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

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April 1, 2016

Abstract

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

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

1 Introduction

While it is well known that there are large nutritional disparities across different socioeconomic groups in the United States, concrete evidence on why these disparities exist has been elusive. Poor diets could be attributed to any of three factors: limited access to healthy foods, higher prices of healthy foods, or preferences for unhealthy foods. Under the assumption that differential access plays an important role in explaining nutritional disparities, the Agricultural Act of 2014 appropriated $125 million in federal funds to be spent annually to promote access to healthy foods in underserved communities (Aussenberg (2014)).[1] Many state and local governments have also introduced programs to improve access by providing loans, grants, and tax credits to stimulate supermarket development and encourage existing retailers to offer healthier foods in food deserts (CDC (2011)).[2,3]

Despite the growing popularity of such programs, little is known about their potential for narrowing nutritional disparities. This paper seeks to fill this gap. In doing so, we make three key contributions to our understanding of socioeconomic disparities in nutrition and spatial disparities in access. First, we construct a dataset describing the nutritional quality of the food products purchased by households across the entire U.S. to provide the most thorough depiction of socioeconomic disparities in nutritional consumption to date.[4] Combining data on the spatial distribution of stores, availability of nutritious products, and relative prices of healthy-to-unhealthy foods, we then provide an equally comprehensive depiction of spatial disparities in access. Finally, in our main contribution, we use the detailed nature of our data to show that spatial disparities in access play a limited role in generating socioeconomic disparities in nutritional consumption. Our results indicate that improving access to healthy foods alone will do little to close the gap in the nutritional quality of grocery purchases across households with different levels of income and education. Even if spatial disparities in access were entirely resolved, over 70% of the existing socioeconomic disparities in nutritional consumption would remain.

While there has long been agreement among researchers that both spatial disparities in access and socioeconomic disparities in nutritional consumption exist, the actual effects of access to healthy foods on food purchases have been heavily contested (Bitler and Haider (2011)).[5] While some studies find no relationship between store density and consumption (see, for example, Pearson et al. (2005) and Kyureghian et al. (2013)), 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 access-improving policies on the food purchases of local households.

The challenge we face in identifying the causal role of access is that socioeconomic disparities in nutritional

[1] In an address to the Mayor's Summit on Food Deserts in 2011, First Lady Michelle Obama "challenged attendees...to look for ways to attract grocery stores and other businesses selling fresh produce to their communities," stating that "studies have shown that people who live in communities with greater access to supermarkets...eat more fresh fruits and vegetables." (Curtis, 2011) She further noted that access "can have a real impact on the health of our families...it's not that people don't know or don't want to do the right thing; they just have to have access to the foods that they know will make their families healthier." .

[2] The USDA formally defines a food desert as a census tract that meets specific criteria for both income and access. In this paper we use the term "food desert" to refer to areas where nutritious food is hard to obtain.

[3] 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.

[4] 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.

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

consumption and access could be driven entirely by differences in demand. To highlight this challenge we present a simple model that nests two mechanisms, one driven by supply and one driven by demand, each of which can independently explain the socioeconomic disparities in purchases that we observe. On the supply side, we suppose that high-socioeconomic status (SES) households are more likely to live in locations where the cost of accessing healthy food is lower. As long as demand is not perfectly inelastic, these differences in access will cause high-SES households to purchase healthier bundles than low-SES households, even if preferences are homothetic and tastes do not vary systematically across socioeconomic groups. On the demand side, we suppose that preferences are non-homothetic and tastes vary systematically with SES. Even if access is identical across households, these differences in demand will cause high-SES households to purchase healthier bundles than low-SES houesholds. Since either mechanism is sufficient to generate the observed correlation between consumption and access, this correlation alone is not sufficient to uncover the role that access plays in generating nutritional disparities separately from the role of demand-side factors. [6]

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

Our cross-sectional results indicate that eradicating spatial disparities in retail access would resolve less than a third of the observed disparities in nutritional consumption. When we control for access by looking at households living in the same census tract, nutritional disparities between households that are above versus below the national medians for both income and education are reduced by 32%. It is possible, though, that households living in the same neighborhood still have differential access, either because they live in different locations within the neighborhood or because of differences in mobility. To eliminate differences in access entirely, we look at purchases made within a given store. The results from the within-store analysis mirror those from the within-location analysis: the socioeconomic gap in the healthfulness of food purchases is reduced by less than a quarter when we only compare purchases in the same store. In both the within-location and within-store analyses, the majority of the disparities that we observe between households across the entire U.S. persist when we control for access. Even if spatial disparities in access are entirely resolved, at least 68% of the existing nutritional disparities would remain.

Policies aimed at improving access can broadly be divided into two categories: those that incentivize the entry

[6] In the appendix, we present a parametric version of this model that is more explicit about these mechanisms and shows how each can independently explain the observed socioeconomic disparities in *both* access and consumption. In particular, stores in high-SES neighborhoods may offer more nutritious food products because of differences in wholesale and retail costs (e.g., healthy foods cost more and rents are higher in high-SES neighborhoods). These differences in access could in turn lead to differences in consumption, even if high-SES and low-SES households have identical demand conditional on access. On the other hand, high-SES households may have higher demand for healthy foods than low-SES households. While differences in consumption would follow directly, differences in supply could likewise arise due to within-group preference externalities.

of new stores, and those that encourage existing retailers to offer more healthful products. Our second empirical strategy leverages observed changes in retail environments over our sample period to directly measure how households in our data responded to changes in access and to compare the effectiveness of store entry versus product expansion policies. While comparing the purchases of the same household over time removes any correlation between changes in access and time-invariant components of household demand, changes in access will likely be correlated with unobserved changes in household tastes. This endogeneity of changes in access to these unobserved taste shocks implies that the observed response of households "treated" with changes in access provide an upper bound for the expected response of households more generally.

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

Despite a large policy literature on the topic, the relationship between access and nutritional consumption has been largely ignored by economists. Methodologically, our paper is closest to the literature that uses the entry of fast food restaurants and large retailers, such as Walmart, to identify a causal relationship between retail environments and obesity (Currie et al. (2010); Anderson and Matsa (2011); Courtemanche and Carden (2011)). Our paper departs from these previous studies in two important dimensions. First, we are concerned not just with the relationship between access and nutritional consumption, but rather the interaction between access, nutritional consumption, and socioeconomic status.[7] This is important for evaluating the effectiveness of current policies, as recent efforts to improve access do so with the intent of reducing disparities in consumption across different socioeconomic groups. Second, we look directly at the mechanism, food purchases, by which we expect changes in retail environments to impact obesity, rather than obesity itself. While access may have a causal impact on obesity, it need not work through the hypothesized mechanism, and the mechanism is of greater concern from a policy perspective.

If disparities in retail access do not generate the consumption disparities that we observe, then something else is to blame. There are a range of explanations for disparities in purchases, including differences in tastes or social norms, 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

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

are most important for explaining the large disparities that persist when we look at households in the same retail environment.

The paper proceeds as follows. In Section 2, we describe the datasets that we use. In Section 3, we document (i) how the nutritional quality of purchases varies across households with different levels of income and education and (ii) how access to nutritious foods varies across markets with different observable characteristics. In Section 4, we present a simple theoretical framework to demonstrate how the detailed nature of our data can be used in two complementary analyses to bound the role that access plays in generating consumption disparities. Section 5.1 implements our cross-sectional approach by looking at whether consumption disparities persist when we control for residential or retail location. Section 5.2 takes an alternative, time-series approach and examines whether we observe the healthfulness of household purchases responding to changes in local access. In Section 6, we provide a discussion of our results and conclude.

2 Data

We combine six datasets that together describe the nutritional quality of grocery purchases that households make, the food stores located in the neighborhoods where these households reside, the nutritional quality of the products offered in these stores, and the demographics of these neighborhoods. Below we introduce each dataset and highlight the features most relevant for our analysis. The interested reader may refer to Appendix A for additional details.

The first dataset is the Homescan data collected by the National Consumer Panel (NCP) and provided by Nielsen. The Homescan data contains transaction-level purchase information for a representative panel of 114,286 households across the U.S. between 2006 and 2011. Households in the panel use a scanner provided by the 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. Items that do have a UPC are included as "random-weight" purchases. This data has three features that are useful for our analysis. First, we observe household demographic data reported on an annual basis. We use this information to measure two dimensions of socioeconomic status that are posited to impact a household's consumption decisions: income and education. Second, we observe the census tract in which each household resides. We use this information to measure the degree to which socioeconomic disparities in consumption persist when we control for each household's retail environment. Finally, we observe household purchases over a period of between six months and six years. This time series variation allows us to measure the responses of households to observed changes in their retail environments.

While the Homescan data describes the stores in which panelists shop and the products that they purchase at these stores, it only provides a limited picture of the retail environments in which households are making their purchase decisions. We use two additional datasets, both maintained by Nielsen, to obtain a more comprehensive picture of the retail environments that households face. To see the full set of stores available to households, we use the Nielsen TDLinx data, a geo-coded census of food stores in the U.S. We use this data to calculate concentration indexes that summarize the number of stores to which households have access. To see the full set of food products available at a subset of these stores, we use the Nielsen Scantrack data provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. The Scantrack data contains weekly sales and quantities by UPC collected by point-of-sale systems in over 30,000 participating retailers across the U.S. We use this data to calculate indexes that summarize both the nutritional quality and the relative prices of products offered by each store in the dataset.

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

The final dataset that we use is the five-year pooled (2008-2012) American Community Survey (ACS). The ACS contains demographic information for each census tract in the U.S. 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 Socioeconomic Disparities in Nutritional Consumption and Access

3.1 Disparities in Nutritional Consumption

We begin by documenting the extent of disparities in nutritional consumption across households with different levels of income and education. We focus on the *quality* rather than the quantity of food a household purchases since the latter is affected by the extent to which a household eats at restaurants, and a propensity for eating out is likely related to household characteristics.[8] We measure the quality of household purchases using two complementary indexes, both of which are calculated at a monthly frequency for each household in our sample. As results are consistent across indexes, we only present one here. Our preferred measure, the "nutrient score," measures the extent to which a household's grocery purchases deviate from the nutrient composition recommended in the USDA's Dietary Guidelines for Americans (DGA). The interested reader may refer to Appendix C to view results using our alternative measure of household purchase quality.[9]

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

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

[9]Our second index, the "expenditure score," measures the extent to which a household's grocery purchases deviate from the expenditure shares recommended by the Thrifty Food Plan. The plan was designed by USDA Center for Nutrition Policy and Promotion (CNPP) based on recommendations from the DGA. Our expenditure score follows the measure used by Volpe et al. (2013a). Refer to Appendix C for results using this measure.

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

where j indexes nutrients, pc_{jht} denotes the amount of nutrient j per calorie in household h's grocery purchases in month t, and pc_j^{DGA} is the amount of nutrient j in the DGA recommended diet per calorie consumed.[10,11] The guidelines indicate whether to consider the recommendation for a given nutrient as a lower bound or an upper bound. We assign the nutrients for which the recommendation is an upper bound to the unhealthful category (total fat, saturated fat, sodium, and cholesterol) and the nutrients for which the recommendation is a lower bound to the healthful category (fiber, iron, calcium, Vitamin A, and Vitamin C).[12] The nutrient score penalizes households for purchasing less (more) than the recommended amount of healthful (unhealthful) nutrients per calorie. To account for differences in the units in which nutrients are measured, we normalize the deviations of household nutrient purchases from the DGA's recommendations. We follow Volpe et al. (2013b) and summarize the normalized deviations using an inverse squared loss function. Finally, as there are no clear guidelines as to which nutrients are most important for health, the index construction gives equal weight to all nutrients. For example, an underconsumption of fiber and an overconsumption of saturated fat are treated the same.

While useful for analysis, one drawback of indexes in general is that they can be difficult to interpret. To demonstrate that our nutrient score accords with intuition, in Table 1 we show how this measure of nutritional quality varies across three sample bundles. The first bundle consists of only healthy products, the second bundle contains a mix of healthy and unhealthy products, and the third bundle consists of only unhealthy products. We determine the food products included in each these bundles by selecting among the most widely purchased UPCs in each of the USDA Center for Nutrition Policy and Promotion's (CNPP) 13 healthful and 10 unhealthful food categories.[13]

Table 1 yields two takeaways. First, we see that the relative nutrient scores accord with intuition: that is, the healthy bundle has a higher nutrient score than the mixed bundle which in turn has a higher nutrient score than the unhealthy bundle. Second, we see that the nutrient score correlates well with more naive measures of nutrition, including the percent of calories from fruits and vegetables, the percent of calories soda, and total calories. While we can go beyond these previous measures and distinguish between bundles with equal calories from fruits, vegetables, and soda but different nutrient compositions both within and across product categories, it is reassuring to note that our index is correlated with these recognizable measures of healthfulness.[14]

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

[11] We exclude nutrient scores that are more than twice the distance between the 90th and 50th percentiles from our analysis (nearly 5% of household-month scores), as they likely reflect measurement error. Our results are qualitatively robust, however, to the inclusion of outliers.

[12] Some of these nutrients are identified as "nutrients of concern" in the DGA while others are not. We use all of the available recommended nutrients, regardless of whether they are nutrients of concern, as our goal is to assess the overall healthfulness of individual diets rather than larger public health concerns. Our nutrient score 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.

[13] Refer to Table A.10 for a list of the CNPP healthful and unhealthful food categories.

[14] We replicate our analysis with these familiar measures of nutrition in place of our nutrient score in Appendix C.

Table 1: Healthfulness of Sample Bundles

	Amount (OZ)		
Sample Bundle:	Healthy	Mixed	Unhealthy
Healthy			
Cereal- Ready to eat	12.25	6.125	0
Russet Potatoes	160	80	0
Broccolli Florets	12	6	0
Carrots	16	8	0
Kidney Beans	30	15	0
Iceberg Lettuce	16	8	0
Strawberries	16	8	0
Orange Juice - No Pulp	64	32	0
Low-fat Yogurt	36	18	0
Boneless Chicken Breast	48	24	0
Tuna - Chunk Light	20	10	0
Creamy Peanut Butter	18	9	0
Eggs - Grade A Large	24	12	0
Unhealthy			
Potato Chips	0	5.5	11
Milk - 2% Fat	0	64	128
American Cheese	0	6	12
Bacon	0	8	16
Breakfast Scramble	0	12	24
Butter Grade AA	0	4	8
Coca Cola	0	72	144
Oreo Cookies	0	1.125	2.25
Mayo	0	1.875	3.75
Frozen Pizza	0	56.60	113.20
Nutrient Info			
Nutrient Score	0.85	0.77	0.2
Total Calories	12,160	15,343	18,525
Total Calories Per OZ	25.75	32.84	40.08
Fat (grams per 100 cal.)	3.2	4.61	5.54
% Calories from Candy	0.00%	0.98%	1.62%
% Calories from Soda	0.00%	5.47%	9.07%
% Calories from Fruit & Veg	7.15%	2.84%	0.00%

Note: The above table shows how measures of nutritional quality vary across three sample bundles. To determine the food products included in each of these bundles, we select among the most widely purchased UPCs in each CNPP food category.

We are interested in the extent to which the nutritional quality of household purchases varies systematically with household characteristics. In Table 2, we regress household-month nutrient scores on household income, household education, and other demographics with year-month fixed effects.[15] We see that wealthier and more educated households purchase more healthful foods. Although both effects are statistically significant, the standardized coefficients reported in column (4) 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 over twice as large as disparities across income levels controlling for education.

One can see this graphically in Figure 1, which depicts the average nutrient scores for households with income

[15]Refer to Table A.6 for regression results by individual nutrients. That is, we run the same regressions as in Table 2, but instead of the household nutrient scores the dependent variable is the normalized deviation of the household's per calorie consumption of a given nutrient from the recommended consumption.

and education above and below the respective medians. In addition to confirming that average scores vary more across education groups than across income groups, these bar charts also provide a way to interpret the relative magnitudes of nutrient scores across different socioeconomic groups. Comparing the high-income, high-education average with the low-income, low-education average, we see that the scores of households with above median income and education are on average 23% of a standard deviation higher than the scores of households with below median income and education.

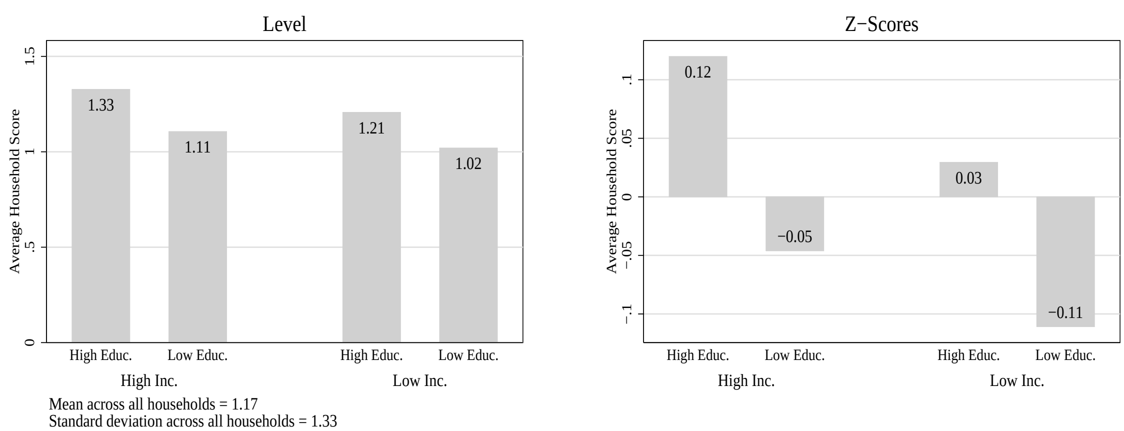
Table 2: Household Characteristics and Nutritional Quality of Purchases

	Ln(Nutrient Score)			
	(1)	(2)	(3)	(4)
Ln(Income)	0.0989***		0.0487***	0.0307***
	(0.0029)		(0.0031)	(0.0020)
Ln(Education)		0.646***	0.557***	0.0731***
		(0.014)	(0.015)	(0.0020)
Observations	3,356,636	3,356,636	3,356,636	3,356,636
R^2	0.013	0.017	0.017	0.017
Standardized	No	No	No	Yes

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

Notes: Observations are at the household-month level. Standard errors are clustered by household. All regressions include year-month fixed effects and controls for household demographics, including household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic. Refer to Table A.4 for the full regression results.

