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ABSTRACT

The poor diets of many consumers are often attributed to limited access to healthy foods. In this paper, we use detailed data describing the healthfulness of household food purchases and the retail landscapes in which these consumers are making these decisions to study the role of access 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 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 controlling for access: even in the same store, more educated households purchase more healthful foods. Consistent with this result, we further find that the nutritional quality of purchases made by households with low levels of income and education respond very little when new stores enter or when existing stores change their product offerings. Together, our results indicate that policies aimed at improving access to healthy foods in underserved areas will leave most of the socioeconomic disparities in nutritional consumption intact.

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1 Introduction

It is well known that there are large nutritional disparities across different socioeconomic groups in the United States, but little is known about why such disparities exist. Poor diets are often attributed to three factors: limited access to healthy foods (food deserts), preferences for unhealthy foods, and higher prices of healthy foods. Under the assumption that differential access is to blame for nutritional disparities, the Agricultural Act of 2014 introduced $125 million to be spent annually in each of the next five years to promote access to healthy foods in underserved communities (Aussenberg, 2014). Many states have also introduced programs to improve access by providing loans, grants, and tax credits to stimulate supermarket development and to encourage retailers to offer healthy foods in food deserts (CDC, 2011).[1]

Despite the growing popularity of such programs, little is known about their success in narrowing nutritional disparities. This paper measures the maximal impact of these policies by quantifying the role that access plays in generating socioeconomic disparities in nutritional consumption.[2] We first employ novel data describing the nutritional quality of food products available to and purchased by U.S. households to characterize the degree of socioeconomic disparities in access to and consumption of nutritious foods. While access and consumption are correlated, the direction of causality is unclear: since households sort into neighborhoods and retailers cater to local tastes, consumption disparities across locations with differential access reflect not only the role of access but also demand-side factors. We use a theoretical framework to demonstrate that we can separately identify the overall contribution of demand-side factors by looking at the purchases made by households living in the same location or shopping in the same store. Using detailed residential and shopping location information, we empirically identify an upper bound for the role that access plays in generating consumption disparities. We complement this cross-sectional approach with an analysis of natural experiments in which we observe the retail environments of households in our sample changing over time. Together, 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 different socioeconomic groups. While equating access would help to reduce differences in nutritional consumption across different income groups, over 90% of the disparities across education groups would remain.

Using two novel measures of the healthfulness of household purchases, we first document significant differences in the nutritional quality of foods purchased by different socioeconomic groups across the U.S. This generalizes the results of previous studies which 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 comprehensive picture of the nutritional consumption of household purchases, we combine consumption data from Nielsen with nutritional information from Gladson and IRI to construct a dataset describing the full nutritional profile of the grocery purchases made by over 100,000 households from 52 markets across the U.S. between 2006 and 2011.[4] We calculate two complementary household-level

[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] We focus on purchases of food for consumption at home rather than food at restaurants for two reasons. First, detailed data on the nutritional quality of food purchased at restaurants is limited. Second, recent efforts to improve access focus primarily on the entry of grocery stores and other retail outlets that offer healthful products rather than the entry of healthful restaurants. It could be the case, however, that there are systematic differences across socioeconomic groups in the nutritional quality of food consumed away from home, and these differences could either mitigate or exacerbate the disparities in home consumption that we observe. We are currently working to measure the nutritional

indexes, an "expenditure score" and a "nutrient score," that represent the healthfulness of the products purchased relative to USDA category-level expenditure recommendations and FDA recommendations for per calorie nutrient consumption, respectively.[5] 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. The products purchased by households in the highest terciles for income and education are 40% closer to both USDA recommendations for food category expenditure shares and FDA recommendations for per calorie nutrient consumption than the products purchased by households in the lowest terciles of income and education.

Next, we provide the most comprehensive picture of the healthfulness of products available at retail locations across the U.S. to date and quantify the degree to which retail environments differ by socioeconomic status. Consistent with previous studies, we find that access to healthy foods is greater in wealthier and more educated neighborhoods (Beaulac et al. (2009); Ver Ploeg et al. (2009)).[6] Using geo-coded data on the location of over 200,000 retailers across the U.S., we first document that there are large disparities in the concentration of stores across neighborhoods with different socioeconomic profiles. We then use weekly store-level sales data from Nielsen to identify the products that are available at over 30,000 participating retailers between 2006 and 2011. Analogous to the household-level analysis, we merge the Nielsen data with nutritional information from Gladson and IRI to calculate two complementary store-level healthfulness indexes. We find small, but statistically significant, correlations between observable market characteristics and the store-level healthfulness indexes, with stores in high-income and high-education neighborhoods offering more healthful products. Together, these results indicate that households residing in wealthier and more educated neighborhoods have access to significantly more stores, with the average store in their neighborhood stocking products that are slightly more nutritious.

While there is agreement among researchers that spatial and socioeconomic disparities in nutrition exist, the actual effects of access to healthy foods on food purchases is heavily contested (Bitler and Haider (2011)). 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. Up to this point, data limitations have led to measurement and identification issues which have hindered a clear understanding of the role that access plays in generating nutritional disparities.[7]

The detailed nature of our data allows us to go beyond existing work in examining the direction of causality in the relationship between nutritional availability and nutritional consumption. In two complementary analyses, we 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. As we expect disparities in consumption that are due to differential access to exist only between households living in different neighborhoods, we first look

quality of food consumed away from home to examine both how consumption at home and consumption away from home are related and how this relationship impacts nutritional disparities.

[5]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. Our nutrient score directly measures the healthfulness of the relative quantities of macro-nutrients in the products purchased.

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

[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 on 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.

at whether consumption disparities persist when we control for the residential locations of households. While the association between income and the healthfulness of food purchases is reduced by half when we control for the household's census tract, the relationship between education and healthfulness is only reduced by 10%. While informative, our "within-location" approach has its limitations. It is possible 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 (e.g. car ownership). 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 association between income and the healthfulness of food purchases is cut in half when we look at purchases made within the same store, whereas the association between education and nutritional quality is only reduced by 10%. 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. We conclude that disparities in access play a minimal role in explaining observed disparities in nutritional consumption.

We present a simple model to formalize the intuition behind this empirical approach. The model nests two mechanisms, one driven by demand and one driven by supply, each which can independently explain the socioeconomic disparities in access to healthy foods that we observe. The demand-side explanation relies on within-group preference externalities: In a monopolistically competitive retail industry, firms will cater to the prevalent tastes in the local market. If high-socioeconomic households have stronger tastes for healthy foods, then it follows that more healthful food products will be sold in high-socioeconomic 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) marginal costs of retailing are increasing in the share of high-socioeconomic status residents in a neighborhood but do not vary across products. These assumptions imply that firms in neighborhoods with a greater share of high-socioeconomic status residents have a comparative advantage in the distribution of nutritious products. As a result, they will sell more healthful food products than stores in low-socioeconomic neighborhoods, even if high- and low-socioeconomic households have identical tastes. The model serves to demonstrate that the differences that we observe in the healthfulness of purchases made by high- and low-socioeconomic status households living in the same location act as a lower bound for the component of socioeconomic disparities in nutritional consumption that can be explained by factors other than the retail environment. We therefore conclude that the difference between the disparities we observe across locations and the disparities that we observe within locations is an upper bound for the component of the existing disparities in purchases that can be explained by the retail environment alone.

Improving access in underserved areas will only be effective in resolving socioeconomic disparities in nutritional consumption insofar as the nutritional quality of purchases made by households with low levels of income and education improves in response to these changes. We leverage observed changes in retail environments over time to measure how households in our data responded to changes in access in the past. 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. Improving the concentration and nutritional quality of stores in the average low-income and low-education neighborhood to match those of the average high-income and high-education neighborhood would only close the gap in nutritional consumption across these groups by 1-3%. Limited responsiveness of household purchases to store entry is observed 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 that store entry has no lasting impact on the nutritional quality of household purchases at these stores. These results again indicate that policies aimed at improving access to healthful foods will do little to resolve the observed 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 the literature in economics which uses the entry of fast food restaurants and large retailers, such as Walmart, to identify a causal relationship between retail environments and obesity more generally (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.[8] This is important from a policy perspective, as current policies aim to reduce disparities in consumption across socioeconomic groups. From a methodological perspective, our focus on disparities allows us to use both cross-sectional and time-series variation to consider the impact of retail environments on disparities in health behaviors. 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 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 in explaining the large disparities that persist when we look at households in the same location.

