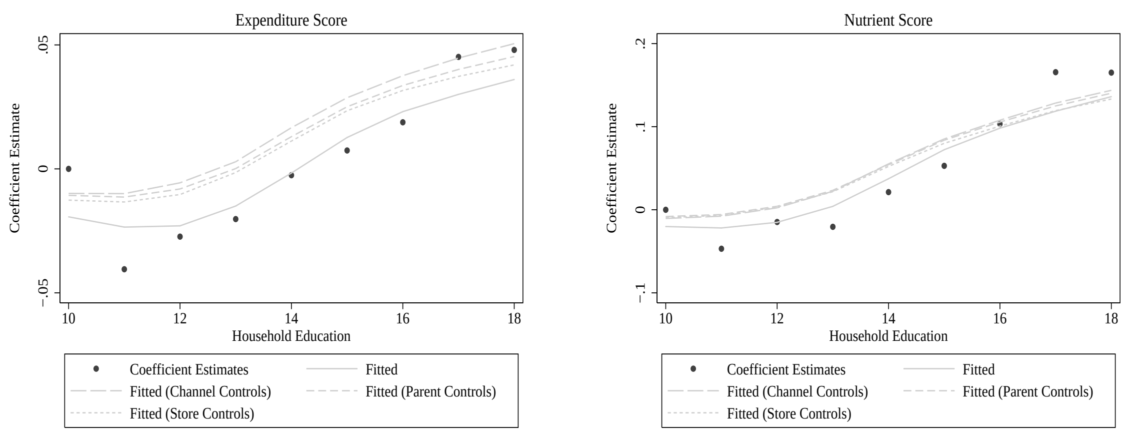
These results are visually depicted in Figures 10 and 11, where we have replicated the regressions in Table 6 with household income and education dummies in place of levels. The dots and solid lines represent the point estimates and the smoothed kernel of these estimates, respectively, from the specifications in columns (1) and (5) of Table 6. The dashed lines represent the smoothed kernels of the point estimates from columns (2) through (4) and columns (6) through (8), where we subsequently add more detailed controls for retail outlet. It is clear from Figure 10 that the healthfulness scores of household-store-specific bundles are not monotonic in income. The relationship becomes more monotonic once we control for channel fixed effects, indicating that the curvature of the regression coefficients without these controls is due to compositional differences in the types of stores where high-income and low-income households shop. Overall, the inclusion of store controls moves the association between income and nutritional quality closer to zero. For the nutrient score, this result is most noticeable for the highest levels of income, where the association between income and the healthfulness of household purchases is greatest in the absence of controls. Looking to Figure 11, we see that the relationship between education and the nutritional quality of household purchases is again more persistent: the inclusion of store controls has barely any effect on the association between the healthfulness of household-store food purchases and education at all levels of education.

Figure 10: Income Effects with Store Controls



Notes: The above plots depict how the association between income and the nutritional quality of household purchases changes when we control for access using store fixed effects. The dots in each plot are the coefficient estimates on income dummies from an expenditure-share-weighted regression of log household-store-month scores on income dummies, log education, other household demographics, and month-year fixed effects. The solid line depicts the smoothed kernel of these estimates. The dashed lines reflect the smoothed kernels of the coefficients on income dummies from the same regression with the addition of fixed effects for either store channel, store parent, or store ID.

Figure 11: Education Effects with Store Controls

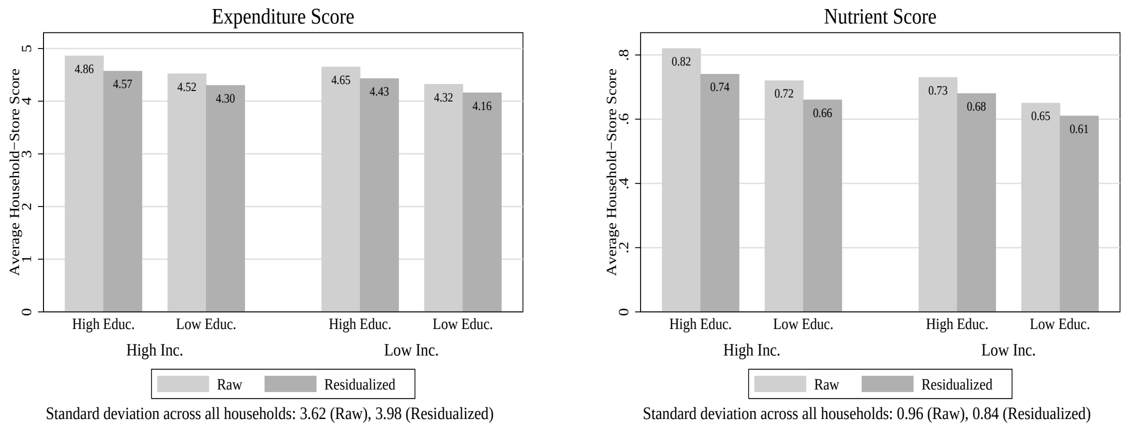


Notes: The above plots depict how the association between education and the nutritional quality of household purchases changes when we control for access using store fixed effects. The dots in each plot are the coefficient estimates on education dummies from an expenditure-share-weighted regression of log household-store-month scores on education dummies, log income, other household demographics, and month-year fixed effects. The solid line depicts the smoothed kernel of these estimates. The dashed lines reflect the smoothed kernels of the coefficients on education dummies from the same regression with the addition of fixed effects for either store channel, store parent, or store ID.

As discussed in Section 4.2.1, Table 6 and Figures 10 and 11 likely understate the overall socioeconomic disparities in nutritional consumption that persist within stores. Since disparities by education are larger than those by income, the 50% reduction in disparities across income groups that we observe when controlling for retail location do not translate into a 50% reduction in overall disparities. This is confirmed in Figure 12, where we display the average household-store scores across households with different socioeconomic profiles alongside the same averages for these scores residualized from store fixed effects. These store fixed effects are estimated in regressions that are similar to those displayed in columns (4) and (8) of Table 6, but instead of controlling for income and education continuously we include dummies for above-median income, above-median education, and the interaction of the two. Mirroring what we saw for the within-census tract results in Section 4.2.1, the gap between the expenditure and nutrient scores of households that are above versus below median income and

education are each only 24% lower when we control for the exact retail location.

Figure 12: Residualized Expenditure and Nutrient Scores Across Households-Stores



Notes: The figure above presents average raw and residualized household-store-level expenditure and nutrient scores across households with different socioeconomic profiles. Residualized scores are obtained by subtracting store fixed effects estimated in regressions of the log scores against demographic controls, including interacted income and education group fixed effects, month fixed effects, and store dummies. Households are considered high income (HI) if their size-adjusted household income falls above the median level across all households ($39,221) and low income (LI) otherwise. Households are considered high education (HE) if the average years of education of their household head(s) falls above the median across all households (13.98 years) and low education (LE) otherwise. 33% of households are HI/HE, 17% are HI/LE, 17% are LI/HE, and 33% are LI/LE. These results are for January 2010; they are representative of the other months in the Homescan data.

4.3 Time-Series Approach

As discussed above, our model suggests a second alternative approach to examine the impact that improving access would have on household consumption. Here, we exploit the panel nature of our data to study how household purchases in our sample responded to changes in the availability of healthful foods in their area.

Over the six years in our sample, we observe changes in the retail environments of households. The retail environment of a household can change for three reasons: 1) the household moves to a different census tract with different access, 2) the stores in a household's neighborhood change the products they offer, and 3) stores enter and/or exit a household's neighborhood. We first consider how the healthfulness of household purchases responds to changes in retail environments driven by any of these three factors. Noting that household moves are endogenous, we next look at households that reside in the same census tract throughout the sample. Finally, since many state and federal policies targeting food deserts focus on store entry, we use an event study analysis to examine how households in our data respond to changes in access that occur when a store enters their neighborhood.

4.3.1 Time-Varying Kernel Densities of Access Measures

To capture changes in retail environments, we use time-varying kernel densities of store concentration and store nutritional quality. The concentration indexes are as before, where we use a kernel density of store indicators to account for differences in the distance-weighted number of stores. Similarly, we construct kernel densities of both the store expenditure and the store nutrient scores to measure differences in the distance-weighted availability of recommended products.[60]

[60] As before, we use a Gaussian kernel with a bandwidth of 20km. Letting S_t denote the universe of stores in time t, E_{slt} the expenditure score of store s in census tract l in time t, and d_{sl} the distance between store s and the centroid of census tract l, the expenditure score kernel density for census tract l in time t is given by $\sum_{s=1}^{S_t} \frac{E_{slt}}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{d_{sl}}{20}\right)^2}$. Similarly, letting N_{slt} denote the nutrient score of store s in census

In Table 7, we examine how household purchases in our sample respond to changes in these measures of access. Columns (1) and (5) are analogous to Table 5 in that they explore how the quality of monthly household purchases varies with income and education. In contrast to the analysis presented in Table 5, however, we control for the local retail environment in Table 7 using continuous measures of the concentration and healthfulness of surrounding stores rather than with household location fixed effects. Even after controlling for these dimensions of access, both measures of household purchase quality are increasing in income and education. Household expenditure scores are positively related to store concentration and distance-weighted store expenditure scores, although the magnitudes of these coefficients are small, especially once one recalls the limited variation in store expenditure scores. Household nutrient scores are significantly related to store concentration but not to distance-weighted store nutrient scores. This indicates that conditional on the concentration of stores, households in areas where stores stock products that are closer to the FDA's nutrient recommendations do not come significantly closer to meeting the FDA's recommendations themselves.

Table 7: Response of Nutritional Quality of Household Purchases to Changes in Retail Access

	Ln(Expenditure Score)				Ln(Nutrient Score)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Income)	0.0235^{***}				0.0717^{***}			
	(0.0015)				(0.0032)			
Ln(Education)	0.199^{***}				0.615^{***}			
	(0.0068)				(0.015)			
Ln(Store Concentration)	0.00140^{*}	-0.000923	-0.000897	0.00662	0.0409^{***}	0.00565	0.00507	-0.0134
	(0.00071)	(0.0027)	(0.0027)	(0.0066)	(0.0016)	(0.0063)	(0.0063)	(0.017)
Ln(Store Score Density)	0.0558^{*}	0.0149	0.0178	0.00120	0.0104	0.0633^{***}	0.0691^{***}	0.0636^{***}
	(0.024)	(0.025)	(0.025)	(0.025)	(0.017)	(0.013)	(0.013)	(0.014)
Ln(Conc.)*Ln(Inc.)			-0.00149	-0.00191			0.00441^{***}	0.00447^{***}
			(0.0012)	(0.0013)			(0.00092)	(0.00098)
Ln(Conc.)*Ln(Educ.)			-0.0151	-0.0196^{*}			0.0216^{***}	0.0197^{**}
			(0.0081)	(0.0088)			(0.0060)	(0.0063)
Ln(Score)*Ln(Inc.)			0.00966^{***}	0.00969^{***}			0.0357^{***}	0.0369^{***}
			(0.0027)	(0.0029)			(0.0068)	(0.0072)
Ln(Score)*Ln(Educ.)			0.0241	0.0341			0.149^{***}	0.146^{***}
			(0.018)	(0.020)			(0.033)	(0.035)
Observations	3,187,956	3,187,956	3,187,956	2,877,746	3,187,956	3,187,956	3,187,956	2,877,746
R^2	0.066	0.435	0.435	0.438	0.032	0.327	0.327	0.329
Demographic Controls	Yes	No	No	No	Yes	No	No	No
Household Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Non-Movers Only	No	No	No	Yes	No	No	No	Yes
Elasticity w.r.t. Conc.	0.00140	-0.000923	0.00121	0.00933	0.0409	0.00565	0.00104	-0.0172
Elasticity w.r.t. Score	0.0558	0.0149	0.0112	-0.00638	0.0104	0.0633	0.0390	0.0332

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Observations are at the household-month level. Standard errors are clustered by household. All regressions include year-month fixed effects. Log income and education are both demeaned. Demographic controls include household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic.

