The Geography of Poverty and Nutrition: Food Deserts and Food Choices Across the United States

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Abstract

We study how much and why healthful eating varies by income in the United States. Using the Nielsen Homescan and retail scanner data, we find that the highest-income quartile of households buy groceries that are 0.25 standard deviations more healthful than the lowest-income quartile. Stores in low-income neighborhoods offer fewer produce items and overall less-healthful groceries. Notwithstanding, we find no evidence to support the hypothesis that the low availability of healthful groceries causes unhealthful eating. Using an event study framework, we find that nearby supermarket entry does not increase households' produce purchases or the overall healthfulness of grocery purchases. The reason is that supermarket entry largely diverts expenditures from other supermarkets, which moderates the effects of entry on choice sets. We then estimate a formal demand model and use estimated preferences to decompose differences in purchasing patterns between low- and high-income households. We find that 92% of the nutrition-income gradient is driven by differences in demand across products, while only 8% can be attributed to differences in supply. The demand impact can be broken down into 72% due to differences in UPC demand, 25% due to product group demand differences, and -5% due to nutrient preferences. The 8% supply effect is entirely driven by different product offerings, with prices playing essentially no role.

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I Introduction

Studies by Chetty, Hendren, Kline, and Saez (2014), Saez and Piketty (2003), and many others have drawn increased attention to the causes and consequences of socioeconomic inequality. These consequences play out in many different ways, including educational opportunities, health outcomes, and involvement with the criminal justice system. In this paper, we study one important correlate of socioeconomic status – what we eat and drink, which in turn affects our health – and quantify the economic mechanisms that drive the nutrition-income relationship.

Obesity is now one of the most important health problems in the U.S. and many other countries. Thirty-five percent of American adults are obese, up from 15 percent in the late 1970s, and an additional 34 percent are overweight (NCHS 2013, 2014).[1] Obesity is estimated to be responsible for 10-27 percent of US medical costs, amounting to several hundred billion dollars annually (Finkelstein *et al.* 2009, Cawley *et al.* 2015). At least for women, there are meaningful socioeconomic differences in obesity: low-income women are 45 percent more likely than high-income women to be obese, and women who have not completed college are about 70 percent more likely than those who have (Ogden *et al.* 2010). It is well-established that there are socioeconomic differences in what people eat and drink and that these choices are a leading contributor to obesity.[2]

Economists might propose four broad categories of explanations for why income could be associated with more healthful eating: prices, availability, preferences, and information. Healthful foods could either cost more per calorie or could cost relatively more in low-income areas.[3] Healthful foods could be less available in low-income areas, either because of preference externalities or because of higher costs.[4] Income could be associated with preferences, either for the taste of healthful foods or for correlates of healthfulness such as perishability. Finally, higher-income households could be better informed about what foods are healthful and the benefits of healthful eating.

Teasing apart these explanations for the nutrition-income relationship is crucial for understanding whether and how policymakers should intervene. For example, the public health literature and public policy debate have given substantial attention to the hypothesis that low availability of healthful foods in low-income neighborhoods causes the poor to eat less healthfully.[5] A number of

[1] Overweight and obese, are defined as having Body Mass Index (BMI) of at least 25 and 30 kg/m^2, respectively, where BMI is weight divided by height squared.

[2] Results from the National Health and Nutrition Examination Survey (NHANES) show that high-income adults get a larger share of their calories from protein and fiber and a smaller share from sugar and cholesterol (USDA 2014a).

[3] Cutler, Glaeser, and Shapiro (2003), Lakdawalla and Philipson (2002), and Philipson and Posner (1999) highlight the importance of prices and argue that cost decreases for unhealthful foods are largely responsible for the obesity increase of the past 40 years.

[4] Recent empirical evidence provides some indirect support for mechanisms that could generate differences in availability: Ellickson (2006, 2007) highlights the role of fixed costs in grocery retail, which are necessary for preference externalities, and people who moved to higher-income neighborhoods in the Moving to Opportunity randomized experiment were less likely to be obese (Kling, Liebman, and Katz (2007), Ludwig *et al.* (2011)).

[5] In an influential review article, Bitler and Haider (2011) write that "it appears that much of the existing research implicitly assumes that supply-side factors cause any food deserts that exist." However, "we are unaware of any

policies are built around this hypothesis: for example, the US Healthy Food Financing Initiative allocates $125 million annually in grants, loan subsidies, and technical assistance for grocers in underserved areas.[6] Such policies could increase both efficiency and equity if they address market failures, reduce costs, and affect purchases. But if the nutrition-income relationship is primarily driven by preference differences, it is less clear that supply-side policies will have any effect, let alone be welfare-enhancing.

Our paper combines reduced-form analyses with a structural demand model to quantify the relative importance of prices, availability, preferences, and information in generating the nutrition-income relationship. We exploit a rich combination of datasets, including Nielsen Homescan, a 60,000-household, nationally-representative panel survey of grocery consumption, Nielsen RMS, which provides product-level sales data for 35,000 retail stores nationwide, data on foods' nutritional content and perishability, geocoded data on entry of new supermarkets, and additional survey-based measures of Homescan households' nutritional knowledge and information sets.

We begin by laying out the relevant stylized facts, some of which are already well-known in the public health literature. First, there is a meaningful nutrition-income relationship in grocery purchases: the top income quartile buys groceries that are 0.25 standard deviations more healthful than the bottom quartile, as measured by our Health Index, which scores purchases based on U.S. government recommendations. Second, healthful food costs more for all households, although the relative price is not as high for low-income households. Third, the average store in low-income neighborhoods offers less healthful groceries than in high-income neighborhoods. This is almost entirely explained by the fact that there are fewer "supermarkets" (by which we mean large grocery stores, supercenters, and club stores) and more drug and convenience stores in low-income neighborhoods. Thus, differences in local availability of healthful groceries could in principle cause income-related differences in purchases. Fourth, however, even low-income households buy the vast majority of their groceries from supermarkets. This is made possible by the fact that the mean (median) shopping trip is five (three) miles one-way, which moderates the role that local neighborhood supply conditions play in constraining choice sets.

Of course, supply and demand for healthful foods is determined in equilibrium. To test whether supply causes less healthful purchases, we exploit supply shifts from supermarket entry, conditional on household fixed effects. We find that when supermarkets enter nearby, grocery expenditures shift markedly toward the entrant chains. However, these expenditures are primarily diverted from

study that has systematically examined whether supply or demand factors explain the existence of food deserts."

[6]The 2001 Food Poverty Eradication Bill required local and national governments in the United Kingdom to document and take actions to eliminate food deserts. In the U.S., the Healthy Food Financing Initiative has awarded over $140 million since 2011 through a suite of programs that finance and provide technical assistance to grocery stores, farmers markets, and other suppliers of healthful foods in under-served areas (TRF 2015a). Pennsylvania's Fresh Food Financing Initiative provided $85 million grants and loans to retailers offering fresh foods in under-served low-income areas (TRF 2015b). Projects aimed at "eliminating food deserts" were eligible for the $100 million in Community Transformation Grants under the Affordable Care Act (HHS 2011).

other supermarkets, not from drug stores and convenience stores – even for households living in zip codes with no supermarkets. Thus, entry likely reduces transport costs, but effects on choice sets are muted. We find tightly-estimated zero effects on two measures of healthful purchases: the share of calories from produce and the Health Index of all grocery purchases. We can bound the effects of supermarket entry within a 10-minute drive at no more than 1/6 the inter-income-quartile range of produce calorie share and no more than 1/32 the inter-income-quartile range of Health Index. Thus, having fewer supermarkets nearby explains essentially none of the nutrition-income relationship.

If availability does not explain the nutrition-income relationship, then what does? We use the framework of Gelbach (2015) to measure the contributions of observable household covariates to the unconditional nutrition-income correlation. The correlation is only 16 percent as strong when conditioning on household fixed effects, which suggests that little of the nutrition-income relationship can be attributed to the short-term effects of a relaxed budget constraint. Building on the finding of Handbury, Rahkovsky, and Schnell (2015) that education is an important contributor to the nutrition-income relationship, we find some evidence that information sets (measured by occupational knowledge and responses to a food knowledge quiz) are also relevant. More than half of the nutrition-income correlation is unexplained by standard household demographics and census tract indicators, which suggests that factors such as unobserved preferences may be important. Consistent with this, we find evidence that early-life habits (measured by the average Health Index in the household head's state of birth) are correlated with current purchases for observationally-equivalent households that currently reside in the same state.

Finally, we formalize our reduced form results in a demand model based on Dubois, Griffith, and Nevo (2014). The model allows for Constant Elasticity of Substitution (CES) preferences over individual product UPCs, combined with Cobb-Douglas preferences for product groups (milk, breads, candy, vegetables, etc.) and aggregate preferences over specific macronutrients (saturated fat, sugar, salt, etc.). Like many continuous demand systems, the functional form assumptions are somewhat restrictive, but this approach has the benefit of giving a simple and transparent estimating equation.

These estimates show that preferences for healthful macro nutrients do not systematically vary across the income distribution. Low income households dislike unhealthful cholesterol and sodium more than higher income households. However, higher income households have a stronger demand for fruit and fiber. In contrast, we find substantial preference heterogeneity across product group categories and individual UPCs. Higher income households prefer produce and prepared foods, while lower-income households prefer to consume more frozen foods. It appears other product characteristics, such as shelf life, lead lower income households to choose less healthful foods, as opposed to a direct preference to consume unhealthful nutrients.

Finally, we use our model of food demand to decompose the nutrition-income gradient into

causes due to supply versus household preferences. We find that 92% of the nutrition-income gradient is driven by differences in demand across products, while only 8% can be attributed to differences in supply. The demand impact can be broken down into 72% due to differences in UPC demand, 25% due to product group demand differences, and -5% due to nutrient preferences. The 8% supply effect is entirely driven by different product offerings, with prices playing essentially no role.

Our paper fits within a broad literature on the economics of nutrition and health; see Cawley (2015) for a recent review. Anderson and Matsa (2011), Currie, DellaVigna, Moretti, and Pathania (2010), Davis and Carpenter (2009), and Dunn (2010) study the effects of proximity to fast food restaurants on food consumption and obesity, complementing our analysis of supermarket entry. Their results are qualitatively consistent with ours in that they suggest that the causal impact of unhealthful food supply is small, relative to either the overall obesity rate or the nutrition-income relationship. Courtemanche and Carden (2011) study the effects of Walmart Supercenter entry on obesity, using the Holmes (2011) instrument for Walmart expansion (distance from the headquarters in Bentonville, Arkansas).[7] Also using the Holmes (2011) instrument, Volpe, Okrent, and Leibtag (2013) study the effects of supercenter expansion on the healthfulness of grocery purchases.[8]

Our reduced form analysis in Section IV is broadly comparable to the existing work of Handbury, Rahkovsky, and Schnell (2015), and our results echo their conclusion that grocery store entry does not significantly affect healthful eating. We make several incremental contributions, such as showing *why* entry has little effect on healthfulness – households travel long distances to shop, so supermarket entry largely diverts expenditures from other supermarkets. Relative to their paper, we make two more discrete contributions. First, our research question is to understand and decompose the multiple causes of the nutrition-income relationship, while their main contribution is to "show that spatial disparities in access play a limited role in generating socioeconomic disparities in nutritional consumption" (page 1). Second, our structural demand model extends the reduced form results and allows us to fully decompose the sources of the nutrition-income relationship.

In the public health literature, Larson, Story, and Nelson (2009) review 54 studies documenting differences in food access across neighborhoods. These studies are typically either detailed inventories of product availability at specific retailers in specific local areas (e.g. Sharkey, Horel, and Dean (2010)) or nationwide studies of store counts by neighborhood income without detailed product data (e.g. Powell *et al.* (2007)). Even in establishing stylized facts, the Nielsen Homescan and RMS data in our paper and in Handbury, Rahkovsky, and Schnell (2015) are groundbreaking in

[7] Courtemanche and Carden (2011) find that Supercenters increase BMI and obesity. Our results that supermarket entry does not significantly affect nutritional content per calorie consumed provide support for their interpretation that the mechanism is reduced prices per calorie.