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 shows how we measure 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 could each generate the observed disparities in both purchases and access, and we demonstrate how geo-coded household purchase data can be used to identify the role of access, separately from demand-side factors, in generating consumption disparities. Sections 4.2 and 4.3 implement this procedure by looking at whether consumption disparities persist when we control for residential or retail location. Section 5 takes an alternative, time-series approach and examines whether we observe the healthfulness of household purchases responding to changes in local access. Section 6 concludes.

[8] Currie et al. (2010) examine differences by race. They find greater responsiveness among whites then blacks, which is likely consistent with our results.

2 Data

We use six different datasets that together describe the nutritional quality of food purchases that households make, the 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)[9] and provided by Nielsen. The Homescan data contains transaction-level purchase information for a representative panel of 114,286 households across the U.S. 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. After scanning the Universal Product Code (UPC) of each item purchased, the household records the date, store name, quantity purchased, and price.[10] 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 provides us with information on the location and demographics of each household in the panel. For each year that a household is in the NCP panel, we observe the census tract in which the household resides and a range of demographic characteristics. We use the demographic data to measure two dimensions of socioeconomic status which are posited to impact a household's consumption decisions: income and education.[11,12]

While the NCP Homescan data describes the stores in which Homescan panelists shop and that products that they purchase in these stores, it only provides a limited picture of the retail environments in which households are making their consumption 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 the 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 detailed 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.[13] To see the full set of food products available at a subset of these stores, we combine the TDLinx data with the Nielsen Scantrack (RMS) data provided by the Kilts-Nielsen Data Center at University of Chicago Booth School of Business.[14] The RMS data contains UPC-level weekly sales values and quantities generated from point-of-sale systems in over 30,000 participating retailers across the U.S.[15] We use this data to calculate indexes that

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

[10] See Harding and Lovenheim (2014) for detailed descriptions of how households are recruited and how households are encouraged to continue reporting purchases on a weekly basis.

[11] 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).

[12] Households record the male and/or female 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. For our analysis, we exclude households in which either household head reports only a grade school education, as there are too few observations to obtain precise estimates for these households. We assign each household head a number of years of education, assuming that some high school is equal to 10 years, some college is equal to 14 years, and post-graduate is equal to 18 years. For households with both a male and a female head, we take the average years of education across household heads.

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

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

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

summarize the nutritional quality of products offered by each store in the dataset.[16,17,18]

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. 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.[19] We merge the Gladson and IRI data with the Nielsen Homescan and RMS data to obtain the full nutritional profiles of products we observe being purchased by households and sold in stores.[20] In Sections 3.1 and 3.2, we describe how we use this information to measure the healthfulness of households' grocery purchases and the healthfulness of products available at the store level, respectively.

The final dataset that we use contains tract-level demographics from the 2010 U.S. Census.[21] 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.

3 Stylized Facts

3.1 Disparities in Nutritional Consumption

We begin by documenting the extent of the disparities in nutritional consumption across households with different demographics. 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. We measure the quality of household purchases using two complementary indexes. We calculate these indexes at a monthly frequency for each household in the sample. The first index 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 USDA food category. This index follows the measure used in Volpe et al. (2013). We will refer to this as the "expenditure score." Given the nutritional information we have from Gladson and IRI, however, we can go further than looking at expenditures on food group categories. We therefore also calculate a "nutrient score" that directly measures the healthfulness of the relative quantities of macro-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

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

[17] Despite this detailed information on prices and product offerings, the RMS 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 RMS 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 RMS store on the same day.

[18] One concern with the RMS data is that participation of retailers may systematically vary across neighborhoods. As shown in Figure A.1, we cannot reject that the average share of TDLinx stores appearing in the RMS sample is the same across tracts with different demographics.

[19] 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 updates the entry and includes a time stamp of when the product was updated. 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.

[20] These merges are not perfect. Only 45% of the UPCs in the Homescan data and 57% of the UPCs in the RMS data are in the Gladson or IRI nutrition data. 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.

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

based on inverse squared loss functions that penalize households with purchases above (below) the recommended amounts in unhealthful (healthful) food categories or nutrients.

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 observed grocery expenditures in month t 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.[22] 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.[23,24] 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 ($c \in C_{unhealthful}$). We follow Volpe et al. (2013) and take the inverse of the squared loss function so that higher scores are indicative of healthfulness.[25]

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

$$Nutrient\ Score_{ht} = \left[\sum_{j \in J_{healthful}} \left(\frac{nutr_{jht} - nutr_j^{FDA}}{nutr_j^{FDA}} \right)^2 | nutr_{jht} < nutr_j^{FDA} \right. \\ \left. + \sum_{j \in J_{unhealthful}} \left(\frac{nutr_{jht} - nutr_j^{FDA}}{nutr_j^{FDA}} \right)^2 | nutr_{jht} > nutr_j^{FDA} \right]^{-1}$$

where j indexes a specific nutrient, $nutr_{jht}$ denotes the amount of nutrient j per calorie contained in household h's observed purchases in month t, and $nutr_j^{FDA}$ is the amount of nutrient j that the FDA recommends an individual consume per calorie as part of a 2,000 calorie diet.[26] 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

[22]We use the recommended individual expenditure shares from the "liberal food plan" to construct the household recommended expenditure shares. 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 share for each household member, $sh_{ch}^{CNPP} = \sum_i w_i recshare_{ic}$, where i is a household member whose age and gender determine his/her weight (w_i). The recommended category c expenditure share, $recshare_{ic}$, is taken from Carlson et al. (2007).

[23]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 groups are instead healthful.

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

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

[26]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 Dec. 4, 2014).

is an upper bound to the unhealthful category. These nutrients are fat, saturated fat, sodium, and cholesterol. The FDA recommendation is considered a lower bound for fiber, iron, calcium, Vitamin A, and Vitamin C, and we allocate these nutrients to the healthful category.[27] The nutrient score penalizes households for purchasing less (more) than the recommended amount of healthful (unhealthful) nutrients per calorie. We normalize the deviation of households' nutrient purchases from the FDA's recommendations to account for differences in the units in which nutrients are measured.[28]

The two scores consider the healthfulness of consumer purchases from two complementary perspectives, and each measure has its benefits and its weaknesses.[29] The expenditure score is more closely related to consumer demand, since consumers choose foods rather than nutrients. Furthermore, the purchases of food groups, such as fruits and vegetables, are used by many other studies, and thus the expenditure score is more comparable to previous research.[30] Finally, the expenditure score takes into account other micronutrients, such as zinc and potassium, which are not displayed on the nutritional facts panel and are therefore excluded from the nutrient score. The nutrient index, on the other hand, distinguishes between products in the same food category, e.g. regular versus low-fat yogurt, 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, poor and rich consumers purchase identical quantities of cheese, but rich consumers purchase more expensive varieties, then for equal expenditures rich and poor consumers will have different expenditure scores. The nutrient score, on the other hand, will reflect that both groups have similar diets.[31]

Table 1 shows the associations of household expenditure and nutrient scores with log household income and years of education, conditional on other demographics.[32] 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 approximately 50% larger than the disparities across income levels controlling for education. One can see this graphically in Figure 1, which depicts the average log expenditure and nutrient scores for households with income and education above and below the respective medians.[33] For both measure, the average score varies more across education groups than across income groups.

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[27] Some of these nutrients are identified as "nutrients of concern" in the USDA's Nutritional Guidelines for Americans, but 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.

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

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

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

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

[32] 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, 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.

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

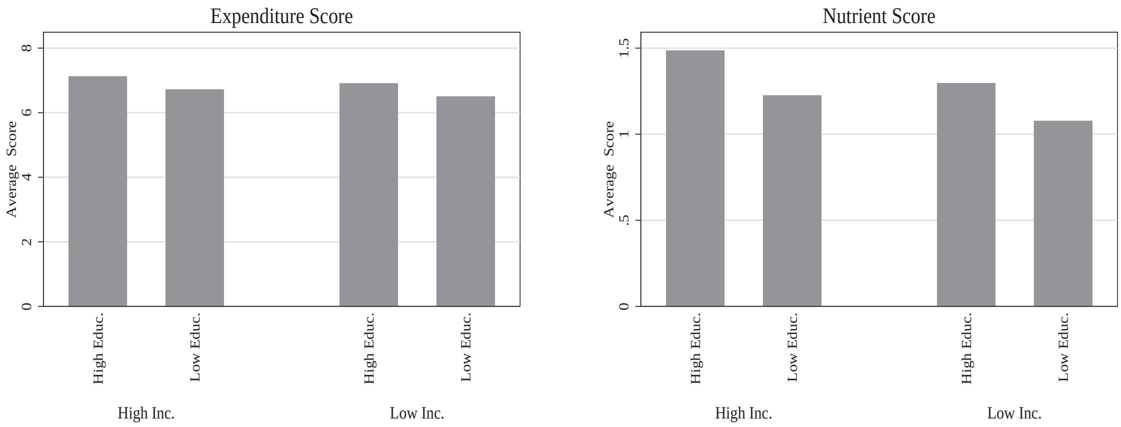
Table 1: Consumer Characteristics and Nutritional Quality of Purchases

	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, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic.