While we control for household demographics in columns (1) and (5) of Table 7, households may sort spatially by unobservable characteristics that are correlated with tastes for healthy foods. If stores are sorted according to these unobservable characteristics, the coefficients on store concentration and store scores in columns (1) and (5) will be biased upwards. On the other hand, if households with a taste for healthful foods sort into residential neighborhoods with fewer stores or with stores that offer less nutritious products, then the coefficients will be biased downwards. To account for both observable and unobservable household characteristics, we add household fixed effects in columns (2) through (4) and columns (6) through (8). When we control for the household, the coefficients are identified off of the time-series variation in purchases and retail environments.[61] In columns (2) and

tract l in time t, the nutrient score kernel density for census tract l in time t is given by $\sum_{s=1}^{S_t} \frac{N_{slt}}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{d_{sl}}{20}\right)^2}$.

[61] Since demographics are nearly constant across our sample period for a given household, we no longer control for income, education, and

(6), we do not observe the nutritional quality of household purchases responding to changes in the concentration of retail outlets in the household's vicinity. While household expenditure scores likewise do not respond to changes in the distance-weighted density of store expenditure scores, household nutrient scores do respond slightly to improvements in the nutrient composition of products sold by stores in their neighborhood.

To explore whether the responsiveness of household purchases to changes in the retail environment varies by the socioeconomic status of the household, we interact the access kernel densities with income and education in columns (3) and (7). In column (3), we see that the statistically insignificant average response of household-level expenditure scores masks a statistically significant difference in the responsiveness of households by income: households with higher levels of income improve their expenditure scores when offered a more nutritionally-balanced mix of food groups in their neighborhood stores. In column (7), we see similar socioeconomic disparities in the responsiveness of household nutrient scores with respect to changes both in the density of local stores and the nutritional quality of the products offered in these stores.

Even when we control for both observable and unobservable household characteristics using household fixed effects, one might still be concerned that households progressively sort into locations based on their tastes throughout our sample. In columns (4) and (8) of Table 7, we limit the sample to households who live in the same census tract for all years that they are in the panel. The results are very consistent across samples, which indicates that the variation in household retail environments that is driving our results is due either to store entry, store exit, or changes in the product offerings of incumbent stores. Though this variation is not exogenous to the overall market in which these stores are located, these shifts in aggregate demand are more likely the result of households moving into or out of the neighborhood than shifts in the individual demand of incumbent households whose responses we are measuring.

To get a better sense of what the magnitudes of the coefficients in Table 7 imply, we consider how a low-SES household would respond to a change in their retail environment equivalent to moving from the average low-SES neighborhood to the average high-SES neighborhood. We focus on a household with income and education at the 25th percentile in each dimension, i.e. $32,500 in annual income and 13 years of education. The elasticities of expenditure and nutrient scores for such a household implied by the coefficients from each regression specification are presented in the bottom row of Table 7.[62] Moving from the average low-SES neighborhood to the average high-SES neighborhood translates to an increase of 1.96 in the log store concentration index, an increase of 0.005 in the log distance-weighted average of store expenditure scores, and an increase of 0.053 in the log distance-weighted average of store nutrient scores. Combined with the estimated elasticities displayed in columns (3) and (7), these improvements in access imply that the household expenditure and nutrients scores of a typical low-SES household would improve by 0.002 and 0.004 log units, respectively, if they were to move from the average low-SES to the average high-SES neighborhood. Comparing these changes to the socioeconomic disparities in household scores shown in Figure 1, we see that only 3% of the gap in expenditure scores and only 1% of the gap in the nutrient scores would be removed by closing the gap in access to healthy foods.

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other household demographics.

[62]Note that log income and education are demeaned in these regressions, so the elasticities are calculated as $\beta_0 + \beta_1 \left(\ln 13 - \ln \overline{Educ}\right) + \beta_2 \left(\ln 32500 - \ln \overline{Inc}\right)$, where β_0, β_1, and β_2 are the coefficients on the density, the density interacted with demeaned education, and the density interacted with demeaned income, respectively; $\overline{Educ}$ is the sample mean education level (14.3 years); and $\overline{Inc}$ is the sample mean income ($50,852).

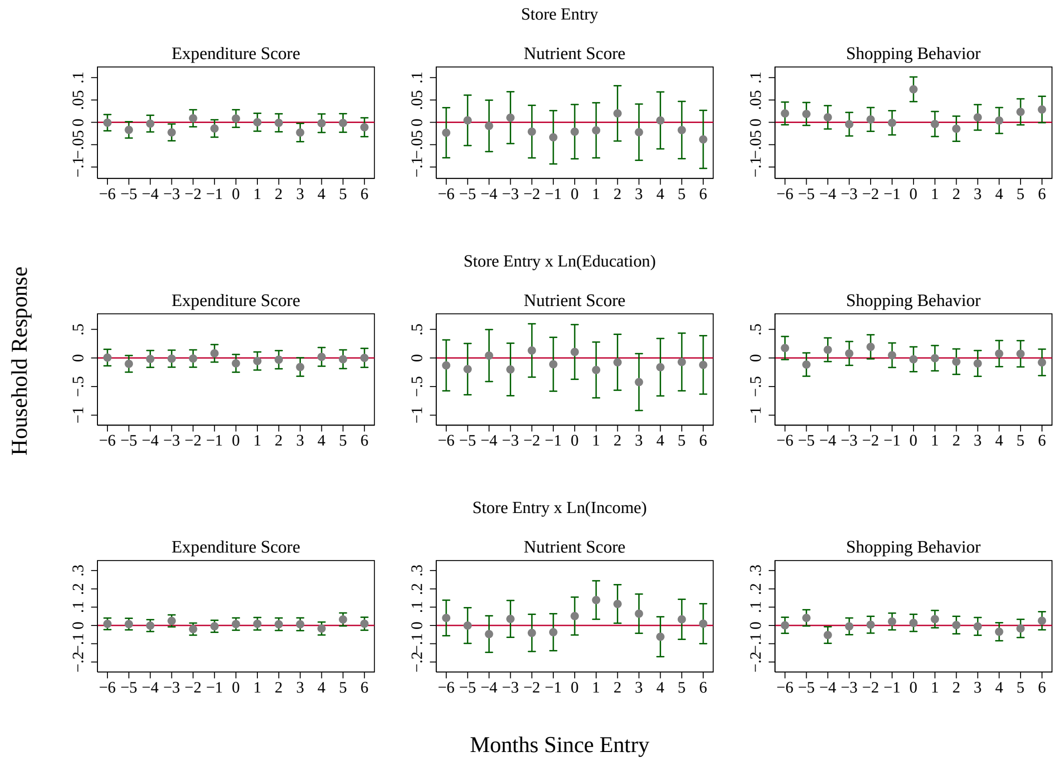
4.3.2 Event Study Analysis of Store Entry

Though some policies aimed at eradicating food deserts encourage incumbent stores to change their product offerings, most do so by encouraging store entry. It is therefore worthwhile to consider how households respond to changes in their retail environments that are related to these entry events alone. We define a store as entering in a given month if (i) the store is first observed in the Scantrack data in that month and (ii) the store's parent company already appears at least once in the dataset prior to that month. We require the parent company to already be in the dataset to avoid confusing growth in the retailers included in the dataset with actual store entry. Similarly, we define a store as exiting in a given month if (i) the store is not observed in any month after that month and (ii) the store's parent company continues to be observed in the data after that month. We require the parent company to remain in the dataset to avoid confusing a decline in the retailers included in the dataset with actual store exit.

To measure household responses to extensive margin adjustments in their retail environments, we use an event study specification. Specifically, we regress the log of household expenditure and nutrient scores on household fixed effects, month-year fixed effects, and dummies for each of the six months before, the month of, and the six months after the entry of a grocery store within 2km of a household's census tract centroid. We plot the coefficients on the time-since-entry dummies in the first two columns of Figure 13. The top panel displays the average response across all households. We do not see any statistically significant response in the nutritional quality of the average household's purchases to store entry. The second and third panels display the gradient in the response with respect to household education and income, respectively. Here, we see that the response of household nutrient scores to entry is increasing with income in the first two months after entry. Together with the null impact of store entry on the average household's nutrient score, this implies that the nutrient scores of households with above-average income improve temporarily for the first two months after store entry, while the nutrient scores of households with below-average income actually deteriorate over the same time period before returning to their original levels within three months.

The third column of plots in Figure 13 show that the general lack of responsiveness of household scores to store entry is not due to the fact that household shopping behavior itself fails to respond. Here, we run the same event study specification using an indicator for whether the household visits a new store in a given month as the dependent variable. We define a store s as a "new" store for a given household in month t if we observe the household making a purchase in store s in period t but not in period $t-1$. In the first panel of the third column, the significantly positive coefficient in month zero indicates that households change the mix of stores they shop at when a new grocery store enters their neighborhood. The coefficients on the time-since-entry dummies interacted with household education and income, displayed in the second and third rows of the third column, indicate that the likelihood to try a new store in the month of entry does not vary with these socioeconomic characteristics. Together, the results in Figure 13 indicate that while households are changing where they shop when a new store enters, they are not changing the healthfulness of the foods they purchase.

Figure 13: Event Study Analysis of Store Entry



Notes: The above plots display the results from an event study analysis of store entry. The first(second) column depicts the coefficient estimates on dummies for months before, during, and after store entry from a regression of log household-level expenditure(nutrient) scores on household fixed effects, month-year fixed effects, and dummies for each of the six months before, the month of, and the six months after the entry of a grocery store within 2km of a household's census tract centroid. The third column depicts the results from a regression of an indicator for whether the household shopped in a new store in that month on the same independent variables.

Store entry decisions are endogenous to local demand conditions. Since a profit-maximizing firm will choose to enter in the most profitable location, we expect food purchases to react more strongly to entry and exit that we actually observe than to entry and exit that is induced by policies which ignore local demand. Given the minimal response of household purchases to changes in access that we see in our data, we expect the response of household purchases to access-improving policies to be even more limited.[63]

5 Discussion and Conclusion

Despite the absence of evidence drawing a causal link between disparities in retail access and disparities in nutritional consumption, much of the discussion surrounding food deserts assumes that equalizing access will decrease nutritional disparities across different socioeconomic groups. Such an assumption underlies policies which aim to improve the quality of food purchases by increasing the availability of healthful products in areas with unhealthful consumption. Contrary to this assumption, our analysis indicates that the large socioeconomic disparities in nutritional consumption that we document across households are not driven by the relatively limited differences in access to healthy foods that we observe across neighborhoods with different socioeconomic compositions.

[63]One might suspect that improvements in access in underserved neighborhoods will be met with greater responses of household purchases. To see if this is the case, we replicate the analysis from Table 7 and Figure 13 looking only at households residing in tracts in the lowest quartile for either the store concentration, expenditure score, or nutrient score densities. The results, presented in Table A.15 and Figure A.9, are nearly identical to those estimated on the full sample.