[8] Volpe, Okrent, and Leibtag (2013) find that supercenter expansion reduces the healthfulness of grocery purchases. Their results could differ from ours for a number of reasons. Relative to their paper, we benefit from having precise dates and geocoded locations of store entry for several different supermarket chains, which allows more precise identification.

that they provide both large nationwide samples *and* detailed product availability and purchase information. There are small handful of studies in the public health literature that examine food consumption before vs. after supermarket entry, e.g. Cummins *et al.* (2005), Cummins, Flint, and Matthews (2015), Elbel *et al.* (2015), and Wrigley, Warm, and Margetts (2003). However, according to a major report by the U.S. Department of Agriculture (2009, page v), "the findings are mixed," perhaps because the standard in this literature has been to study entry of *one* retail establishment, which limits statistical power and generalizability and makes it more difficult to establish a credible counterfactual. By contrast, our paper and Handbury, Rahkovsky, and Schnell (2015) evaluate the effects of *thousands* of supermarkets as they enter and exit across the U.S. during a ten-year period.

Sections II through IX, respectively, present data, stylized facts, reduced form empirical analysis, structural demand model, structural estimates, and the conclusion.

II Data

II.A Nielsen Homescan and Retail Scanner Data

We use the Nielsen Homescan Panel for 2004-2013 to measure grocery purchases.[9] Homescan includes about 39,000 households each year for 2004-2006, and about 61,000 households each year for 2007-2013. Homescan households record UPCs of all consumer packaged goods they purchase from any outlet. We consider only food and drink purchases, and we further exclude alcohol and health and beauty products such as vitamins.

We focus on explaining income-related differences in grocery purchases, not overall diets, because Homescan does not include data on food purchased in restaurants.[10] One additional limitation of Homescan is that most households only record purchases of packaged items with UPCs, not non-packaged groceries such as bulk produce and grains. For 2004-2006, however, the data also include an 8,000-household "magnet" subsample that also recorded prices and weights of non-packaged groceries. We use the magnet data for robustness checks.[11] Appendix Figure A1 shows that about 60 percent of magnet households' produce calories are from packaged goods that are observed in the full Homescan sample, and this proportion does not vary statistically by income.[12]

[9] See Einav, Leibtag, and Nevo (2010) for a recent validation study of Homescan.

[10] The National Health and Nutrition Examination Survey (NHANES) finds that Americans consume 34 percent of calories away from home, including 25 percent in restaurants (USDA 2014b). For all income groups, the share of healthful and unhealthful macronutrients (protein, carbohydrates, saturated fat, etc.) consumed away from home is about the same as the share of calories consumed away from home, so grocery purchases are not a systematically biased measure of overall diet healthfulness.

[11] The magnet data continue after 2006, but panelists now record only expenditures and not weights purchased. Because prices per unit weight can vary substantially across stores and neighborhoods, we do not use these data to construct food purchases.

[12] After excluding canned, frozen, and dried produce, about 39 percent of magnet households' fresh produce calories are from packaged items. Households with incomes less than about $20,000 buy about five percentage points less of

Homescan households report demographic variables such as income, educational attainment, presence of children, and race. In addition to the standard Homescan data, we observe occupation, results of a food knowledge quiz, and state of birth from add-on surveys carried out by Bronnenberg, Dubé, and Gentzkow (2012) and Bronnenberg *et al.* (2015).[13] Panel A of Table 1 presents descriptive statistics for Homescan households. In the usual case where there are two household heads, we use the mean of age, education, and other variables observed for both heads. Table 1 and all other Homescan results are weighted for national representativeness.

their fresh produce calories from packaged items, but the proportion is constant at moderate and high incomes.

[13]Panelists were asked to identify the most common additive to table salt (correct answer: iodine), the scientific name for baking soda (correct answer: sodium bicarbonate), and the most common ingredient of granulated sugar (correct answer: sucrose). The "Food knowledge" variable is the share of these questions answered correctly, normalized to mean 0, standard deviation 1.

Table 1: **Data: Descriptive Statistics**

Panel A: Nielsen Homescan Households

Variable	Non-missing observations	Mean	Standard deviation
Household income ($000s)	545,907	62.2	45.4
Years education	545,907	13.9	2.07
Age	545,907	52.4	14.4
1(Have children)	545,907	0.33	0.47
Health occupation	278,801	0.054	0.21
Food knowledge	224,130	0	1

Panel B: Zip Code Establishment Counts

Variable	Mean	Standard deviation
Grocery	2.41	4.53
Grocery (<10 employees)	1.17	3.49
Grocery (10-49 employees)	0.58	0.99
Grocery (>50 employees)	0.66	1.19
Supercenters/club stores	0.15	0.45
Drug stores	1.57	2.58
Convenience stores	4.52	5.73
Meat/fish/produce stores	0.40	1.15

Panel C: UPC Characteristics

Variable	Mean	Standard deviation
Package size (grams)	714	1481
Calories	1203	3225
Grams per 1000 calories		
Fat	34.2	32.2
Saturated fat	11.2	13.2
Cholesterol	0.085	0.28
Sodium	9.85	225
Carbohydrates	153	184
Fiber	12.2	31.3
Sugar	73.6	76.0
Protein	31.9	38.5

Notes: Homescan statistics are at the household-by-year level, and observations are weighted for national representativeness. Health occupation and Food knowledge are from Homescan add-on surveys carried out by Bronnenberg, Dubé, and Gentzkow (2012) and Bronnenberg *et al.* (2015). Food knowledge is the share the following questions answered correctly: identify the most common additive to table salt (correct answer: iodine), the scientific name for baking soda (correct answer: sodium bicarbonate), and the most common ingredient of granulated sugar (correct answer: sucrose). Zip code establishment counts are from Zip Code Business Patterns data for 2004-2013. UPC characteristics are for all 1.54 million UPCs that ever appear in the Nielsen Homescan or RMS data.

The Nielsen Retail Scanner Data (RMS) consists of weekly prices and sales volumes for each UPC sold at approximately 35,000 stores at 94 retail chains for 2006-2013. We exclude liquor stores. RMS includes 53, 32, 55, and 2 percent of sales in the grocery, mass merchandiser, drug, and convenience store channels, respectively. Analogous to Homescan, RMS does not include sales of bulk produce and other non-packaged items.

II.B Grocery Retail Establishments

Studying the effects of grocery store entry requires reliable data on store open dates to avoid attenuation bias. Some datasets, such as InfoUSA and the National Establishment Time Series, might be reasonable for cross-sectional analyses, but they do not sufficiently precisely record the open dates of new establishments; see Bitler and Haider (2011, page 162) for further discussion. Furthermore, to measure true changes in availability experienced by consumers, we must use actual new establishments, not store locations that continue to operate but change management.

We measure entry with two datasets. First, we gathered the exact store open dates and addresses for three specific chains of large grocery stores and/or supercenters.[14] This dataset includes 1914 new stores opened between January 2004 and December 2013. Second, we use Zip Code Business Patterns (ZBP), which gives a count of establishments by NAICS code and employment size category for every zip code as of March 10th of each year. The ZBP data are drawn from tax records, the U.S. Census Company Organization Survey, and other administrative data. Panel B of Table 1 presents ZBP descriptive statistics.

II.C Nutrition Facts and the Health Index

We purchased UPC-level nutrition facts from Gladson, and we gathered nutrition facts for non-packaged items from the USDA National Nutrient Database for Standard Reference (USDA 2014c). We model demand for individual macronutrients (protein, fat, sugar, etc.), but we also want to characterize goods and preferences using a one-dimensional index of healthfulness. The most natural option is the USDA's Healthy Eating Index HEI, which was designed to score entire diets on an easily-understandable range from 0-100. However, the HEI has sharp non-linearities because it values a balanced diet, so an item's contribution to the HEI depends on the other items consumed. This is less appropriate for datasets like Homescan and RMS where consumers' full diets are not observed.

We therefore construct a modified version of the HEI that is based on the same U.S. government dietary recommendations but is linear and additively separable in macronutrients. The U.S. government Dietary Guidelines are clearly organized around "good" macronutrients to "increase" vs. "bad" macronutrients to "reduce." According to the Dietary Guidelines, the "good" macronu-

[14] The Nielsen user agreement does not allow us to identify specific retailers.

trients are fruits, vegetables, protein and fiber, while the "bad" macronutrients are saturated fat, sugar, sodium, and cholesterol. Our raw Health Index $H(\mathbf{x})$ is the sum of good minus bad nutrients in a UPC, weighting each by its recommended daily intake (RDI): $H(\mathbf{x}) = \sum_k G_k \frac{g_k}{r_k} - (1 - G_k) \frac{g_k}{r_k}$, where g_k is the grams of macronutrient k, r_k is the RDI for a normal adult, and G_k takes value 1 for "good" macronutrients and 0 for "bad" macronutrients. For example, the RDI for vegetables is about 130 grams per day, so a vegetable UPC weighing 130 grams would have $H(\mathbf{x}) = 1$. Packaged items in the Nielsen "candy" product group have an average $H(\mathbf{x})$ of -5. For reduced-form analyses in Sections III and IV.A, we normalize the raw Health Index per calorie consumed to have mean zero, standard deviation one across households. Panel C of Table 1 presents nutritional summary statistics across all UPC codes in the Nielsen Homescan and RMS data. See Appendix A.B for additional details on the Health Index.

III Stylized Facts: Consumption and Supply of Healthful Foods

III.A Higher income is correlated with more healthful grocery purchases

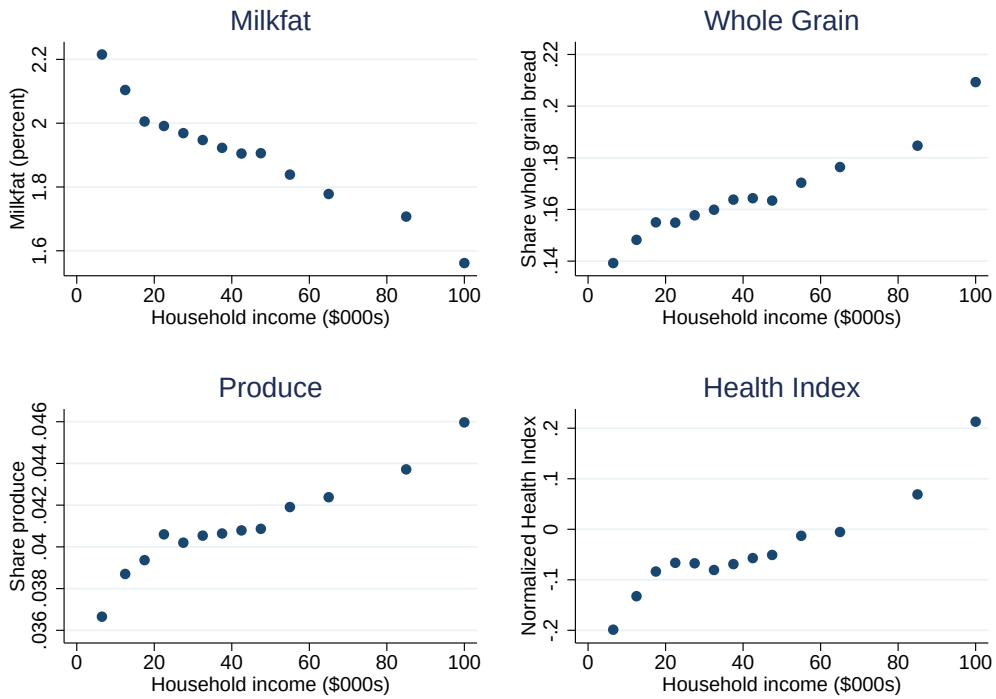
The basic result that eating patterns vary by income has been well-documented through the NHANES survey (USDA 2014a), which began in the 1960s. Using the Homescan data, Figure 1 presents four different measures of the nutrition-income relationship: the milkfat of milk purchases, share of bread calories from whole grain breads, share of calories from produce, and normalized Health Index. The four measures paint a consistent picture: low-income consumers purchase higher-fat milk, less whole-grain breads, less produce, and lower-Health Index items.[15] Households with income above $75,000 (approximately the top quartile) get about 0.6 percentage points (15 percent) more calories from produce than households with income below $25,000 (approximately the bottom quartile), and their normalized Health Index is 0.25 standard deviations higher.[16] This is the basic fact that our empirical analyses aim to explain.