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 statuses. 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 Disparities in Access

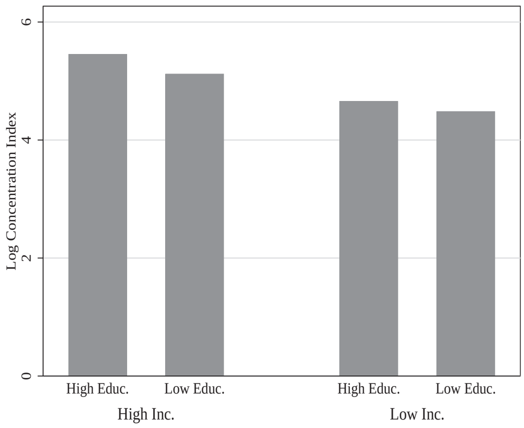
We now turn to documenting the disparities in the availability of healthy foods across locations. We start by looking at simple concentration indexes that reflect the spatial distribution of retail food stores surrounding the census tracts where households in our dataset reside. The concentration indexes are kernel densities based on store location 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 calculate the concentration kernel density for census tract l in time t as a Gaussian kernel with a bandwidth of 20km:[34]

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

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

Figure 2 shows how store concentration indexes for 2010 vary with census tract demographics from the U.S. Census.[35] We see that there is spatial correlation between income, education, and the concentration index: wealthier and more educated census tracts have a higher concentration of stores in their vicinity. In contrast with what we saw in Section 3.1, however, the average score varies more with neighborhood income than with neighborhood education. This suggests that education matters more for consumption whereas income matters more for access.

Figure 2: Store Concentration Indexes Across Census Tracts



Notes: The figure above presents average concentration indexes across census tracts with different socioeconomic statuses. Tracts are considered high income (HI) if their median household income falls above the median level across all tracts ($48,747) 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 (23.68%) and low education (LE) otherwise. 43% of tracts are HI/HE, 10% are HI/LE, 10% are LI/HE, and 37% are LI/LE. These results are for 2010; they are representative of the other years in the TDLinx sample.

Table 2 displays the associations of tract-level concentration indexes with tract-level demographics. Figure 2 is formalized in column (1): as expected, median income within a tract is positively associated with store concentration, whereas the share of college-educated households has a significantly negative, but comparatively small, 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 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.

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

Table 2: Neighborhood Characteristics and Store Concentration

	(1) All	(2) Grocery	(3) Convenience	(4) Drug	(5) Mass Merch.	(6) Club
Ln(Median Income)	1.317***	1.538***	1.234***	1.546***	1.093***	4.731***
	(0.027)	(0.030)	(0.026)	(0.033)	(0.039)	(0.11)
Ln(College-Educated Share)	-0.0442**	-0.0164	-0.0400**	-0.0412*	-0.288***	-0.596***
	(0.016)	(0.018)	(0.015)	(0.019)	(0.023)	(0.067)
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. These results are for 2010; they are representative of the other years in the TDLinx sample.

While kernel densities of the number of stores allow us to examine store concentrations, these measures ignore the fact that all stores are not equal. Importantly, stores differ in the products they sell, even within store types. To account for spatial disparities in nutritional availability across neighborhoods, we use the RMS data to compute healthfulness indexes for each of the stores in the RMS panel that we are able to match to location information in the TDLinx data.

To summarize the nutritional content of the products sold 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 sold in a store during a month such that their relative expenditure shares reflect the national average.[36] Let U_t denote the universe of UPCs sold nationally in month t, S_t the set of stores in the sample in month t, and v_{ust} the total sales of UPC u in store s in month t. The expenditure score for store s in month t can be written as

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

where c again indexes the CNPP food categories.[37] 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, $U_{st} = \{U_t | v_{ust} > 0\}$ is the set of UPCs with positive sales in store s in month t, and $v_{ut} = \sum_{s \in S_t} v_{ust}$ is the total value of sales of UPC u across all stores S_t in the national RMS sample in month t. We look at the distance from this representative

[36]Neither of the store-level indexes defined below use any information on the quantity of sales of products in a store-month. We use national 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 customers 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.

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

household's category expenditure share from the CNPP's recommended category c expenditure share 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 $sh_{c\bar{h}}^{CNPP}$.[38]

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

$$\begin{aligned} Nutrient\ Score_{st} \quad = \quad & \left[\sum_{j \in J_{healthful}} \left(\frac{nutr_{jst} - nutr_j^{FDA}}{nutr_j^{FDA}} \right)^2 |nutr_{jst} < nutr_j^{FDA} \right. \\ & \left. + \sum_{j \in J_{unhealthful}} \left(\frac{nutr_{jst} - nutr_j^{FDA}}{nutr_j^{FDA}} \right)^2 |nutr_{jst} > nutr_j^{FDA} \right]^{-1} \end{aligned}$$

Here, $nutr_j^{FDA}$ is the FDA's recommendation for the per calorie consumption of nutrient j and $nutr_{jst}$ is the per calorie amount of nutrient j that we expect to be purchased by a representative household in store s in month t, calculated as

$$nutr_{jst} = \left(\frac{\sum_{u \in U_{st}} v_{ut} n_u^j}{\sum_{u \in U_{st}} v_{ut} cal_u} \right)$$

where n_u^j is the amount of nutrient j in UPC u and cal_u denotes the quantity of calories in UPC u.[39,40,41]

In Figure 3, we see that the extent of the variation in the nutritional quality of available products across stores depends on which measure of food quality we are using. There is almost no variation in the average expenditure scores of stores across neighborhoods with different socioeconomic characteristics.[42,43] There is more variation in nutrient scores, but it is still limited compared to the degree of variation that we observed across households with different socioeconomic characteristics in Section 3.1. Still, we see that stores in high-income neighborhoods stock foods with higher nutrient scores than stores in low-income neighborhoods. Store nutrient scores are lowest in neighborhoods with both low income and low education.[44]

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

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

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

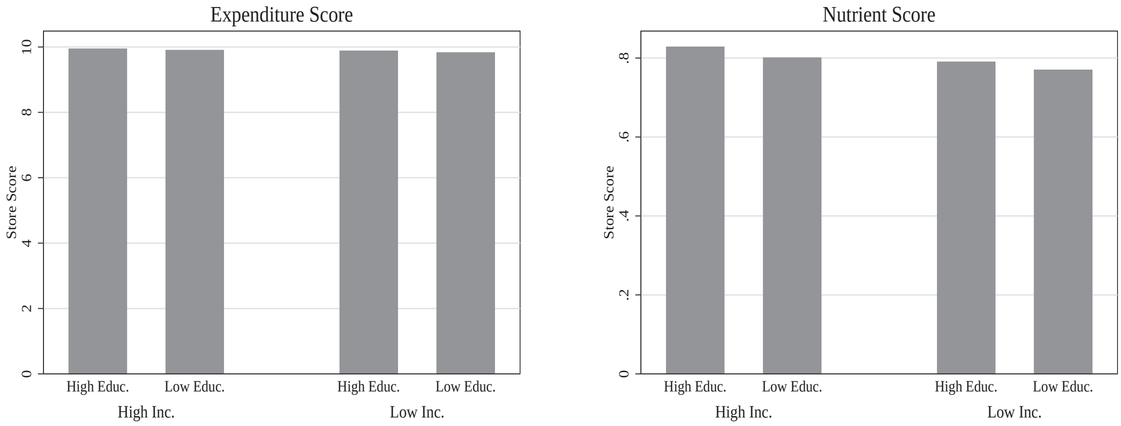
[41]As with the expenditure scores, we drop store nutrient scores that are more than twice the distance between the 90th and 50th percentiles (approximately 5% of store-month scores).

[42]The lack of differences in the average expenditure score across stores in different neighborhoods does not imply that expenditure scores do not vary across stores at all. The differences in expenditure scores are actually quite pronounced when we look across store type instead of store location. Nielsen categorizes each store in the RMS data into one of four channels: food, convenience, drug, or mass merchandise. Looking to Figure A.7 in the appendix, we see that food stores have higher expenditure scores than convenience stores, for example.