Figure 1: Nutrient Scores Across Households



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

3.2 Spatial Disparities in Access

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

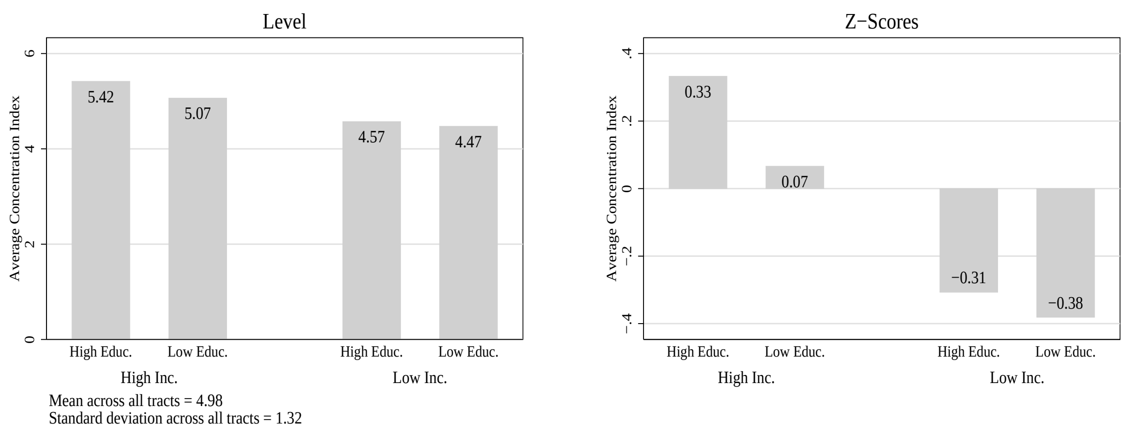
3.2.1 Store Concentration

We begin by looking at simple concentration indexes that reflect the spatial distribution of retail food stores in and around each census tract in the U.S. The concentration indexes are kernel densities based on store locations from the TDLinx data. Let d_{sl} denote the distance between store s and the centroid of census tract l, and let S_t denote the universe of stores in our sample in time t. We define the concentration index for census tract l in time t as a Gaussian kernel with a bandwidth of 20km:[16]

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

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

Figure 2: Store Concentration Indexes Across Census Tracts



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

In Table 3, we regress tract-year concentration indexes on tract-level characteristics. Figure 2 is formalized in column (1): median income within a tract is positively associated with store concentration, whereas the share of college-educated households has a significantly negative, but comparatively negligible, association with store concentration. Columns (2) through (6) display the relationship between tract-level demographics and store-type-specific concentration indexes. That is, the dependent variable is the concentration of a certain store type, such as grocery stores, instead of the concentration of all food stores. We see that the results in column (1) do not mask significant differences across store types: high-income neighborhoods have significantly more stores of *all* types than low-income neighborhoods.

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

Table 3: Neighborhood Characteristics and Store Concentration

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

Standard errors in parentheses

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

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

3.2.2 Store Inventory and Pricing

While kernel densities of the number of stores allow us to examine disparities in the spatial distribution of retailers, this measure ignores the fact that all stores are not equal. Importantly, stores may differ in the products and prices they offer, even within store types. To account for spatial disparities in these dimensions of nutritional availability across neighborhoods, we use the Scantrack data to compute healthfulness and price indexes for each of the stores in the Scantrack panel that we are able to match to location information in the TDLinx data.[17]

To summarize the nutritional content of the products offered in a given store in a given month, we use a store-level variant of the nutrient score defined for households in Section 3.1.[18] The store-level nutrient score reflects the per calorie nutrients that a representative household would purchase in store s in month t. The household is nationally representative in that they purchase *all* of the products available in a store such that their relative UPC-level expenditure shares for that store reflect the national average.[19]

The nutrient score for store s in month t can be written as

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

where j again indexes nutrients, $J_{Healthful}$ and $J_{Unhealthful}$ are defined as in Section 3.1, and pc_j^{DGA} is the DGA's recommendation for the per calorie consumption of nutrient j. pc_{jst} is the per calorie amount of nutrient j that would be purchased by a representative household in store s in month t, calculated as

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

[17] Refer to Appendix A for details on this match.

[18] As with the nutritional quality of household purchases, we measure the nutritional quality of store-level product offerings using various indexes. We only present results for our preferred index here, although the interested reader may refer to Appendix D.1 for results using alternative measures of the nutritional quality of product offerings.

[19] Our store-level nutrient score does not use any information on actual store-level sales. We use national-sales weights rather than store-sales weights in order to capture the relative importance of products to a nationally representative consumer rather than a store-specific representative consumer. Indexes based on store-sales weights will be biased towards the tastes of the households visiting that store and, therefore, will mechanically be correlated with the demographics of the store's local community. By using national weights we are able to control for the relative importance of UPCs to the typical consumer without introducing this bias.

where pc_{ju} is the per calorie amount of nutrient j in UPC u, U_{st} is the set of all UPCs with positive sales in store s in month t, and v_{ut} is the total value of sales of UPC u across all stores in the national Scantrack sample in month t.[20]

Before proceeding to a formal analysis of access, in Table 4 we explore how availability differs for the three sample bundles introduced in Section 3.1. The top half of Table 4 shows the percentage of Scantrack stores in which the entirety of each bundle can be purchased, whereas the bottom half shows the percentage of census tracts in which the entirety of each bundle can be found in at least one store. Table 4 yields two takeaways. First, we see that the unhealthy bundle is available in more stores and across more census tracts than the healthy bundle. Second, availability measured by stores is greater than availability measured by census tracts. This indicates census tract availability is not being driven by a single store; rather, when a bundle can be found within a given census tract, it can likely be found within multiple stores in that tract.

[20]We exclude store nutrient scores that are more than twice the distance between the 90th and 50th percentiles from our analysis (approximately 5% of store-month scores), as they likely reflect measurement error. Our results are qualitatively robust, however, to the inclusion of outliers.

Table 4: Cost and Availability of Sample Bundles

	Healthy	Bundle Mixed	Unhealthy
Store-level			
Availability			
All Tracts	35.87%	35.81%	69.55%
HI/HE Tracts	38.16%	38.11%	73.39%
HI/LE Tracts	35.60%	35.54%	69.41%
LI/HE Tracts	32.54%	32.54%	65.81%
LI/LE Tracts	33.02%	32.93%	63.92%
Cost Per OZ (Std Dev.)			
All Tracts	0.111 (0.014)	0.117 (0.011)	0.119 (0.012)
HI/HE Tracts	0.115 (0.014)	0.12 (0.011)	0.121 (0.012)
HI/LE Tracts	0.109 (0.013)	0.115 (0.01)	0.118 (0.011)
LI/HE Tracts	0.11 (0.012)	0.116 (0.01)	0.119 (0.01)
LI/LE Tracts	0.104 (0.012)	0.111 (0.009)	0.116 (0.01)
Cost Per 100 Calorie (Std Dev.)			
All Tracts	0.432 (0.054)	0.355 (0.033)	0.297 (0.029)
HI/HE Tracts	0.448 (0.052)	0.364 (0.032)	0.301 (0.03)
HI/LE Tracts	0.421 (0.051)	0.35 (0.031)	0.294 (0.027)
LI/HE Tracts	0.426 (0.048)	0.352 (0.03)	0.296 (0.026)
LI/LE Tracts	0.404 (0.046)	0.339 (0.028)	0.29 (0.025)
Tract-level			
Availability			
All Tracts	28.31%	28.27%	47.52%
HI/HE Tracts	33.23%	33.19%	54.55%
HI/LE Tracts	24.98%	24.94%	42.90%
LI/HE Tracts	28.24%	28.24%	49.00%
LI/LE Tracts	22.15%	22.09%	38.16%
Cost Per OZ (Std Dev.)			
All Tracts	0.112 (0.014)	0.117 (0.01)	0.12 (0.011)
HI/HE Tracts	0.116 (0.013)	0.12 (0.01)	0.122 (0.012)
HI/LE Tracts	0.108 (0.013)	0.114 (0.01)	0.118 (0.01)
LI/HE Tracts	0.11 (0.012)	0.115 (0.009)	0.119 (0.01)
LI/LE Tracts	0.104 (0.012)	0.111 (0.009)	0.117 (0.009)
Cost Per 100 Calorie (Std Dev.)			
All Tracts	0.433 (0.053)	0.355 (0.032)	0.299 (0.027)
HI/HE Tracts	0.449 (0.051)	0.364 (0.031)	0.304 (0.029)
HI/LE Tracts	0.421 (0.05)	0.349 (0.03)	0.295 (0.026)
LI/HE Tracts	0.427 (0.046)	0.351 (0.028)	0.297 (0.025)
LI/LE Tracts	0.404 (0.045)	0.338 (0.027)	0.291 (0.024)

Note: The first part of the table presents bundle availability and cost at the store level; the second part reports bundle availability and cost at the tract level. Bundle availability is calculated as the share of stores (tracts) that offer all the products (or similar products) listed in the corresponding bundles of Table 1. Bundle cost is the sum of products between purchase amount and average price of similar products across all products in the bundle. Similar products are defined to be products in the same product module and whose description contains same key words as in the description of the exact products in the bundle. For example, the similar products for "Tuna–Chunk Light" are products in the module of "SEAFOOD-TUNA-SHELF STABLE" and containing key words "TUNA WTR CHK LT".

We are interested in the extent to which the nutritional quality of store offerings varies systematically with neighborhood characteristics. In Table 5, we regress the store-month nutrient scores on store-specific, market-level variables.[21] Since the concentration indexes are at the tract level, we define neighborhood socioeconomic characteristics by tract in Figure 2 and Table 3. Here, we instead treat space continuously and look at how the

[21]Refer to Tables A.7 and A.8 for regression results by healthful and unhealthful nutrients, respectively. That is, we run the same regressions as in Table 5, but instead of the store nutrient score the dependent variable is the normalized deviation of the nationally representative household's per calorie consumption from the recommended per calorie consumption of a particular nutrient.

socioeconomic status of residents in the general vicinity of a store covaries with the nutritional quality of the products available in that store. We measure the average socioeconomic profile surrounding a store using kernel densities of median household income and college-educated shares for census tracts in the store's vicinity as reported in the ACS.[22]

Looking first to column (1), we see that store nutrient scores covary with neighborhood demographics. Stores in wealthier and more educated neighborhoods tend to offer a range of products whose nutrient content, on the whole, better accords with the DGA recommendations. To examine whether this variation in nutritional offerings can be attributed to regional differences, in column (2) we control for DMA, a Nielsen market definition of similar geographic scope as Metropolitan Statistical Areas. In column (3), we further control for store chain interacted with DMA. While income is positively associated with the nutrient scores of stores across DMAs, this association disappears when we control for store chain. This suggests that the main effect of income on nutritional availability comes through the particular retailers that locate in an area, rather than systematic differences in the types of products that a particular retailer offers. The association between local education and the range of products offered in stores, however, persists even after introducing controls for DMA and DMA-store chain interactions. This implies that chains of stores offer a healthier mix of products in more educated neighborhoods, even within the same DMA.

Table 5: Neighborhood Characteristics and Nutritional Quality of Product Offerings

	Ln(Nutrient Score)		
	(1)	(2)	(3)
Ln(Median Household Income Density)	0.108***	-0.101***	0.0106
	(0.0058)	(0.013)	(0.0077)
Ln(College-Educated Share Density)	0.00676	0.104***	0.00999
	(0.0058)	(0.0087)	(0.0057)
Observations	1,239,022	1,239,022	1,239,022
R^2	0.243	0.305	0.466
Fixed Effects	None	DMA	DMAxChain

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

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

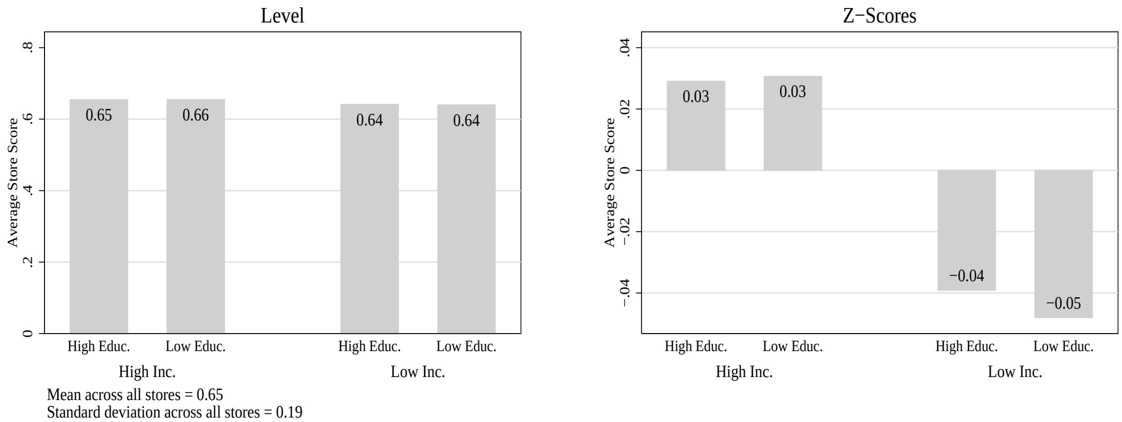
Figure 3 depicts how store nutrient scores vary with tract demographics from the ACS. It is striking how much less variation there is in the levels of the nutritional quality of product offerings across neighborhoods than in the levels of the nutritional quality of purchases across households as observed in Section 3.1.[23] While these differences are more pronounced when compared to the standard deviation of scores across all stores, this is a mechanical artifact of the generally limited variation in the healthfulness of product offerings across all stores. The z-scores presented on the right-hand panel of Figure 3 demonstrates that differences in neighborhood demographics explain more of the relatively small degree of overall variation in nutrient scores across stores than differences in household demographics explain of the larger degree of overall variation in nutrient scores across households (with high-income, high-education neighborhood stores having nutrient scores 0.42 standard deviations above

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

[23] The differences in expenditure scores are more pronounced when we look across store type instead of store location. Looking to Figure A.4, we see that grocery stores have higher nutrient scores than convenience stores, for example. This difference is more pronounced for our alternative measure of nutritional quality, which is based on the distribution of expenditures across healthy and unhealthy product categories.

low-income, low-education neighborhood stores, relative to the 0.23 standard deviation gap between high-SES and low-SES households.[24]

Figure 3: Nutrient Scores Across Stores: Available Products

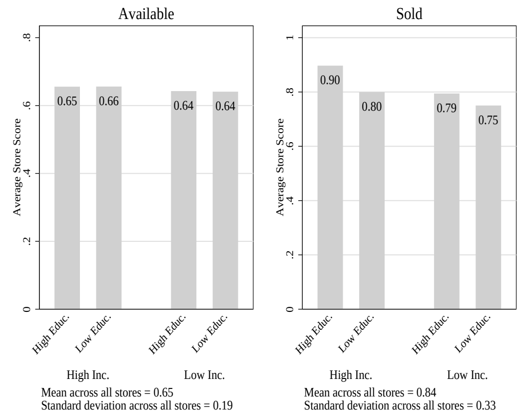


Notes: The figure above presents average store-level expenditure and nutrient scores across census tracts with different socioeconomic compositions. Tracts are considered high income (HI) if their median household income falls above the median level across all tracts ($47,299) and low income (LI) otherwise.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

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

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

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



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

Given the disconnect between the nutritional quality of products available and the nutritional quality of products actually sold across neighborhoods, it is unlikely that differences in product availability drive the observed differences in sales. At the very least, these results suggest that nutritional disparities in the products sold across stores cannot be explained by any constraint imposed by differences in the availability of nutritious food products alone. That said, there are other store policies, such as pricing and amenities, that may also influence household purchases. Even though a product is on the shelf in a low-SES neighborhood, the product may be prohibitively expensive or offered in an unkept section of the store such that the item is not truly “accessible” to households in that neighborhood.

The Scantrack data includes the prices offered to consumers, allowing us to examine the role of differential pricing directly. One commonly cited hypothesis for why low-income consumers eat less healthy foods is that unhealthy calories are less expensive than healthy calories.[25] Since low-income consumers face tighter budget constraints and food is a necessity good, they will allocate more of their expenditure towards cheaper, less healthful foods than high-income consumers. While relative prices may be a key driver of nutritional disparities in general, they are only relevant for this paper insofar as the pricing practices of the stores in low-SES neighborhoods lead low-SES households to purchase *even more* unhealthy foods than they would if they had access to the prices offered by stores in high-SES neighborhoods. If store pricing is to blame for the relative unhealthfulness of sales in low-SES neighborhoods, it must be the case that either (a) these stores charge higher prices for all food products, limiting their customers’ consumption possibilities and forcing them to allocate even more of their expenditure towards cheaper products than they would otherwise, or (b) these stores charge relatively more than stores in high-SES neighborhoods for healthful versus unhealthful food products. We explore these hypotheses by looking at the spatial distribution of prices for all food products, as well as the distribution of the prices offered for healthy relative to unhealthy foods. As documented in Appendix D.2, we find that differences in pricing alone cannot be driving consumption disparities: stores in high-SES neighborhoods charge more than stores in low-SES neighborhoods for

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

all products on average, and healthful foods are actually relatively more expensive than unhealthful foods in these neighborhoods. Therefore, if anything, pricing patterns should cause store sales in low-SES neighborhoods to be more, as opposed to less, healthful than store sales in neighborhoods with wealthier and more educated residents.