We can benchmark the importance of these differences using correlational evidence from the public health literature. Using fiber as an example, the top income quartile purchases groceries with approximately one additional gram of fiber per 1000 calories relative to the bottom quartile (7.40 vs. 6.39 grams). Montonen *et al.* (2003) find that consuming one additional gram of fiber per 1000 calories is conditionally correlated with a 9.4 percent decrease in type-2 diabetes.

[15] Appendix Figure A3 re-creates the figure using the magnet subsample for 2004-2006, which includes bulk purchases as well as packaged items. The results are noisier due to the smaller sample, but qualitatively similar.

[16] Appendix Figure A2 presents an analogue to Figure 1, but considering each individual macronutrient. Consistent with NHANES, the most economically and statistically significant relationships in Homescan are that higher-income households tend to get a larger share of calories from protein and fiber and a smaller share from sugar. Higher-income households also tend to consume more sodium and saturated fat, although the difference is smaller in percent terms, and cholesterol intake does not vary significantly by income. Thus, although the Recommended Daily Intakes impose specific weights on macronutrients in our Health Index, higher-income diets would tend to be classified as "more healthful" unless the weights change substantially.

Figure 1: **Healthful Purchases by Household Income**



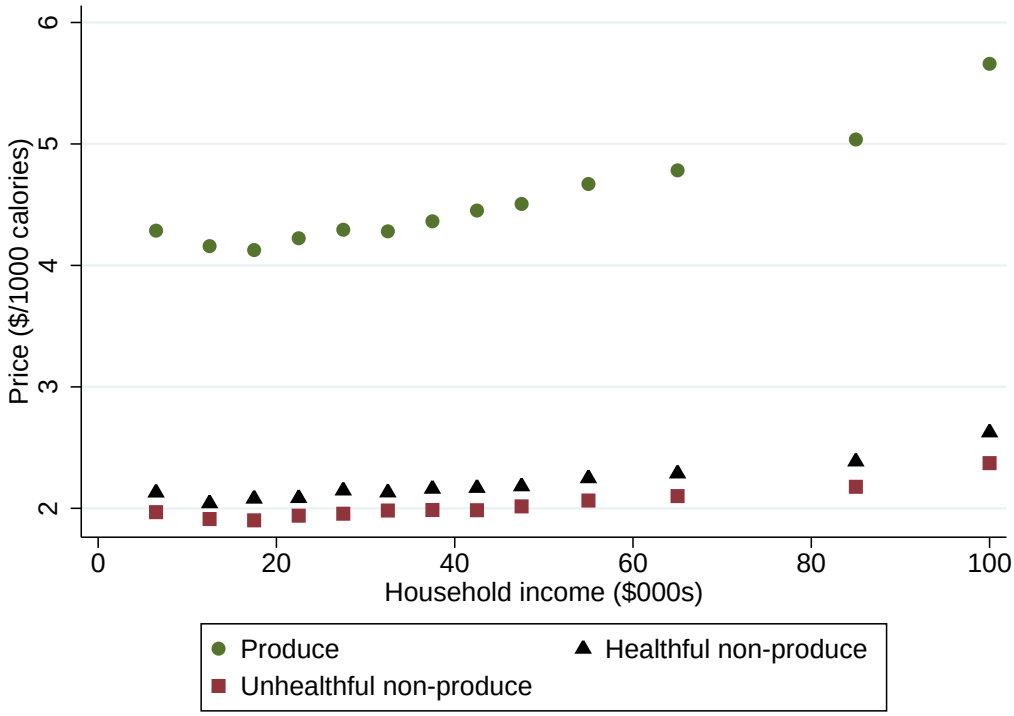
Notes: Nielsen Homescan data for 2004-2013. The x-axis presents nominal income bins; household incomes larger than $100,000 are coded as $100,000. Milkfat is the calorie-weighted average milkfat of milk purchases, whole grain is the calorie-weighted average share of bread, buns, and rolls purchases that are whole grain, produce is the share of calories from fresh, canned, dried, and frozen fruits and vegetables, and Health Index is the average Health Index per 1000 calories across all UPCs purchased. Health Index is normalized to mean zero, standard deviation one across households.

III.B Healthful food costs more, but relatively more for high-income households

Public health studies typically find that healthful diets cost more per calorie; see Rao *et al.* (2013) for a meta-analysis of 27 studies. A simple way to quantify this in the Homescan data is to take all Homescan grocery purchases for 2012 and divide them into three groups: produce, above-median Health Index non-produce, and below-median Health Index non-produce. Figure 2 presents the mean price per calorie for each of these three groups, by household income category. Broda, Leibtag, and Weinstein (2009) show that higher-income Homescan consumers pay slightly more for the same UPCs. The upward slope of price per calorie in income reflects that finding, along with the fact that higher-income households purchase different and more expensive UPCs. This figure quantifies two additional facts. First, across all income groups, produce and healthful non-produce UPCs cost more per calorie than relatively unhealthful non-produce UPCs. This could cause low-income households to purchase less healthful items in order to more cheaply satisfy minimum calorie

needs. Second, however, the relative price of produce and healthful non-produce UPCs increases in income. As Handbury, Rahkovsky, and Schnell (2015) point out, this relative price difference should cause low-income households to purchase more healthful groceries. Our demand model will allow us to quantify the effects of these price differences.

Figure 2: **Price per Calorie of Homescan Purchases by Household Income**



Notes: This shows the average price per calorie across 2012 Homescan transactions by income bin; household incomes larger than $100,000 are coded as $100,000. "Produce" includes fresh, canned, and dried produce. "Healthful" vs. "unhealthful" non-produce refer to above-median vs. below-median Health Index purchases.

III.C Stores in low-income neighborhoods offer less healthful groceries

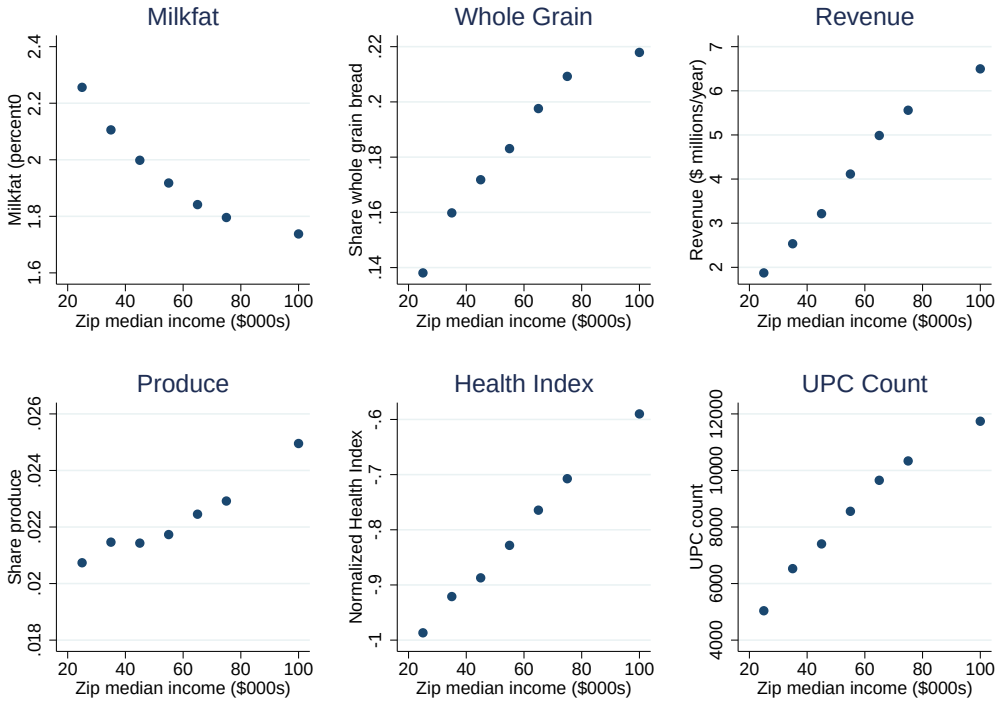
The left four panels of Figure 3 present the healthfulness of items offered in RMS stores, again measured by the mean milkfat of milk UPCs, share of bread UPCs that are whole grain, share of UPCs that are produce, and mean Health Index. All four panels show a consistent result: stores in wealthier zip codes offer more healthful items.[17][18] This is broadly consistent with the public health

[17] We do not observe locations more precisely than zip codes. As we show below, Americans drive long distances to shop, so the zip code is a reasonably appropriate measure of local supply.

[18] Unlike the nutrition-income relationship in consumption from Figure 1, the weights in the Health Index could matter for the conclusion that supply is more healthful in higher-income neighborhoods. Figure A5 shows that stores in higher-income neighborhoods offer UPCs with more protein and fiber and less sugar and sodium per 1000 calories. However, they also offer more of two "bad" macronutrients, saturated fat and cholesterol.

literature, e.g. Larson, Story, and Nelson (2009), and with Handbury, Rahkovsky, and Schnell's (2015) analysis of the RMS data. The two panels at the right of Figure A7 show that RMS stores are significantly smaller in low-income neighborhoods: the mean store in zip codes with median household income below $30,000 offers fewer than 6,000 UPCs, while the mean store in zip codes with median household income larger than $100,000 offers more than 12,000 UPCs.

Figure 3: **Store Average Healthfulness and Size by Zip Code Median Income**



Notes: Using Nielsen RMS data for year 2012, we constructed calorie-weighted mean milkfat of all milk UPCs, the calorie-weighted share of bread, buns, and rolls UPCs that are whole grain, the calorie-weighted share of UPCs that are produce, and the calorie-weighted mean health index, across all UPCs offered in each store. The left four panels of this figure presents the means of these variables across stores within categories of zip code median income. The right two panels present mean revenues and UPC counts by zip code income category, also using Nielsen RMS data.

Table 2 formalizes these correlations in store-level regressions using 2012 Nielsen RMS data. Each column presents results of a regression of store healthfulness (as measured by the count of produce UPCs offered or the calorie-weighted mean Health Index of UPCs offered) on zip code median income. Columns 1 and 4 confirm that stores in higher-income zip codes offer substantially more produce UPCs and overall healthier items. Columns 2 and 5, however, show that conditioning on store size (as measured by revenues from grocery items with UPCs) explains essentially all of the income-healthfulness relationship: large stores sell more healthful groceries and are much more

likely to enter in higher-income zip codes. Columns 3 and 6 show that even when excluding the revenue variable, store type explains 85 to 90 percent of the income-healthfulness relationship. Store type indicators alone explain 92 and 73 percent of the variance in produce UPC counts and mean Health Index, respectively.

By definition, supercenters such as Walmart Supercenter, Target, and Meijer have full lines of grocery and produce items, and club stores such as Sam's Club and Costco typically do also. By contrast, Table 2 shows that drug stores, convenience stores, and other mass merchants such as regular Walmart have much smaller produce selections and less healthful selections overall. We refer to large grocers, supercenters, and club stores as "supermarkets," with the understanding that supermarkets carry more produce and more healthful items.