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

[44]We see similar results at the neighborhood level. We calculate kernel densities of the healthfulness and nutrient scores of the stores around each census tract centroid and find very little variation in the expenditure scores and only a small amount of variation in the nutrient scores of stores in the vicinity of high- and low-socioeconomic status census tracts.

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 statuses. 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 RMS sample.

We formalize these results in Table 3 by regressing the store nutritional availability indexes on store-specific, market-level variables. In Figures 2 and 3, we defined neighborhood socioeconomic characteristics at the tract level. Here, we treat space continously, looking at how the socioeconomic statuses 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 status in the vicinity of a store with kernel densities of median income and college-educated shares of census tracts surrounding a store, using a Gaussian kernel with a bandwidth of 20km.[45] 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 $w_{sl} = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{d_{sl}}{20}\right)^2}$.

In columns (1) and (4) of Table 3, we regress store expenditure and nutrient scores on kernel densities of household income and education. The results confirm what we saw in Figure 3: store nutrient scores are associated with the socioeconomic status of local residents, whereas store expenditure scores are not. Stores in wealthier and more educated neighborhoods tend to offer a range of products whose macro-nutrient content, on the whole, better accords with the FDA recommendations. In the subsequent columns, we control for DMA (a Nielsen market definition of similar geographic scope to a Metropolitan Statistical Area), store chain, and chain interacted with DMA. Interestingly, the differences in store nutrient scores across neighborhoods with different college-educated shares persist both when we look within local markets and within chains in these markets. Chains appear to be changing their product offerings across stores even within the same DMA.

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

Table 3: Neighborhood Characteristics and Nutritional Quality of Product Offerings

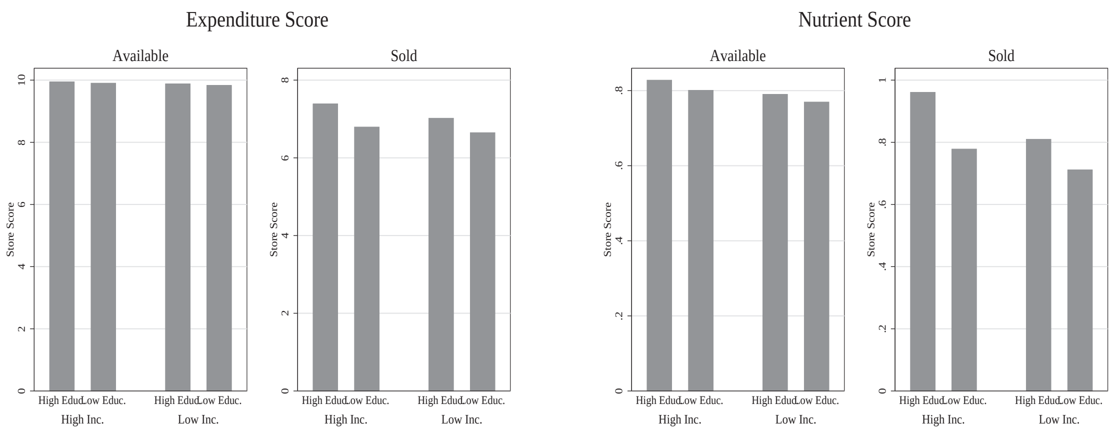
	Ln(Expenditure Score)			Ln(Nutrient Score)		
	(1)	(2)	(3)	(4)	(5)	(6)
Median Household Income Density	0.0171	0.161***	-0.00523	0.0874***	0.184***	0.0239***
	(0.0093)	(0.024)	(0.012)	(0.0083)	(0.019)	(0.0060)
College-Educated Share Density	0.00603	0.00435	0.0539***	0.0320***	-0.0461**	0.0319***
	(0.011)	(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 regressions include year-month fixed effects. All variables are standardized. DMA refers to designated market area and DMAxCh is the intersection of DMA and store chain.

In Figure 3 and Table 3, we saw that stores surrounded by high-socioeconomic status neighborhoods tend to offer products that are at least as healthy, if not healthier, than stores in low-socioeconomic status neighborhoods. Recall that the store expenditure and nutrient scores used in this analysis were computed using national sales weights and, therefore, do not reflect local demand. It is worthwhile to note that we observe much larger disparities in scores based on the actual sales of each store. Figure 4 compares the healthfulness of products available to the healthfulness of the typical bundle of products actually purchased across neighborhoods with different socioeconomic compositions.

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



Notes: The figure above presents average store-level expenditure and nutrient scores, computed using either store-specific or national sales weights, across census tracts with different socioeconomic statuses. 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 RMS sample.

The relative magnitudes of the differences in the healthfulness of products sold and available in stores across socioeconomically diverse neighborhoods suggest that it is unlikely that differences in product availability drive the observed differences in sales. We confirm this in Table 4 where we see that stores in higher income and more educated neighborhoods tend to 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 (availability) expenditure scores in Figure 3 and Table 3 above.

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 regressions include year-month fixed effects. All variables are standardized. In columns (1) and (2), the relevant score is the expenditure score; in columns (3) and (4), the relevant score is the nutrient score.

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. This does not imply that access, more broadly defined, cannot explain the differences in product sales. Stores with identical expenditure or nutrient scores for the products offered may provide different levels of access to nutritious foods because one store offers lower quality versions of these products at higher prices. 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)). Our analysis below will control for all differences in access across stores in order to obtain an upper bound on the role that these factors play in explaining socioeconomic differences in household purchases.

4 Role of Access in Explaining Consumption Disparities

We have demonstrated both that there are large socioeconomic disparities in the nutritional content of household grocery purchases and that there are spatial disparities in the concentration and offerings of retail outlets. The direction of 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 by income and education into locations based on factors unrelated to their taste for grocery products (e.g. housing prices, proximity to employment opportunities) and spatial disparities in product availability arise because stores are catering to local demand. In reality, there are likely feedback effects between household demand and access.

We now introduce a simple theoretical framework in which local tastes and retail costs both influence the spatial distribution of retail food products. The intuition is provided below; the interested reader may refer to Appendix

B for further details. We use this framework to motivate the empirical approach that we take to identify the causal link between access and the nutritional quality of household purchases in Sections 4.2 and 4.3.

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 socioeconomic status, with locations differing in the proportion of their population from each socioeconomic group. Two types of foods, 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 purchase the technology to produce a differentiated food product from the relevant input. 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. For simplicity, we assume that households are immobile and can only shop in retail stores in their location.[46] Retail is monopolistically competitive, so the number of healthful and unhealthful food products a store stocks will depend on the demand for each type of product in the retailer's location.

We demonstrate two mechanisms through which a correlation between the spatial distribution of healthful foods and the spatial distribution of socioeconomic class can emerge. First, we allow for high-socioeconomic individuals to have a stronger taste for healthful food products than low-socioeconomic individuals.[47] Assuming that there are fixed costs in the distribution of differentiated food products, these heterogeneous tastes and the spatial sorting of households by demographic class will result in firms in high-socioeconomic neighborhoods offering more healthful food products than firms in low-socioeconomic neighborhoods. The second mechanism works through supply, rather than demand. The assumption that healthful foods sell at a higher wholesale price than unhealthful food products, 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 high-socioeconomic share of the neighborhood population, firms in high-socioeconomic share locations will have a comparative advantage in the production of high-quality goods.

The theory delivers two key results. First, it confirms that the socioeconomic disparities in the availability and purchases of healthful food products are overdetermined. Each mechanism alone is sufficient to generate the socioeconomic disparities in the healthfulness of food purchases across households and 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 socioeconomic status is due solely to differences in tastes across households. If the spatial disparities in nutritional consumption are entirely due to preference externalities, the model predicts that the socioeconomic disparities in nutritional consumption within a location should be as

[46]This assumption is innocuous for the purpose of distinguishing the role access plays in determining household's grocery purchases. Household mobility would be relevant in considering counterfactuals, however, since households may migrate across locations in response to changes in economic activity.

[47]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-socioeconomic status 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.

large as they are between locations. If the estimated disparities within locations are smaller than those across locations, then the difference between the two can be interpreted as an upper bound for the role that access, as opposed to tastes, plays in explaining the socioeconomic disparities in nutritional consumption across households. That is, if retail environments were equalized across locations, we could not expect the resulting nutritional gap between high- and low-socioeconomic households to be any less than the estimated disparity between high- and low-socioeconomic households who currently live in the same retail environment.