If differential access is entirely to blame for nutritional disparities, then any systematic differences in the nutritional quality of household purchases that we observe when looking across the entire U.S. should disappear when we compare households living in the same neighborhood or shopping in the same store. On the contrary, we observe households with higher levels of income and education making purchases that are significantly closer to USDA recommendations for food category expenditure shares and FDA recommendations for per-calorie nutrient content than households with lower levels of income and education, even when we control for residential or retail location. These cross-sectional results indicate that most of the existing socioeconomic disparities in nutritional consumption cannot be reduced be improving access alone: even if spatial disparities in access across the U.S. are entirely resolved, over two-thirds of the disparities in the nutritional purchases of households with different levels of income and education would remain.

We stress that even though socioeconomic disparities diminish when we control for residential or retail location, it is unlikely that resolving spatial disparities in access will reduce disparities across the entire U.S. to the same extent. There are two reasons for this. First, if households are sorting into retail environments on unobservables that are correlated with their taste for healthy foods, then the socioeconomic disparities that we observe for households living in the same location or shopping in the same store will be smaller, on average, then the socioeconomic disparities that would persist across the full cross-section of households if access were equated. The second reason is mechanical. Even if households are sorting by income and education alone, and not by unobservables, it is possible that the degree of this sorting is so high that it leaves little variation in income and education across households in the same retail environment. Sampling error in household purchases, which results in noisy measures of the nutritional content of these purchases, could potentially outweigh the residual variation in income and education after controlling for residential or purchase location, resulting in attenuation bias.[64] Therefore, while our estimates indicate that equating access across the entire U.S. could not reduce existing socioeconomic disparities by more than a third, it is likely the true impact would be even smaller.

Policies that target access in the hope of improving the healthfulness of local consumption do so both by encouraging existing retailers to offer more healthful products and by stimulating store entry. These policies will only be effective insofar as the healthfulness of household purchases respond to changes in their retail environment. Contrary to this ideal, we find that the response of a given household's purchases to changes in their local access is very limited. Moving the typical low-SES household to the typical high-SES neighborhood would only serve to reduce the gaps in nutritional consumption between these two groups by 1-3%. In fact, our time-series regressions and event study results suggest that wealthier and more educated households respond more than low-SES households when a new store enters or existing retailers change the products they offer in their neighborhood. This differential behavioral response suggests that, if anything, socioeconomic disparities within a given neighborhood will actually *increase* when access to nutritious food in the neighborhood improves.

Despite the limited responsiveness of household purchases to changes in access that we observe in our data, it is again likely that, on average, households across the entire U.S. will respond even less to changes in their retail environments. Improvements in access to healthy foods are more likely to occur in close proximity to sample households with growing tastes for these products, so the changes in the purchases of these households will reflect

[64] One might also be concerned that the disparities that we estimate controlling for household location and store choice are identified from only a small subset of the sample that lives in the same areas and shops in the same stores. We investigate this possibility. The distributions of income and education residualized from other demographics and month and year effects are extremely similar to the distributions of income and education residualized from other demographics, month and year effects, and location or store effects. Therefore, we are identifying the "within-location" and "within-store" effects over a similar support of income and education as used in the regressions without location or store controls.

not only changes in access but also changes in tastes. This correlation between the time-variant component of demand and changes in access yield an upward-biased estimate of the effect of access-improving policies that are implemented independent of changes in local demand conditions. Therefore, while our estimates indicate that the nutritional quality of household purchases respond minimally to changes in their retail environment, it is likely that the impact of policy-induced changes on nutritional consumption would be even smaller.

The bounds that we estimate using our time-series strategy (1-3%) are lower than those estimated in our cross-sectional approach (20-30%) by a full order of magnitude. As we are identifying different, yet related, treatment effects on different, selected populations, it is no suprise that our results are not quantitatively identical. In fact, as we expect differences in demand within a household over time to be more limited than differences in demand across households living in the same location, we would expect the upward bias due to the correlation between unobserved tastes and retail environments to be greater in the cross-section than in the time-series. Furthermore, to the extent that our intertemporal estimates are identified by variation in access driven by supply-side factors, such as changes in retail rents and zoning, and not taste shocks, our time-series estimates will provide a less upward-biased estimate of the true response of households to policies that equalize access. [65] Despite these differences, however, our two empirical approaches reassuringly lead to the same qualitative conclusion: differences in access are not to blame for differences in nutritional consumption.

Taken together, our results provide strong evidence that policies which aim to reduce nutritional disparities by improving access to healthful foods will leave much of the disparity unresolved. Differences in demand across socioeconomic groups yield empirically relevant disparities above and beyond those that could also be attributed to the sorting of households by income, education, and unobservable tastes across residential locations or stores. Resolving disparities in access to healthful food products will not resolve these disparities, at least not in the short run. In the longer run, it is possible that improved access to healthful foods could impact demand indirectly by providing households with increased exposure to more healthful food products. Further analysis is required to understand which factors are most important in explaining why demand varies across socioeconomic groups with equal access.

[65] A second, more concerning, potential explanation for the difference is attenuation bias. While this bias would push our cross-sectional estimate further above the true disparities that we expect to persist if access were equalized, as discussed above, it would yield a downward bias on our time-series estimate of the elasticity of household purchases with respect to access. The consistency of our time-series results with previous work finding that the purchases of *many* households respond very little to a single, government-sponsored food store entry (Elbel et al. (2015)) alleviates this concern.

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Appendix

A Supplementary Tables and Figures

Table A.1: Distribution of Household Income by Year

	Year					
Income Category	2006	2007	2008	2009	2010	2011
Under 5,000	0.01	0.01	0.01	0.01	0.01	0.01
5,000-7,999	0.01	0.01	0.01	0.01	0.01	0.01
8,000-9,999	0.01	0.01	0.01	0.01	0.01	0.01
10,000-11,999	0.02	0.02	0.01	0.01	0.01	0.01
12,000-14,999	0.03	0.02	0.02	0.02	0.02	0.02
15,000-19,999	0.05	0.04	0.04	0.04	0.04	0.04
20,000-24,999	0.07	0.06	0.06	0.06	0.06	0.06
25,000-29,999	0.07	0.06	0.06	0.06	0.06	0.06
30,000-34,999	0.07	0.07	0.07	0.07	0.07	0.06
35,000-39,999	0.06	0.07	0.06	0.06	0.06	0.06
40,000-44,999	0.07	0.06	0.06	0.06	0.06	0.06
45,000-49,999	0.07	0.06	0.06	0.06	0.06	0.06
50,000-59,999	0.10	0.11	0.11	0.11	0.11	0.10
60,000-69,999	0.09	0.09	0.09	0.09	0.08	0.08
70,000-99,999	0.16	0.18	0.19	0.19	0.20	0.20
100,000-124,999	0.06	0.08	0.09	0.08	0.14	0.15
125,000-149,999	0.02	0.02	0.02	0.03	0.00	0.00
150,000-199,999	0.02	0.02	0.02	0.02	0.00	0.00
200,000 +	0.01	0.01	0.01	0.01	0.00	0.00
Total	37,786	63,350	61,440	60,506	60,658	62,092

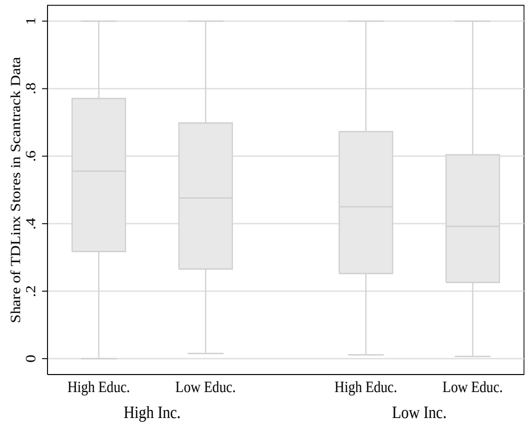
Table A.2: Distribution of Male Household Head Education by Year

Year	Grade School	Some High School	Graduated High School	Some College	Graduated College	Post College	Total
2006	0.013	0.050	0.253	0.292	0.265	0.127	27,439
2007	0.010	0.046	0.255	0.294	0.273	0.121	47,786
2008	0.010	0.045	0.254	0.291	0.277	0.123	46,199
2009	0.009	0.042	0.256	0.288	0.280	0.124	45,280
2010	0.009	0.041	0.253	0.286	0.286	0.126	45,465
2011	0.008	0.040	0.245	0.285	0.294	0.128	46,565

Table A.3: Distribution of Female Household Head Education by Year

Year	Grade School	Some High School	Graduated High School	Some College	Graduated College	Post College	Total
2006	0.005	0.031	0.277	0.315	0.264	0.108	33,963
2007	0.005	0.026	0.268	0.320	0.278	0.103	57,317
2008	0.004	0.025	0.264	0.319	0.280	0.107	55,634
2009	0.004	0.023	0.263	0.314	0.287	0.109	54,699
2010	0.004	0.022	0.256	0.311	0.296	0.111	54,747
2011	0.004	0.021	0.247	0.309	0.303	0.116	56,135

Figure A.1: Share of TDLinx Stores Appearing in the Scantrack Sample Across Tracts



Notes: The figure above presents the average share of TDLinx stores included in the Scantrack sample across tracts with different socioeconomic compositions. Stores are weighted by sales in constructing the shares. Tracts are considered high income (HI) if their median household income falls above the median level across all tracts ($47,299) and low income (LI) otherwise. Tracts are considered high education (HE) if their share of college-educated residents falls above the median across all tracts (22.5%) and low education (LE) otherwise. 53% of tracts are HI/HE, 8% are HI/LE, 12% are LI/HE, and 27% are LI/LE. These results are for January 2010; they are representative of other months in the Scantrack sample and other years in the TDLinx sample.

Table A.4: Healthful and Unhealthful Food Categories

Healthful	Unhealthful
Whole grain products	Non-whole grain breads, cereals, rice, pasta, pies, pastries, snacks, and flours
Potato products	Whole milk products
Dark green vegetables	Cheese
Orange vegetables	Beef, pork, veal, lamb, and game
Canned and dry beans, lentils, and peas	Bacon, sausage, and luncheon meats
Other vegetables	Fats and condiments
Whole fruits	Soft drinks, sodas, fruit drinks, and ades
Fruit juices	Sugars, sweets, and candies
Reduced fat, skim milk, and low-fat yogurt	Soups
Chicken, turkey, and game birds	Frozen or refrigerated entrées
Eggs and egg mixtures	
Fish and fish products	
Nuts, nut butters, and seeds	

Notes: We determine which CNPP food categories are healthful and unhealthful using the recommendations from the Quarterly Food-at-Home Price Database (QFAHPD) indicators for which of 52 food groups are healthful and unhealthful. We aggregate the 52 QFAHPD food groups to the 24 CNPP food categories using the correspondence created by Volpe and Okrent (2013). In doing so, we find that two CNPP food categories, cheese and meat, contain both healthful and unhealthful food groups. Since the vast majority of cheese and meat purchases are of UPCs that fall into the unhealthful QFAHPD food groups, we assume that the aggregate CNPP cheese and meat categories are unhealthful. All of our results are robust to assuming that these food categories are instead healthful.

Table A.5: Healthful and Unhealthful Nutrients

Healthful	Unhealthful
Fiber	Total Fat
Iron	Saturated Fat
Calcium	Trans Fat
Vitamin A	Sodium
Vitamin C	Cholesterol

Notes: The FDA indicates whether to consider its recommendation for a given nutrient as a lower bound or an upper bound. We assign the nutrients for which the FDA recommendation is an upper bound to the unhealthful category.