Table 2: **Healthful UPC Availability at Nielsen RMS Stores**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Count of Produce UPCs			Mean Health Index		
ln(Zip Median Income)	419.1	22.64	61.92	0.300	-0.0596	0.0121
	(9.334)***	(5.940)***	(3.644)***	(0.00908)***	(0.00591)***	(0.00643)*
ln(Annual revenue)		373.0			0.338	
		(1.548)***			(0.00182)***	
1(Large grocery)			1581.8			1.408
			(4.016)***			(0.00284)***
1(Small grocery)			1053.6			1.119
			(11.60)***			(0.0321)***
1(Supercenter)			639.6			1.032
			(5.893)***			(0.00424)***
1(Convenience store)			-68.20			0.230
			(0.741)***			(0.00770)***
1(Other mass merchant)			54.50			0.202
			(1.038)***			(0.00393)***
Constant	-3972.8	-4833.9	-589.9	-4.071	-4.851	-1.471
	(100.3)***	(61.32)***	(39.58)***	(0.0977)***	(0.0569)***	(0.0696)***
Observations	34917	34917	34917	34917	34917	34917
R^2	0.0470	0.799	0.923	0.0284	0.757	0.816

Notes: 2012 Nielsen RMS data at the store level. ln(Annual revenue) is revenue in 2012 from observed grocery items with UPCs. "Large" ("small") grocery stores are those with at least (less than) $5 million in observed revenue. Drug stores are the omitted store type in columns 3 and 6. Robust standard errors, clustered by zip code, in parentheses. *, **, ***: Statistically significant with 10, 5, and 1 percent confidence, respectively.

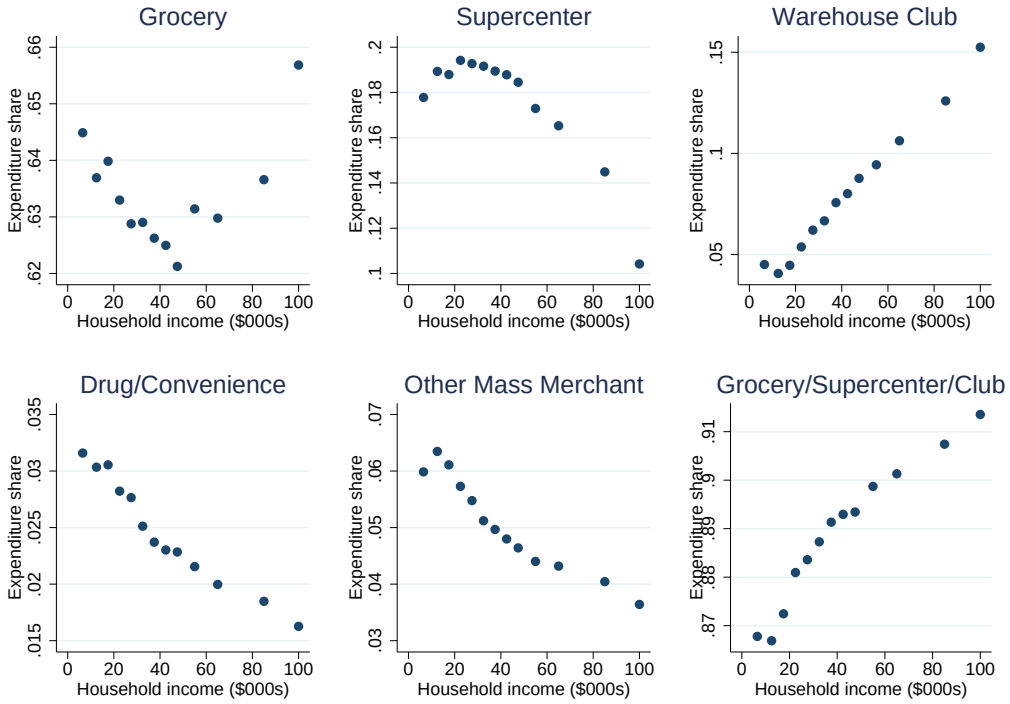
Consistent with Figure 3 and Table 2, Appendix B.B shows that low-income neighborhoods tend to have fewer large grocery stores and more more drug and convenience stores per capita. The ZBP data show that 23 percent of zip codes (weighted by population) are "food deserts," i.e. they have no large grocery stores, supercenters, or club stores. By contrast, 32 percent of low-income zip

codes (the lowest quartile, with median househld income less than $40,000) are food deserts. This lower concentration of healthful stores has generated support among policymakers for incentivizing entry into low-income neighborhoods.

III.D Expenditure shares at healthful store types vary little by income

To what extent are the differences in local store types actually associated with differences in shopping patterns? Figure 4 shows grocery expenditure shares by store type. The fact that low-income households are more likely to shop at drug and convenience stores parallels the neighborhood variation in store concentration in Appendix B.B. As Broda, Liebtag, and Weinstein (2009) point out, however, the expenditure share differences are relatively small. For households with income below $25,000, about 87 percent of expenditures are at store types offering more healthful items (grocery stores, club stores, and supercenters). Expenditure shares at healthful store types increase roughly monotonically in income to about 91 percent for households with income greater than $75,000.

Figure 4: **Grocery Expenditure Shares by Household Income**



Notes: Nielsen Homescan data for 2004-2013. The x-axis presents nominal income bins; household incomes larger than $100,000 are coded as $100,000. Another 5-6 percent of expenditures are at channels not plotted, including bakeries, butchers, candy stores, liquor stores, fruit stands, and fish markets; this proportion is fairly constant by income.

We consider multiple reasons for income differences in healthful eating, and no one reason is likely to explain all of the difference. Indeed, for the four percentage point difference in expenditure shares at healthful store types to explain the 0.25 standard deviation difference in normalized Health Index between the lowest and highest income quartile, purchases at unhealthful store types would need to have a normalized Health Index 6.25 standard deviations lower. In reality, the normalized Health Index of purchases at unhealthful store types is 0.38 standard deviations lower.

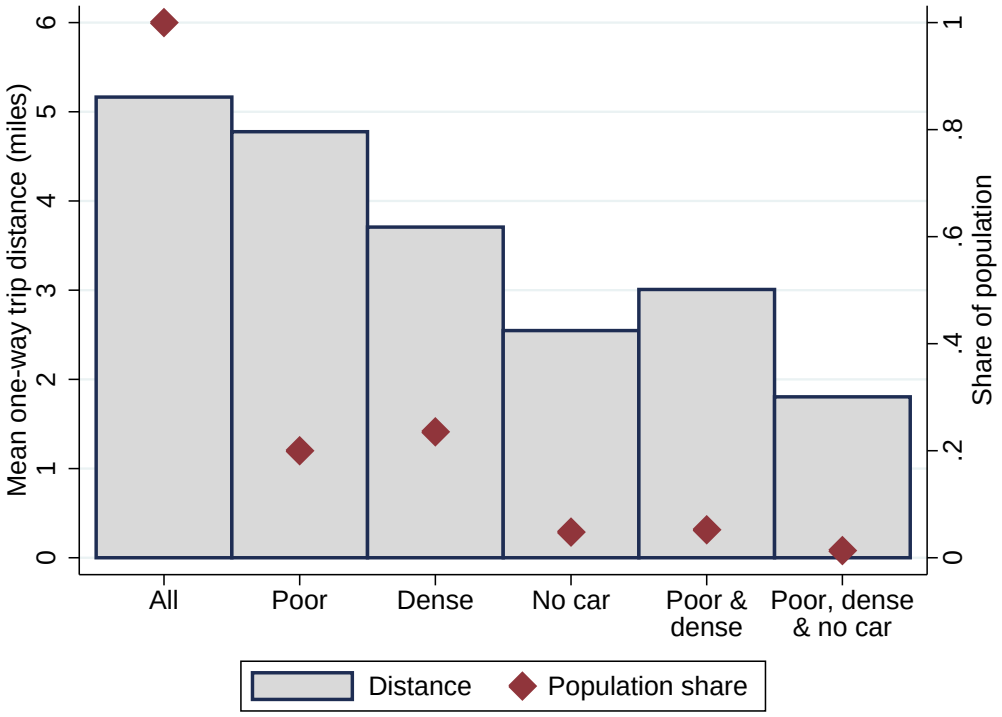
These real but minor expenditure share differences highlight that living in a "food desert" only affects consumers' choice sets if they do not travel elsewhere for groceries. The 2009 National Household Travel Survey (NHTS) is a nationally-representative survey that gathers demographics, vehicle ownership, and "trip diaries" for 150,000 households nationwide. Figure 5 shows average one-way distances for trips beginning or ending in "buying goods: groceries/clothing/hardware store."

The data show that Americans travel a long way for shopping, typically in cars. The mean (median) trip is 5.2 (3.0) miles, and 90 percent of shopping trips are by car. Even low-income and urban subgroups typically travel some distance. "Poor" households (defined as those with household income less than $25,000) travel a mean of 4.8 miles, with 80 percent of trips by auto. We define "Dense" census tracts as those with at least 4,000 people per square mile. These tracts contain 24 percent of US households; for comparison, Chicago has about 12,000 people per square mile, and Phoenix has 3200. "Poor" households in dense neighborhoods, which represent five percent of US households, travel a mean of 3.0 miles, with 64 percent of trips by auto. Only 4.8 percent of households do not own a vehicle; they travel a mean of 2.5 miles, with 25 percent of trips by auto.[19] Appendix Figure A6 presents median travel distances and the share of trips by auto for the same subgroups.

Long travel distances explain why even households in zip codes without large grocery stores, supercenters, and chain stores still make large shares of their grocery expenditures at these store types.

[19]These results are broadly consistent with USDA (2009), which finds that 2.2 percent of US households live more than a mile from a supermarket and do not have access to a vehicle.

Figure 5: **Shopping Trip Distances by Household Income**



Notes: Data are from the 2009 National Household Travel Survey. Bars represent the mean one-way trip distance for trips beginning or ending in "buying goods: groceries/clothing/hardware store." "Poor" means household income less than $25,000, "Dense" means Census tract population density greater than 4,000 people per square mile, and "No car" means that the household does not own a car.

IV Reduced Form Empirical Analysis: Explaining the Nutrition-Income Relationship

This section presents reduced form evidence on causes of the nutrition-income relationship. This complements our upcoming structural demand model by presenting results that are less amenable to the structural framework. First, we use event studies to measure the effect of supermarket entry on purchases. Second, we show which observables moderate the correlation between Health Index and income.

IV.A Effects of Retailer Entry

We use household-by-quarter data in an event study framework to measure effects of supermarket entry on grocery purchases. Using the google maps application program interface (API), we downloaded the driving time (assuming no congestion delay) between each Census tract centroid and

the address of each entering store.[20] S_{mct} is the count of our 1914 observed store entries that have previously occurred within driving distance band m of Census tract c as of quarter t or earlier. We use two distance bands, $m \in [0, 10)$ minutes and $m \in [10, 15)$ minutes; 10 and 15 minutes are the median and 75th percentile of shopping travel times in the 2009 NHTS. For $m \in [0, 10)$ minutes, S_{mct} takes value 0 for 87.6 percent of observations, 1 for 10.7 percent of observations, 2 for 1.3 percent of observations, and 3, 4, or 5 for the remaining 0.25 percent.

Y_{ict} is an outcome for household i living in census tract c in quarter t, μ_{dt} is a vector of Census division-by-quarter of sample indicators, and ϕ_{ic} is a household-by-Census tract fixed effect. A small portion of Homescan households relocate across Census tracts, and the household-by-Census tract fixed effect identifies variation in supply due to entry, not relocation. The regression is:

$$Y_{ict} = \sum_{m} \tau_m S_{mct} + \mu_{dt} + \phi_{ic} + \varepsilon_{ict} \tag{1}$$

Standard errors are clustered by household. The τ_m coefficients measure the effect of entry under the identifying assumption that store entry is exogenous to within-household preference changes over time. While retailers carefully plan entry and exit in response to local population growth and changes in local demographics, entry is likely uncorrelated with within-household demand changes conditional on division-by-quarter fixed effects.