4.2 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: Consumer Characteristics and Nutritional Quality of Purchases: Controlling for Location

	Ln(Expenditure Score)			Ln(Nutrient Score)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Income)	0.0265***	0.0229***	0.0183***	0.0905***	0.0636***	0.0408***
	(0.0016)	(0.0016)	(0.0016)	(0.0036)	(0.0037)	(0.0036)
Ln(Education)	0.220***	0.210***	0.183***	0.691***	0.675***	0.602***
	(0.0076)	(0.0075)	(0.0078)	(0.017)	(0.017)	(0.018)
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	No	County	Tract	No	County	Tract

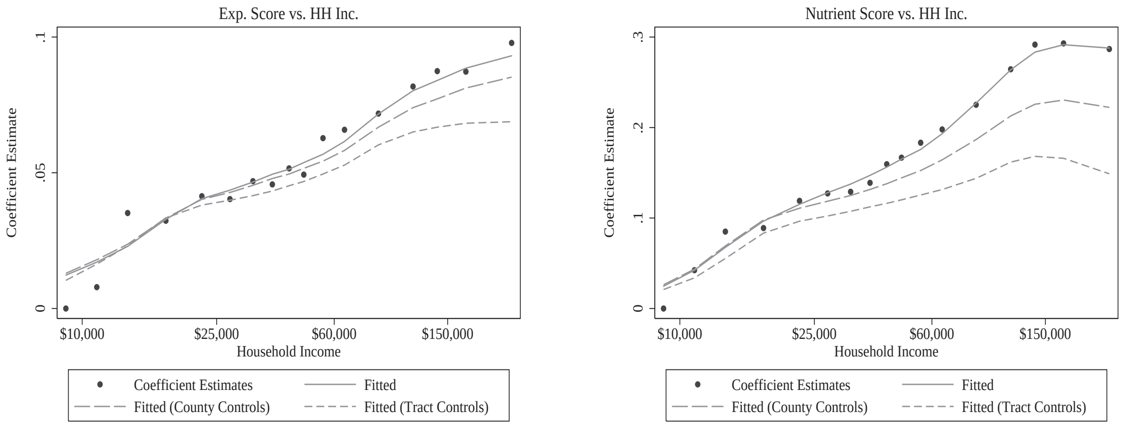
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Observations are at the household-month level. Standard errors are clustered by household. All 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, 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 5 and 6. The figures display the coefficients on income and education when the same analysis as shown in Table 5 is done using income and education dummies instead of levels. The dots in Figure 5 are the coefficient estimates on the income dummies in the specification without household location controls plotted against the relevant income levels. The solid line depicts the smoothed value of these estimates. The dashed lines reflect the smoothed kernel densities of the coefficient estimates 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 quality is more pronounced when quality is measured using the nutrient score.

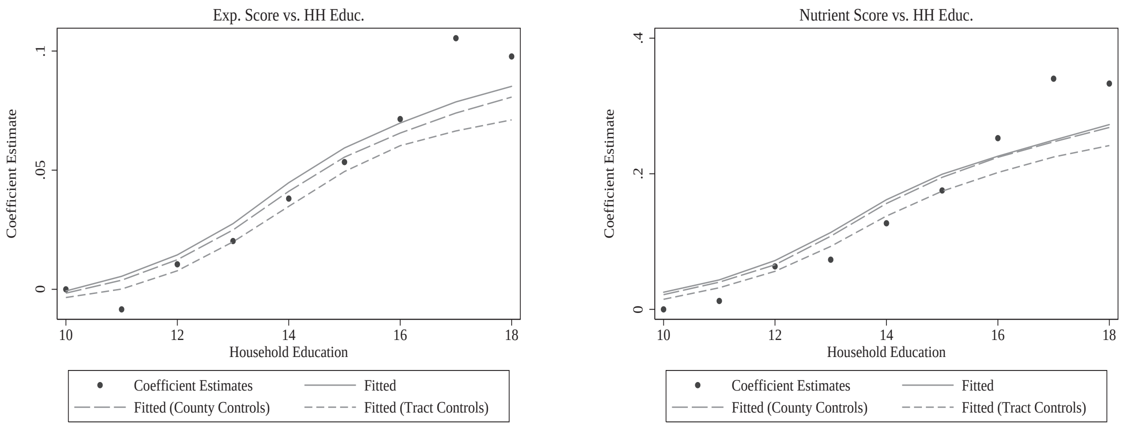
Looking to Figure 6, we see that the relationship between education and each measure of quality is more persistent: for both the expenditure and the nutrient score, the addition of county or census tract fixed effects does little to reduce the association between education and the nutritional quality of household purchases.

Figure 5: 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 6: 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.

4.3 Controlling for Store

One concern with the within-location analysis 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 differentially impact the ability of households to travel to stores. To entirely remove the impact of access, we now turn to a within-store analysis. By including fixed effects for the store in which a purchase is observed, we can explore how the nutritional quality of purchases varies with the characteristics of households shopping in the same store.

Here, we calculate expenditure and nutrient scores for the purchases that households make in specific stores in each month. We then regress these household-store-month scores against household demographics, time fixed effects, and store controls. 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. The results of this analysis, shown in Table 6, paint a similar picture as the within-location analysis presented above. The healthfulness of household-store-month 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.

Table 6: Consumer 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)	0.0266***	0.0316***	0.0294***	0.0274***	0.0754***	0.0738***	0.0551***	0.0461***
	(0.0030)	(0.0025)	(0.0025)	(0.0022)	(0.0043)	(0.0041)	(0.0040)	(0.0037)
Ln(Education)	0.170***	0.165***	0.155***	0.149***	0.448***	0.443***	0.424***	0.408***
	(0.014)	(0.012)	(0.011)	(0.0099)	(0.021)	(0.019)	(0.019)	(0.017)
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	No	Channel	Parent	Store	No	Channel	Parent	Store

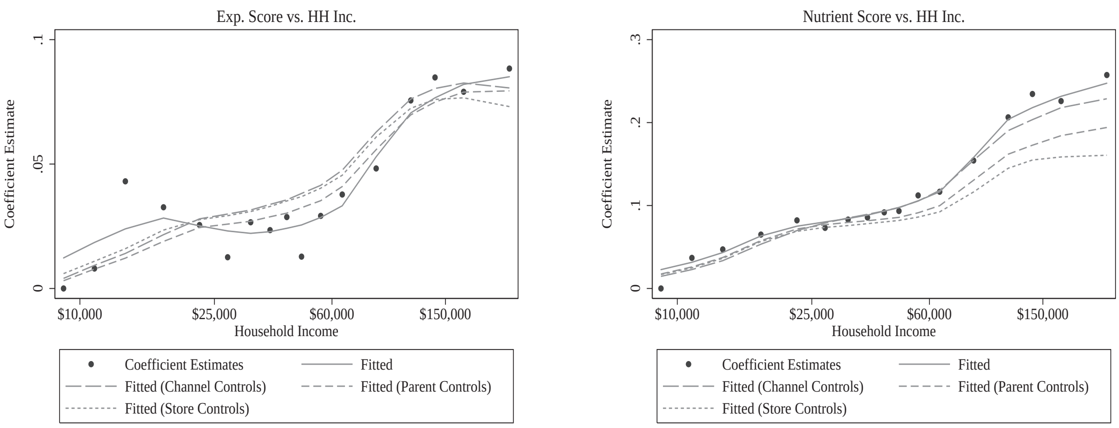
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Observations are at the household-store-month level. Standard errors are clustered by household. All 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, 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 of available products 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), while the association between household nutrient scores and income falls to a little over 50% of its original value. This indicates that at least half of the observed disparity between the store-specific shopping bundles purchased by households with different incomes 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%.

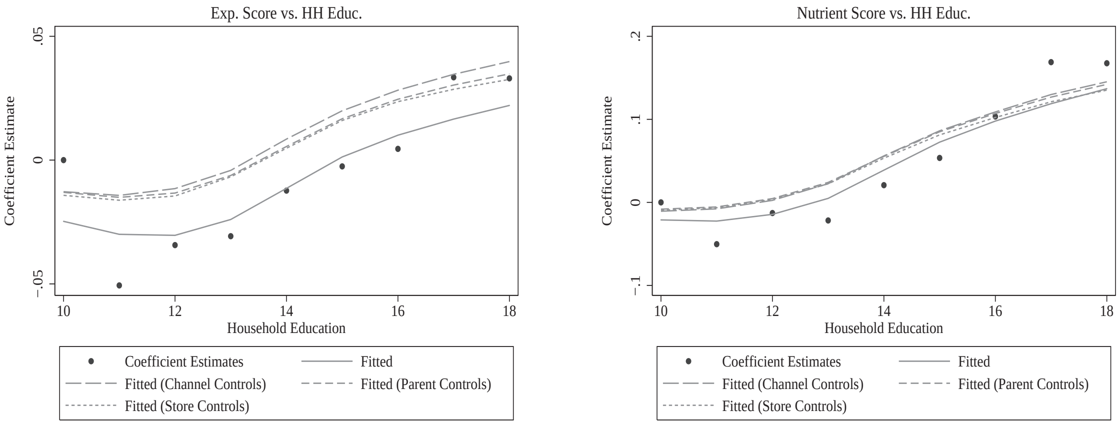
These results are visually depicted in Figures 7 and 8, where we have replicated the regressions in Table 6 with household income and education dummies in place of levels. The dots and solid lines represent the point estimates and kernel of these estimates from the specifications in columns (1) and (5) of Table 6. The dashed lines represent the kernel 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 7 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- and low-income households shop. Overall, the inclusion of store controls moves the association between income and nutritional quality closer to zero. For both the expenditure and the nutrient score, this result is most noticeable for the highest levels of income, where the association between income and quality is the greatest in the absence of controls. Looking to Figure 8, we see that the relationship between education and quality is again more persistent: the inclusion of store controls has barely any effect on the association between the nutrient score for household-store food purchases and education at all levels of education.