Table A.6: Household Characteristics and Nutritional Quality of Purchases: Full Regression Results

	Ln(Expenditure Score)				Ln(Nutrient Score)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Income)	0.0424***		0.0241***	0.0426***	0.146***		0.0893***	0.0636***
	(0.0013)		(0.0014)	(0.0024)	(0.0028)		(0.0030)	(0.0021)
Ln(Education)		0.247***	0.203***	0.0743***		0.798***	0.635***	0.0939***
		(0.0060)	(0.0065)	(0.0024)		(0.013)	(0.014)	(0.0021)
Ln(Avg. HH Head Age)	0.0328***	0.0392***	0.0437***	0.0285***	0.0440***	0.0616***	0.0783***	0.0206***
	(0.0036)	(0.0035)	(0.0035)	(0.0023)	(0.0079)	(0.0078)	(0.0078)	(0.0021)
HH Heads Married	0.0436***	0.0458***	0.0417***	0.0557***	0.103***	0.113***	0.0972***	0.0525***
	(0.0034)	(0.0033)	(0.0033)	(0.0045)	(0.0073)	(0.0072)	(0.0072)	(0.0039)
Female HH Head Only	-0.0526***	-0.0690***	-0.0634***	-0.0743***	0.0885***	0.0337***	0.0544***	0.0257***
	(0.0040)	(0.0040)	(0.0040)	(0.0047)	(0.0086)	(0.0086)	(0.0086)	(0.0040)
Male HH Head Only	0.0340***	0.0210***	0.0224***	0.0178***	-0.111***	-0.153***	-0.148***	-0.0475***
	(0.0047)	(0.0047)	(0.0047)	(0.0037)	(0.010)	(0.010)	(0.010)	(0.0032)
Kids Present	0.0258***	0.0179***	0.0210***	0.0250***	0.0838***	0.0574***	0.0686***	0.0330***
	(0.0024)	(0.0024)	(0.0024)	(0.0028)	(0.0055)	(0.0054)	(0.0054)	(0.0026)
Race: White	0.00789*	0.0101**	0.00888*	0.00892*	0.0589***	0.0667***	0.0620***	0.0251***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0085)	(0.0084)	(0.0084)	(0.0034)
Race: Black	0.00323	0.00389	0.00164	0.00129	-0.0863***	-0.0830***	-0.0913***	-0.0289***
	(0.0045)	(0.0045)	(0.0045)	(0.0035)	(0.0099)	(0.0098)	(0.0098)	(0.0031)
Race: Asian	-0.00872	-0.0155*	-0.0199**	-0.00855**	0.00766	-0.0113	-0.0272*	-0.00473*
	(0.0061)	(0.0061)	(0.0061)	(0.0026)	(0.013)	(0.013)	(0.013)	(0.0022)
Hispanic	0.0130***	0.0153***	0.0142***	0.00867***	0.0402***	0.0480***	0.0439***	0.0108***
	(0.0036)	(0.0036)	(0.0036)	(0.0022)	(0.0080)	(0.0080)	(0.0079)	(0.0020)
Observations	3,440,297	3,440,297	3,440,297	3,440,297	3,440,297	3,440,297	3,440,297	3,440,297
R^2	0.061	0.064	0.066	0.066	0.022	0.026	0.029	0.029
Standardized	No	No	No	Yes	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Observations are at the household-month level. Standard errors are clustered by household. All regressions include year-month fixed effects and household size dummies.

Table A.7: Household Characteristics and Nutritional Quality of Purchases: Healthful Food Categories

	(1) Whole grain	(2) Potatoes	(3) Dark green veg	(4) Orange veg	(5) Legumes	(6) Other veg
Ln(Income)	-0.040***	-0.039***	0.14***	0.0067**	0.051***	0.047***
	(0.0023)	(0.0019)	(0.0034)	(0.0022)	(0.0029)	(0.0021)
Ln(Education)	0.060***	-0.073***	0.024***	0.029***	0.011***	0.028***
	(0.0023)	(0.0018)	(0.0035)	(0.0018)	(0.0029)	(0.0021)
Observations	3,615,984	3,615,984	3,615,984	3,615,984	3,615,984	3,615,984
R^2	0.093	0.016	0.111	0.024	0.245	0.031
	(7) Whole fruits	(8) Fruit juice	(9) Skim milk	(10) Chicken	(11) Eggs	(12) Fish
Ln(Income)	0.022***	0.015***	0.042***	0.012***	-0.040***	-0.036***
	(0.0023)	(0.0024)	(0.0027)	(0.0018)	(0.0021)	(0.0026)
Ln(Education)	0.072***	0.061***	0.098***	-0.010***	-0.0099***	-0.0045
	(0.0023)	(0.0024)	(0.0026)	(0.0017)	(0.0019)	(0.0026)
Observations	3,615,984	3,615,984	3,615,984	3,615,984	3,615,984	3,615,984
R^2	0.050	0.025	0.060	0.126	0.017	0.051

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable is the difference between a household's expenditure share and the recommended expenditure share on a particular food category in a given month. Standard errors are clustered by household. All variables are standardized. All regressions include year-month fixed effects and controls for household demographics, including household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic.

Table A.8: Household Characteristics and Nutritional Quality of Purchases: Unhealthful Food Categories

	(1) Non-whole grain	(2) Whole milk	(3) Cheese	(4) Beef	(5) Bacon
Ln(Income)	0.0023	-0.061***	0.015***	-0.045***	-0.0074***
	(0.0019)	(0.0024)	(0.0021)	(0.0021)	(0.0019)
Ln(Education)	-0.015***	-0.035***	0.041***	-0.067***	-0.023***
	(0.0018)	(0.0023)	(0.0021)	(0.0021)	(0.0018)
Observations	3,615,984	3,615,984	3,615,984	3,615,984	3,615,984
R^2	0.017	0.015	0.020	0.025	0.005
	(6) Fats	(7) Soft drinks	(8) Sweets	(9) Soups	(10) Frozen
Ln(Income)	-0.020***	-0.039***	-0.026***	0.040***	0.019***
	(0.0017)	(0.0021)	(0.0020)	(0.0019)	(0.0024)
Ln(Education)	-0.0026	-0.061***	-0.031***	0.0021	-0.015***
	(0.0017)	(0.0020)	(0.0019)	(0.0019)	(0.0023)
Observations	3,615,984	3,615,984	3,615,984	3,615,984	3,615,984
R^2	0.032	0.034	0.038	0.012	0.019

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable is the difference between a household's expenditure share and the recommended expenditure share on a particular food category in a given month. Standard errors are clustered by household. All variables are standardized. All regressions include year-month fixed effects and controls for household demographics, including household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic.

Table A.9: Household Characteristics and Nutritional Quality of Purchases: Healthful Nutrients

	Fiber	Iron	Calcium	Vitamin A	Vitamin C
Ln(Income)	0.079***	0.015***	0.060***	0.051***	0.043***
	(0.0020)	(0.0020)	(0.0019)	(0.0017)	(0.0015)
Ln(Education)	0.075***	0.052***	0.079***	0.054***	0.052***
	(0.0019)	(0.0019)	(0.0019)	(0.0016)	(0.0014)
Observations	3,590,548	3,590,548	3,590,548	3,590,548	3,590,548
R^2	0.034	0.012	0.030	0.015	0.014

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable is the normalized deviation of a household's per-calorie consumption from the recommended per-calorie consumption of a particular nutrient in a given month. Standard errors are clustered by household. All variables are standardized. All regressions include year-month fixed effects and controls for household demographics, including household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic.

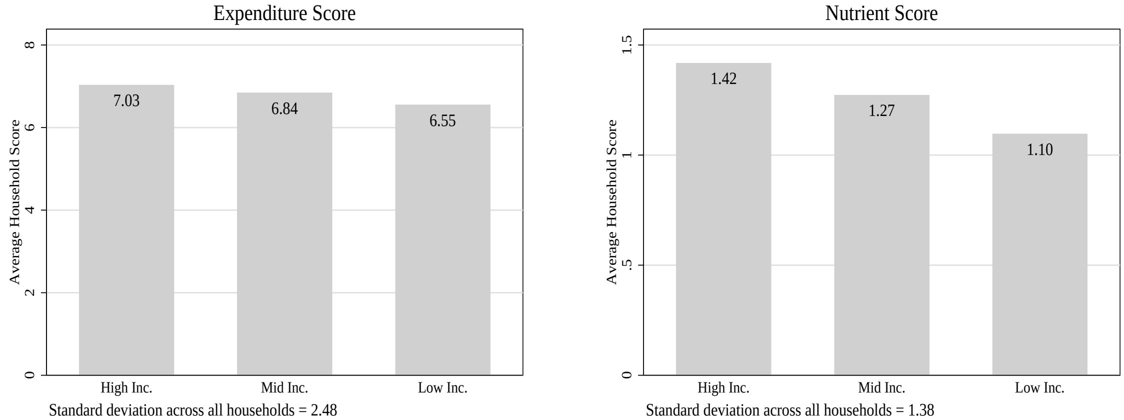
Table A.10: Household Characteristics and Nutritional Quality of Purchases: Unhealthful Nutrients

	Total Fat	Sat. Fat	Sodium	Cholesterol
Ln(Income)	-0.039***	-0.0043***	-0.0096***	0.000035
	(0.0023)	(0.00054)	(0.0016)	(0.0018)
Ln(Education)	-0.064***	-0.012***	-0.036***	-0.0012
	(0.0022)	(0.00052)	(0.0015)	(0.0017)
Observations	3,590,548	3,590,548	3,590,548	3,590,548
R^2	0.020	0.009	0.024	0.016

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

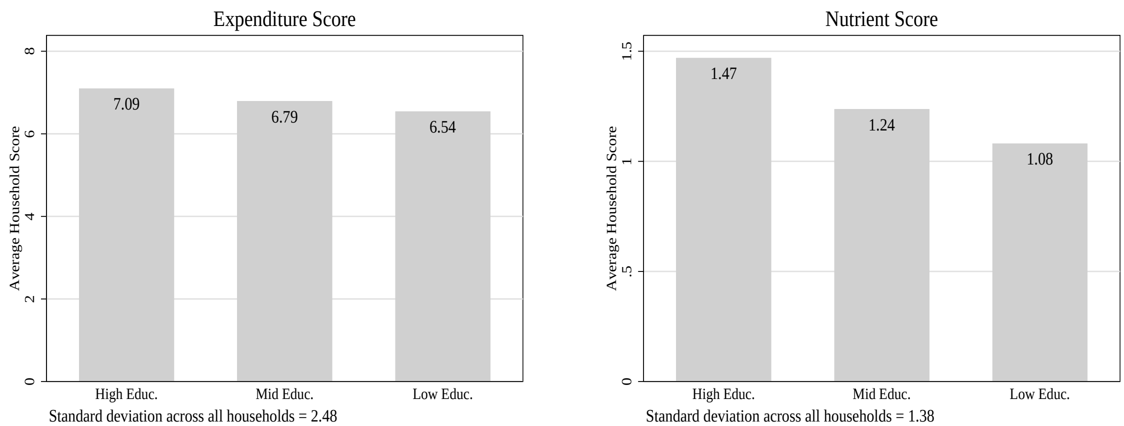
Notes: The dependent variable is the normalized deviation of a household's per-calorie consumption from the recommended per-calorie consumption of a particular nutrient in a given month. Standard errors are clustered by household. All variables are standardized. All regressions include year-month fixed effects and controls for household demographics, including household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic.