Figure 6 illustrates how store entry within ten minutes of household i affects purchases in event time. There is no omitted category, so we shift all coefficient estimates so that the coefficient for the quarter immediately preceding entry is fixed to zero.[21] The top two panels present expenditure shares (in units of percentage points), showing that entry clearly affects purchasing patterns. The dependent variable in the top left panel is the combined expenditure share across the several retail chains we observe in our entry dataset. Expenditures at entering retailers increase by seven to eight percentage points, and most of the adjustment occurs within the first four quarters after entry.[22] This approach is likely to understate the expenditure share increase at the specific entering store, as the entrant store will reduce expenditures at other stores owned by the same retailer or by the other retailers in our entry dataset. The top right figure shows the change in combined expenditures at grocery stores, supercenters, and club stores, which as we have shown above tend to offer more healthful items and a wider variety of produce. To the extent that supermarket entry simply diverts sales from these store types, the actual changes in product availability (and thus

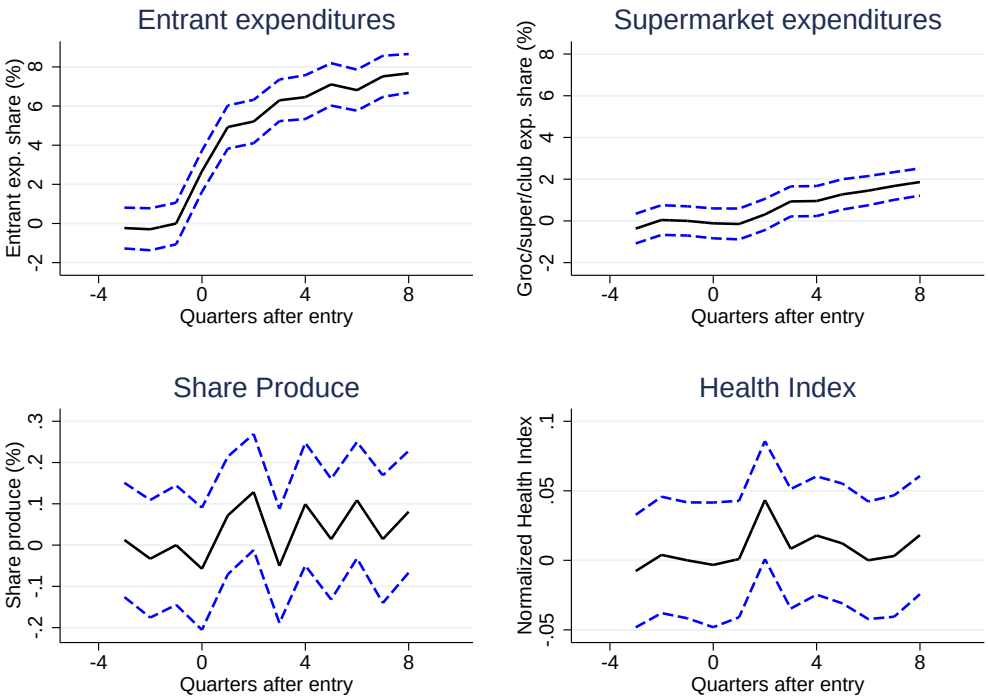
[20] In earlier drafts, we used geographic distances, as do Handbury, Rahkovsky, and Schnell (2015). Because driving five miles in a dense city takes much more time than driving five miles in a suburban area, drive time is a more precise measure of travel costs.

[21] These estimates are from a modified version of Equation (1) that substitutes event-time quarter indicators in place of S_{mct}. Homescan is an unbalanced panel, so to make the figures clearer, we eliminate compositional effects by identifying the coefficients in Figure 6 using only the balanced set of households that are observed for all three quarters before entry and all eight quarters after entry.

[22] This gradual adjustment of purchases is consistent with the results of Atkin, Faber, and Gonzalez-Navarro (2014), who study retail expansion in Mexico.

the possible effects on healthful purchases) are more limited. Indeed, the combined expenditure share at groceries, supercenters, and club stores increases by less than two percentage points by the eighth quarter after entry. Thus, a substantial effect of supermarket entry is to divert sales from other supermarkets.[23] The bottom two panels show produce consumption and average Health Index per 1000 calories in event time. There is no statistically significant trend before or after entry.

Figure 6: **Known Retailer Entry in Event Time**



Notes: This figure presents effects of entry by several chains of large grocers and/or supercenters, using household-by-quarter Homescan data with household-by-Census tract fixed effects and Census division-by-quarter of sample indicators. The top two panels present effects on expenditure shares, in units of percentage points. The bottom two panels present effects on healthful purchasing. Share Produce is the share of calories from fresh, canned, dried, and frozen fruits and vegetables, in units of percentage points. Health Index is the average Health Index per 1000 calories purchased. Health Index is normalized to mean zero, standard deviation one across households.

Table 3 presents estimates of Equation (1), using the same dependent variables as Figure 6. Panel A considers effects on expenditure shares, first at the entrant retailers and then at all grocery stores, supercenters, and club stores. As expected, all effects are larger for stores entering within

[23]These results are consistent with those of Hwang and Park (2015), who look at a subset of Walmart Supercenters that opened between 2003 and 2006.

ten minutes of a household's Census tract centroid than for stores entering 10-15 minutes away. Columns 1 and 2 consider the full Homescan sample, columns 3 and 4 limit the sample to low-income households, and columns 5 and 6 consider households in "food deserts": zip codes with zero large (>50 employee) grocery stores, supercenters, or club stores in 2003, the year before the regression sample begins. The expenditure share changes are larger for low income households and households in food deserts. However, consistent with Figure 6, 80 percent or more of entrant chains' expenditure share increase is diverted sales from other supermarkets, while less than 20 percent is diverted from specialty retailers, drug and convenience stores, and other mass merchants, which typically offer a less healthful product selection. Appendix Table A5 shows that most of this diversion is from other mass merchants; even in food deserts, expenditure shares at drug and convenience stores drop by only a fraction of a percentage point.

Panel B of Table 3 presents effects on the produce share of calories consumed and the Health Index per 1000 calories, where the former is in units of percentage points and the latter is again normalized to standard deviation 1 across households. Consistent with Figure 6, entry has no statistically significant effect on these measures of healthful eating. Appendix Table A5 shows that there is no effect of entry on these same two measures of healthful eating when using three alternative definitions of food deserts.

What share of the nutrition-income relationship can be explained by supermarket entry? The 90 percent confidence interval on column 3 of Panel B shows that entry within a 10-minute drive increases bottom income quartile households' produce calorie share by no more than 0.1 percentage points, which is about 1/6 of the gap between the top and bottom income quartiles from Figure 1. Using an analogous calculation, entry increases bottom income quartile households' Health Index by no more than 0.008 standard deviations, which is 1/32 of the gap between the top and bottom income quartiles.

Table 3: **Effects of Supermarket Entry**

Panel A: Effects on Expenditure Shares

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Full Sample		Income<$25,000		"Food Desert" Zip Codes	
Expenditure shares at store type:	Entrants	Grocery/ Super/Club	Entrants	Grocery/ Super/Club	Entrants	Grocery/ Super/Club
Post entry: 0-10 minutes	4.532	0.759	5.228	1.027	5.011	1.079
	(0.249)***	(0.156)***	(0.616)***	(0.417)**	(0.767)***	(0.430)**
Post entry: 10-15 minutes	1.049	0.149	0.990	0.0277	1.540	0.451
	(0.165)***	(0.116)	(0.405)**	(0.319)	(0.394)***	(0.276)
Observations	2,168,142	2,168,142	346,046	346,046	523,198	523,198
Dependent var. mean	19	88	21	85	22	88

Panel B: Effects on Healthful Eating

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Full Sample		Income<$25,000		"Food Desert" Zip Codes	
Dependent variable:	Share Produce	Health Index	Share Produce	Health Index	Share Produce	Health Index
Post entry: 0-10 minutes	-0.00162	-0.0000531	-0.0170	-0.0238	0.102	-0.0206
	(0.0291)	(0.00852)	(0.0649)	(0.0192)	(0.102)	(0.0260)
Post entry: 10-15 minutes	-0.00188	-0.00267	0.0353	-0.00859	-0.0136	0.0128
	(0.0191)	(0.00704)	(0.0459)	(0.0217)	(0.0466)	(0.0148)
Observations	2,168,150	2,168,076	346,047	346,039	523,199	523,176
Dependent var. mean	4.2	0.00	4.0	-0.12	4.2	-0.053

Notes: Data are at the household-by-quarter level. "Food Desert" zip codes are those with no grocery stores with 50 or more employees, supercenters, or club stores in 2003. Expenditure shares are in units of percentage points. Share Produce is the share of calories from fresh, canned, dried, and frozen fruits and vegetables, in units of percentage points. Health Index is the average Health Index per 1000 calories purchased. Health Index is normalized to mean zero, standard deviation one across households. Reported independent variables are indicators for whether a specific retailer has entered within a 0-10 or 10-15 minute drive from the household's Census tract centroid; regressions also include Census division-by-quarter of sample indicators and household-by-Census tract fixed effects. Robust standard errors, clustered by household, in parentheses. *, **, ***: Statistically significant with 10, 5, and 1 percent confidence, respectively.

These regressions include entry by only a limited set of retailers, which could reduce both power and generalizability. Appendix C.A presents parallel estimates using zip code-by-year counts of large grocery stores, supercenters, and club stores from Zip Code Business Patterns. These estimates are closely consistent with the results in Table 3: even in food deserts, the main effect of supermarket entry is to divert expenditures from other supermarkets, so consumers' choice sets are largely unchanged. Entry has tightly-estimated zero effects on produce share and Health Index for the full sample as well as the low-income and "food desert" subsamples.

IV.B Decomposing the Correlation Between Health Index and Income

If entry explains little of the nutrition-income relationship, what does explain it? Using the 2004-2013 Homescan data, we regress the normalized calorie-weighted average Health Index of household i's purchases in year t, denoted H_{it}, on natural log income $\ln I_{it}$ and year indicators μ_t, adding covariates X_{it}:

$$H_{it} = \beta_1 \ln I_{it} + \beta_2 X_{it} + \mu_t + \varepsilon_{it}. \tag{2}$$

Standard errors are clustered by household.

The goal is to estimate how much each covariate X_k explains β_1, the nutrition-income relationship. As Gelbach (2015) points out, this is equivalent to determining the omitted variables bias in β_1 from omitting X_k. To do this, we estimate the full model in Equation (2), which gives coefficients $\hat{\beta}_{2k}$. We then estimate auxiliary regression $\ln I_{it} = \Gamma X_{itk} + \mu_t + \epsilon_{it}$ to determine $\hat{\Gamma}$, the covariance between income and the "omitted variable" X_k. Then, variable X_k's estimated contribution to the nutrition-income relationship is just the omitted variables bias formula: $\hat{\delta}_k = \hat{\Gamma}_k \hat{\beta}_{2k}$. If $\tilde{\beta}_1$ denotes the estimated "unconditional" relationship between H and $\ln I$ (without conditioning on X), variable X_k's estimated contribution to the nutrition-income relationship is:

$$\tilde{\delta}_k = \frac{\hat{\Gamma}_k \hat{\beta}_{2k}}{\tilde{\beta}_1}. \tag{3}$$

Table 4 presents results. Each column considers a different set of X covariates. Panel B ("Full Model") presents estimates of the full Equation (2) with different X covariates, while Panel A ("Unconditional Estimates") presents the $\hat{\beta}_1$ from Equation (2) in the same sample but excluding the X covariates. In columns 2 and 3, each variable's $\tilde{\delta}_k$ is in italics.