Figure 7: 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 8: 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.

4.4 Discussion

In the analysis above, we find that conditional on education, the association between household income and the nutritional content of household purchases is cut in half when we control for either the household's residential location or the store in which the household is shopping. The effects of education conditional on income, however, are much more persistent: only 10% of the existing disparities in consumption across education groups can be attributed to differences in access. This suggests that over half of the socioeconomic disparities in nutritional consumption across income groups and nearly all of the socioeconomic disparities in nutritional consumption across education groups would remain even if spatial disparities in access to nutritious foods were resolved.

The fact that socioeconomic disparities persist, even looking across households shopping in the same store, indicates that 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 and education across residential locations or stores. This suggests that 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 low-income and less educated households with an 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 shopping in the same stores.

The fact that socioeconomic disparities diminish when we control for household location does not necessarily indicate that access alone explains this portion of the disparity. As discussed above, tastes could be reflected in a household's store or location choices. If households are well sorted residentially or across stores by income or education, we are less likely to see within-location or within-store disparities in purchases. The first reason for this is mechanical. It is possible that the spatial sorting by income and education leaves little variation in these dimensions across households living in the same neighborhood or shopping in the same store. 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.[48] The second reason is that the retail environment itself is determined by household tastes. If neighborhoods are segregated by socioeconomic status and stores sort spatially to cater to local tastes, then we might not expect to see much variation in the choice sets of households living in the same location. To the extent that this is the case, we expect there to be less scope for differences in the healthfulness of households' purchases within locations (or stores) than across them. These possibilities suggest that, if anything, the results above overstate the role of access in generating disparities across income and education groups and contribute to our belief that we have identified an upper bound on the role of access in explaining nutritional disparities in consumption.

5 Response of Household Purchases to a Changing Retail Environment

Before concluding, we take an alternative approach to further examine the potential impact that improving access would have on household consumption. Specifically, we look at how household purchases in our sample respond 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 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.

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 the store indexes, both for the expenditure and the nutrient score, to measure differences in the distance-weighted availability of recommended products.[49]

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. As in Table 5, both measures of household purchase quality are significantly related to income and education. Household expenditure scores are positively related to store concentration and distance-weighted store expenditure scores, although the magnitudes of these

[48] 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.

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

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 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, 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.[50] In columns (2) 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, however, respond positively to the distance-weighted density of store nutrient scores in their vicinity.

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

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

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 be concerned about households progressively sorting into different 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 household with low levels of income and education would respond to a change in their retail environment equivalent to moving from the average low-income, low-education neighborhood to the average high-income, high-education 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 household expenditure and nutrient scores implied by the coefficients from each regression specification are presented in the bottom row of Table 7.[51] Moving from the average low-income, low-education neighborhood to the average high-income, high-education 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 low-socioeconomic household would improve by 0.002 and 0.004 log units, respectively, if they were to move from a low-socioeconomic to a high-socioeconomic neighborhood. Comparing these changes to the socioeconomic disparities in household-level 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.

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 RMS 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

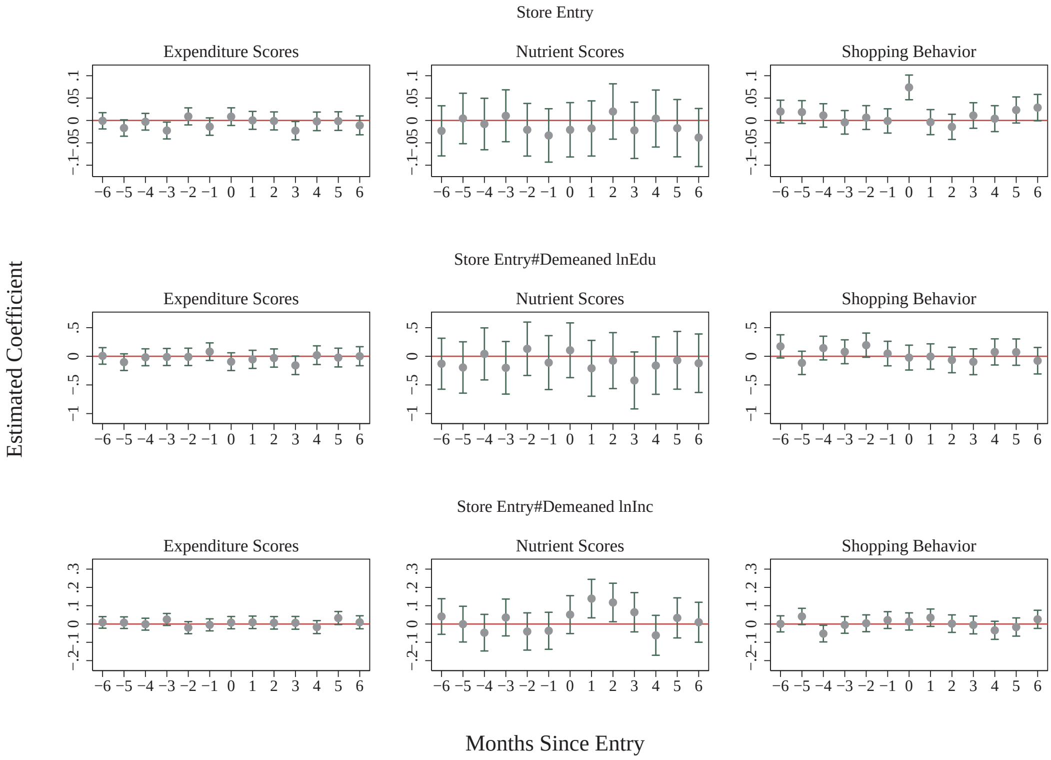
[51] Note that log income and education are demeaned in these regressions, so the elasticities are calculated as $\beta_0 + \beta_1 \left(\ln 13 - \ln \overline{Educ}\right) + \beta_2 \left(\ln 32500 - \ln \overline{Inc}\right)$, where β_0, β_1, and β_2 are the coefficients on the density, the density 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).

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 9. 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 households' 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 9 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 9 indicate that while households are changing where they shop when a new store enters, they are not changing the healthfulness of the foods that they purchase.

Figure 9: 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.[52]

Overall, these results indicate that the nutritional quality of household purchases responds very little, if at all, to changes in retail environments. This suggests that policies which either encourage the entry of new stores offering healthy foods or encourage existing retailers to offer more healthful products will do little on their own to resolve socioeconomic disparities in nutritional consumption. One possibility for the differential responses across socioeconomic groups to changing retail environments observed in Table 7 and Figure 9 is that stores offering more healthful products may also charge higher prices for healthful foods, deterring lower socioeconomic status households from purchasing these items. If this is the case, policies aimed at improving access to healthful foods will only be effective if they pair improved access with subsidies or tax breaks to encourage entry with pricing controls. We plan to explore the role that differential price sensitivities and budget constraints play in generating

[52]To confirm this hypothesis, future versions of this paper will address the endogeneity of store entry by instrumenting for actual entry using predicted entry. Predicted entry will be estimated as a function of moments of the pre-existing retail environment, which we expect to make locations more (or less) attractive to future entrants of different types due to competition, cannibalization, and agglomeration.

nutritional disparities in future work.

6 Conclusion

Despite the absence of evidence drawing a causal link between disparities in retail access and disparities in nutritional consumption, much of the literature on food deserts has assumed that equalizing access will decrease nutritional disparities across different demographic 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 suggests that disparities in nutritional consumption are not driven by differential access to healthy food products. Even when looking at purchases made within the same store, much of the disparities that we observe when looking across stores remain. We also observe a limited response of household purchases to changes in retail access that have occurred in the past. 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.