Figure A.2: Household Expenditure and Nutrient Scores by Income Terciles



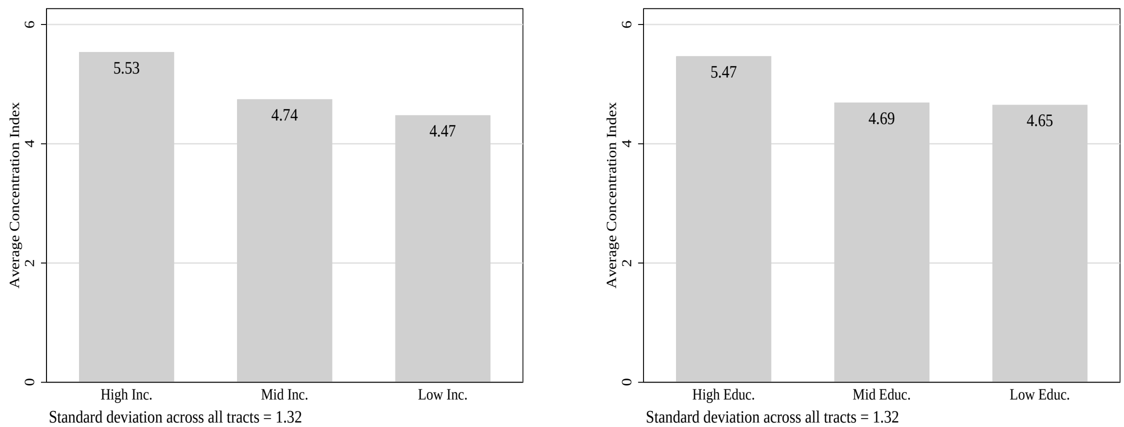
Notes: The figure above presents average household-level expenditure and nutrient scores across households with different levels of income. Households are considered high income if their size-adjusted household income falls above $50,214, middle income if their income is between $50,214 and $30,782, and low income if their income is below $30,782. Approximately one third of households fall into each of the three income categories. These results are for January 2010; they are representative of the other months in the Homescan data.

Figure A.3: Household Expenditure and Nutrient Scores by Education Terciles



Notes: The figure above presents average household-level expenditure and nutrient scores across households with different levels of education. Households are considered high education if the average years of education for their household head(s) falls above 14.98 years, middle education if their average education is between 14.98 and 13.29 years, and low education if their average education is below 13.29 years. Approximately one third of households fall into each of the three education categories. These results are for January 2010; they are representative of the other months in the Homescan data.

Figure A.4: Concentration Indexes by Income and Education Terciles



Notes: The figure above presents average concentration indexes across census tracts with different median incomes and different shares of college-educated households. Tracts are considered high income (HI) if their median household income falls above \$55,728, middle income (MI) if their median income is between \$41,010 and \$55,728, and low income (LI) if their median income is below \$41,010. 39% of tracts are HI, 34% are MI, and 27% are LI. Tracts are considered high education (HE) if their share of college-educated residents is above 30.04%, middle education (ME) if their share of college-educated residents in between 17.08% and 30.04%, and low education (LE) if their share of college-educated residents is below 17.08%. 39% of tracts are HE, 34% are ME, and 27% are LE. These results are for 2010; they are representative of the other years in the TDLinx sample.

Table A.11: Neighborhood Characteristics and Nutritional Quality of Product Offerings: Healthful Categories

	(1) Whole grain	(2) Potatoes	(3) Dark green veg	(4) Orange veg	(5) Legumes	(6) Other veg
Median Household Income Density	0.00772	0.00397	0.0498***	0.0296***	0.0415***	0.00501
	(0.0065)	(0.0062)	(0.0100)	(0.0080)	(0.0093)	(0.0045)
College-Educated Share Density	-0.0356***	0.0745***	-0.00961	0.00199	-0.00983	0.00642
	(0.0070)	(0.0071)	(0.0100)	(0.0080)	(0.0092)	(0.0046)
Observations	1,237,176	1,237,176	1,237,176	1,237,176	1,237,176	1,237,176
R^2	0.479	0.076	0.012	0.205	0.037	0.183
	(7) Whole fruits	(8) Fruit juice	(9) Skim milk	(10) Chicken	(11) Eggs	(12) Fish
Median Household Income Density	-0.00424	-0.00221	0.0278***	-0.00571*	0.0482***	0.0110
	(0.0057)	(0.0062)	(0.0069)	(0.0023)	(0.0070)	(0.0057)
College-Educated Share Density	-0.0296***	-0.0336***	0.0478***	0.0131***	0.0269***	-0.0317***
	(0.0061)	(0.0067)	(0.0080)	(0.0022)	(0.0080)	(0.0061)
Observations	1,237,176	1,237,176	1,237,176	1,237,176	1,237,176	1,237,176
R^2	0.602	0.487	0.188	0.071	0.262	0.307

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable is the difference between the predicted expenditure share and the recommended expenditure share on a particular food category for a nationally representative household within each store. Observations are at the store-month level. Standard errors are clustered by store. All variables are standardized. All regressions include year-month fixed effects.

Table A.12: Neighborhood Characteristics and Nutritional Quality of Product Offerings: Unhealthful Categories

	(1) Non-whole grain	(2) Whole milk	(3) Cheese	(4) Beef	(5) Bacon
Median Household Income Density	-0.00720	-0.00353	-0.0217**	-0.00613	0.00589
	(0.0093)	(0.0072)	(0.0081)	(0.011)	(0.0050)
College-Educated Share Density	-0.0425***	-0.0378***	0.0502***	0.0203	-0.0284***
	(0.0100)	(0.0077)	(0.0084)	(0.011)	(0.0051)
Observations	1,237,176	1,237,176	1,237,176	1,237,176	1,237,176
R^2	0.112	0.416	0.016	0.024	0.467
	(6) Fats	(7) Soft drinks	(8) Sweets	(9) Soups	(10) Frozen
Median Household Income Density	0.0142**	-0.00106	-0.00618	-0.00111	0.00201
	(0.0046)	(0.0062)	(0.0066)	(0.0076)	(0.0081)
College-Educated Share Density	0.0286***	-0.0328***	-0.0272***	-0.0438***	0.0327***
	(0.0050)	(0.0066)	(0.0071)	(0.0082)	(0.0084)
Observations	1,237,176	1,237,176	1,237,176	1,237,176	1,237,176
R^2	0.284	0.589	0.442	0.286	0.046

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Notes: The dependent variable is the difference between the predicted expenditure share and the recommended expenditure share on a particular food category for a nationally representative household within each store. Observations are at the store-month level. Standard errors are clustered by store. All variables are standardized. All regressions include year-month fixed effects.

Table A.13: Neighborhood Characteristics and Nutritional Quality of Product Offerings: Healthful Nutrients

	Fiber	Iron	Vitamin A	Vitamin C
Median Household Income Density	0.0749***	0.102***	0.0613***	0.0894***
	(0.010)	(0.010)	(0.010)	(0.0098)
College-Educated Share Density	0.0213*	0.0167	0.0141	-0.0134
	(0.010)	(0.010)	(0.011)	(0.0097)
Observations	1,237,176	1,237,176	1,237,176	1,237,176
R^2	0.089	0.039	0.058	0.049

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

Notes: The dependent variable is the normalized deviation of the predicted per-calorie consumption from the recommended per-calorie consumption of a particular nutrient for a nationally representative household within each store. Observations are at the store-month level. Standard errors are clustered by store. All variables are standardized. All regressions include year-month fixed effects.

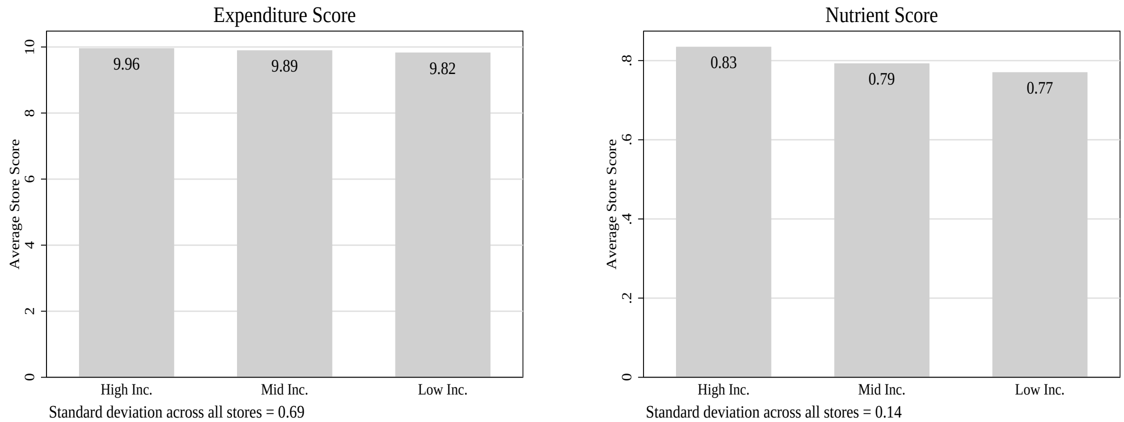
Table A.14: Neighborhood Characteristics and Nutritional Quality of Product Offerings: Unhealthful Nutrients

	Total Fat	Sat. Fat	Trans Fat	Sodium	Cholesterol
Median Household Income Density	-0.128***	-0.0447***	0.0740***	0.0220*	0.0508***
	(0.0063)	(0.0045)	(0.0076)	(0.010)	(0.011)
College-Educated Share Density	0.0618***	-0.0155***	0.0155*	0.00601	0.00227
	(0.0062)	(0.0044)	(0.0076)	(0.011)	(0.011)
Observations	1,237,176	1,237,176	1,237,176	1,237,176	1,237,176
R^2	0.302	0.234	0.149	0.070	0.009

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

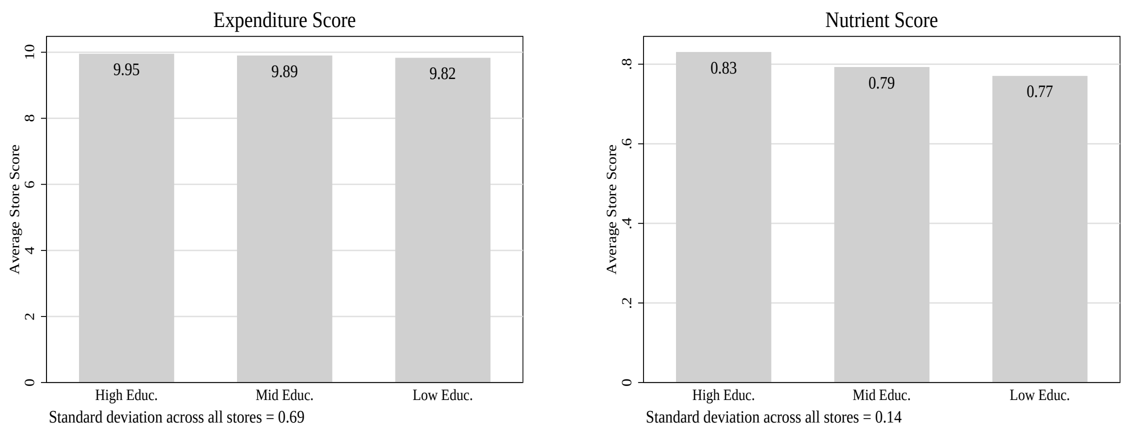
Notes: The dependent variable is the normalized deviation of the predicted per-calorie consumption from the recommended per-calorie consumption of a particular nutrient for a nationally representative household within each store. Observations are at the store-month level. Standard errors are clustered by store. All variables are standardized. All regressions include year-month fixed effects.