Income could be associated with Health Index either through a direct effect or because of additional factors correlated with income. To test this, column 1 presents estimates of the within-household correlation between normalized Health Index and income, conditional on household fixed effects. The point estimate is 0.0153, meaning that a 100 log point increase in income within-household is associated with a 0.0153 standard deviation increase in Health Index.[24] This coefficient reflects more than just the causal impact of relaxing the budget constraint. For example, if additional income results from a new time-consuming job, this could also increase preferences for quickly-preparable foods. Notwithstanding, the coefficient is only 16 percent of the unconditional estimate in the same sample without household fixed effects from Panel A. Unless factors other than the budget constraint are large and negatively correlated with healthful eating, this suggests

[24]The Homescan household income variable is actually the income from two calendar years prior. To maximize sample size in our main estimates, we use this standard variable. However, to estimate the effects of within-household income variation, we must use income exactly contemporaneous with purchases. This limits the sample to household-by-year observations where the household is also observed two years later.

that the great majority of the nutrition-income relationship is driven by long-term effects of income and correlates of income, not by the short-term effects of a tighter budget constraint.[25]

Column 2 presents estimates using X variables that are recorded by Nielsen and thus observed for the full Homescan sample. When omitting all X variables, the unconditional estimates show that a 100 log point increase in household income is associated with a 0.119 standard deviation increase in Health Index. Controlling for education, age, children, race, and census tract indicators attenuates the coefficient to 0.0765. We present each variable's $\tilde{\delta}_k$ below the standard error. Education explains 22.8 percent of the nutrition-income correlation, a result which is qualitatively consistent with results in Handbury, Rahkovsky, and Schnell (2015). This suggests that health knowledge, information, and cognition might be important, as Cutler and Lleras-Muney (2010) have argued. The Census tract indicators explain 28.6 percent of the nutrition-income correlation. Because local supply by definition varies little within census tract, it is tempting to conclude that this share of the nutrition-income correlation could be attributable to local supply differences. However, the census tract indicators also control for demand-side factors that vary between neighborhoods and are correlated with income. Age, children, and race explain smaller shares of the nutrition-income correlation.

To further explore the importance of health knowledge and information, we consider X_k variables from the Bronnenberg, Dubé, and Gentzkow (2012) and Bronnenberg *et al.* (2015) add on surveys. The sample is smaller than in column 2 because the surveys were delivered only in 2010 and therefore do not cover all households in the 2004-2013 panel. Column 3 shows that working in a health-related occupation (which includes doctors, dentists, nurses, nutritionists, physical therapists, and others) is associated with 0.0432 standard deviation higher Health Index. This is statistically significant in alternative regressions where food knowledge is excluded, but it is not significant conditional on food knowledge, suggesting that these two variables measure similar mechanisms. A one standard deviation increase in food knowledge is associated with a 0.0676 standard deviation increase in the Health Index. These results further suggest the importance of information in determining demand. Both health occupation and food knowledge are positively correlated with income and Health Index, but they explain only a small amount of the nutrition-income correlation: 0.6 and 4.7 percent, respectively.

To the extent that the nutrition-income correlation is driven by preferences, we can also try to explore the source of those preferences. One hypothesis is that eating habits developed early in life have lasting effects on preferences. Different states have very different eating patterns: as we show in Appendix Figure A8, the deep south (Louisiana, Mississippi, and Alabama in particular) have the lowest Health Index of purchases in the Homescan data, while Colorado, the west coast, and New England have the highest Health Index. We observe state of birth from the surveys by Bronnenberg,

[25]One additional caveat is that income could be measured with different amounts of error within- vs. between households. If only within-household variation is subject to measurement error, one approach would be to instrument using county-level income variation. However, we find that this substantially reduces power.

Dubé, and Gentzkow (2012), so we can construct the average Health Index for the household head's state of birth. Column 3 also shows that this birth state Health Index is highly statistically significantly correlated with the Health Index of current purchases, conditional on indicators for current state of residence, income, age, children, race, and education. While this strongly suggests that early life habit formation plays an important role in health-related preferences, the $\tilde{\delta}_k$ of -0.001 shows that this variable alone explains essentially none of the nutrition-income correlation.

Table 4: **Explaining the Nutrition-Income Correlation**

	(1)	(2)	(3)
Panel A: Unconditional Estimates			
ln(Household income)	0.0972	0.119	0.124
	(0.00688)***	(0.00468)***	(0.0115)***
Panel B: Full Model			
ln(Household income)	0.0153	0.0765	0.103
	(0.00701)**	(0.00451)***	(0.0114)***
ln(Years education)		0.454	0.530
		(0.0277)***	(0.0691)***
		0.228	*0.237*
ln(Age)		0.283	0.296
		(0.0145)***	(0.0410)***
		-0.087	*-0.052*
1(Have children)		-0.187	-0.268
		(0.00703)***	(0.0198)***
		-0.108	*-0.102*
1(White)		-0.0553	-0.0655
		(0.0124)***	(0.0337)*
		0.001	*-0.002*
1(Black)		-0.258	-0.331
		(0.0174)***	(0.0441)***
		0.040	*0.038*
1(Any health occupation)			0.0432
			(0.0434)
			0.006
Food knowledge			0.0676
			(0.00951)***
			0.047
Birth state Health Index			0.413
			(0.166)**
			-0.001
Census tract indicators		Yes	
		0.286	
Household fixed effects	Yes		
State indicators			Yes
Observations	279,791	545,763	127,468
R^2	0.0177	0.474	0.0695

Notes: 2004-2013 Nielsen Homescan data at the household-by-year level. The dependent variable is mean Health Index per 1000 calories of groceries purchased; this is normalized to standard deviation one across households in 2013. All regressions include year indicators. Observations are weighted for national representativeness. Each variable's contribution to the nutrition-income correlation, i.e. $\tilde{\delta}_k$ from Equation (3), is in italics. Robust standard errors, clustered by household, in parentheses. *, **, ***: Statistically significant with 10, 5, and 1 percent confidence, respectively.

V A Model of Nutrient Demand

We build on the model developed by Dubois et al (2013) to model households' demand for nutrients and groceries. Household i purchases groceries each week t by making shopping trips to local stores. Let S_{it} be the set of stores household i is aware of when making their shopping decisions at time t. We assume household i is aware of the prices of products sold within S_{it} in week t. The household elects which stores to shop at and purchases products in the stores to maximize utility. The utility function is:

$$\max_{s_{it}\epsilon S_{it}, x_{it}, y_{it}} U_{it}\left(x_{it}, z_{it}, y_{it}\right) - \alpha_{it} d_i\left(s_{it}\right)$$
$$s.t. \sum_{n=1}^{N} y_{int} p_{int} + p_{0t} x_{it} \leq I_{it}.$$

s_{it} is the set of stores within set S_{it} that the household elected to shop at in week t. $d\left(s_i\right)$ measures the total drive time needed to travel to all the stores. We will allow preferences to vary by household i and time t. $U_{it}\left(x_{it}, z_{it}, y_{it}\right)$ is household i's utility from products purchased in week t and α_{it} is household i's aversion to spending time driving in week t. Within the chosen stores, household i purchases groceries leading to an overall shopping bundle for the week. $y_{it} = \{y_{i1t}, y_{i2t}, ..., y_{iN_{it}t}\}$ is an N_{it}x1 vector of all the quanities (measured in calories) purchased by household i for every food product (UPC) stocked in stores s_{it}.[26] $p_{it} = \{p_{i1t}, p_{i2t}, ...p_{iN_{it}t}\}$ is an N_{it}x1 vector of prices (per calorie) for each product $n\epsilon N_{it}$ in week t. Each product n is characterized by C nutrient characteristics $\{a_{n1}, ..., a_{nC}\}$. Define the N_{it}xC matrix A=$\left\{ \begin{array}{c} a_{11}, ..., a_{1C} \\ ... \\ a_{n1}, ..., a_{nC} \end{array} \right\}$. A measures the nutrient content (in kilograms) per calorie for each of the C nutrients in each of the N_{it} different products. Thus, the Cx1 be vector containing the total nutrient content of household i's bundle of goods, z_{it},can be written as: $z_{it} = A' y_{it}$.

Assuming quanities are continuous, the FOC for each product is:

$$\sum_{c=1}^{C} a_{nc} \frac{\partial U_{it}}{\partial z_{itc}} - \frac{\partial U_{it}}{\partial x_{it}} \frac{p_{int}}{p_{0t}} + \frac{\partial U_{it}}{\partial y_{int}} = 0. \tag{4}$$

We assume the utility function takes the form:

$$U_{it}\left(x_{it}, z_{it}, y_{it}\right) = \sum_{j=1}^{J} \mu_{ijt} log\left(\sum_{k=1}^{K_j} f_{ikjt}\left(y_{ikjt}\right)\right) + \sum_{c=1}^{C} h_{ic}\left(z_{ict}\right) + \gamma_i x_{it}.$$

[26] N_{it} is the number of products stocked in stores s_{it}.

Products have been grouped into J product categories, with K_j products within each group. An individual product is indexed by kj. $f_{ikjt}(y_{ikjt})$ measures the sub-utility household i gets from product kj in week t. μ_{ijt} measures how much household i enjoyed product group j in week t for reasons other than nutrient content. $h_c(z_{ict})$ measures the utility value household i gets from z_{ict} kilograms of nutrient c. γ_i measures the marginal utility household i gets from consuming the outside good (all other non-grocery consumption).

This setup allows household i to get value out of product jk through two mechanisms. First, household i gets direct value from consuming products in group j, as represented by $\mu_{ijt} log\left(\sum_{k=1}^{K_j} f_{ikjt}(y_{ikjt})\right)$. This term represents that households value food consumption and variety in food consumption for reasons other than products' direct nutrient levels. Further, this terms allows for dimishing marginal utility from consuming large amounts of any one product or any one product group. Second, the household values the nutrient levels of the total bundle of groceries, as measured by $\sum_{c=1}^{C} h_{ic}(z_{ict})$. This terms combines the total amount of nutrients across all the products consumed, allowing for direct preferences over nutrients, such as fat, sugar, or protien, to not depend on the exact product source of the nutrient. The combination of these two mechanisms allows households to diversity their food consumption across many types of products and product groups, but still adjust their consumption within and across product groups to account for the fact that the nutrient content of the food impacts the desirablilty of its consumption.

Plugging in these functional forms to equation (4), multiplying both sides by y_{ijkt}, and normalizing the price of the outside good to one gives:

$$\mu_{ijt}\frac{f'_{kjt}(y_{ikjt})\,y_{ikjt}}{\sum_{l=1}^{Lj} f_{ljt}(y_{ikjt})} + \sum_{c=1}^{C} a_{kjc} y_{ijkt} h'_c(z_{ict}) = \gamma_i p_{kjt} y_{ikjt}. \tag{5}$$

We allow the within product group subutility functions to be fexible CES functions of the form:$f_{ikjt}(y_{ikjt}) = \lambda_{ikjt} y_{ijkt}^{\theta_{ijt}}$. θ_{ijt} determines the extent to which household i's utility from individual products diminishes with calories purchased for products within product group j in week t. λ_{ikjt} allows for household i have a different taste for each individual product k within product group j in week t. This allows for very flexible hetergeneity across individual products and product groups for reasons other than nutrient value.

The nutritent utility functions are parameterized as: $h_c(z_{ict}) = \beta_{ic} z_{ict}$. Plugging these into equation (5), and summing equation (5) across all products within product group j and summing over all weeks t in year T yields:

$$\sum_{t\epsilon T}\frac{\mu_{ijt}\theta_{ijt}}{\gamma_i} + \sum_{c=1}^{C}\frac{\beta_{ic}}{\gamma_i}\sum_{k=1}^{K_j}\sum_{t\epsilon T} a_{kjc} y_{ijkt} = \sum_{t\epsilon T}\sum_{k=1}^{K_j} p_{kjt} y_{ikjt}. \tag{6}$$

$\sum_{t\epsilon T}\sum_{k=1}^{K_j} p_{kjt} y_{ikjt}$ measures household i's annual expenditure on product group j. $\sum_{t\epsilon T}\frac{\mu_{ijt}\theta_{ijt}}{\gamma_i}$

captures how much household i would consume of product group j, absent the nutritional value of products in product group j. μ_{ijt} measures household i's taste for product group j in week t. household i's $\sum_{c=1}^{C} \frac{\beta_{ic}}{\gamma_i} \sum_{k=1}^{K_j} \sum_{t \epsilon T} a_{kjc} y_{ijkt}$ captures how much additional expenditure will be allocated to product group j based on the desirability of its nutrient contents.