The manner in which healthful products are presented, including their shelf space and department cleanliness, may also make these products relatively less attractive in certain stores (see, for example, Zenk et al. (2011)). We do not have the qualitative data required to assess whether these differences can help explain socioeconomic differences in store sales. In Section 5.1, we use fixed effects to control for *all* differences in access across neighborhoods and even across stores in order to obtain an upper bound on the role that these factors jointly play in explaining socioeconomic differences in household purchases.

4 Theoretical Framework

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

In this section, we introduce a simple and quite general theoretical framework in which socioeconomic status and local supply both influence household food purchases. This framework demonstrates the challenge that the previous literature has faced in identifying the causal link between access and the nutritional quality of household purchases. It also suggests two ways in which we can use the detailed nature of our data to overcome this challenge. In Sections 5.1 and 5.2, we apply each of these approaches to empirically bound the impact that improving access can have on socioeconomic disparities in the healthfulness of household purchases. The interested reader may refer to Appendix E for a more parametric approach to this theory.

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

Consider a representative household of SES h living in location l. The household decides how much to consume of each of a set of grocery varieties indexed by nutritional quality $q = 1, ..., Q$ and an outside good z. The household selects these products to maximize utility subject to their budget constraint, which is determined by the cost of accessing healthy food products in their location l, $p_l(q)$, and the household's income y_h. The cost of access reflects not only the retail price of food products, but also travel costs and storage. This cost will be infinite if products of a certain quality level are entirely unavailable to consumers in a location. The household's problem is therefore given by

$$\max_{\{x(q)\}_{q=1,\ldots,Q},z} U_h(x(q),z) \text{ subject to } \sum_{q=1}^{Q} p_l(q)x(q) + p_l(z)z \leq y_h$$

where $x(q)$ denotes the quantity of each product quality q purchased by the household.

The solution to the household's problem yields a Marshallian demand curve for products of each quality q, $x_h(q, \mathbf{P}_l)$, where the consumption of products of quality q can vary with consumer SES, h, and the vector of access costs in a location, $\mathbf{P}_l$. The possibility that demand is also a function of consumer income, y_h, is accounted for by the fact that this demand function is indexed by h.

Denote the average quality of the food products consumed by households with socioeconomic status h across all locations Q_h. If $\lambda_h(l)$ denotes the population share of type-h households in location l, the sales-weighted average quality of products purchased by type-h households across all locations is

$$Q_h = \frac{1}{\sum_{l=1}^{M} \lambda_h(l)} \sum_{l=1}^{M} \sum_{q=1}^{Q} \lambda_h(l) s_h(q, \mathbf{P}_l) q$$

where the within-grocery expenditure share on products of quality q is given by $s_h(q, \mathbf{P}_l) = \frac{x_h(q,\mathbf{P}_l)}{y_h - p_l(z) z_h(\mathbf{P}_l)}$.

This expression highlights two distinct mechanisms that can each generate the socioeconomic disparities in nutritional consumption documented in Section 3. The first mechanism is driven by supply. Suppose that demand did not vary with SES, such that $s_H(q, \mathbf{P}_l) = s_L(q, \mathbf{P}_l) = s(q, \mathbf{P}_l)$ in any given market l. Under this assumption, the sales-weighted average quality of purchases varies with SES only through differences in the spatial distribution of households by SES:

$$Q_h = \frac{1}{\sum_{l=1}^{M} \lambda_h(l)} \sum_{l=1}^{M} \sum_{q=1}^{Q} \lambda_h(l) s(q, \mathbf{P}_l) q$$

If high-SES households tend to live in locations where the cost of accessing food products incentivizes all households to purchase healthier foods, regardless of their socioeconomic status, there would be a positive correlation between the spatial distribution of high-SES households and access to healthful food products. Mathematically, this would imply a positive correlation between$\lambda_H(l) = 1 - \lambda_L(l)$ and $\partial s(q, \mathbf{P}_l)/\partial q$ across locations, presumably because $\partial f(q, \mathbf{P}_l)/\partial q$, where $f(q, \cdot)$ is an index function reflecting the relative cost of products of quality q. In practice, we expect that it might cost less to access healthy foods in high-SES neighborhoods because local firms cater to local high-SES tastes for these products. However, if demand does not vary with SES, such cost differences could arise as the result of a combination of wholesale unit costs and retailing costs. In Appendix E, for example, we demonstrate that differences in wholesale and retail costs (healthy foods cost more and rents are higher in high-SES neighborhoods) provide firms in high-SES neighborhoods with a comparative advantage in the distribution of nutritious products.

The second mechanism is driven by differences in demand. If high-SES households purchase relatively more healthy products than low-SES households in all locations regardless of access, then high-SES consumption shares, $s_H(q, \mathbf{P}_l)$, would be more correlated with quality than low-SES consumption shares (i.e., $s_H(q, \mathbf{P}_l)/s_H(q', \mathbf{P}_l) > s_L(q, \mathbf{P}_l)/s_L(q', \mathbf{P}_l)$ if $q > q'$ for all l). This differential taste for quality could arise for a variety of reasons. If $y_H > y_L$, this could be the result of income effects. That is, households with lower incomes may spend more on low quality products either because they cost less or because there are complementarities between consumption of the outside good z and the quality of grocery products (as in our parametric model in Appendix E). High-SES households might also spend more on high quality products because they attain more utility from these products, regardless of their expenditure on the outside good as the result of, for example, differences in educational attainment. For the purpose of this paper we remain agnostic as to why high-SES households spend more on healthy foods within locations. We simply seek to measure the role that these demand-side factors, relative to supply-side differences in access, play in generating the differences in purchases that we see across households living in all locations.

In the analysis below, we will attempt to disentangle these two forces by looking at the relative quality of products purchased by (i) a cross-section of households with different incomes and education levels but living or shopping in the same location (switching off the main supply-side source of heterogeneity) and (ii) the panel of households facing varying retail environments but constant income and education (switching off the main demand-side source of heterogeneity).

First, we look at the socioeconomic disparities in the purchases of households that live or shop in the same retail environment. Within a location, the average quality of products purchased across type-h households reduces to

$$Q_h(l) = \sum_{q=1}^{Q} s_h(q, \mathbf{P}_l) q$$

Comparing the average quality across high-SES and low-SES households, we have that

$$Q_H(l) - Q_L(l) = \sum_{q=1}^{Q} \left(s_H(q, \mathbf{P}_l) - s_L(q, \mathbf{P}_l) \right) q$$

If high-SES households have relatively higher expenditure shares on high-quality products, then we will have that $Q_H(l) > Q_L(l)$ on average across locations. To the extent that these differences in demand yield preference externalities or home market effects, such that higher quality products are easier to access in locations where there is high demand for them, differences in aggregate local demand will play a role in generating the correlation between $\lambda_H(l)$ and $\partial s_h(q, \mathbf{P}_l)/\partial q$. Looking within locations we will ignore these effects, whereby potentially underestimating the role of demand-side factors and, in turn, providing an upper-bound for the role of access.

In order to get a more precise estimate of the role of access, we then look at how the purchases of households change over time in response to changes in supply. Consider the market above with locations recast as markets that are separated by time instead of by space. Consider the change in the quality of products purchased by a type-h household between time t and $t + 1$:

$$Q_h(t) - Q_h(t + 1) = \sum_{q=1}^{Q} \left(s_h(q, \mathbf{P}_t) - s_h(q, \mathbf{P}_{t+1}) \right) q$$

If the prices, or availability, of healthy food products decreased relative to unhealthy food products, we would see the average healthfulness of the products consumed increase. Assuming that a household's income and tastes are constant over time—or at least over the time horizen that we consider empirically—we can estimate the elasticity of healthfulness in response to changes in access by regressing changes in the healthfulness of household purchases against variables that summarize local prices and product availability. It is possible that tastes vary over time, however, and we expect that changes in availability across markets will be correlated with unobserved changes in the prevalent tastes of local residents. While the tastes of any one panelist household might not reflect the prevalent local tastes (a household's tastes may not change or may change in the opposite direction), we expect that the tastes of our sample households are, on average, correlated and covary with local tastes. As a result, we expect that our estimate of the elasticity of household purchases with respect to changes in their retail environment to be subject to an upward omitted variable bias. We will therefore also interpret these elasticities as an upper bound for the true elasticity that we expect to govern the response of purchases to improved access that is driven by policy as opposed to endogenous firm responses to changes in market fundamentals. As the correlation between time-variant components of a given household's demand and their retail access is likely more limited than the correlation between unobservable components of the household's tastes and where they choose to live or shop, we expect our time-series results to yield a tighter bound than our cross-sectional approach.

5 Role of Access in Explaining Consumption Disparities

We now implement the empirical strategies suggested by our model to identify the causal role of access in explaining consumption disparities. We begin by taking a cross-sectional approach and compare the disparities that persist when comparing households living in the same residential location or shopping in the exact same store to the disparities that exist across the entire U.S. Leveraging observed changes in households' retail environments over our panel, we then directly measure how the nutritional consumption of households in our sample responds to a changing retail environment. This analysis further allows us to explore the relative effectiveness of two common policy types: incentivizing store entry, or incentivizing existing stores to offer more healthful products.

5.1 Looking Within Locations and Stores

In the analysis that follows, we control for access to see whether the nutritional disparities remain. We begin by controlling for location, where location is defined as either a county or a census tract. While informative, 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 yield differences in the ability of households to travel to stores. Therefore, we further present a within-store analysis that controls for these factors. Specifically, we study how the nutritional quality of purchases varies with the characteristics of households shopping in the same store. To characterize the disparities that exist within stores, we first calculate household-store-month nutrient scores that reflect the nutritional quality of the purchases that a given household makes in a specific store in a given month.

In columns (1) of Table 6, we replicate the regression analysis from column (4) of Table 2 for the sample of households with non-missing county and census tract information. In columns (2) and (3), 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. Comparing column (1) to columns (2) and (3), 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. This within-location analysis indicates that 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 6: Household Characteristics and Nutritional Quality of Purchases: Controlling for Access

	Ln(Nutrient Score)						
	Geographic Controls			Store Controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(Income)	0.0297***	0.0127***	0.00354	0.0253***	0.0245***	0.0165***	0.0111***
	(0.0024)	(0.0024)	(0.0024)	(0.0026)	(0.0025)	(0.0025)	(0.0022)
Ln(Education)	0.0807***	0.0796***	0.0714***	0.0476***	0.0472***	0.0459***	0.0447***
	(0.0024)	(0.0023)	(0.0025)	(0.0026)	(0.0025)	(0.0024)	(0.0022)
Observations	3191196	3191196	3191196	4165852	4165852	4165852	4165852
R^2	0.019	0.036	0.161	0.014	0.060	0.069	0.109
FEs	No	County	Tract	No	Channel	Chain	Store

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

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

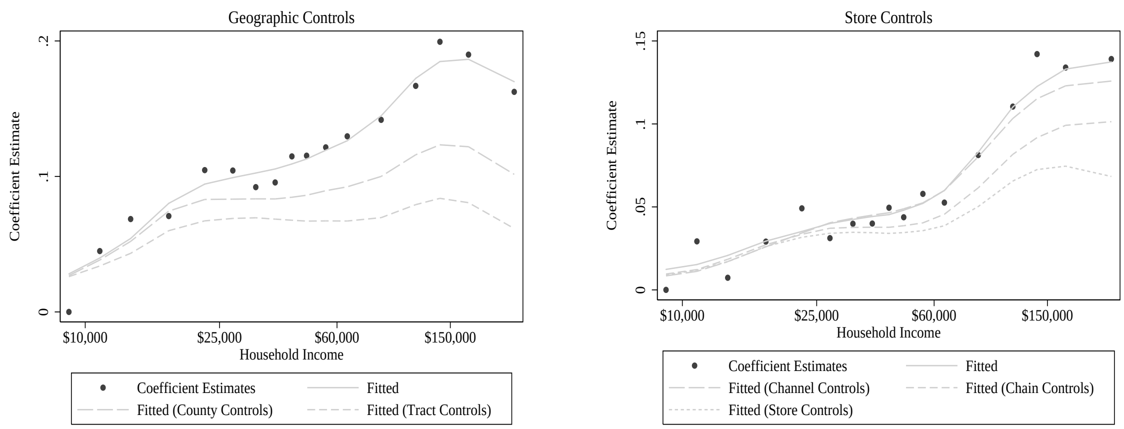
In column (4) of Table 6, we regress household-store scores against household demographics, time fixed effects, and various levels of store controls.[26] We see that the healthfulness of household-store purchases are increasing in both income and education. When we control for access by looking within stores of the same type (i.e., grocery, drug, mass merchandise, or convenience) the association between the nutrient score and income falls slightly, but not by a statistically significant margin. In Section 3.2, we saw that the store-level nutrient scores vary even across stores in the same chain. Therefore, to hold a household's shopping environment fixed, we need to control for the exact store in which the household is shopping. When we include store fixed effects, the association between household purchase quality and income is reduced by about 50%. This indicates that at least half of the observed disparity between the store-specific shopping bundles purchased by households with different levels of income can be explained by tastes. We stress that the remaining component could be explained by either tastes or access: households may shop at different stores either because they are more accessible or because they offer products better suited to their tastes. Access plays a smaller role in explaining the relationship between nutritional quality and household education: moving from columns (4) to (7), we see that the associations between household purchase quality and household education falls by around 10%.

These results are visually depicted in Figures 5 and 6. The subplots display the coefficients on income and education when the same analysis as shown in Table 6 is replicated using income and education dummies instead of levels. The dots in Figure 5 (6) are the coefficient estimates on income (education) dummies in the specification without household location or store controls plotted against the relevant income (education) levels. The solid line depicts the smoothed kernel of these estimates. In the left subplots of Figures 5 and 6, the dashed lines reflect the smoothed kernels of the coefficient estimates on income or education dummies of the point estimates from columns (2) and (3) of Table 6, where we subsequently add more detailed controls for household location. Analogously, in the right subplots of Figures 5 and 6, the dashed lines represent the smoothed kernels of the point estimates from columns (5) through (7), where we subsequently add more detailed controls for retail outlet. We see that adding location or store controls dampens the association between income and nutritional quality, whereas the relationship between education and nutritional quality is more persistent. In fact, the addition of census tract or store fixed effects does little to reduce the association between education and the healthfulness of household

[26]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.

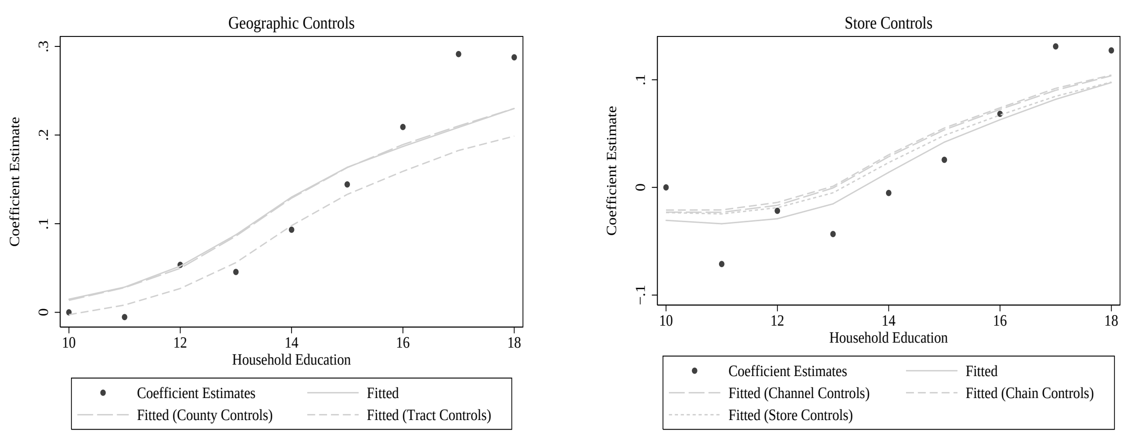
purchases.

Figure 5: Income Effects with Geographic and 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 either location or store controls. Observations in the left subplot are at the household-month level, whereas observations in the right subplot are at the household-store-month level. The dots in each plot are the coefficient estimates on income dummies from an expenditure-weighted regression of log household nutrient 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 geographic or store controls.