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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 +	0.11	0.12	0.14	0.14	0.14	0.15
Total counts	37786	63350	61440	60506	60658	62092

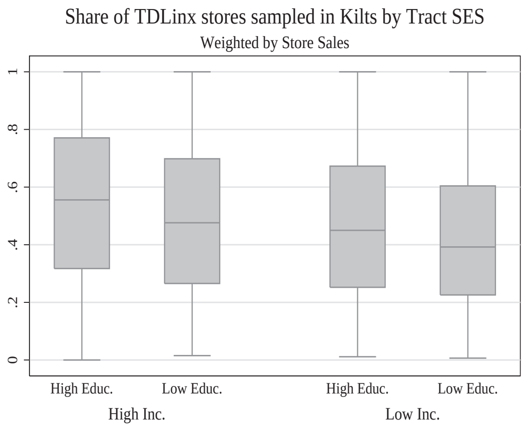
Table A.2: Distribution of Male Household Head Education by Year

Year	Grade School	Some High School	Graduated High School	Some College	Graduated College	Post College Grad	Total Counts
2006	0.013	0.050	0.253	0.292	0.265	0.127	27439
2007	0.010	0.046	0.255	0.294	0.273	0.121	47786
2008	0.010	0.045	0.254	0.291	0.277	0.123	46199
2009	0.009	0.042	0.256	0.288	0.280	0.124	45280
2010	0.009	0.041	0.253	0.286	0.286	0.126	45465
2011	0.008	0.040	0.245	0.285	0.294	0.128	46565

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

Year	Grade School	Some High School	Graduated High School	Some College	Graduated College	Post College Grad	Total Counts
2006	0.005	0.031	0.277	0.315	0.264	0.108	33963
2007	0.005	0.026	0.268	0.320	0.278	0.103	57317
2008	0.004	0.025	0.264	0.319	0.280	0.107	55634
2009	0.004	0.023	0.263	0.314	0.287	0.109	54699
2010	0.004	0.022	0.256	0.311	0.296	0.111	54747
2011	0.004	0.021	0.247	0.309	0.303	0.116	56135

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



Notes: The figure above presents the average share of TDLinx stores included in the RMS sample across tracts with different socioeconomic statuses. 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 RMS sample and other years in the TDLinx sample.

Table A.4: Healthful and Unhealthful Food Categories

Healthful food categories	Unhealthful food categories
All whole-grain products	Non-whole-grain breads, cereals, rice, pasta, pies, pastries, snacks, and flours
All potato products	Whole milk products
Dark-green vegetables	All cheese
Orange vegetables	Beef, pork, veal, lamb, and game
Canned and dry beans, lentils, and peas	Bacon, sausages, 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 entrees
Eggs and egg mixtures	
Fish and fish products	

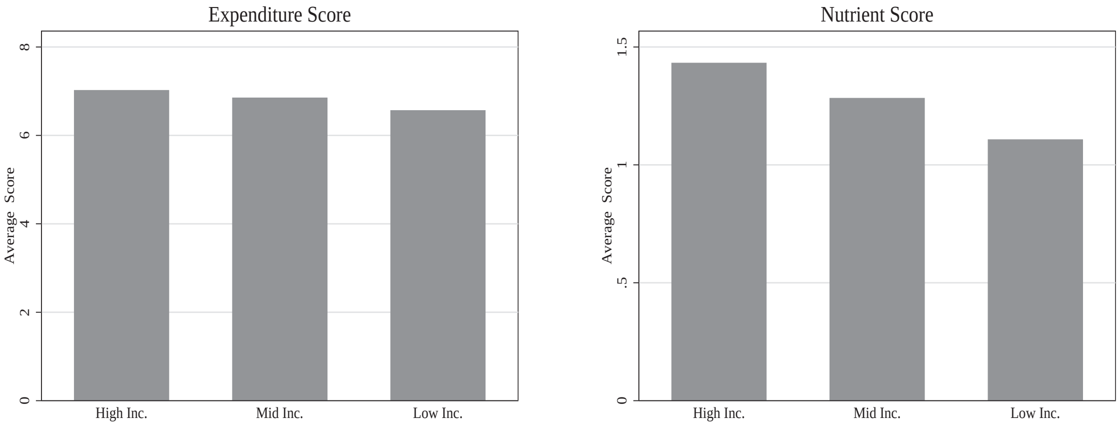
Notes: We determine which CNPP food categories are healthful and unhealthful using the recommendations from the Quarterly Food-at-Home Price Database (QFAHPD) indicators for which of 52 food groups are healthful and unhealthful. We aggregate the 52 QFAHPD food groups to the 24 CNPP food categories using 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 groups are instead healthful.

Table A.5: Healthful and Unhealthful Nutrients

Healthful nutrients	Unhealthful nutrients
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.

Figure A.2: Expenditure and Nutrient Scores Across Households 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.

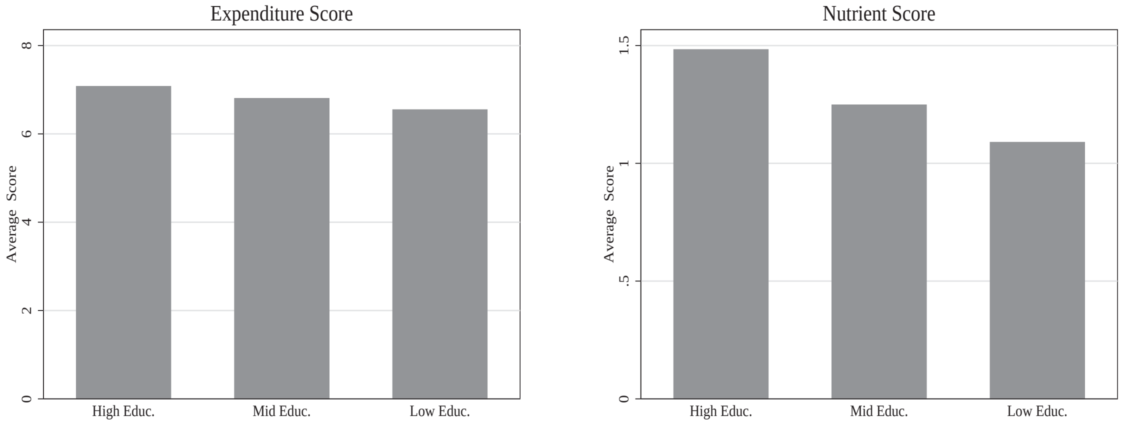
Table A.6: Consumer Characteristics and Nutritional Quality of Purchases: Full Regression Results

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

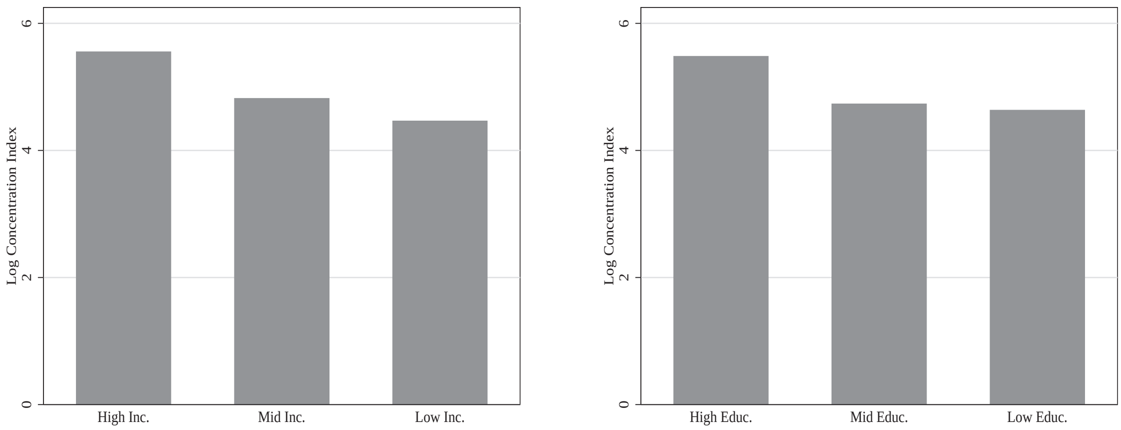
Notes: Observations are at the household-month level. Standard errors are clustered by household. All regressions include year-month fixed effects and household size dummies.