It will be useful for estimation to rewrite equation 6 by solving for total calories purchased by household i in product group j in year T. Define total calories purchased by household i in product group j in year T as: $Y_{ijT} = \sum_{t \epsilon T} \sum_{k \epsilon J} y_{ikjt}$. equation 6 can now be written as:

$$\sum_{t \epsilon T} \frac{\mu_{ijt} \theta_{ijt}}{\gamma_i} + \sum_{c=1}^{C} \frac{\beta_{ic}}{\gamma_i} \tilde{a}_{iTjc} Y_{ijT} = \tilde{p}_{ijT} Y_{ijT}., \tag{7}$$

where $\tilde{p}_{ijT}$is the calorie weighted average price paid per calorie by household i in product group j in year T. Similary, $\tilde{a}_{iTjc}$is the calorie weighted average amount of nutrient c per calorie in products purchased by household i in product group j in year T. Equation 7 can now be solved for total calories, Y_{ijT} :

$$Y_{ijT} = \frac{\sum_{t \epsilon T} \frac{\mu_{ijt} \theta_{ijt}}{\gamma_i}}{\tilde{p}_{ijT} - \sum_{c=1}^{C} \frac{\beta_{ic}}{\gamma_i} \tilde{a}_{iTjc}}. \tag{8}$$

Finally, taking logs of both sides yields:

$$log(Y_{ijT}) = log(\sum_{t \epsilon T} \frac{\mu_{ijt} \theta_{ijt}}{\gamma_i}) + log(\tilde{p}_{ijT} - \sum_{c=1}^{C} \frac{\beta_{ic}}{\gamma_i} \tilde{a}_{iTjc}). \tag{9}$$

A desirable property of this model is that it admits substantial flexibility and heterogeneity in preferences at the UPC level, as measured by $f_{ikjt}(y_{ikjt}) = \lambda_{ikjt} y_{ijkt}^{\theta_{ijt}}$. λ_{ikjt} allows each household to have heterogenous preferences for each UPC in each week. The model also admits preference heterogeneity in product group preferences (including the outside good) over time and across households as measured by $\frac{\mu_{ijt} \theta_{ijt}}{\gamma_i}$, while at the same time capturing the utility value of nutrients, as measured by $\sum_{c=1}^{C} \frac{\beta_{ic}}{\gamma_i} \tilde{a}_{iTjc}$. One of the most desirable properties of the model is that is allows for estimation of nutrient and product group preferences from data has been aggregated to the annual product group level. This allows us to focus on estimation of preferences for nutrients without dealing with the parameters driving preferences at the UPC level or the dynamics in purchase behavior at the weekly level.

VI Estimation

Equation 9 will be the estimating equation to identify households' preferences for product groups and nutrients. All estimation will be done on data aggregated to annual product group consumption

measures, as shown in equation 8.[27] We will estimate heterogenous preferences across households of different income types. Household i's type is denoted $b(i)$. We now define the household i's preference for product group j in year T by the mean preference across years and households of type $b(i)$, and its deviation from this mean:

$$log(\sum_{t \epsilon T} \frac{\mu_{ijt}\theta_{ijt}}{\gamma_i}) = \bar{\delta}_{b(i)j} + \widetilde{\delta_{ijT}}. \tag{10}$$

We also allow for one of the product nutrients to be unobserved to the econometrician that varies across household types. This is to capture unobserved overall quality differences of products bought by different types of households. Let c_u denote the unobserved product nutrient and C_o denote the set of observable product nutrients. Preferences for nutrients and the outside good will vary by household type $b(i)$ for estimation.

$$\sum_{c=1}^{C} \frac{\beta_{b(i)c}}{\gamma_{b(i)t}} \tilde{a}_{iTjc} = \sum_{c=1}^{C_o} \tilde{\beta}_{b(i)c} \tilde{a}_{iTjc} + \tilde{\alpha}_{b(i)c_u} \tag{11}$$

$$\tilde{\beta}_{b(i)c} = \frac{\beta_{b(i)c}}{\gamma_{b(i)}},$$

$$\tilde{\alpha}_{b(i)c_u} = \frac{\beta_{b(i)c_u}}{\gamma_{b(i)}} \tilde{a}_{c_u}. \tag{12}$$

Plugging equations (10) and 11 into equation 9 gives:lo

$$log(Y_{ijT}) = \bar{\delta}_{b(i)j} + \widetilde{\delta_{ijT}} + log(\tilde{p}_{ijT} - \sum_{c=1}^{C_o} \tilde{\beta}_{b(i)c} \tilde{a}_{iTjc} + \tilde{\alpha}_{b(i)c_u}). \tag{13}$$

Equation (13) will be our main estimating equation. It relates total annual calories purchased in product group j by household i in year T (Y_{ijT}), to a fixed effect for each product group and household type $\left(\bar{\delta}_{b(i)j}\right)$, the average kilograms of each nutrient c per calorie in the bundle of products consumed by household i in product group j ($\tilde{a}_{iTjc}$), the value of unobserved nutrient $\left(\tilde{\alpha}_{b(i)c_u}\right)$, and a residual $\left(\widetilde{\delta_{ijT}}.\right)$[28] The product group by household type fixed effects capture the utility different types of household gain from each product group if all product groups offered zero nutritional content. The coefficients on the nutrient contents of the bundle of products $\left(\tilde{\beta}_{b(i)c}\right)$ capture how much households of type $b(i)$value the nutrient c. The residual represents household i's idiosyncratice preference for product group j in year T.

To identify households' preferences for nutrients and product groups we use non-linear least

[27] We will now refer to an annual time periods as T, weeks are still indexed by t.

[28] Note that we can not disentangle the preference for the unobserved nutrient from the total quantity of the unobserved nutrient. We estimate the combined effect of the value of the chosen quantity of the unobserved nutrient for each household type.

squares. The key identifying assumption is that indiviudual households idiosyncratric preferences for product groups are uncorrelated with their preferences for nutrients. This identification assumption could potentially be violated, for example, if households purchased salty foods because they prefer product groups that have longer shelf lives. We will not be able to seperate out how much of a preference for salty foods is due to a true nutrition value of sodium versus other impacts of sodium on the product. Essentially, we will be identifying the value of nutrients from a nutrition standpoint along with all the other impacts nutrients have on the desirability of food (taste, shelf life, ease of preparation.) It is hard to think that supply-side instrumental variables could solve this problem as it would be challenging to create variation only in the nutrtion value of a product, without impacting it taste or shelf life.

Intuitively, the model will identify a strong preference for a given nutrient if variation in the intensity of that nutrient across product groups is strongly correlated with calories consumed within product groups across households or over time. Preference for nutrients are distringuished from a direct preference for the product group by whether the calories consumed in a given product group remains fixed, regardless of variation in nutrient content.

The main model estimates will explore preference heterogeneity based on household income. We bucket households into types based on whether their household income is below $25,000, between $25,000 and $50,000, between $50,000 and $75,000, and above $75,000.

VII Results

We report the model estimates below. Table (5)reports the average product fixed effects for seven different categories of food. The coefficients have been normalized to represent the expenditure each type of household would choose for each category of food if all foods contained no nutrients. These preference represent the relative desirability of different foods for reasons other than nutrition.[29]

[29]Specifically, we take the estimated fixed effects for each product group within each income group $\left(\bar{\delta}_{b(i)j}\right)$and sum them across product groups within the more aggregate product category listed in Table (5). We then divide this sum by the sum of all the prouduct group fixed effects. For example, the reported expenditure share on Dry Grocery for Inc$\leq 25,000$: $\frac{\sum_{j \epsilon DryGrocery} \bar{\delta}_{Inc \leq 25K,j}}{\sum_{l=1}^{64} \bar{\delta}_{Inc \leq 25K,l}} = 0.5174$.

Table 5: **Average Preferences for Product Categories by Household Income**

	Dry Grocery	Prepared Foods	Frozen	Meat	Dairy	Produce	Alcohol
Inc$\leq 25K$	0.5592	0.0943	0.0779	0.0438	0.1324	0.0360	0.0564
	[0.00002]	[0.000007]	[0.00001]	[0.000004]	[0.00001]	[0.000004]	[0.000008]
$25K < Inc \leq 50K$	0.5562	0.0964	0.0759	0.0445	0.1332	0.0396	0.0542
	[0.00001]	[0.000004]	[0.000006]	[0.000002]	[0.000008]	[0.000002]	[0.000004]
$50K < Inc \leq 75K$	0.5523	0.0979	0.0747	0.0439	0.1353	0.0426	0.0532
	[0.00005]	[0.000005]	[0.000006]	[0.000002]	[0.000009]	[0.000002]	[0.000004]
$75K < Inc$	0.5449	0.0985	0.0729	0.0400	0.1367	0.0485	0.0586
	[0.00001]	[0.000004]	[0.000004]	[0.000002]	[0.000007]	[0.000002]	[0.000003]
# of Product Groups	36	5	8	2	10	1	3

Notes: Parameter estimates are normalized to sum to one for each income group. The magnitudes represent households' expenditure shares on each product category if all products had no nutritional content. The model estimates a seperate parameter for each calorie shares for each of the 66 product groups. This table aggregates these estimates into six broad categories. Standard errors cluster by household and use the delta method.

Table (5) shows that even without differences in nutritional content across product groups, there are differences in the types of products consumed across the income distribution. The lowest income group spends 8.3% more on frozen foods, 5.0% more on prepared foods, and 1.7% more on dry groceries than the highest income group.[30] The highest income group spends 14.5% more on fresh meat and 6.3% more on dairy than the lowest income group. The higher income households appear to prefer products with shorter shelf life (more meat and dairy, less frozen and dry grocery), or possibly products that require more work to prepare (more fresh meat, less frozen and prepared foods). Produce and alcohol budget shares do not vary much across the income distribution. To the extent that dry groceries, prepared foods, and frozen goods are relatively less healthy than fresh meat and dairy, these preferences for products groups show that some of the nutritional differences between the low and high income households need not be due to a direct difference in preference for nutrients. Rather, these differences could be partially due to a preference for product groups characteristics, such as shelf life and food prep time, which is correlated with nutrient content. Section XX below will perform a formal calculation to measure what these product group preference differences drive nutrtional outcomes.

Table 6 reports the estimated preferences for product nutrients across the four income groups. These have been normalized such that units represent how many kilograms of the nurtient offers the same utility value as a kilogram of fat.[31] This normalization removes differences in the marginal utility of a dollar ($\gamma_{b(i)}$) across the income groups.

Preferences for carbs, fiber, sugar, and cholestol and fruit are linked with household income. However, the higher income groups do not always exhibit more desire for healthy nutrients. Higher income groups have a stronger desire for fiber and fruit and a weaker taste for sugar, leading them to make more healthy choies. Carbs are twice as desirable to the highest income group than to the lowest (relative to fat). Fiber is undesirable to all households, however the higher income groups are willing to tolerate it more. Sugar is 39% less desirable to the highest income group than the lowest. Fruit 400% more desirable to the highest income group than the lowest.[32]

However, the higher income groups also have a stronger desire of cholesterol, leading them to make less healthy choices on this dimension. Cholesterol is 23% more desirable to the highest income group than to the lowest. There does not appear to be a significant income link to households' preferences over the other nutrients that enter the health index (saturated fat, protein, sodium, and vegetables). Overall, higher income households have slightly more desire for healthy nutrients.

[30] These percentages are calculated by taking the difference in expenditure shares between the bottom income group and the top and then dividing this by the expenditure share of the top income group.

[31] Appendix Taable A6 reports the raw point estimates for nutrient preferences measured in dollars. These estimates clearly show a declining marginal utility of a dollar across the income groups.