Figure A.5: Store Expenditure and Nutrient Scores by Income Terciles: Available Products



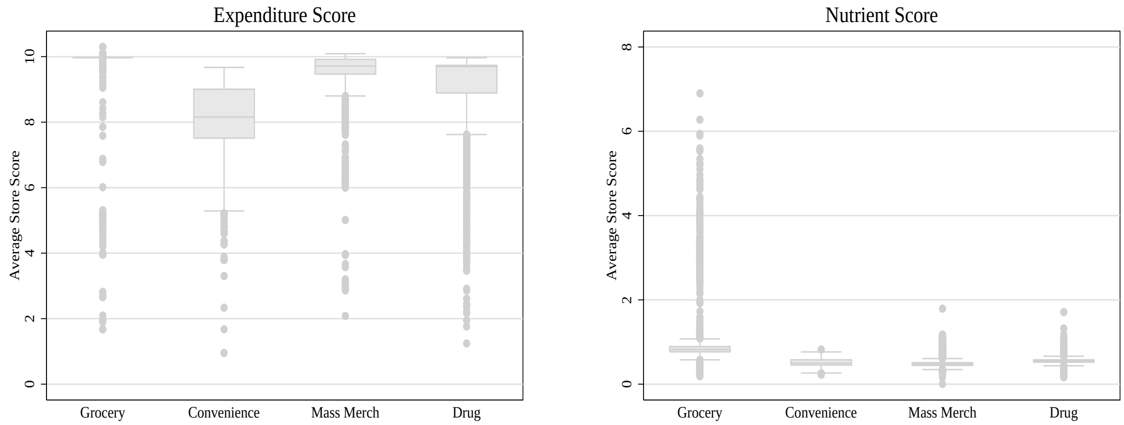
Notes: The figure above presents average store-level expenditure and nutrient scores across census tracts with different levels of income. Tracts are considered high income (HI) if their median household income falls above $55,728, middle income (MI) if their median income is between $41,010 and $55,728, and low income (LI) if their median income is below $41,010. 44% of tracts are HI, 24% are MI, and 32% are LI. These results are for January 2010; they are representative of the other months in the Scantrack sample.

Figure A.6: Store Expenditure and Nutrient Scores by Education Terciles: Available Products



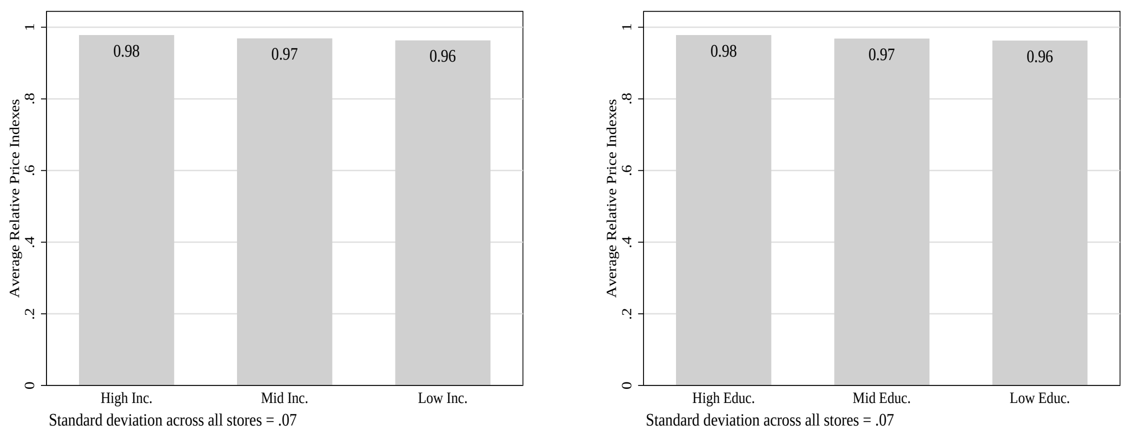
Notes: The figure above presents average store-level expenditure and nutrient scores across census tracts with different shares of college-educated residents. Tracts are considered high education (HE) if their share of college-educated residents falls above 30.04%, middle education (ME) if their share of college-educated residents is between 17.08% and 30.04%, and low education (LE) if their share of college-educated residents is below 17.08%. These results are for January 2010; they are representative of the other months in the Scantrack sample.

Figure A.7: Store Expenditure and Nutrient Scores Across Channels



Notes: The figure above presents distributions of store-level expenditure and nutrient scores by channel. Stores in the Scantrack data are divided into four channels: grocery, convenience, mass merchandise, and drug. These results are for January 2010; they are representative of the other months in the Scantrack sample.

Figure A.8: Relative Price Indexes by Income and Education Terciles



Notes: The figure above presents average store-level relative price indexes across tracts with different socioeconomic compositions. Tracts are considered high income (HI) if their median household income falls above $55,728, middle income (MI) if their median income falls between $41,010 and $55,728, and low income (LI) otherwise. Tracts are considered high education (HE) if their share of college-educated residents falls above 30.04%, middle education (ME) if their share of college-educated residents falls between 17.1% and 30.04%, and low education (LE) otherwise. These results are for January 2010; they are representative of the other months in the Scantrack sample.

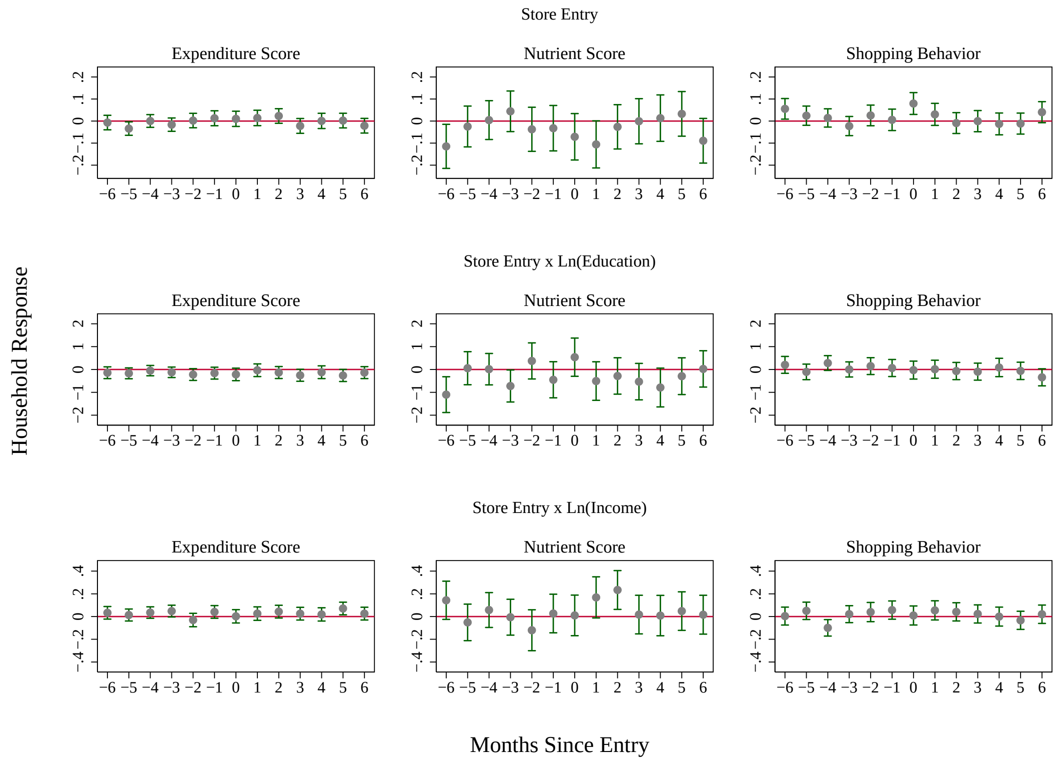
Table A.15: Response of Nutritional Quality of Household Purchases to Changes in Retail Access - Households in Underserved Neighborhoods

	Ln(Expenditure Score)				Ln(Nutrient Score)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Income)	0.0225***				0.0691***			
	(0.0018)				(0.0039)			
Ln(Education)	0.201***				0.589***			
	(0.0081)				(0.018)			
Ln(Store Concentration)	0.00191*	0.000895	0.000857	-0.00150	0.0496***	0.0151	0.0149	0.0125
	(0.00082)	(0.0036)	(0.0036)	(0.0083)	(0.0018)	(0.0084)	(0.0084)	(0.021)
Ln(Store Score Density)	0.0411	0.0123	0.0157	-0.000568	-0.0166	0.0543***	0.0606***	0.0539***
	(0.027)	(0.026)	(0.026)	(0.026)	(0.019)	(0.015)	(0.015)	(0.016)
Ln(Conc.)*Ln(Inc.)			-0.000784	-0.00130			0.00333*	0.00310*
			(0.0014)	(0.0015)			(0.0014)	(0.0014)
Ln(Conc.)*Ln(Educ.)			-0.0132	-0.0112			0.0262**	0.0268**
			(0.0098)	(0.011)			(0.0085)	(0.0090)
Ln(Score)*Ln(Inc.)			0.00787**	0.00806*			0.0186*	0.0158
			(0.0030)	(0.0033)			(0.0092)	(0.0097)
Ln(Score)*Ln(Educ.)			0.0199	0.0196			0.149***	0.165***
			(0.021)	(0.022)			(0.045)	(0.047)
Observations	1,617,786	1,617,786	1,617,786	1,461,881	1,617,786	1,617,786	1,617,786	1,461,881
R^2	0.064	0.450	0.450	0.452	0.031	0.348	0.348	0.350
Demographic Controls	Yes	No	No	No	Yes	No	No	No
Household Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Non-Movers Only	No	No	No	Yes	No	No	No	Yes
Elasticity w.r.t Conc.	0.00191	0.000895	0.00224	-0.0000904	0.0496	0.0151	0.0115	0.00914
Elasticity w.r.t Score	0.0411	0.0123	0.0111	-0.00520	-0.0166	0.0543	0.0413	0.0344

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Observations are at the household-month level. Standard errors are clustered by household. All regressions include year-month fixed effects. Log income and education are both demeaned. Demographic controls include household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic.

Figure A.9: Event Study Analysis of Store Entry - Households in Underserved Neighborhoods



Notes: The above plots display the results from an event study analysis of store entry. The first(second) column depicts the coefficient estimates on dummies for months before, during, and after store entry from a regression of log household-level expenditure(nutrient) scores on household fixed effects, month-year fixed effects, and dummies for each of the six months before, the month of, and the six months after the entry of a grocery store within 2km of a household's census tract centroid. The third column depicts the results from a regression of an indicator for whether the household shopped in a new store in that month on the same independent variables. A tract is defined as being underserved if it falls in the lowest quartile for either its concentration index, its expenditure score density, or its nutrient score density.

B Theoretical Framework

B.1 Set-up

There are M locations indexed by l. Each location l has a population of size N composed of heterogeneous individuals whose socioeconomic status (SES), indexed by h, can take one of two values, low (L) or high (H). We rank locations by their share of high-SES households, with higher l locations having larger shares of high-SES households. We assume that the share of high-SES households in a neighborhood is exogenously determined.