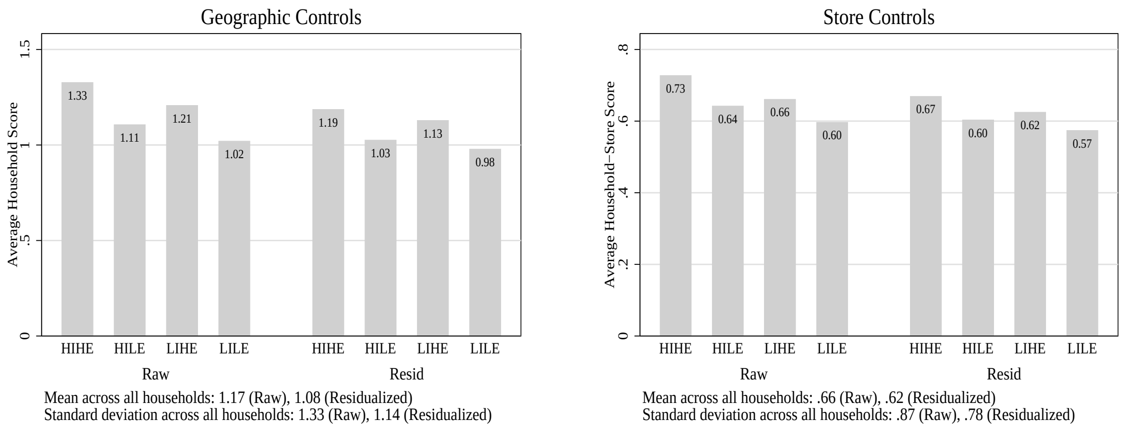
Figure 6: Education Effects with Geographic and Store Controls



Notes: The above plots depict how the association between education and the nutritional quality of household purchases changes when we control for access using either location or store controls. Observations in the left subplot are at the household-month level, whereas observations in the right subplot are at the household-store-month level. The dots in each plot are the coefficient estimates on education dummies from an expenditure-weighted regression of log household nutrient 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 geographic or store controls.

In Section 3, we saw that the disparities across education groups are larger than those across income groups. The fact that education disparities are also more persistent than income disparities within location suggests that much of the overall disparities between households remain intact within locations, even though up to half of the income disparities are resolved when controlling for access. We test whether this is the case by residualizing household nutrient scores from either tract or store fixed effects estimated in regressions that are similar to those depicted in columns (3) and (7) of Table 6. Instead of controlling for the continuous values of income and education, however, we control for income and education by including dummies for above-median income, above-median education, and the interaction between the two. Figure 7 depicts the average residuals for households in different income and education groups. Comparing these residualized averages to the averages of the unadjusted nutrient scores originally presented in Figure 1, we see that the gap between thenutrient scores of households that are above versus below median income and education are only 32% or 24% lower when we control for household location or exact retail location, respectively.

Figure 7: Residualized Nutrient Scores Across Households



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

5.2 Changing Retail Environments

As discussed in Section 4, our model suggests an alternative, time-series approach to examine the impact that improving access would have on household consumption. Here, we exploit the panel nature of our data to study how household purchases in our sample responded to changes in the availability of healthful foods in their area. We further use this approach to compare the effectiveness of two common policies: incentivizing existing stores to offer more healthful products versus incentivizing store entry.

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

5.2.1 Time-Series Analysis

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-level nutrient scores to measure differences in the distance-weighted availability of healthful products.[27]

In Table 7, we examine how household purchases in our sample respond to changes in these measures of access. Column (1) is analogous to Table 6 in that it explores how the quality of monthly household purchases varies with income and education. In contrast to the analysis presented in Table 6, however, we control for local retail environments in Table 7 using continuous measures of the concentration and healthfulness of surrounding stores rather than with household location fixed effects. Even after controlling for these dimensions of access, household purchase quality is increasing in income and education. 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 DGA's nutrient recommendations do not come significantly closer to meeting the DGA's recommendations themselves.

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

	Ln(Nutrient Score)			
	(1)	(2)	(3)	(4)
Ln(Income)	0.0303***			
	(0.0033)			
Ln(Education)	0.543***			
	(0.016)			
Ln(Store Concentration)	0.0370***	0.00219	0.00209	-0.0391*
	(0.0016)	(0.0066)	(0.0066)	(0.018)
Ln(Avg. Store Score)	0.167***	0.0256**	0.0335***	0.0313***
	(0.014)	(0.0085)	(0.0086)	(0.0091)
Ln(Store Conc.)*Ln(Inc)			0.00451***	0.00490***
			(0.00098)	(0.0010)
Ln(Store Conc.)*Ln(Edu)			0.0196**	0.0159*
			(0.0063)	(0.0067)
Ln(Avg. Store Score)*Ln(Inc)			0.0332***	0.0359***
			(0.0064)	(0.0067)
Ln(Avg. Store Score)*Ln(Edu)			0.179***	0.161***
			(0.032)	(0.034)
Observations	3110233	3110233	3110233	2807362
R^2	0.020	0.273	0.273	0.275
Elasticity w.r.t Conc.	0.0370	0.00219	-0.00181	-0.0428
Elasticity w.r.t Score	0.167	0.0256	0.00149	-0.000245
Demographic Controls	Yes	No	No	No
Household Fixed Effects	No	Yes	Yes	Yes
Non-Movers Only	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. Log income and education are both demeaned. Demographic controls include household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic.

While we control for household demographics in columns (1) 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 nutrient scores in column (1) 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). When we control for the household, the coefficients are identified off of the time-series variation in purchases and retail environments.[28] In column (2), we do not observe the nutritional

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

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

quality of household purchases responding to changes in the concentration of retail outlets in the household's vicinity. However, household nutrient scores do respond slightly to improvements in the nutrient composition of products sold by stores in their neighborhood.

To explore whether the responsiveness of household purchases to changes in the retail environment varies by the socioeconomic status of the household, we interact the access kernel densities with income and education in column (3). We see that the statistically insignificant average response of household-level nutrient scores to the concentration of stores in their vicinity masks a statistically significant difference in the responsiveness of households by income: households with higher levels of income and education improve the nutritional quality of their purchases when the concentration of stores in their area increases. We observe a similar socioeconomic disparity in the responsiveness of household nutrient scores within respect to product offerings, suggesting that high-SES households respond more than low-SES households when they are offered a more nutritionally-balanced mix of food groups in their neighborhood stores.

Even when we control for both observable and unobservable household characteristics using household fixed effects, one might still be concerned that households progressively sort into locations based on their tastes throughout our sample. In column (4) 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, indicating 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.

Despite being statistically different than zero, we note that the improvements in nutritional consumption that we observe in Table 7 are very small when compared to the overall socioeconomic disparities in nutritional consumption. To get a sense of what the magnitudes of the coefficients in Table 7 imply, we consider how a low-SES household would respond to a change in their retail environment equivalent to moving from the average low-SES neighborhood to the average high-SES neighborhood. We focus on a household with income and education at the 25th percentile in each dimension, i.e. \$32,500 in annual income and 13 years of education. The elasticities of expenditure and nutrient scores for such a household implied by the coefficients from each regression specification are presented in the bottom row of Table 7.[29] Moving from the average low-SES neighborhood to the average high-SES neighborhood translates to an increase of 0.95 in the log store concentration index and an increase of 0.053 in the log distance-weighted average of store nutrient scores. Combined with the estimated elasticities displayed in column (3), these improvements in access imply that the household nutrients scores of a typical low-SES household would improve by 0.003 log units if they were to move from the average low-SES to the average high-SES neighborhood. Comparing these changes to the socioeconomic disparities in household scores shown in Figure 1, we see that only 1% of the gap in the nutrient scores would be removed by closing the gap in access to healthy foods.

other household demographics.

[29]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).

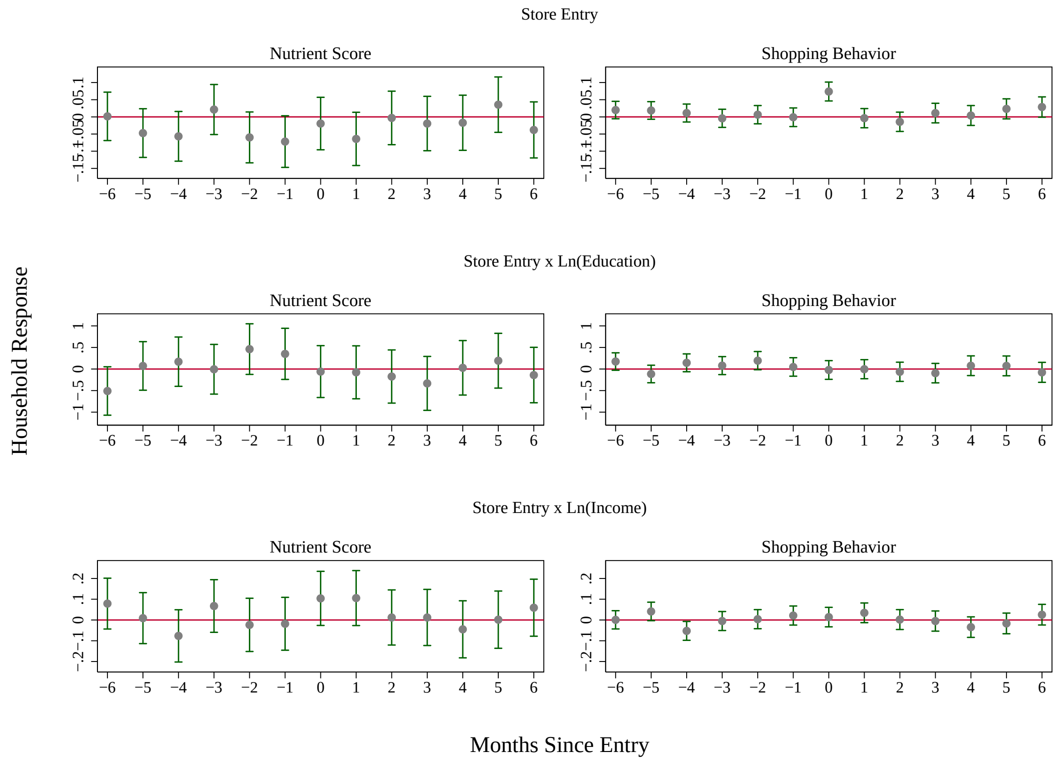
5.2.2 Event Study Analysis of Store Entry

Though some policies aimed at eradicating food deserts encourage incumbent stores to change their product offerings, most do so by encouraging store entry. It is therefore worthwhile to consider how households respond to changes in their retail environments that are related to these entry events alone. We define a store as entering in a given month if (i) the store is first observed in the Scantrack data in that month and (ii) the store's parent company already appeared 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. Analogously, 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.

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 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 column of Figure 8. The top panel displays the average response across all households. We do not see any statistically significant response in the nutritional quality of the average household's purchases to store entry. The second and third panels display the gradient in the response with respect to household education and income, respectively. Here, we see that the response of household nutrient scores to entry is increasing with income in the first two months after entry. Together with the null impact of store entry on the average household's nutrient score, this implies that the nutrient scores of households with above-average income improve temporarily for the first two months after store entry, while the nutrient scores of households with below-average income actually deteriorate over the same time period before returning to their original levels within three months.

The third column of plots in Figure 8 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 8 indicate that while households are changing where they shop when a new store enters, they are not changing the healthfulness of the foods they purchase.

Figure 8: Event Study Analysis of Store Entry



Notes: The above plots display the results from an event study analysis of store entry. The first column depicts the coefficient estimates on dummies for months before, during, and after store entry from a regression of log household-level 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 second 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.

While our estimates indicate that the nutritional quality of household purchases respond minimally to changes in their retail environment, we expect the impact of policy-induced changes to be even more limited. While household fixed effects control for time-invariant components of demand, we have no way of addressing time-variant components of demand with our data. To the extent that store entry is correlated with growing tastes for healthful products, our estimates will reflect the impact of both improved access and healthier tastes. Therefore, the minimal response that we observe in our data is likely to be even more limited in practice.[30]

6 Discussion and Conclusion

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

[30]One might suspect that improvements in access in underserved neighborhoods will be met with greater responses of household purchases. To see if this is the case, we replicate the analysis from Table 7 and Figure 8 looking only at households residing in tracts in the lowest quartile for either the store concentration, expenditure score, or nutrient score densities. The results, presented in Table A.9 and Figure A.5, are nearly identical to those estimated on the full sample.

access to healthy foods that we observe across neighborhoods with different socioeconomic compositions.

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

We stress that even though socioeconomic disparities diminish when we control for residential or retail location, it is unlikely that resolving spatial disparities in access will reduce disparities across the entire U.S. to the same extent. There are two reasons for this. First, if households are sorting into retail environments on unobservables that are correlated with their taste for healthy foods, then the socioeconomic disparities that we observe for households living in the same location or shopping in the same store will be smaller, on average, then the socioeconomic disparities that would persist across the full cross-section of households if access were equated. The second reason is mechanical. Even if households are sorting by income and education alone, and not by unobservables, it is possible that the degree of this sorting is so high that it leaves little variation in income and education across households in the same retail environment. Sampling error in household purchases, which results in noisy measures of the nutritional content of these purchases, could potentially outweigh the residual variation in income and education after controlling for residential or purchase location, resulting in attenuation bias.[31] Therefore, while our estimates indicate that equating access across the entire U.S. could not reduce existing socioeconomic disparities by more than a third, it is likely the true impact would be even smaller.

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

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

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

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

The bound that we estimate using our time-series strategy (1%) is lower than that estimated in our cross-sectional approach (32%) by a full order of magnitude. As we are identifying different, yet related, treatment effects on different, selected populations, it is no suprise that our results are not quantitatively identical. In fact, as we expect differences in demand within a household over time to be more limited than differences in demand across households living in the same location, we would expect the upward bias due to the correlation between unobserved tastes and retail environments to be greater in the cross-section than in the time-series. Furthermore, to the extent that our intertemporal estimates are identified by variation in access driven by supply-side factors, such as changes in retail rents and zoning, and not taste shocks, our time-series estimates will provide a less upward-biased estimate of the true response of households to policies that equalize access. [32] It should therefore be no surprise that our time-series result yield a more exact estimate. Despite these differences, however, our two empirical approaches reassuringly lead to the same qualitative conclusion: differences in access are not to blame for differences in nutritional consumption.

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

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

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Appendix

A Data Appendix

A.1 Household Consumption

To examine the grocery purchases made by households, we use the Nielsen Homescan data. This dataset is collected by the National Consumer Panel (NCP), a joint venture between Nielsen and IRI, and provided by Nielsen through the USDA. As mentioned in Section 2, the Homescan data contains transaction-level purchase information for a representative panel of households across the entire U.S. While the number of participating households varies from year to year, we observe 114,286 unique households over our sample period (2006 and 2011). 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.

Households in the panel use a scanner provided by the NCP to record all of their purchases at a wide variety of stores where food is sold. See Harding and Lovenheim (2014) for a detailed description of how households are recruited and encouraged to report purchases on a weekly basis. After scanning the Universal Product Code (UPC) of each item purchased, the household records the date, store name, quantity purchased, and price. Items that do have a UPC are included as "random-weight" purchases. For these items, households record the quantities and prices for products in aggregated categories. In 2006 there were 43 such categories, such as "candy," "breads," "cakes," "beef," "chicken," and "fish." For 2007 through 2011 the categories were more broadly defined, such as "baked goods," "meat/poultry/fish," "candy/nuts/seeds," "fruits," and "vegetables." While we cannot know the precise nutritional content of random weight purchases, we use the average nutritional characteristics of these categories to infer the nutritional content of these purchases. All of our results are robust to the exclusion of random weight purchases.

In addition to household-level purchase activity, the Homescan data also includes yearly information on demographics and residential location for each household in the panel. We use this demographic information to measure two dimensions of socioeconomic status that are posited to impact a household's consumption decisions: income and education. Households record their income in 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. According to this 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). For education, households record the household head's education in one of six categories: grade school, some high school, high school graduate, some college, college graduate, or post-college graduate. The distributions of household heads across these education categories by sex are recorded in Tables A.2 and A.3. Households in which either household head reports only a grade school education are excluded from our analysis. We assign each household head a number of years of education assuming that some high school corresponds to 10 years, some college corresponds to 14 years, and post college corresponds to 18 years. For households with two household heads, we use their average years of education.

Table A.1: Distribution of Household Income by Year

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

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

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

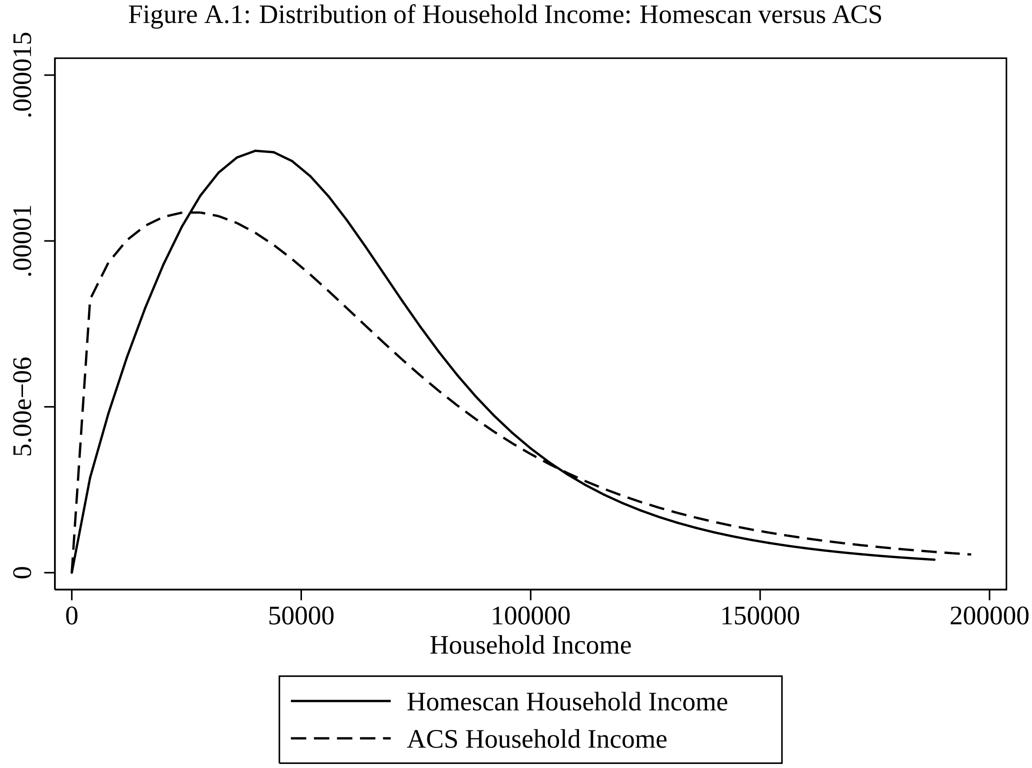
Table A.3: Distribution of Female Household Head Education by Year

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

One concern with using the Homescan data to examine socioeconomic disparities in consumption is that reporting diligence may vary with socioeconomic status. Einav et al. (2008) study the credibility of the self-recorded data in the 2004 Homescan sample. They find that reporting errors in the Homescan data are the same order of magnitude as those commonly found in earnings and employment-status data, although the reporting errors found in the Homescan sample are more pronounced for higher income and more educated households. One potential explanation for this differential reporting is that the incentives offered by Nielsen are too small to encourage wealthy households to consistently report all of their purchases. Across all households, however, Einav et al. (2008) find that purchase locations and quantities are reported more accurately than prices. Our results rely primarily on purchase locations and quantities, although reassuringly our results are qualitatively consistent when we replicate our analyses using measures based on prices (see Appendix D.1 for results based on recommended expenditure shares).