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



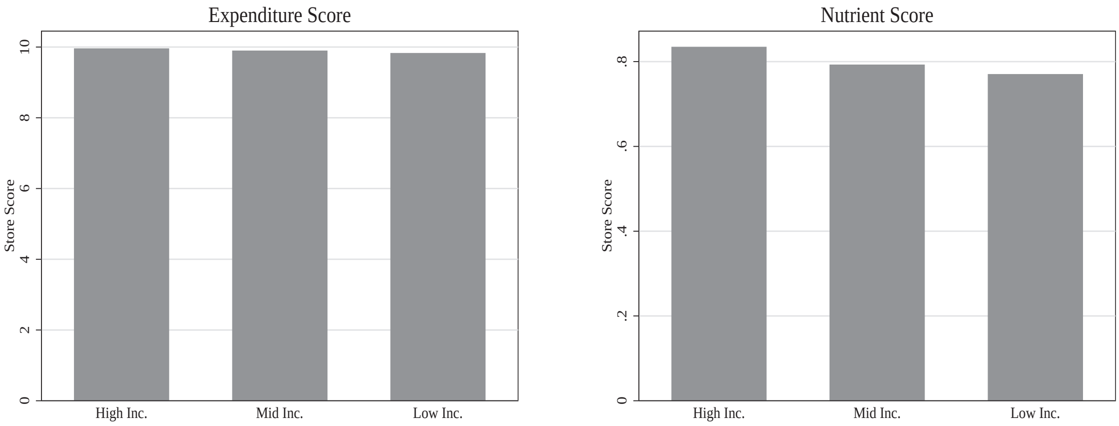
Notes: The figure above presents average household-level expenditure and nutrient scores across households with different levels of education. Households are considered high education if the average years of education for their household head(s) falls above 14.98 years, middle education if their average 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 Terciles of Census Tract Demographics



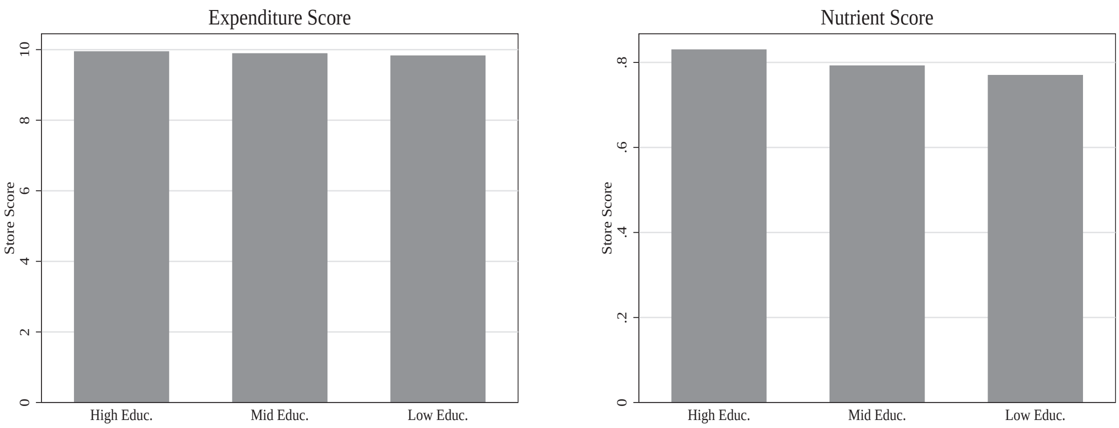
Notes: The figure above presents average concentration indexes across census tracts with different levels of income and different shares of college-educated households. Tracts are considered high income (HI) if their median income falls above \$56,919, middle income (MI) if their median household income is between \$42,558 and \$56,919, and low income (LI) if their median income is below \$42,558.. 36% of tracts are HI, 31% are MI, and 32% are LI. Tracts are considered high education (HE) if their share of college-educated residents is above 31.13%, middle education (ME) if their share of college-educated residents in between 18.34% and 31.13%, and high education (HE) if their share of college-educated residents is below 18.34%. 36% of tracts are HE, 31% are ME, and 32% are LE. These results are for 2010; they are representative of the other years in the TDLinx sample.

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



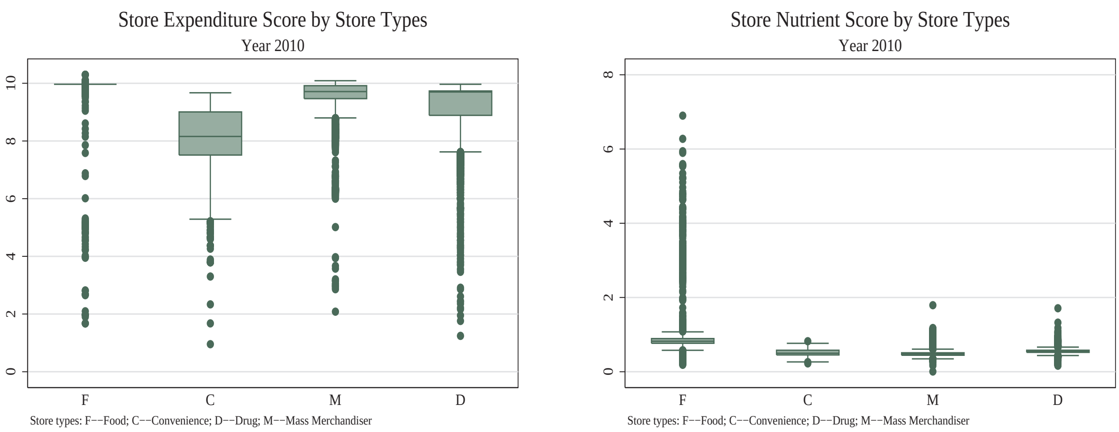
Notes: The figure above presents average store-level expenditure and nutrient scores across census tracts with different levels of income. Tracts are considered high income (HI) if their median household income falls above \$55,729, middle income (MI) if their median income is between \$41,010 and \$55,729, 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 RMS sample.

Figure A.6: Expenditure and Nutrient Scores Across Stores 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 RMS sample.

Figure A.7: Availability Healthfulness and Nutrient Scores Across Channels



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, indexed by h, can take one of two values, low (L) or high (H). We rank locations by their share of high-socioeconomic status households, with higher l locations having larger shares of high-socioeconomic status households. We assume that the share of high-socioeconomic status households in a neighborhood is exogenously determined.

B.1.1 Demand

Consider a representative consumer for socioeconomic status 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,

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

where $\rho_a \in (0, 1)$ reflects the degree of perceived horizontal differentiation between varieties of different healthfulnesses and $\rho_w \in (0, 1)$ reflects the degree of perceived horizontal differentiation between varieties of the same healthfulness. where 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 socioeconomic status 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-socioeconomic households to low-socioeconomic 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-socioeconomic households will spend relatively more than low-socioeconomic 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 socioeconomic status.[53]

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-socioeconomic 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-socioeconomic residents, $s(\lambda_l)$. To reflect higher rents in higher-socioeconomic neighborhoods, we assume that shelf-space costs are increasing in the share of high-socioeconomic status 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

[53] 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-socioeconomic status 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.

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

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

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 defines 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:

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

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-socioeconomic 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 socioeconomic status, high-socioeconomic status households will spend at least as much on high-quality food products as low-socioeconomic status households in the same location. Therefore, if the healthfulness of available products in increasing in the share of high-socioeconomic households in a neighborhood, it follows that high-socioeconomic households will spend more on healthful food products. Even if high-socioeconomic and low-socioeconomic households share the same tastes, all households will spend more on healthful foods in locations where more of these are available. Since high-socioeconomic status households are, by definition, disproportionately located in high-socioeconomic status locations, on average high-socioeconomic 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, $\alpha(q)$:

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

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 socioeconomic status 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

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

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 high-socioeconomic share of 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-socioeconomic status 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-socioeconomic status households spending more on healthful food products, on average, even if they have the same preferences as low-socioeconomic status 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 socio-economic status, 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-socioeconomic and low-socioeconomic 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-socioeconomic to low-socioeconomic 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-socioeconomic status 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 socioeconomic status, and all households earn the same income, we must therefore have that locations with more high-socioeconomic status households can support a greater variety of healthful food products.

B.2.2 Upper Bound for the Impact of Access on Consumption

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.

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 socioeconomic status 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-socioeconomic status 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-socioeconomic relative to low-socioeconomic status 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-socioeconomic status 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-socioeconomic status 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-socioeconomic relative to low-socioeconomic status 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-socioeconomic relative to low-socioeconomic status individuals living in the same location must be attributed to tastes alone. In the context of this model, the within-location variation in healthfulness only provides a lower bound for the role of tastes, because tastes could also explain part (or all) of the differences in availability. 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. We will address each of these below, but it is worth noting that these biases will tend to lead us to further overestimate the role of product availability in explaining the overall socioeconomic disparities in purchases.