B.1.1 Demand

Consider a representative consumer for SES h. For simplicity, we assume that the consumer is immobile and can only shop at retail stores in his location. The preferences of the representative consumer are given by a nested-CES utility function over a continuum of grocery varieties indexed by u. The nests are defined by the healthfulness of the product u, denoted by $q(u) \in \mathbb{Q}$. Let $\mathbb{U}_q$ denote the set of products of the same healthfulness. A consumer of status h in location l will select their grocery purchases, $x(u)$, to maximize utility over the products available in location l, $\mathbb{U}_l$, subject to a budget constraint. The budget constraint is defined by local grocery prices, $p(u, l)$, and

the per-capita grocery expenditure, Y, which we normalize to one. That is,

$$\max_{x(u)} X_h = \left[\int_{q \in \mathbb{Q}} \alpha_h(q) \left(\int_{u \in \mathbb{U}_q} x(u)^{\rho_w} du \right)^{\frac{\rho_a}{\rho_w}} \right]^{\frac{1}{\rho_a}} \text{ subject to } \sum_{u \in \mathbb{U}_l} p(u,l)x(u) \leq Y = 1$$

where $\rho_a \in (0,1)$ reflects the degree of perceived horizontal differentiation between varieties of different nutritional qualities and $\rho_w \in (0,1)$ reflects the degree of perceived horizontal differentiation between varieties of the same healthfulness. We assume that $\rho_a > \rho_w$. The elasticity of substitution between varieties of different healthfulnesses and between varieties of the same healthfulness can be expressed as $\sigma_a = 1/(1-\rho_a)$ and $\sigma_w = 1/(1-\rho_w)$, respectively. We assume that varieties are also differentiated vertically by their degree of healthfulness, so the amount of utility a consumer with SES h gets from a unit of consumption of a given variety is scaled up (or down) by their taste for healthfulness, denoted by $\alpha_h(q(u))$>0.

The demand of a status h consumer in market l can be characterized by their expenditure share on product u:

$$x_h(u,l) = \left(\frac{p(u,l)}{P(q,l)} \right)^{-\sigma_w} \left(\frac{P(q,l)/\alpha_h(q)}{P_h(l)} \right)^{-\sigma_a}$$

where $P(q,l)$ denotes the price index for products of healthfulness q available in market l ($\mathbb{U}_{q,l} = \mathbb{U}_q \cap \mathbb{U}_l$), defined as

$$P(q,l) = \left[\int_{u \in \mathbb{U}_{q,l}} (p(u,l))^{1-\sigma_w} \right]^{\frac{1}{1-\sigma_w}}$$

and $P_h(l)$ denotes the aggregate taste-adjusted price index that consumers of type h face in market l, defined as

$$P_h(l) = \left[\int_{q \in \mathbb{Q}} \left(\frac{P(q,l)}{\alpha_h(q)} \right)^{1-\sigma_a} \right]^{\frac{1}{1-\sigma_a}}$$

A household h's total expenditure on all varieties of quality q is given by

$$x_h(q,l) = \left(\frac{P(q,l)/\alpha_h(q)}{P_h(l)} \right)^{-\sigma_a}$$

The relative expenditure of high-SES to low-SES households on products of the same healthfulness in the same location can be expressed as

$$\frac{\partial x_H(q,l)/x_L(q,l)}{\partial q} = \sigma_a \left(\frac{\alpha_H(q)}{\alpha_L(q)} \right)^{\sigma_a} \left(\frac{P_H(l)}{P_L(l)} \right)^{\sigma_a} \left(\frac{\alpha'_H(q)}{\alpha_H(q)} - \frac{\alpha'_L(q)}{\alpha_L(q)} \right)$$

High-SES households will spend relatively more than low-SES households on healthful products when $\frac{\alpha'_H(q)}{\alpha_H(q)} > \frac{\alpha'_L(q)}{\alpha_L(q)}$ for all q. We assume that this inequality holds in all cases where tastes vary with SES.[66]

[66]To keep the model tractable, we abstract from other reasons why households of different socioeconomic characteristics but the same choice set might purchase different products. For example, we assume that all households have the spending ability and, more importantly, can purchase products in continuous quantities. In doing so, we rule out the possibility that low-SES households may purchase fewer healthful food products because they are, in general, available only in discrete quantities at high prices and, therefore, do not fit within a more constrained budget. To the extent that these factors generate differences in demand across socioeconomic groups facing the same choice set, they could be considered complementary to the heterogeneous taste mechanism that we use here.

B.1.2 Supply

In order to distribute x units of a food product of healthfulness q to a neighborhood with a λ_l share of high-SES residents, we assume that a firm must incur a fixed cost f; a per unit wholesale cost that can vary with product healthfulness, $w(q)$; and a per unit shelf-space cost that can vary with the share of high-SES residents, $s(\lambda_l)$. To reflect higher rents in higher-SES neighborhoods, we assume that shelf-space costs are increasing in the share of high-SES individuals living in the location. We denote the total marginal cost of retail by $c(q,l) = w(q) + s(\lambda_l)$. We assume that there are no economies of scope, so each retailer sells only one variety in any one location l. Taking the behavior of competitors as given, the optimal price charged by a firm producing variety u of healthfulness q in location l is the price that maximizes profits. That is, the firm solves the following problem

$$\max_{p(u,l)} \pi(u,l) = (p(u,l) - c(q,l))\, x(u,l) - f$$

where $x(u,l)$ denotes the demand for variety u in location l, with

$$x(u,l) = \lambda_l x_H(u,l) + (1-\lambda_l) x_L(u,l)$$

where we have normalized the population in each location to one. For all varieties u of quality q sold in location l, the optimal pricing strategy is a proportional mark-up over marginal cost:

$$p(u,l) = \frac{c(q,l)}{\rho_w}$$

We can use this optimal price to rewrite the price index for quality q in location l as

$$P(q,l) = (N(q,l))^{\frac{1}{1-\sigma_w}} \left(\frac{c(q,l)}{\rho_w}\right) \tag{A.1}$$

where $N(q,l)$ is the number of varieties of healthfulness q distributed to location l. The price index for household type h in location l is

$$P_h(l) = \left[\int_{q\in\mathbb{Q}} \left(\frac{P(q,l)}{\alpha_h(q)}\right)^{1-\sigma_a}\right]^{\frac{1}{1-\sigma_a}} = \frac{1}{\rho_w}\left[\int_{q\in\mathbb{Q}} \left(\frac{(N(q,l))^{\frac{1}{1-\sigma_w}}\, c(q,l)}{\alpha_h(q)}\right)^{1-\sigma_a}\right]^{\frac{1}{1-\sigma_a}}$$

Therefore, the quantity of sales of any firm selling a variety of healthfulness q in location l is given by

$$x(q,l) \quad = \quad (N(q,l))^{\frac{\sigma_w+\sigma_a}{1-\sigma_w}} \left(\frac{c(q,l)}{\rho_w}\right)^{\sigma_a} \left[\lambda_l \left(\alpha_H(q) P_H(l)\right)^{\sigma_a} + (1-\lambda_l)\left(\alpha_L(q) P_L(l)\right)^{\sigma_a}\right] \tag{A.2}$$

B.1.3 Equilibrium

We assume that there is free entry into retailing, so active firms earn zero profits. This implies that the scale of firm sales in any given market is given by

$$x(q,l) = \frac{f}{c(q,l)}(\sigma_w - 1) \tag{A.3}$$

B.2 Comparative Statics

B.2.1 Equilibrium Pattern of Product Availability and Consumption Across Locations

Taken together, the zero profit condition (Equation (A.3)), the aggregate demand condition (Equation (A.2)), and the healthfulness-location-specific price index (Equation (A.1)) implicitly define the number of varieties of healthfulness q in each location l as a function of the fixed and marginal costs of producing each variety, the local share of households in each socioeconomic class, and the model parameters:

$$N(q,l) \quad = \quad \Gamma \underbrace{(c(q,l))^K}_{Cost} \underbrace{\left[\lambda_l \left(\alpha_H(q)P_H(l)\right)^{\sigma_a} + (1-\lambda_l)\left(\alpha_L(q)P_L(l)\right)^{\sigma_a}\right]^{\frac{1-\sigma_w}{\sigma_w+\sigma_a}}}_{Demand} \tag{A.4}$$

where $\Gamma = \left[f(\sigma_w - 1)\left(\frac{\sigma_w-1}{\sigma_w}\right)^{\sigma_a}\right]^{\frac{\sigma_w-1}{\sigma_w+\sigma_a}} > 0$ and $K = \frac{(1-\sigma_w)(1+\sigma_a)}{\sigma_a} < 0$. Given the distribution of socioeconomic classes across locations and the retail technology, the pattern of product availability is determined by two forces, each reflected by an individual term in the above expression for product availability. The first, labeled $Cost$, reflects the role that costs play in determining the healthfulness distribution in different locations. The second, labeled $Demand$, reflects the role played by differences in tastes across socioeconomic groups combined with differences in the share of socioeconomic classes in each location's population.

We now demonstrate that each of these mechanisms could individually explain the qualitative patterns that we observe in product availability across neighborhoods and purchases across households. We are interested in showing that the number of healthful, relative to unhealthful, varieties available in a location is increasing in the share of high-SES households in the location (*i.e.*, that $\frac{N(q,l)}{N(q',l)} > \frac{N(q,l')}{N(q',l')}$ for $\lambda > \lambda'$). If tastes are weakly supermodular in quality and household SES, high-SES households will spend at least as much on high-quality food products as low-SES households in the same location. Therefore, if the healthfulness of available products in increasing in the share of high-SES households in a neighborhood, it follows that high-SES households will spend more on healthful food products. Even if high-SES and low-SES households share the same tastes, all households will spend more on healthful foods in locations where more of these are available. Since high-SES households are, by definition, disproportionately located in high-SES locations, on average high-SES households will spend more on healthful food products.

We start by turning both mechanisms off. That is, we assume that **tastes are identical** across consumers, *i.e.*, $\alpha_H(q) = \alpha_L(q) = \alpha(q)$ for all q, and that **wholesale costs are equal** across products of different healthfulnesses, $i.e.\ w(q) = w$ for all q. If wholesale costs are equal across products, then the healthfulness of the varieties available in each location will be determined by the taste shifter, $\alpha(q)$:

$$N(q,l) \quad = \quad \Gamma\left(c(l)\right)^K \left(\alpha(q)P(l)\right)^{1-\sigma_w} \tag{A.5}$$

Since tastes are assumed to be identical across consumers, the distribution of healthfulness of available varieties will be identical across locations. To see this, note that the relative number of varieties of two healthfulness levels, q and q', in location l can be written as the ratio of the common taste shifter for varieties of quality q relative to q'. That is,

$$\frac{N(q,l)}{N(q',l)} \quad = \quad \left(\frac{\alpha(q)}{\alpha(q')}\right)^{1-\sigma_w} \tag{A.6}$$

Since tastes are identical across households and the distribution of healthful products available is identical across locations, Marshallian demand must be also identical across households, regardless of their SES or location.

If we assume that **tastes are identical** (and, for simplicity, do not vary with product quality), $i.e.\ \alpha_H(q) = \alpha_L(q) = \alpha$ for all q, but allow **wholesale costs to vary** with healthfulness, then the zero profit condition reduces to

$$N(q,l) \quad = \quad \Gamma\left(c(q,l)\right)^K \left(\alpha P(l)\right)^{1-\sigma_w} \tag{A.7}$$

Taking the derivative with respect to healthfulness q and location l and imposing that retail costs are equal to the sum of wholesale and shelf costs, *i.e.*, $c(q,l) = w(q) + s(\lambda_l)$, we see that as long as wholesale costs are increasing in quality and shelf-space costs are increasing in λ_l, the healthfulness- and location-specific variety counts are supermodular in quality (q) and the share of high-SES households (λ_l):

$$\frac{\partial N(q,l)}{\partial q \partial \lambda_l} = \Gamma K \left(\alpha P(l)\right)^{1-\sigma_w} \frac{w'(q)s'(\lambda_l)}{\left(w(q)+s(\lambda_l)\right)^{2-K}} > 0 \text{ for } w'(q), s'(\lambda_l) > 0.$$

This result implies that high-SES households are more likely to live in locations with a greater variety of healthful food products. The ratio of the price of healthful relative to unhealthful food products will be identical across locations, so households in locations with a greater variety of healthful food products available will purchase relatively more of these products. As a result, we expect to see high-SES households spending more on healthful food products, on average, even if they have the same preferences as low-SES households. That is, socioeconomic disparities in access to healthful and unhealthful food products alone can generate socioeconomic disparities in household purchases.