While representative of the U.S. as a whole, another concern with the Homescan data is that it may not be representative of different income groups. To explore this concern, in Figure A.1 we compare the distribution of household income in the Homescan sample to the income distribution for households in the American Community Survey (ACS). It is clear from Figure A.1 that the Homescan sample underrepresents households at either end of the income distribution. Despite these discrepancies, the non-parametric plots in Figure 5 demonstrate that our results are consistent across the entire distribution of household income. That is, our results are neither being driven by the center of the distribution, where we observe more households, or the tails, where our sample of households is more limited.

Figure A.1: Distribution of Household Income: Homescan versus ACS



Note: The solid line depicts the fitted distribution of household income from the 2010 Homescan sample; the dashed line depicts the fitted distribution of household income from the 2010 ACS. .

A.2 Retail Environments

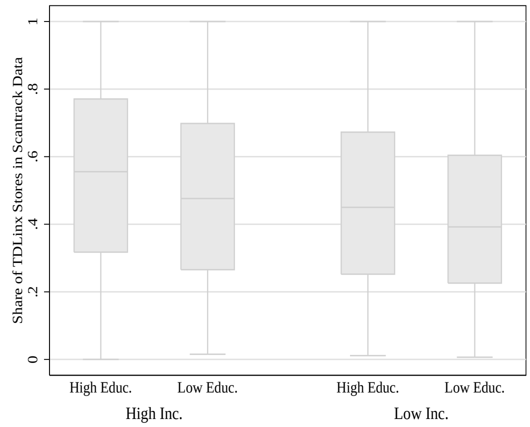
While the Homescan data describes the stores in which panelists shop and the products that they purchase at these stores, it only provides a limited picture of the retail environments in which households are making their purchase decisions. There are two problems with using the Homescan data to characterize retail environments: First, if no household in the Homescan sample shops at a given store, then we do not observe from the data that this store exists. Second, even if we do observe households shopping in a given store, we only observe the products that they actually purchase, not the full variety of products offered. Because of these limitations, we use two additional datasets, both maintained by Nielsen, to obtain a more comprehensive picture of the retail environments that households face. First, in order to observe 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. Stores are divided into five categories in the TDLinx data: grocery, convenience, drug, mass merchandise, and wholesale club. In Section 3.2, we use these categorizations to examine how the distribution of stores by store type systematically varies across neighborhoods with different socioeconomic compositions.

While the TDLinx data tells us about the number and types of stores that households have access to, it provides us with no direct information about product offerings within these stores. To see the full set of food products available at a subset of stores, we use the Nielsen Scantrack data provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business. Information on availability and access to this data is available at http://research.ChicagoBooth.edu/nielsen. The Scantrack data contains weekly sales and quantities by UPC collected by point-of-sale systems in over 30,000 participating retailers across the U.S. Stores are divided into four categories in the Scantrack data: grocery, convenience, drug, and mass merchandise. In Sections 3.2, we show how we use this data to calculate indexes that summarize both the nutritional quality and the relative prices of products offered by each store in the dataset. In calculating these indexes, we assume that every product available in a store is sold to at least one customer each month.

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

One concern with the Scantrack data is that participation of retailers may systematically vary across neighborhoods. However, as shown in Figure A.2, the average share of TDLinx stores appearing in the Scantrack sample is not statistically different across tracts with different demographics.

Figure A.2: Share of TDLinx Stores Appearing in the Scantrack Sample Across Tracts



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

A.3 Nutritional Information

The Nielsen datasets do not contain nutritional information for the products purchased by Homescan panelists or sold by Scantrack stores. We obtain this information from Gladson and IRI. The Gladson Nutrition Database provides nutritional information for over 200,000 unique UPCs throughout the entire length of our sample. For 2008 onwards, we supplement the Gladson data with nutritional information from the IRI database of over 700,000 UPCs. Each database contains information on the quantity of macro-nutrients and vitamins per serving, serving size in weight, and the number of servings per container. Gladson and IRI collect this information directly from product labels. Note that product characteristics can change without a change in the product's UPC. When Gladson receives an updated version of a product that was already in the database, it revises the entry and includes a time stamp of when the change was made. We use a version of the database that includes a snapshot of the market as of July 30th each year. We assume that these product characteristics are relevant for that calendar year.

We merge the Gladson and IRI data with the Homescan and Scantrack data to uncover the full nutritional profiles of products we observe being purchased by households and sold in stores. These merges are not perfect: only 45% of the UPCs in the Homescan data and 57% of the UPCs in the Scantrack data are in either the Gladson or the IRI nutrition database. We impute nutritional information for products not in the Gladson or IRI data using the average for UPCs in the same product module and product group with the same values for all other relevant characteristics, including brand, flavor, form, formula, style, and type. As described in Sections 3.1 and 3.2, we use this information to measure the healthfulness of household grocery purchases and the healthfulness of products offered in stores, respectively.

A.4 Neighborhood Demographics

The final dataset that we use contains tract-level demographic information from the five-year pooled ACS (2008-2012). The Nielsen data identifies household locations using 2000 census tract definitions. We adjust demographics from the ACS to reflect boundaries from 2000. 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.

B Supplementary Tables and Figures

B.1 Socioeconomic Disparities in Nutritional Consumption

Table A.4: Household Characteristics and Nutritional Quality of Purchases: Full Regression Results

	Ln(Nutrient Score)			
	(1)	(2)	(3)	(4)
Ln(Income)	0.0989***		0.0487***	0.0307***
	(0.0029)		(0.0031)	(0.0020)
Ln(Education)		0.646***	0.557***	0.0731***
		(0.014)	(0.015)	(0.0020)
Ln(Avg. HH Head Age)	0.00886	0.0299***	0.0389***	0.00910***
	(0.0082)	(0.0082)	(0.0082)	(0.0019)
HH Heads Married	0.0975***	0.101***	0.0922***	0.0441***
	(0.0076)	(0.0076)	(0.0076)	(0.0036)
Female HH Head Only	0.0720***	0.0307***	0.0421***	0.0176***
	(0.0090)	(0.0090)	(0.0090)	(0.0038)
Male HH Head Only	-0.0227*	-0.0573***	-0.0545***	-0.0155***
	(0.011)	(0.011)	(0.011)	(0.0030)
Kids Present	0.111***	0.0916***	0.0977***	0.0418***
	(0.0057)	(0.0056)	(0.0056)	(0.0024)
Race: White	0.0710***	0.0762***	0.0737***	0.0264***
	(0.0085)	(0.0085)	(0.0085)	(0.0030)
Race: Black	-0.108***	-0.108***	-0.112***	-0.0314***
	(0.010)	(0.0100)	(0.0100)	(0.0028)
Race: Asian	0.0240	0.00243	-0.00637	-0.000978
	(0.013)	(0.013)	(0.013)	(0.0020)
Hispanic	0.0248**	0.0300***	0.0278***	0.00609***
	(0.0082)	(0.0082)	(0.0082)	(0.0018)
Observations	3,356,636	3,356,636	3,356,636	3,356,636
R^2	0.013	0.017	0.017	0.017
Standardized	No	No	No	Yes

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

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

Table A.5: Household Characteristics and Nutritional Quality of Purchases: Healthful Nutrients

	Fiber	Iron	Calcium	Vitamin A	Vitamin C
Ln(Income)	0.023***	0.0024***	0.022***	0.022***	0.015***
	(0.00053)	(0.00064)	(0.0014)	(0.00093)	(0.00045)
Ln(Education)	0.020***	0.015***	0.038***	0.024***	0.014***
	(0.00048)	(0.00060)	(0.0013)	(0.00083)	(0.00042)
Observations	3,505,427	3,505,427	3,505,427	3,505,427	3,505,427
R^2	0.025	0.007	0.021	0.008	0.014

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

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

Table A.6: Household Characteristics and Nutritional Quality of Purchases: Unhealthful Nutrients

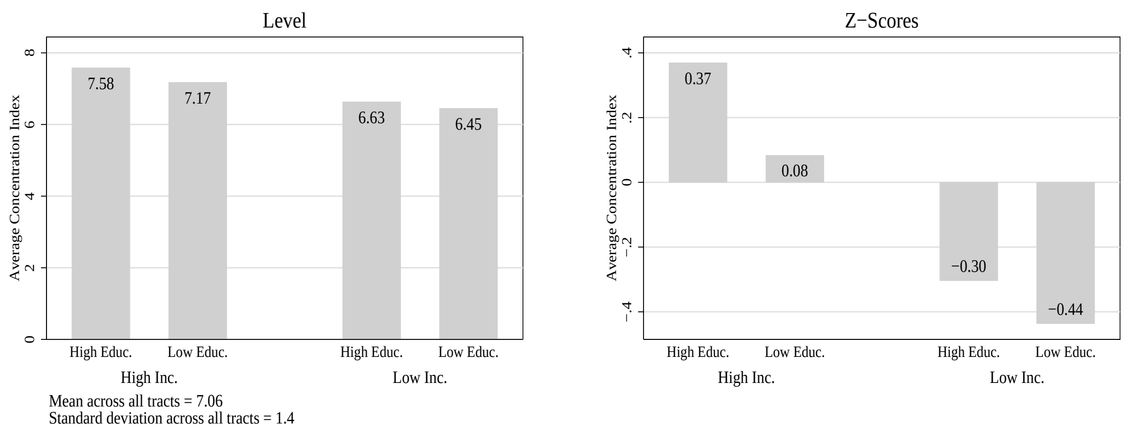
	Total Fat	Sat. Fat	Sodium	Cholesterol
Ln(Income)	-0.020***	0.0021***	0.0017***	-0.0012***
	(0.0021)	(0.00051)	(0.00044)	(0.00012)
Ln(Education)	-0.042***	-0.0067***	-0.011***	-0.0012***
	(0.0020)	(0.00050)	(0.00042)	(0.00012)
Observations	3,505,427	3,505,427	3,505,427	3,505,427
R^2	0.018	0.008	0.013	0.009

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

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

B.2 Spatial Disparities in Access

Figure A.3: Store Concentration Indexes Across Census Tracts



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

Table A.7: Neighborhood Characteristics and Nutritional Quality of Product Offerings: Healthful Nutrients

	Fiber	Iron	Calcium	VitaminA	VitaminC
Ln(Median Household Income Dens)	0.0269***	0.0313***	0.0911***	0.0965***	0.0718***
	(0.0024)	(0.0050)	(0.0088)	(0.0061)	(0.0066)
Ln(College-educated Share Dens)	0.00762**	0.00825	-0.0164	-0.0418***	0.000697
	(0.0023)	(0.0050)	(0.0085)	(0.0061)	(0.0065)
R^2	0.264	0.243	0.054	0.129	0.249
Observations	1237176	1237176	1237176	1237176	1237176

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

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

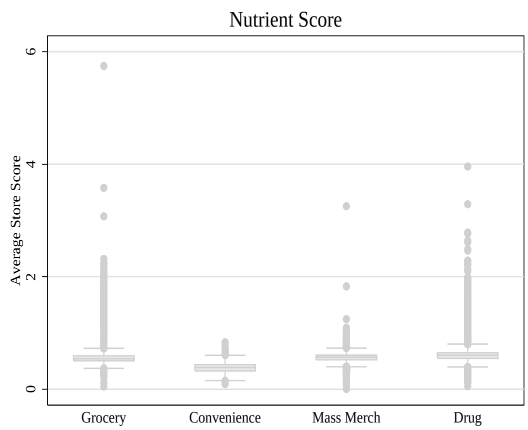
Table A.8: Neighborhood Characteristics and Nutritional Quality of Product Offerings: Unhealthful Nutrients

	TotalFat	SatFat	Sodium	Cholesterol
Ln(Median Household Income Dens)	-0.0315***	-0.0120*	-0.0200*	0.0217***
	(0.0095)	(0.0060)	(0.0086)	(0.0049)
Ln(College-educated Share Dens)	0.0497***	0.00199	0.0263**	-0.0280***
	(0.010)	(0.0063)	(0.0091)	(0.0048)
R^2	0.087	0.223	0.071	0.069
Observations	1237176	1237176	1237176	1237176

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

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

Figure A.4: Store Nutrient Scores Across Channels



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

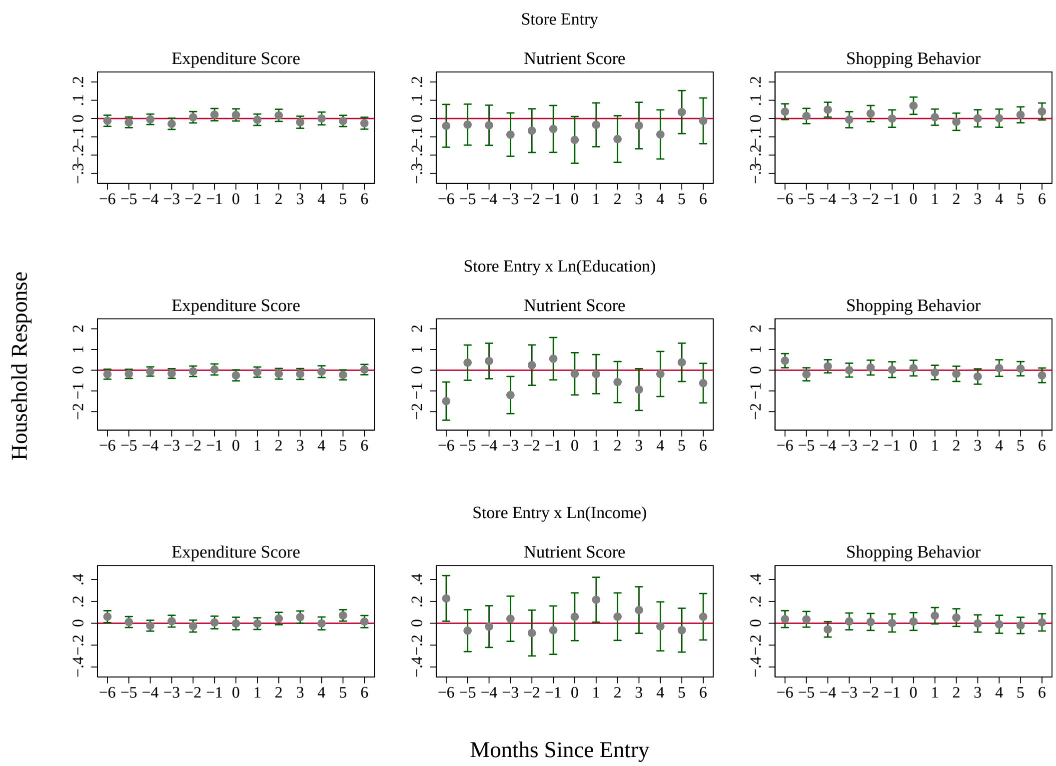
Table A.9: Response of Nutritional Quality of Household Purchases to Changes in Retail Access - Households in Underserved Neighborhoods

	Ln(Expenditure Score)				Ln(Nutrient Score)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Income)	0.0229***				0.0677***			
	(0.0019)				(0.0042)			
Ln(Education)	0.206***				0.589***			
	(0.0087)				(0.019)			
Ln(Store Concentration)	0.000781	0.00361	0.00364	-0.00241	0.0495***	0.0200*	0.0199*	0.0324
	(0.00088)	(0.0042)	(0.0042)	(0.0089)	(0.0019)	(0.0096)	(0.0096)	(0.022)
Ln(Store Score Density)	-0.0148*	-0.0112	-0.00970	-0.0142	-0.0248	0.0528***	0.0584***	0.0510**
	(0.0069)	(0.012)	(0.012)	(0.012)	(0.019)	(0.015)	(0.015)	(0.016)
Ln(Conc.)*Ln(Inc.)			0.000297	-0.000728			0.00216	0.00202
			(0.0014)	(0.0014)			(0.0015)	(0.0016)
Ln(Conc.)*Ln(Educ.)			0.000617	0.00426			0.0244**	0.0243*
			(0.0093)	(0.0099)			(0.0095)	(0.010)
Ln(Score)*Ln(Inc.)			0.00707*	0.00850*			0.0164	0.0154
			(0.0036)	(0.0038)			(0.0099)	(0.010)
Ln(Score)*Ln(Educ.)			-0.00403	-0.00824			0.122*	0.134**
			(0.024)	(0.026)			(0.048)	(0.050)
Observations	1,538,172	1,538,172	1,538,172	1,390,927	1,538,172	1,538,172	1,538,172	1,390,927
R^2	0.064	0.451	0.451	0.453	0.032	0.349	0.349	0.351
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.	0.000781	0.00361	0.00348	-0.00249	0.0495	0.0200	0.0172	0.0297
Elasticity w.r.t Score	-0.0148	-0.0112	-0.0119	-0.0166	-0.0248	0.0528	0.0427	0.0348

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

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

Figure A.5: Event Study Analysis of Store Entry - Households in Underserved Neighborhoods



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

C Alternative Measures of Household Purchase Quality

The USDA Center for Nutrition Policy and Promotion (CNPP) designs food plans for consumers based on recommendations from the DGA. Our second index, the "expenditure score," examines how a household's grocery purchases on each food group deviate from the expenditure share of the Thrifty Food Plan. The expenditure index follows the measure used by Volpe et al. (2013a).