If we instead assume that **the cost functions are identical** across locations, $i.e.$, $c(q,l) = c(q)$ for all l, but allow for **tastes to vary** with SES, the zero profit condition becomes:

$$N(q,l) \quad = \quad \Gamma\left(c(q)\right)^K \left[\lambda_l \left(\alpha_H(q) P_H(l)\right)^{\sigma_a} + (1-\lambda_l)\left(\alpha_L(q) P_L(l)\right)^{\sigma_a}\right]^{\frac{1-\sigma_w}{\sigma_w+\sigma_a}} \tag{A.8}$$

To characterize how the quality distribution is determined by demand, we start by considering the simplest case and compare two locations, l and l', which are populated entirely by high-SES and low-SES consumers, respectively. The ratio of the product counts across the two locations at any given quality level q is given by

$$\frac{N(q,l)}{N(q,l')} \quad = \quad \left(\frac{\alpha_H(q) P_H(l)}{\alpha_L(q) P_L(l')}\right)^{\frac{\sigma_a(1-\sigma_w)}{\sigma_w+\sigma_a}} \tag{A.9}$$

since $\lambda_l = 1$ and $\lambda_{l'} = 0$. Taking the derivative of this function with respect to healthfulness we see that the ratio of varieties available for a given healthfulness level across the two locations will be increasing in healthfulness as long as $\frac{\alpha_L'(q)}{\alpha_L(q)} < \frac{\alpha_H'(q)}{\alpha_H(q)}$. This is the same condition required for the relative expenditure share of high-SES to low-SES households to be increasing in quality:

$$\frac{\partial \frac{N(q,l)}{N(q,l')}}{\partial q} \quad = \quad A \frac{N(q,l)}{N(q,l')}\left(\frac{\alpha_H'(q)}{\alpha_H(q)} - \frac{\alpha_L'(q)}{\alpha_L(q)}\right) > 0 \text{ for } \frac{\alpha_H'(q)}{\alpha_H(q)} > \frac{\alpha_L'(q)}{\alpha_L(q)} \tag{A.10}$$

for $A = \left(\frac{\sigma_a(\sigma_w - 1)}{\sigma_w + \sigma_a}\right) < 0$.

Now, consider two locations with intermediate, but non-equal, shares of high-SES households. When costs are identical across locations, the zero profit condition implies that the scale of firms producing varieties of the same healthfulness is also identical across locations. The number of varieties available at each healthfulness level will be determined solely by demand for products at that healthfulness level. Since demand for healthful varieties is increasing in SES, and all households earn the same income, we must therefore have that locations with more high-SES households can support a greater variety of healthful food products.

B.2.2 Upper Bound for the Role of Access in Generating Cross-Sectional Disparities

We have demonstrated that two separate forces can each individually explain the distribution of product availability and consumption that we observe across locations. The correlation between access and household purchases demonstrated in the previous literature, however, is insufficient to determine the role that differences in access play in driving differences in consumer behavior (or vice versa). In what follows, we show that by comparing the differences in household purchases across locations to those within locations, we can identify an upper bound on the role that access plays in generating these differences. The critical result is that demand alone determines differences in purchases across households with different socioeconomic statuses in the same location. From here, we can show that any sorting across locations based on unobservable tastes will imply that the observed differences in purchases across the selected households who live or shop in the same location are, on average, smaller than the differences in purchases that would persist if access was equalized for all households.

Both access and tastes could be at play in generating the socioeconomic disparities that we observe in purchases across households living in different locations. To see this, note that the expenditures of a household of SES h on products of a given healthfulness q are determined both by their taste for that healthfulness $\alpha_h(q)$, and by the price index of products of that healthfulness in their location:

$$x_h(q,l) = (\alpha_h(q))^{\sigma_a}\left(\frac{P(q,l)}{P_h(l)}\right)^{1-\sigma_a} \tag{A.11}$$

We saw above that high-SES individuals purchase more healthful food products either because there are more of these products available in the locations where they live and/or because they have a stronger taste for these products. To see this mathematically, note that the average expenditure share of healthfulness q varieties for high-SES relative to low-SES individuals living across two locations, l and l', is given by

$$\begin{aligned}\frac{x_H(q)}{x_L(q)} &= \left(\frac{\lambda_l x_H(q,l) + \lambda_{l'} x_H(q,l')}{(1-\lambda_l)x_L(q,l) + (1-\lambda_{l'})x_L(q,l')}\right)\left(\frac{2-\lambda_l-\lambda_{l'}}{\lambda_l+\lambda_{l'}}\right) \\ &= \underbrace{\left(\frac{\alpha_H(q)}{\alpha_L(q)}\right)^{\sigma_a}}_{Tastes}\underbrace{\left(\frac{\lambda_l\left(\frac{P(q,l)}{P_H(l)}\right)^{1-\sigma_a} + \lambda_{l'}\left(\frac{P(q,l')}{P_H(l')}\right)^{1-\sigma_a}}{(1-\lambda_l)\left(\frac{P(q,l)}{P_L(l)}\right)^{1-\sigma_a} + (1-\lambda_{l'})\left(\frac{P(q,l')}{P_L(l')}\right)^{1-\sigma_a}}\right)}_{Availability}\left(\frac{2-\lambda_l-\lambda_{l'}}{\lambda_l+\lambda_{l'}}\right)\end{aligned} \tag{A.12}$$

The first term reflects taste differences alone. The second term reflects differences in access that, as we outlined above, could be the result of either firms catering to local tastes or to supply-side factors, such as the complementarities between healthfulness and local distribution costs proposed above. These differences in local product availability are reflected through the local price indexes, with $P(q,l)$ decreasing in the number of healthfulness q

varieties that are available in location l. There are relatively more healthful varieties available in a location l where there are more high-SES individuals, so the local healthfulness q price index will be lower, relative to the overall price index a household faces in a location ($P_H(l)$ or $P_L(l)$), in high-λ_l locations relative to locations with a lower share of high-SES residents. This correlation implies that the numerator of the availability term is increasing in quality (since $1-\sigma_a<0$), whereas the denominator is falling in quality.

If we instead look at the average expenditure share of healthfulness q varieties for high-SES relative to low-SES individuals living in the same location, l, this availability term no longer varies with product quality:

$$\frac{x_H(q,l)}{x_L(q,l)}=\left(\frac{\alpha_H(q)}{\alpha_L(q)}\right)^{\sigma_a}\left(\frac{P_L(l)}{P_H(l)}\right)^{1-\sigma_a} \tag{A.13}$$

Any systematic variation that we observe in the healthfulness consumed by high-SES relative to low-SES individuals living in the same location must be attributed to tastes alone.

Note that this within-location variation in healthfulness only provides a lower bound for the role of tastes in generating differences in the healthfulness of purchases across socioeconomic groups, because tastes could also explain part (or all) of the differences in the availability of products in locations where these households reside. Further, in the context of the model, the within-location variation in healthfulness also exactly identifies the disparity that would persist were availability to be equalized across all locations at the level observed in location l. This model is highly stylized, so there are various additional reasons why within-location socioeconomic disparities in healthfulness may reflect more than differences in tastes alone. Important factors that the model abstracts from include the mobility of both products and households between locations, unobserved heterogeneity in tastes across households within the same socioeconomic class, and differences in the mobility of households and the availability of products within locations. These biases will tend to lead us to further overestimate the role of product availability in explaining the overall socioeconomic disparities in purchases. Take, for example, unobserved heterogeneity in tastes. Suppose that households sort into retail locations based on tastes. We can reflect this heterogeneity and sorting by allowing the taste coefficients α, to vary with SES and location, such that the tastes for a product with healthfulness q for a household with SES h in location l is denoted$\alpha_{h,l}(q)$. Under this assumption, we now have that the relative expenditures of high-SES to low-SES households in the same location l can be written:

$$\frac{x_{H,l}(q,l)}{x_{L,l}(q,l)}=\left(\frac{\alpha_{H,l}(q)}{\alpha_{L,l}(q)}\right)^{\sigma_a}\left(\frac{P_{L,l}(l)}{P_{H,l}(l)}\right)^{1-\sigma_a} \tag{A.14}$$

Under the new assumption that households are spatially sorted by heterogeneous tastes, this relative expenditure no longer exactly identifies the disparity that would persist were availability equalized across all locations at the level observed in location l. In particular, since $Corr\left(\alpha_{H.l}(q),\alpha_{L.l}(q)\right)\geq Corr\left(\alpha_{H.l}(q),\alpha_{L.l'}(q)\right)$ for any two locations l and l', then $x_{H,l}(q,l)/x_{L,l}(q,l)\leq x_{H,l}(q,l)/x_{L,l'}(q,l)$ for any two locations l and l'. The relative expenditures of high-SES and low-SES residents in the same location therefore provides a lower bound on the true amount of variation that will persist in the full cross-section of households if access were to be equalized across all locations.

B.2.3 Upper Bound for the Role of Changing Access on Consumption Disparities

If we recast locations as markets that are separated by time instead of by space, we can use the model presented above to interpret the changes that we observe in household purchases over time as their retail environments

change. Our goal is to estimate the impact that policies to improve access in underserved areas will have on household purchases without any changes in tastes over time. This is unlikely to be the case in the data, however. The observed changes in access are likely to be correlated with unobserved changes in tastes since households sort into neighborhoods that offer consumption amenities that suit their tastes and stores select their product offerings to cater to local tastes. To see this, consider how the average expenditure share of healthfulness q varieties varies for a household of the same SES h between a market l and another market l'. When deriving this expenditure share for Equation (A.11) above, we assumed that tastes do not vary across markets. This is reasonable when thinking about how household expenditures vary across geographic markets in a single time period, but less reasonable when considering how expenditures vary for a given household over time. Extending Equation (A.11) to allow for tastes to vary over time, we can see that the relative expenditures in market l relative to market l' depend on the change in tastes across the two markets as well as the change in availability:

$$\frac{x_h(q,l)}{x_h(q,l')} = \underbrace{\left(\frac{\alpha_h(q,l)}{\alpha_h(q,l')}\right)^{\sigma_a}}_{Tastes} \underbrace{\left(\frac{P(q,l)}{P(q,l')}\frac{P_h(l')}{P_h(l)}\right)^{1-\sigma_a}}_{Availability} \tag{A.15}$$

Given the fixed costs of differentiated good production, stores cater to the tastes in a market. Therefore, changes in availability across markets will be correlated with unobserved changes in the prevalent tastes of local residents. While the tastes of any one panelist household might not reflect the prevalent local tastes (a household's tastes may not change or may change in the opposite direction), we expect that the tastes of our sample households are, on average, correlated and covary with local tastes. As a result, we expect that our estimate of the elasticity of household purchases with respect to changes in their retail environment to be subject to an upward omitted variable bias. Therefore, we interpret these elasticities as an upper bound for the true elasticity that we expect to govern the response of purchases to improved access that is driven by policy as opposed to endogenous firm responses to changes in market fundamentals.