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

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

where c indexes TFP food categories, sh_{cht} denotes the percent of household h's grocery expenditures in month t spent on products in category c, and sh_{ch}^{TFP} is the category c expenditure share, also in percent units, that the TFP

Table A.10: Healthful and Unhealthful Food Categories

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

Notes: We determine which TFP 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. The QFAHPD categories were created by USDA using Nielsen data, see Todd et al. (2010)for more details. We aggregate the 52 QFAHPD food groups to the 24 TFP food categories using the correspondence created by Volpe and Okrent (2013). In doing so, we find that two TFP 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 TFP cheese and meat categories are unhealthful. All of our results are robust to assuming that these food categories are instead healthful.

recommends for a household with the same gender-age profile as household h.[33] Dietary Guidelines for Americans issued recommendations on consumption of foods for various demographic groups, and on which food groups are healthful and unhealthful.[34] Based on these recommendations CNPP designed a Thrifty Food Plan for healthy eating and calculated expected expenditure shares for different food groups. We matched the TFP food groups with Nielsen products using the Quarterly Food-at-Home Price Database (QFAHPD) developed by Todd et al. (2010).[35]

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 ($c \in C_{Unhealthful}$).[36] We follow Volpe et al. (2013a) and take the inverse of the squared loss function so that higher scores are indicative of healthfulness.[37]

The expenditure and nutrient scores consider the healthfulness of consumer purchases from two complementary perspectives, and each measure has its strengths and its weaknesses.[38] Since consumers choose foods rather than nutrients, the expenditure score is more closely related to consumer demand. Furthermore, expenditures on specific food groups, such as fruits and vegetables, are used by many other studies, and thus the expenditure score is more

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

[34] Refer to Table A.10 for the full list of healthful and unhealthful food categories that we use.

[35] We aggregate the 52 QFAHPD food groups to the 24 TFP food categories using the correspondence created by Volpe and Okrent (2013). In doing so, we find that two TFP 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 TFP cheese and meat categories are unhealthful. All of our results are robust to assuming that these food categories are instead healthful.

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

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

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

comparable to previous research.[39] Finally, the expenditure score takes into account other nutrients, such as zinc and potassium, which are not displayed on the nutritional facts panel and are therefore not included in the nutrient score. The nutrient score, on the other hand, distinguishes between products in the same food category, e.g. frozen fish fillets versus fish sticks, that will be missed by the expenditure score. The nutrient score is also not sensitive to systematic variations in the price of foods purchased by different socioeconomic groups. If, for example, low-income and high-income consumers purchase identical quantities of cheese, but high-income consumers purchase more expensive varieties, then for all else equal expenditure scores will differ by income. The nutrient score, on the other hand, will reflect that both groups have similar diets.[40]

The tables and figures below replicate our main analysis using the expenditure score in place of the nutrient score. The disparities across socioeconomic groups are very similar to those that we saw in the nutrient score and, if anything, more persistent when controling for household location or store.

Table A.11: Household Characteristics and Nutritional Quality of Purchases

	Ln(Expenditure Score)			
	(1)	(2)	(3)	(4)
Ln(Income)	0.0426***		0.0242***	0.0427***
	(0.0013)		(0.0014)	(0.0024)
Ln(Education)		0.249***	0.205***	0.0749***
		(0.0060)	(0.0065)	(0.0024)
Observations	3356636	3356636	3356636	3356636
R^2	0.062	0.065	0.066	0.066
Std Coef	No	No	No	Yes

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

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

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

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

Table A.12: Household Characteristics and Nutritional Quality of Purchases: Healthful Food Categories

	(1)Whole-grain	(2)Potatoes	(3)Dark-green-veg	(4)Orange-veg	(5)Legumes	(6)Other-veg	(7)Whole-fruits
Ln(Income)	-0.040***	-0.039***	0.14***	0.0067**	0.051***	0.047***	0.022***
	(0.0023)	(0.0019)	(0.0034)	(0.0022)	(0.0029)	(0.0021)	(0.0023)
Ln(Education)	0.060***	-0.072***	0.024***	0.029***	0.011***	0.028***	0.072***
	(0.0023)	(0.0018)	(0.0035)	(0.0018)	(0.0029)	(0.0021)	(0.0023)
Observations	3616076	3616076	3616076	3616076	3616076	3616076	3616076
R^2	0.093	0.016	0.111	0.024	0.245	0.031	0.050

	(8)Fruit-juice	(9)Skim-milk	(10)Chicken	(11)Fish	(12)Nuts	(13)Eggs
Ln(Income)	0.015***	0.042***	0.012***	-0.036***	0.028***	-0.040***
	(0.0025)	(0.0027)	(0.0018)	(0.0026)	(0.0019)	(0.0021)
Ln(Education)	0.061***	0.098***	-0.010***	-0.0045	0.046***	-0.0099***
	(0.0024)	(0.0026)	(0.0017)	(0.0026)	(0.0019)	(0.0019)
Observations	3616076	3616076	3616076	3616076	3616076	3616076
R^2	0.025	0.060	0.126	0.051	0.037	0.017

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

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

Table A.13: Household Characteristics and Nutritional Quality of Purchases: Unhealthful Food Categories

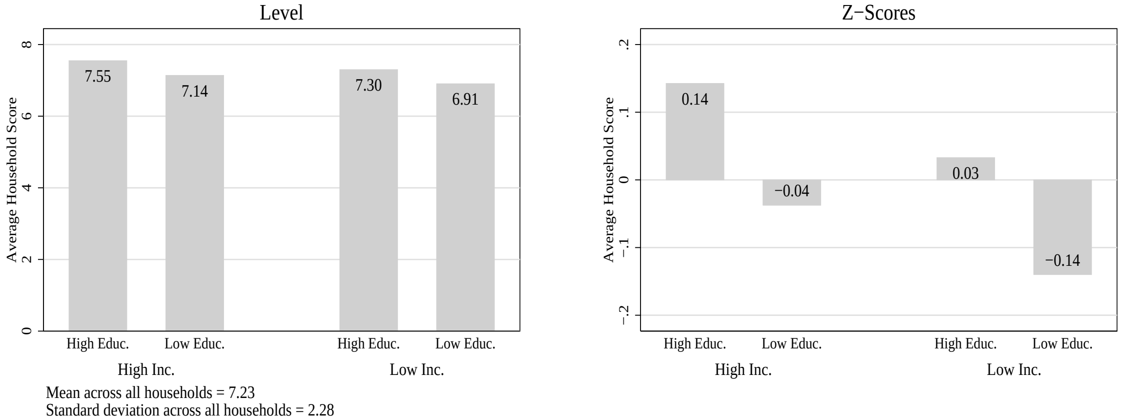
	(1)Non-whole-grain	(2)Whole-milk	(3)Cheese	(4)Beef	(5)Bacon
Ln(Income)	0.0023	-0.061***	0.015***	-0.045***	-0.0074***
	(0.0019)	(0.0024)	(0.0021)	(0.0021)	(0.0019)
Ln(Education)	-0.015***	-0.035***	0.041***	-0.067***	-0.023***
	(0.0018)	(0.0023)	(0.0021)	(0.0021)	(0.0018)
Observations	3616076	3616076	3616076	3616076	3616076
R^2	0.017	0.015	0.020	0.025	0.005

	(6)Fats	(7)Soft-Drink	(8)Sugars	(9)Soups	(10)Frozen
Ln(Income)	-0.020***	-0.039***	-0.026***	0.040***	0.019***
	(0.0017)	(0.0021)	(0.0020)	(0.0019)	(0.0024)
Ln(Education)	-0.0026	-0.061***	-0.031***	0.0021	-0.015***
	(0.0017)	(0.0020)	(0.0019)	(0.0019)	(0.0023)
Observations	3616076	3616076	3616076	3616076	3616076
R^2	0.032	0.034	0.038	0.012	0.019

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

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

Figure A.6: Expenditure Scores Across Households



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

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

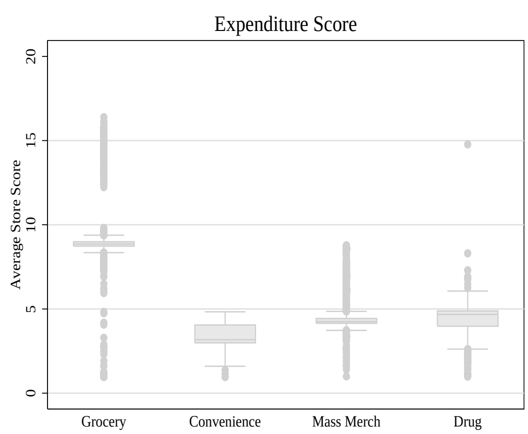
	Ln(Exp. Score, Natl. Wgts)		
	(1)	(2)	(3)
Ln(Median Household Income Dens)	0.0367**	0.142***	-0.0331***
	(0.012)	(0.021)	(0.0026)
Ln(College-educated Share Dens)	0.0114	-0.0250	0.0294***
	(0.012)	(0.016)	(0.0018)
R^2	0.011	0.125	0.977
FEs	None	DMA	DMAxCh
Obs	1239023	1239023	1239023

Standard errors in parentheses

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

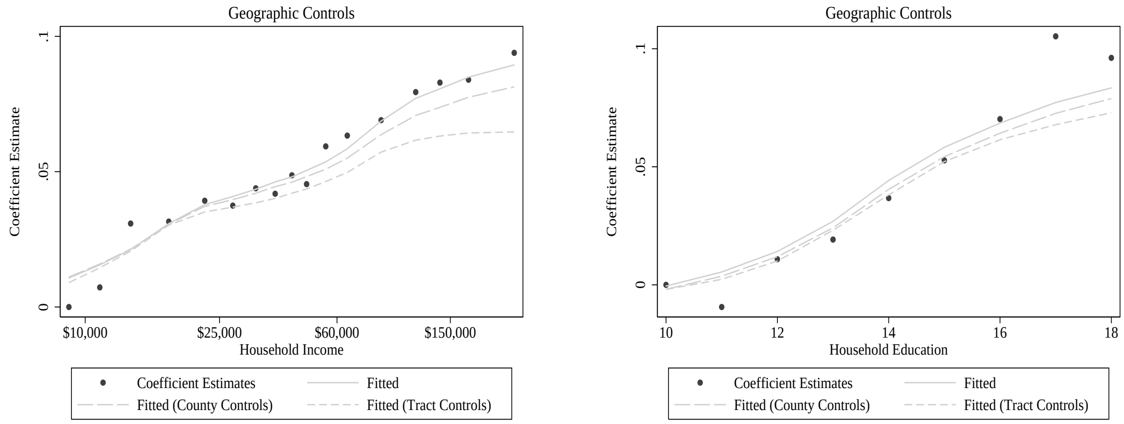
Notes: Observations are at the store-month level. Standard errors are clustered by store. All variables are standardized. All regressions include year-month fixed effects. DMA refers to designated market area, and DMAxCh is the interaction of DMA and store chain.

Figure A.7: Store Expenditure Scores Across Channels



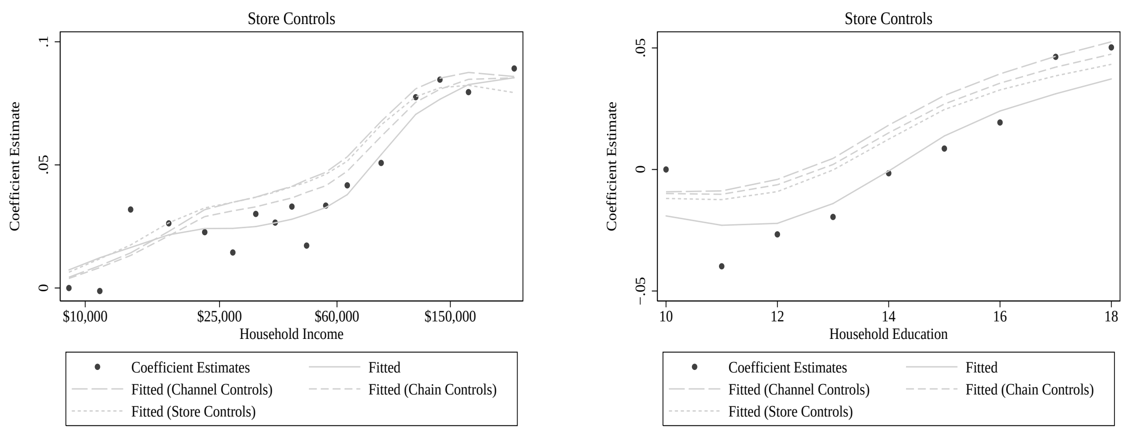
Notes: The figure above presents distributions of store-level expenditure scores by channel. Stores in the Scantrack data are divided into four channels: grocery, convenience, mass merchandise, and drug. These results are for January 2010; they are representative of the other months in the Scantrack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

Figure A.8: Income and Education Effects with Geographic Controls



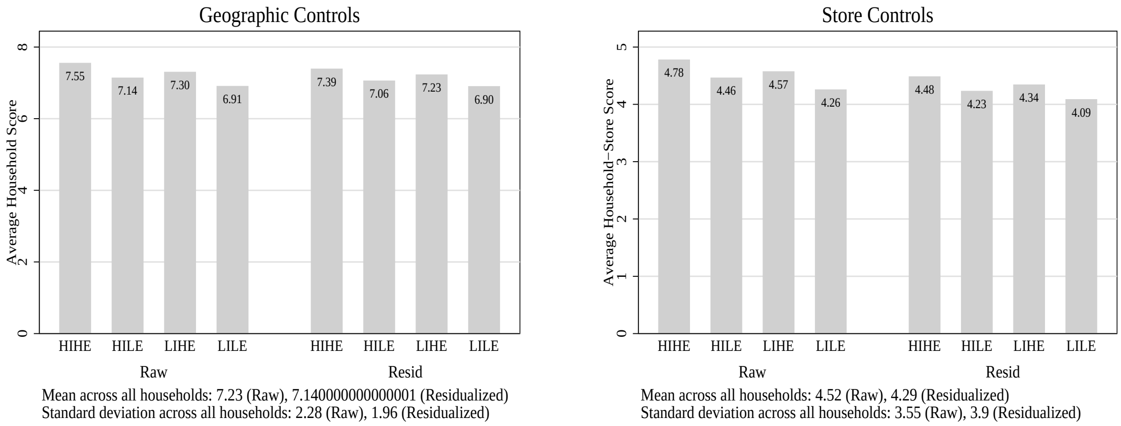
Notes: The above plots depict how the association between income and the nutritional quality of household purchases changes when we control for access using location fixed effects. The dots in each plot are the coefficient estimates on income dummies from an expenditure-weighted regression of log household-month 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 A.9: Income and 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.

Figure A.10: Residualized Expenditure Scores Across Households



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

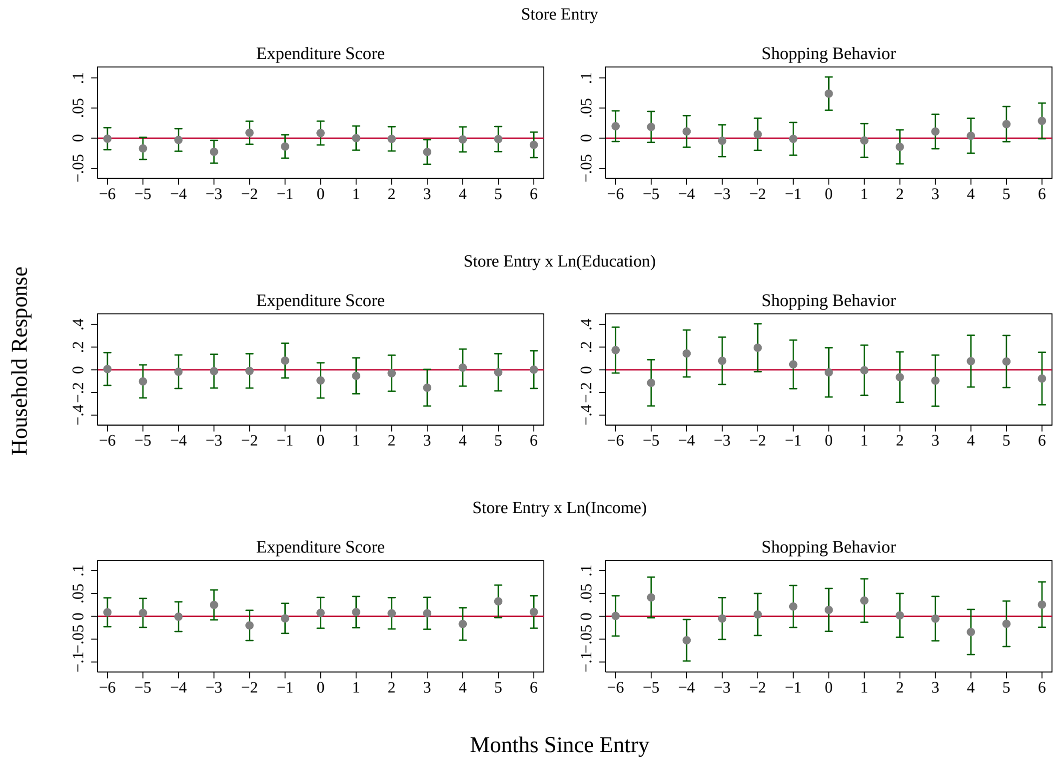
Table A.15: Response of Nutritional Quality of Household Purchases to Changes in Retail Access

	Ln(Expenditure Score)			
	(1)	(2)	(3)	(4)
Ln(Income)	0.0238***			
	(0.0015)			
Ln(Education)	0.202***			
	(0.0068)			
Ln(Store Concentration)	0.00153*	-0.000951	-0.000989	0.00815
	(0.00071)	(0.0027)	(0.0027)	(0.0066)
Ln(Avg. Store Score)	-0.00563	0.00753	0.00932	0.00267
	(0.0057)	(0.011)	(0.011)	(0.011)
Ln(Store Conc.)*Ln(Inc)			-0.00121	-0.00173
			(0.0011)	(0.0012)
Ln(Store Conc.)*Ln(Edu)			-0.00448	-0.00372
			(0.0076)	(0.0084)
Ln(Avg. Store Score)*Ln(Inc)			0.0107***	0.0111**
			(0.0032)	(0.0034)
Ln(Avg. Store Score)*Ln(Edu)			-0.000489	-0.00357
			(0.021)	(0.023)
Observations	3110233	3110233	3110233	2807362
R^2	0.067	0.436	0.436	0.439
Elasticity w.r.t Conc.	0.00153	-0.000951	-0.0000202	0.00928
Elasticity w.r.t Score	-0.00563	0.00753	0.00456	-0.00198
Demographic Controls	Yes	No	No	No
Household Fixed Effects	No	Yes	Yes	Yes
Non-Movers Only	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. Log income and education are both demeaned. Demographic controls include household size dummies, average head of household age, a dummy for marital status of household heads, dummies for households with either a female or male household head only, a dummy for the presence of children, and dummies for whether the household reports being white, black, Asian, or Hispanic.

Figure A.11: Event Study Analysis of Store Entry



Notes: The above plots display the results from an event study analysis of store entry. The first column depicts the coefficient estimates on dummies for months before, during, and after store entry from a regression of log household-level expenditure 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 second 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.

Table A.16: Residualized Household Scores

Nutrient Score

	HI/HE	LI/LE	Diff	t-stat
Raw	0.727	0.597	**0.131**	13.0
Residualized (Chain FEs)	0.694	0.579	0.115	12.1
Residualized (Parent FEs)	0.684	0.579	0.105	11.2
Residualized (Store FEs)	0.669	0.574	**0.095**	10.5

	HI/HE	LI/LE	Diff	t-stat
Raw	1.327	1.020	**0.307**	19.9
Residualized (County FEs)	1.299	1.023	0.276	18.3
Residualized (Tract FEs)	1.186	0.978	**0.208**	15.8

Expenditure Score

	HI/HE	LI/LE	Diff	t-stat
Raw	4.778	4.256	**0.522**	12.8
Residualized (Chain FEs)	4.606	4.147	0.460	9.8
Residualized (Parent FEs)	4.579	4.144	0.435	9.3
Residualized (Store FEs)	4.484	4.086	**0.398**	8.8

	HI/HE	LI/LE	Diff	t-stat
Raw	7.551	6.907	**0.644**	24.7
Residualized (County FEs)	7.519	6.925	0.595	23.1
Residualized (Tract FEs)	7.390	6.901	**0.489**	21.8

Expenditure Share on Soda

	HI/HE	LI/LE	Diff	t-stat
Raw	0.067	0.078	-0.012	-16.4
Residualized (County FEs)	0.067	0.077	-0.010	-14.6
Residualized (Tract FEs)	0.064	0.071	-0.007	-11.9

Expenditure Share on Fruit and Vegetables

	HI/HE	LI/LE	Diff	t-stat
Raw	0.097	0.078	0.018	27.2
Residualized (County FEs)	0.095	0.079	0.016	24.3
Residualized (Tract FEs)	0.089	0.077	0.012	20.9

Total Calories (1000s)

	HI/HE	LI/LE	Diff	t-stat
Raw	109.118	124.625	-15.507	-21.4
Residualized (County FEs)	110.025	122.442	-12.417	-17.4
Residualized (Tract FEs)	107.945	117.728	-9.783	-15.9

D Alternative Measures of Available Product Quality

D.1 Store Inventory

The expenditure score for store s in month t can be written as

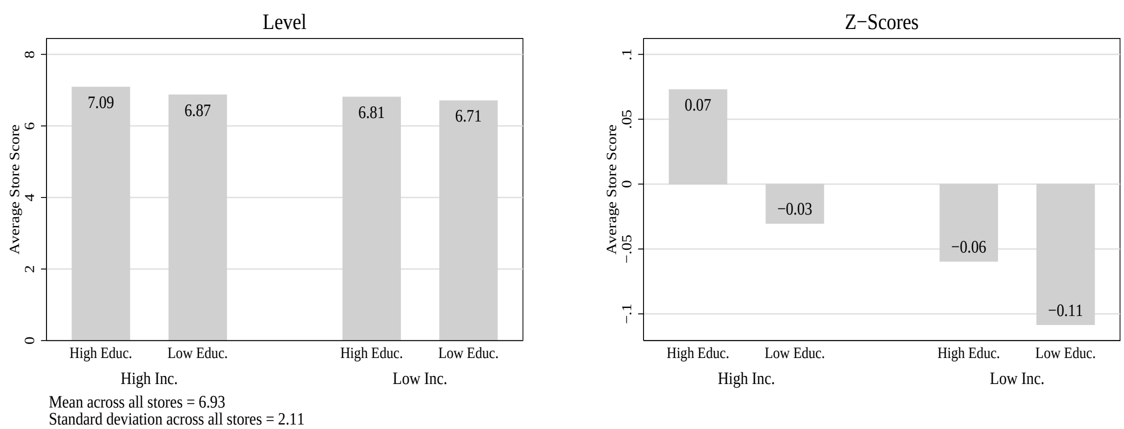
$$Expenditure\ Score_{st} = \left[\sum_{c \in C_{Healthful}} \left(sh_{cst} - sh_{c\bar{h}}^{TFP} \right)^2 | sh_{cst} < sh_{c\bar{h}}^{TFP} \right.$$
$$\left. + \sum_{c \in C_{Unhealthful}} \left(sh_{cst} - sh_{c\bar{h}}^{TPF} \right)^2 | sh_{cst} > sh_{c\bar{h}}^{TFP} \right]^{-1}$$

where c again indexes TFP food categories.[41] 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 TFP-category c UPCs with positive sales in store s in month t, U_{st} is the set of all UPCs with positive sales in store s in month t, and v_{ut} is the total value of sales of UPC u across all stores in the national Scantrack sample in month t. We look at the distance of this representative household's category expenditure shares from the TFP's recommended category expenditure shares for a "typical" household, consisting of a male of age 19-50, a female of age 19-50, one child of age 6-8, and one child of age 9-11. We denote the recommended expenditure share in category c for this modal household by $sh_{c\bar{h}}^{CNPP}$.[42][43],

Figure A.12: Expenditure Scores Across Stores: Available Products



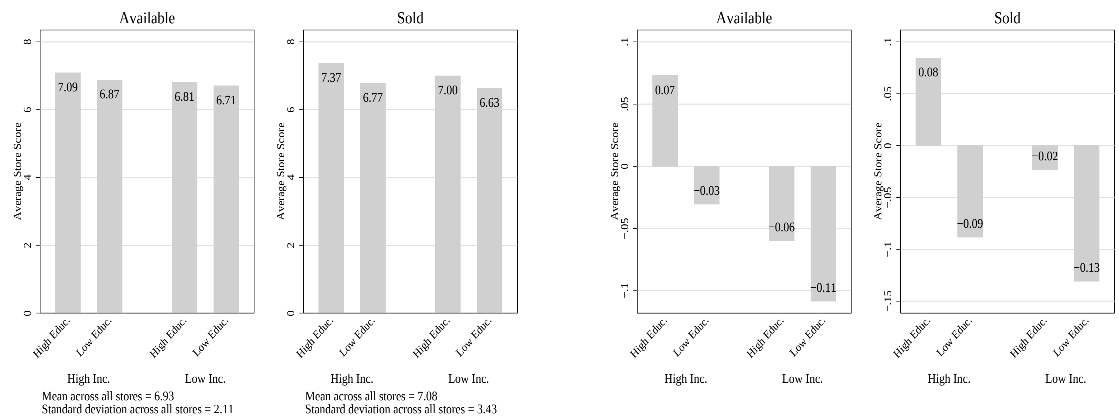
Notes: The figure above presents average store-level expenditure and nutrient scores across census tracts with different socioeconomic compositions. Tracts are considered high income (HI) if their median household income falls above the median level across all tracts ($47,299) and low income (LI) otherwise.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

[41] Refer to Table A.10 for the full list of healthful and unhealthful food categories that we use.

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

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

Figure A.13: Expenditure Scores Across Census Stores: Available versus Sold



Notes: The figure above presents average store-level expenditure and nutrient scores, computed using either store-sales or national-sales weights, across census tracts with different socioeconomic compositions. Tracts are considered high income (HI) if their median household income falls above the median level across all tracts ($47,299) and low income (LI) otherwise. Tracts are considered high education (HE) if their share of college-educated residents falls above the median share across all tracts (22.5%) and low education (LE) otherwise. 54% of tracts are HI/HE, 7% are HI/LE, 11% are LI/HE, and 28% are LI/LE. In each subfigure ("Expenditure Score", "Nutrient Score"), the plot on the left ("Available") replicates the availability indexes presented in Figure A.12 above, while the plots on the right ("Sold") reflect store-level scores calculated using the observed sales in each store. These results are for January 2010; they are representative of the other months in the Scantrack sample.

Table A.17: Neighborhood Characteristics and Nutritional Quality of Product Offerings: Healthful Categories

	(1)Whole-grain	(2)Potatoes	(3)Dark-green-veg	(4)Orange-veg	(5)Legumes	(6)Other-veg	(7)Whole-fruits
Ln(Median Household Income Dens)	0.0190***	0.0513***	0.0567***	0.0443***	0.0242*	0.0778***	0.0814***
	(0.0054)	(0.011)	(0.010)	(0.0078)	(0.010)	(0.011)	(0.011)
Ln(College-educated Share Dens)	-0.00717	-0.0277*	-0.00140	-0.0181*	-0.0335**	-0.0226*	-0.00797
	(0.0055)	(0.011)	(0.010)	(0.0078)	(0.011)	(0.011)	(0.010)
R^2	0.245	0.015	0.028	0.332	0.037	0.016	0.027
Observations	1237176	1237176	1237176	1237176	1237176	1237176	1237176

	(8)Fruit-juice	(9)Skim-milk	(10)Chicken	(11)Fish	(12)Nuts	(13)Eggs
Ln(Median Household Income Dens)	0.0834***	0.102***	0.0113*	0.0634***	-0.0665***	0.0330***
	(0.0097)	(0.010)	(0.0046)	(0.0061)	(0.0093)	(0.010)
Ln(College-educated Share Dens)	0.0276**	0.0253**	-0.00665	0.0158*	0.0513***	-0.0137
	(0.010)	(0.0098)	(0.0048)	(0.0062)	(0.0093)	(0.010)
R^2	0.053	0.033	0.011	0.106	0.059	0.037
Observations	1237176	1237176	1237176	1237176	1237176	1237176

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

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

Table A.18: Neighborhood Characteristics and Nutritional Quality of Product Offerings: Unhealthful Categories

	(1)Non-whole-grain	(2)Whole-milk	(3)Cheese	(4)Beef	(5)Bacon
Ln(Median Household Income Dens)	-0.0739***	0.0679***	0.0488***	0.0352***	-0.0166
	(0.0062)	(0.0089)	(0.011)	(0.011)	(0.0098)
Ln(College-educated Share Dens)	0.0745***	-0.00856	0.00644	-0.0143	0.00537
	(0.0062)	(0.0089)	(0.011)	(0.011)	(0.010)
R^2	0.201	0.078	0.010	0.025	0.056
Observations	1237176	1237176	1237176	1237176	1237176

	(6)Fats	(7)Soft-Drink	(8)Sugars	(9)Soups	(10)Frozen
Ln(Median Household Income Dens)	0.0248*	-0.0549***	-0.0399***	0.0148	0.0387***
	(0.010)	(0.010)	(0.010)	(0.0096)	(0.011)
Ln(College-educated Share Dens)	0.00362	-0.0420***	0.00602	0.0225*	0.0133
	(0.011)	(0.011)	(0.010)	(0.0100)	(0.011)
R^2	0.064	0.069	0.091	0.133	0.012
Observations	1237176	1237176	1237176	1237176	1237176

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

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

D.2 Store Pricing

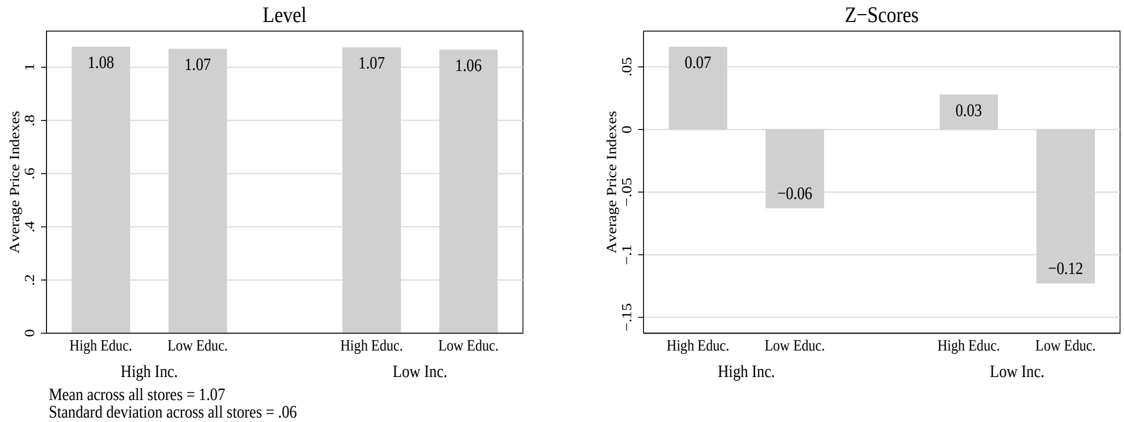
We first study whether stores in low-SES neighborhoods charge higher prices across all food products. We define the aggregate price index for store s in month t as

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

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

Figure A.14 shows how these aggregate price indexes vary with tract demographics from the ACS. Not surprisingly, we see that prices are relatively higher in census tracts with higher levels of income and education. This suggests that low-income households facing tight budget constraints would be even more constrained in their purchases if they shopped in high-SES neighborhoods than they are shopping in low-SES neighborhoods.

Figure A.14: Aggregate Price Indexes Across Census Tracts



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

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

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

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

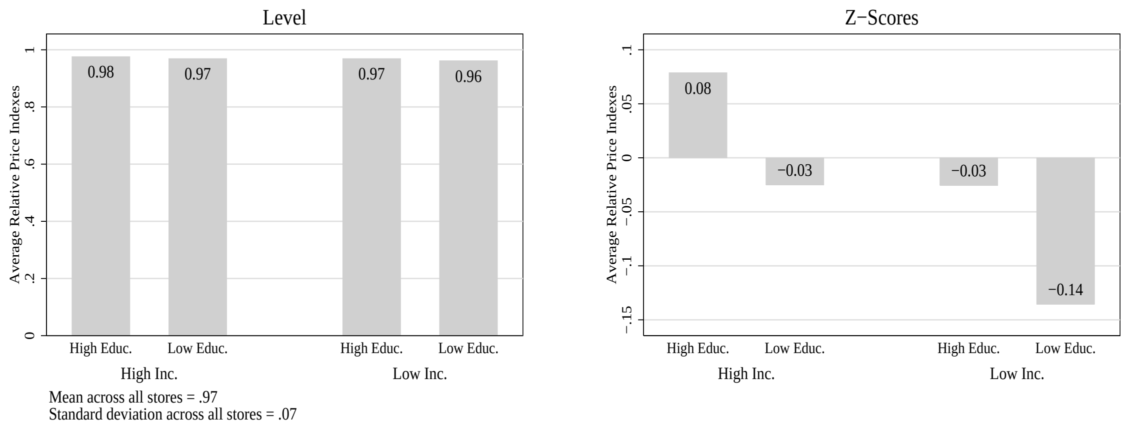
$$P_{st}^{Unhealthful} = \prod_{u \in U_{st}^{Unhealthful}} \left(\frac{p_{ust}}{p_{ut}} \right)^{\frac{v_{ut}}{\sum_{u \in U_{st}^{Unhealthful}} v_{ut}}}$$

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

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

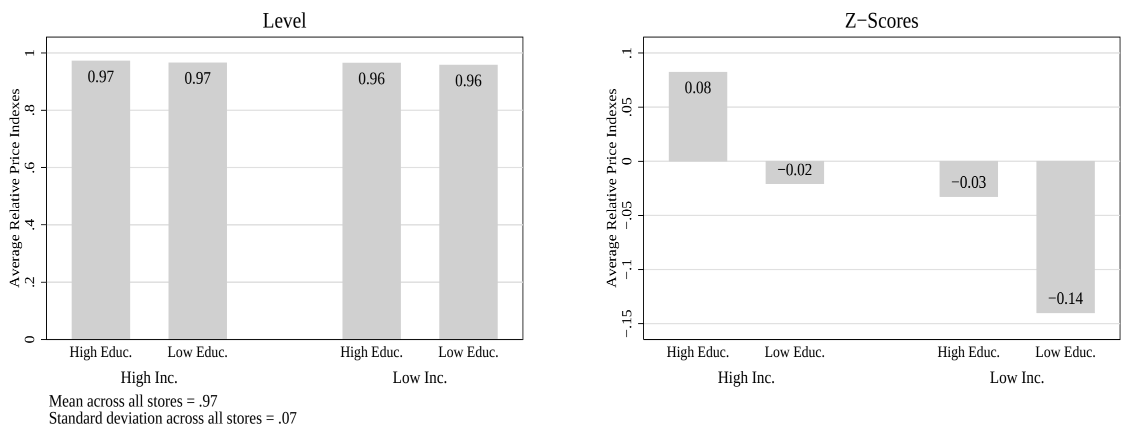
Figure A.15 shows how relative price indexes vary with tract demographics from the ACS. Perhaps strikingly, we see very little variation in relative price indexes across neighborhoods. If anything, relative price indexes are higher in census tracts with higher levels of income and education. Based on these price patterns alone, we would expect the sales of stores in low-SES neighborhoods to be more, as opposed to less, healthful than the sales of stores in neighborhoods with wealthier and more educated residents.

Figure A.15: Relative Price Indexes Across Census Tracts



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

Figure A.16: Relative Price Indexes Across Census Tracts (Based on Storable Products)



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

E Theoretical Framework with Functional Form Assumptions

E.1 Set-up

There are M locations indexed by l. Each location l has a equal population normalized to equal one composed of heterogeneous individuals who differ in their income. We assume that the income distribution of households in each neighborhood is exogenously determined. We also assume that each household is immobile and can shop only at the retail stores in his or her location.

E.1.1 Demand

Household preferences are similar to those in Handbury (2013). Households have a two-tier utility where the upper-tier depends on utility from grocery shopping U_G and the consumption of an outside good z:

$$U = U(U_G(z), z)$$

Outside good expenditure z is increasing in income, both by assumption and in the Nielsen Homescan data. In what follows, we refer to z as indexing a households' income level.

Preferences for groceries are given by a nested-CES utility function over a continuum of 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 household 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, $y - z$, which we normalize to one. That is,

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

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

The grocery demand of a household with income level z in market l can be characterized by their expenditure share on product u:

$$x(u,l,z) = \left(\frac{p(u,l)}{P(q,l)} \right)^{-\sigma_w} \left(\frac{P(q,l)/\alpha(q(u),z)}{P(l,z)} \right)^{-\sigma_a}$$

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 $P(l,z)$ denotes the aggregate taste-adjusted price index that consumers with income level z face in market l, defined as

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

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

$$x(q,l,z) = \left(\frac{P(q,l)/\alpha(q,z)}{P(l,z)}\right)^{-\sigma_a}$$

Assume that there are two types of households, one with high socioeconomic status (SES) and outside good consumption z_H and another with low SES and outside good consumption z_L. The relative expenditure of high-SES to low-SES households on products of the same healthfulness in the same location can be expressed as

$$\frac{\partial x(q,l,z_H)/x(q,l,z_L)}{\partial q} = \sigma_a \left(\frac{\alpha(q,z_H)}{\alpha(q,z_L)}\right)^{\sigma_a} \left(\frac{P(l,z_H)}{P(l,z_L)}\right)^{\sigma_a} \left(\frac{\alpha_1(q,z_H)}{\alpha(q,z_H)} - \frac{\alpha_1(q,z_L)}{\alpha(q,z_L)}\right) \tag{A.1}$$

High-SES households will spend relatively more than low-SES households on healthful products when $\frac{\alpha_1(q,z_H)}{\alpha(q,z_H)} > \frac{\alpha_1(q,z_L)}{\alpha(q,z_L)}$ for all q. We assume that this inequality holds in all cases where tastes vary with SES.

Here we have assumed that preferences vary with socioeconomic status due to variation in the exogenous taste-shifters. This can be thought of as a reduced-form way of capturing the variation in demand that arises endogenously from complementarities between non-food products and the quality of food products. For example, the results here carry through in a model that instead uses the nested-logit demand system from Fajgelbaum et al. (2011) and assumes that high- and low-SES households earn different incomes. In that model, the differences in consumption arise endogenously due to a complementarity between the quality of the differentiated food product purchased and the quantity of a homogeneous outside good. We choose to use the nested-CES model above because it allows for us to "turn-off" the non-homotheticity in demand, in order to demonstrate how the observed differences in demand across high- and low-SES households can be generated by supply-side mechanisms alone. The Fajgelbaum et al. (2011) nested-logit model is a variant of the vertical differentiation model from Shaked and Sutton (1982, 1983).

In the classic models of vertical differentiation, variation in the demand for quality is isomorphic with variation in households' price sensitivities, which would generate your more standard "income effect" (where households with lower incomes purchase lower quality products because they cost less). Here, however, the α parameters that govern demand for quality are different to the σ parameters that govern households' price elasticities. We could, therefore, allow for households' demand for quality and price sensitivities to vary with their income or socioeconomic status as in Handbury (2013). The results below follow through in an extension of this model where the key substitution elasticity governing how prices influence how households allocate expenditure across healthy and unhealthy products, σ_a, varies with income. In this case, the derivative in equation (A.1) above becomes:

$$\frac{\partial x(q,l,z_H)/x(q,l,z_L)}{\partial q} = \left(\frac{x(q,l,z_H)}{x(q,l,z_L)}\right) \left\{ \underbrace{\left[(\sigma_a(z_L) - \sigma_a(z_H))\frac{P_1(q,l)}{P(q,l)}\right]}_{\text{Price Sensitivity}} + \underbrace{\left[\sigma_a(z_H)\left(\frac{\alpha_1(q,z_H)}{\alpha(q,z_H)}\right) - \sigma_a(z_L)\left(\frac{\alpha_1(q,z_L)}{\alpha(q,z_L)}\right)\right]}_{\text{Tastes}} \right.$$

where there is an extra term related to the difference in the price sensitivities of high- and low-SES households. When high-SES households are less price sensitive in switching across product quality groups, that is, $\sigma_a(z_L) > \sigma_a(z_H)$, and high quality products are relatively more expensive than low quality products, $P_1(q,l) > 0$, then this term will be positive, driving high-SES households to consume relatively more healthful products than low-SES households. The second term is similar to the derivative in equation (A.1), except that each quality elasticity has a z-specific price elasticity coefficient. This term will be positive, driving high-SES households to consume relatively more healthful products, when $\left(\frac{\alpha_1(q,z_H)}{\alpha(q,z_H)}\right)\left(\frac{\alpha_1(q,z_L)}{\alpha(q,z_L)}\right)^{-1} > \frac{\sigma_a(z_H)}{\sigma_a(z_L)}$; that is, when the relative quality elasticity across H and L households is greater than the relative substitution elasticity (which governs the relative degree of price sensitivity). We present the version of the model where only taste parameters vary with income as this version of the model is more tractable and provides a clearer intuition for the main results.

E.1.2 Supply

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

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

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

$$x(u,l) = \lambda_l x(u,l,z_H) + (1-\lambda_l) x(u,l,z_L)$$

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

$$P(q,l) = (N(q,l))^{\frac{1}{1-\sigma_w}} \left(\frac{c(q,l)}{\rho_w}\right) \tag{A.2}$$

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

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

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

$$x(q,l) \quad = \quad (N(q,l))^{\frac{\sigma_w-\sigma_a}{1-\sigma_w}} \left(\frac{c(q,l)}{\rho_w}\right)^{-\sigma_a} \left[\lambda_l \left(\alpha(q,z_H)P(l,z_H)\right)^{\sigma_a} + (1-\lambda_l)\left(\alpha(q,z_L)P(l,z_L)\right)^{\sigma_a}\right] \tag{A.3}$$

E.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

$$x(q,l) = \frac{f}{c(q,l)}(\sigma_w - 1) \tag{A.4}$$

E.2 Comparative Statics

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

Taken together, the zero profit condition (Equation (A.4)), the aggregate demand condition (Equation (A.3)), and the healthfulness-location-specific price index (Equation (A.2)) implicitly define the number of varieties of healthfulness q in each location l as a function of the fixed and marginal costs of producing each variety, the local share of households in each socioeconomic class, and the model parameters:

$$N(q,l) \quad = \quad \Gamma \underbrace{(c(q,l))^K}_{Cost} \underbrace{\left[\lambda_l \left(\alpha(q,z_H)P(l,z_H)\right)^{\sigma_a} + (1-\lambda_l)\left(\alpha(q,z_L)P(l,z_L)\right)^{\sigma_a}\right]^{\frac{\sigma_w - 1}{\sigma_w - \sigma_a}}}_{Demand} \tag{A.5}$$

where $\Gamma = \left[f(\sigma_w - 1)\left(\frac{\sigma_w - 1}{\sigma_w}\right)^{-\sigma_a}\right]^{\frac{1-\sigma_w}{\sigma_w - \sigma_a}} > 0$ and $K = \frac{(1-\sigma_w)(\sigma_a - 1)}{\sigma_a} < 0$. 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 healthfuln9ess distribution in different locations. The second, labeled $Demand$, reflects the role played by differences in tastes across socioeconomic groups combined with differences in the share of socioeconomic classes in each location's population.

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

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

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

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,

$$\frac{N(q,l)}{N(q',l)} = \left(\frac{\alpha(q)}{\alpha(q')}\right)^{\frac{\sigma_a(\sigma_w-1)}{\sigma_w-\sigma_a}} \tag{A.7}$$

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

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

$$N(q,l) = \Gamma\left(c(q,l)\right)^K \left(\alpha P(l)\right)^{\frac{\sigma_a(\sigma_w-1)}{\sigma_w-\sigma_a}} \tag{A.8}$$

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

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

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

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

$$N(q,l) = \Gamma\left(c(q)\right)^K \left[\lambda_l \left(\alpha(q,z_H)P(l,z_H)\right)^{\sigma_a} + (1-\lambda_l)\left(\alpha(q,z_L)P(l,z_L)\right)^{\sigma_a}\right]^{\frac{\sigma_w-1}{\sigma_w-\sigma_a}} \tag{A.9}$$

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

$$\frac{N(q,l)}{N(q,l')} = \left(\frac{\alpha(q,z_H)P(l,z_H)}{\alpha(q,z_L)P(l,z_L)}\right)^{\frac{\sigma_a(\sigma_w-1)}{\sigma_w-\sigma_a}} \tag{A.10}$$

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 $\frac{\alpha_1(q,z_H)}{\alpha(q,z_H)} > \frac{\alpha_1(q,z_L)}{\alpha(q,z_L)}$. This is the same condition required for the relative expenditure share of high-SES to low-SES households to be increasing in quality:

$$\frac{\partial \frac{N(q,l)}{N(q,l')}}{\partial q} = A\frac{N(q,l)}{N(q,l')}\left(\frac{\alpha_1(q,z_H)}{\alpha(q,z_H)} - \frac{\alpha_1(q,z_L)}{\alpha(q,z_L)}\right) > 0 \text{ for } \frac{\alpha_1(q,z_H)}{\alpha(q,z_H)} > \frac{\alpha_1(q,z_L)}{\alpha(q,z_L)} \tag{A.11}$$

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

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

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

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

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

$$x(q,l,z) = (\alpha(q,z))^{\sigma_a}\left(\frac{P(q,l)}{P(l,z)}\right)^{1-\sigma_a} \tag{A.12}$$

We saw above that high-SES households purchase more healthful food products either because there are more of these products available in the locations where they live and/or because they have a stronger taste for these products. To see this mathematically, note that the average expenditure share of healthfulness q varieties for high-

SES relative to low-SES individuals living across two locations, l and l', is given by

$$\begin{aligned}\frac{x(q,z_H)}{x(q,z_L)} &= \left(\frac{\lambda_l x(q,l,z_H)+\lambda_{l'}x(q,l',z_H)}{(1-\lambda_l)x(q,l,z_L)+(1-\lambda_{l'})x(q,l',z_L)}\right)\left(\frac{2-\lambda_l-\lambda_{l'}}{\lambda_l+\lambda_{l'}}\right) \\ &= \underbrace{\left(\frac{\alpha(q,z_H)}{\alpha(q,z_L)}\right)^{\sigma_a}}_{Tastes}\underbrace{\left(\frac{\lambda_l\left(\frac{P(q,l)}{P(l,z_H)}\right)^{1-\sigma_a}+\lambda_{l'}\left(\frac{P(q,l')}{P(l',z_H)}\right)^{1-\sigma_a}}{(1-\lambda_l)\left(\frac{P(q,l)}{P(l,z_L)}\right)^{1-\sigma_a}+(1-\lambda_{l'})\left(\frac{P(q,l')}{P(l',z_L)}\right)^{1-\sigma_a}}\right)}_{Availability}\left(\frac{2-\lambda_l-\lambda_{l'}}{\lambda_l+\lambda_{l'}}\right) \qquad (A.13)\end{aligned}$$

The first term reflects taste differences alone. The second term reflects differences in access that, as we outlined above, could be the result of either firms catering to local tastes or to supply-side factors, such as the complementarities between healthfulness and local distribution costs proposed above. These differences in local product availability are reflected through the local price indexes, with $P(q,l)$ decreasing in the number of healthfulness q varieties that are available in location l. There are relatively more healthful varieties available in a location l where there are more high-SES individuals, so the local healthfulness q price index will be lower, relative to the overall price index a household faces in a location ($P(l,z_H)$ or $P(l,z_L)$), in high-λ_l locations relative to locations with a lower share of high-SES residents. This correlation implies that the numerator of the availability term is increasing in quality (since $1-\sigma_a<0$), whereas the denominator is falling in quality.

This is easy to see in the case where tastes are identical across households:

$$\frac{x(q,z_H)}{x(q,z_L)} = \left(\frac{\lambda_l\left(\frac{P(q,l)}{P(l)}\right)^{1-\sigma_a}+\lambda_{l'}\left(\frac{P(q,l')}{P(l')}\right)^{1-\sigma_a}}{(1-\lambda_l)\left(\frac{P(q,l)}{P(l)}\right)^{1-\sigma_a}+(1-\lambda_{l'})\left(\frac{P(q,l')}{P(l')}\right)^{1-\sigma_a}}\right)\left(\frac{2-\lambda_l-\lambda_{l'}}{\lambda_l+\lambda_{l'}}\right) \qquad (A.14)$$

To the extent that healthful goods are relatively more abundant in locations with many high-SES individuals, $P(q,l)$ will also be lower in these locations for healthful goods. Since, by definition, more high-SES individuals live in the locations with more abundant healthful goods, they will tend to consume more healthful goods on average across the two locations than low-SES individuals, who are more likely to live in locations with fewer healthful goods available.

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

$$\frac{x(q,l,z_H)}{x(q,l,z_L)} = \left(\frac{\alpha(q,z_H)}{\alpha(q,z_L)}\right)^{\sigma_a}\left(\frac{P(l,z_L)}{P(l,z_H)}\right)^{1-\sigma_a} \qquad (A.15)$$

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

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

$$\frac{x(q,l,z_H)}{x(q,l,z_L)} = \left(\frac{\alpha_l(q,z_H)}{\alpha_l(q,z_L)}\right)^{\sigma_a} \left(\frac{P(l,z_L)}{P(l,z_H)}\right)^{1-\sigma_a} \tag{A.16}$$

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

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

If we recast locations as markets that are separated by time instead of by space, we can use the model presented above to interpret the changes that we observe in household purchases over time as their retail environments change. Our goal is to estimate the impact that policies to improve access in underserved areas will have on household purchases without any changes in tastes over time. This is unlikely to be the case in the data, however. The observed changes in access are likely to be correlated with unobserved changes in tastes since households sort into neighborhoods that offer consumption amenities that suit their tastes and stores select their product offerings to cater to local tastes. To see this, consider how the average expenditure share of healthfulness q varieties varies for a household of the same SES h between a market l and another market l'. When deriving this expenditure share for Equation (A.12) above, we assumed that tastes do not vary across markets. This is reasonable when thinking about how household expenditures vary across geographic markets in a single time period, but less reasonable when considering how expenditures vary for a given household over time. Extending Equation (A.12) to allow for tastes to vary over time, we can see that the relative expenditures in market l relative to market l' depend on the change in tastes across the two markets as well as the change in availability:

$$\frac{x(q,l,z)}{x(q,l',z)} = \underbrace{\left(\frac{\alpha_l(q,z)}{\alpha_{l'}(q,z)}\right)^{\sigma_a}}_{Tastes} \underbrace{\left(\frac{P(q,l)}{P(q,l')}\frac{P(l',z)}{P(l,z)}\right)^{1-\sigma_a}}_{Availability} \tag{A.17}$$

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