[32] These estimates for the value of fruit measures the nutrient desirability of fruit other than through our standard observed macronutrients. This reflects the value of the vitamins found in fruit.

Table 6: Preferences for Nutrients by Household Income

Income	Carbs	Fat	Saturated Fat	Fiber	Protein	Sugar	Sodium	Cholesterol	Fruit	Vegetables
Inc$\leq 25K$	0.095	1.000	-0.200	-0.587	0.329	0.256	-0.710	-36.348	0.004	-0.066
	[0.0107]		[0.0158]	[0.0222]	[0.0131]	[0.0085]	[0.0271]	[1.746]	[0.0025]	[0.0027]
$25K < Inc \leq 50K$	0.104	1.000	-0.222	-0.578	0.283	0.242	-0.753	-29.272	0.007	-0.063
	[0.0074]		[0.0109]	[0.0155]	[0.0086]	[0.0058]	[0.0206]	[1.123]	[0.0018]	[0.0019]
$50K < Inc \leq 75K$	0.133	1.000	-0.240	-0.510	0.270	0.215	-0.712	-25.485	0.010	-0.064
	[0.0077]		[0.0120]	[0.0164]	[0.0097]	[0.0060]	[0.0217]	[1.175]	[0.0023]	[0.0022]
$75K < Inc$	0.190	1.000	-0.178	-0.431	0.308	0.157	-0.575	-27.895	0.012	-0.069
	[0.0041]		[0.0075]	[0.0101]	[0.0067]	[0.0031]	[0.0126]	[0.8425]	[0.0013]	[0.0015]

Notes: Standard errors are clustered by household. Magnitudes represent kilograms of the nutrient which offers the same utility as a kilgram of non-saturated fat. A given nutrient can enter through multiple preference parameters, such as saturated fat is both valued as fat and satuarted fat. Fiber and sugar are also carbohydrates. Value of fruit and vegetables accounts for value over and beyond macronutient characteristics of the fruit and vegetables.

VIII Decomposing Nutrition Choices into Supply and Demand Forces

Using the model estimates above, we decompose how much of the observed nutrition differences observed across the income groups are due to supply forces (prices and product nutrients) versus demand forces (product group and nutrient preferences). For a given set of prices for each product group ($\tilde{p}_j$), nutrients for each product group j ($\tilde{a}_{jc_1}, ..., \tilde{a}_{jC_o}, \tilde{\alpha}_{c_u}$), product group preferences ($\bar{\delta}_1, .., \bar{\delta}_J$), and nutrient preferences ($\tilde{\beta}_1, ..., \tilde{\beta}_{C_o}$), we can calculate how many calories would be consumed within each product group ($\hat{Y}_j$):

$$\hat{Y}_j = \frac{\bar{\delta}_j}{\tilde{p}_j - \sum_{c=1}^{C_o} \tilde{\beta}_c \tilde{a}_{jc} - \tilde{\alpha}_{c_u}}. \tag{14}$$

To evaluate the healthfulness of this bundle of goods, we calculate the health index, as discussed in Section XX, where w_c are the health index weights on each nutrient:

$$\hat{H} = \sum_j \sum_c w_c \tilde{a}_{jc} \hat{Y}_j. \tag{15}$$

Since we did not estimate parameters determining preferences at the UPC level, our counterfactuals will only allow households to re-optimize across product groups, but not change their relative quantities across UPCs within product groups. While this is a limitation to our counterfactuals, trying to estimates product preferences for all UPCs for each income group would be very challenging. The main issue is that there are many UPCs we observed purcased within one income group, but never observe in the other groups. It would be very hard to attempt to measure preferences for products never consumed by different income groups without making strong assumptions. However, by using composite goods at the product group level, we alleviate this problem by only focusing on preference parameters and product characteristics which can easily be compared across income groups.

Our first counterfactual explores the roles of product group prices in healthy eating differences across the income groups. We will set the product group prices for all income groups to those observed in the highest income group for each product group, but allow each income group to retain their individual product group nutrient characteristics and preferences overs product groups and nutrients. Thus, for each income group $b(i)$, we calculate their product group demand as:

$$\hat{Y}_{b(i)j} = \frac{\bar{\delta}_{b(i)j}}{\tilde{p}_{4j} - \sum_{c=1}^{C_o} \tilde{\beta}_{b(i)c} \tilde{a}_{b(i)jc} - \tilde{\alpha}_{b(i)c_u}}. \tag{16}$$

and then plug in these quantities into the health index formula to summarize the healthiness of this bundle of foods. Figure 7 shows that just by adjusting prices to those observed in the highest

income group, the HealthIndex gap between the income group closes by about 10%. Healthy nutrients are relatively cheaper in higher income areas than lower income.

Second, we now set both prices and product group nutrient levels to those observed in the highest income group and recompute what each income group would purchase:

$$\hat{Y}_{b(i)j} = \frac{\bar{\bar{\delta}}_{b(i)j}}{\tilde{p}_{4j} - \sum_{c=1}^{C_o} \tilde{\beta}_{b(i)c}\tilde{a}_{4jc} - \tilde{\alpha}_{4c_u}}. \tag{17}$$

Figure 7 shows that the health index gap between the income groups decline by an additional 40%. Supply differences in the product makeup within the product groups plays a significant role in healthy eating differences across the income groups. The combination of prices and product nutrients can explain about 50% of the healthy eating gap between the income groups.

We now explore the role of demand differences. We now set product group preferences to those of the highest income, along with the prices and product nutrients observed in the top income group:

$$\hat{Y}_{b(i)j} = \frac{\bar{\delta}_{4j}}{\tilde{p}_{4j} - \sum_{c=1}^{C_o} \tilde{\beta}_{b(i)c}\tilde{a}_{4jc} - \tilde{\alpha}_{4c_u}}. \tag{18}$$

Figure 7 shows that this essentially closes the healthy eating gap completely. The bundles of food chosen by the lower income groups even are slightly healthier than those chosen the top income group.

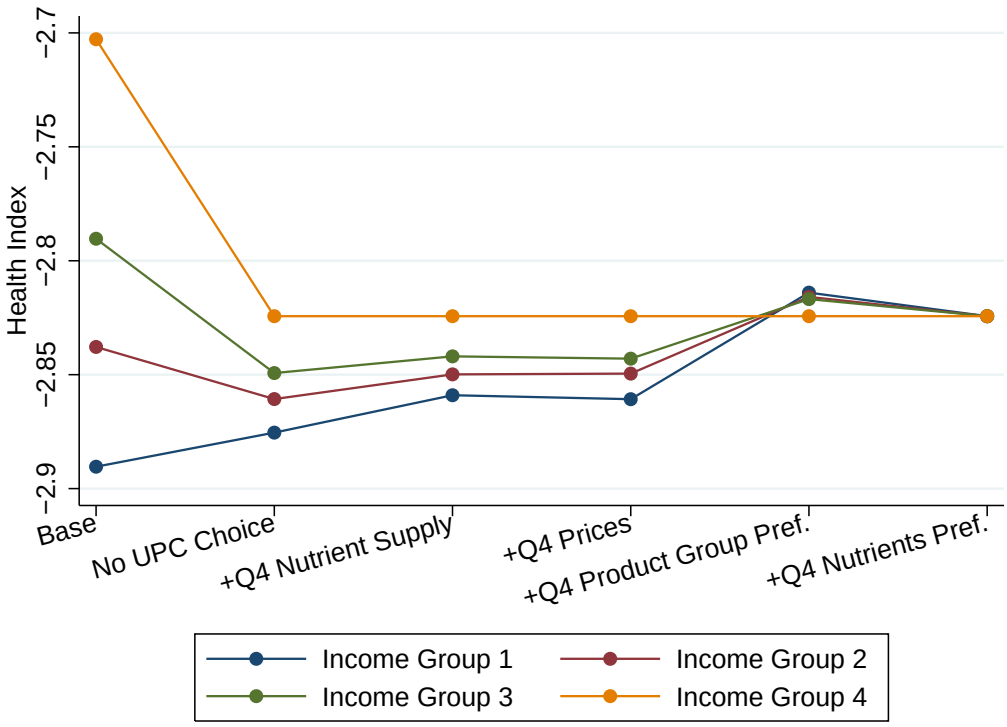
Finally, we now set the nutrient preferences to those of the highest income group, along with prices, product group preferences, and product nutrient levels:

$$\hat{Y}_{b(i)j} = \frac{\bar{\delta}_{4j}}{\tilde{p}_{4j} - \sum_{c=1}^{C_o} \tilde{\beta}_{4c}\tilde{a}_{4jc} - \tilde{\alpha}_{4c_u}}. \tag{19}$$

This mechanically equals the observed purchases of the top income group. Figure 2 shows that now all 4 income groups consume identical bundles and have the same health index level. The additional effect of setting the lower income groups' nutrient preferences to those of the highest income group actually make theses group consume slightly less healthy food.

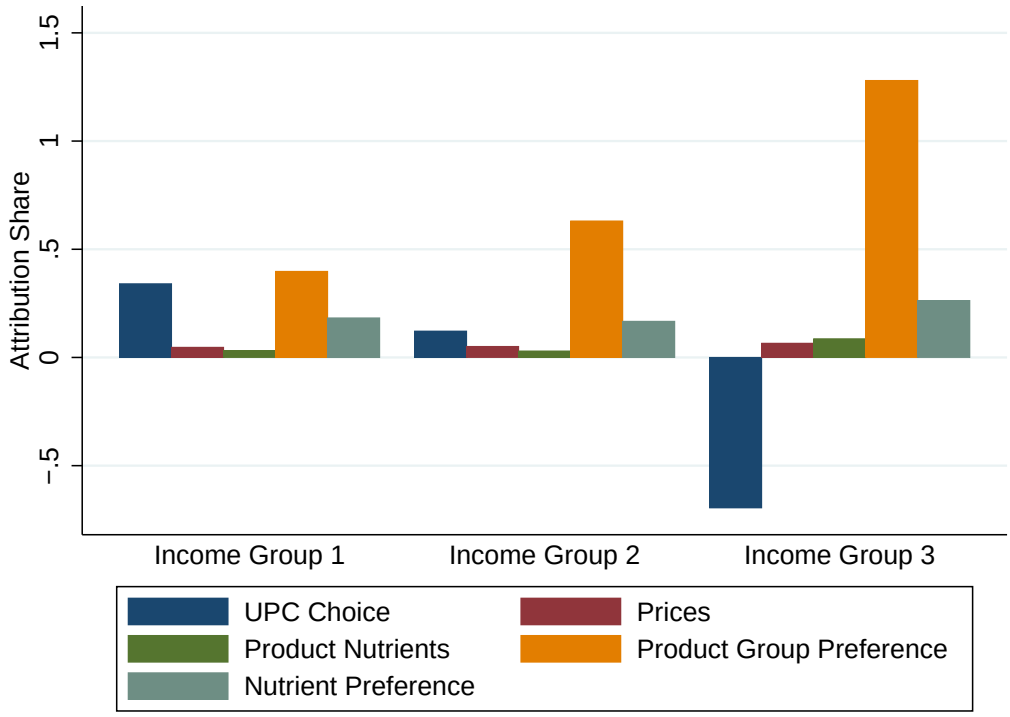
Figure VIII summarizes these effects into how how much of the healthy eating gap can be attributed to each of these supply and demand forces. Overall, prices explain about 10%, product nutrients explain 40%, product group preferences explain 55% and nutrient preferences explain -5%. 50% of the health eating gap is due to supply and 50% is due to demand forces.

Figure 7: **Predicted Health Index for Each Income Group**



Notes:Each category on the x-axis represented a seperate counterfactual calculation. The base catergory measures the health index for each income group when each group retains their true preferences and face their own local supply conditions. The second category sets all prices to those observed in income group 4. The third category sets all prices and product nutrient characteristics to those in group 4. The fourth and fifth categories add on the product group and nutrient preferences, respectively.

Figure 8: **Percent of Health Index Differences From Supply & Demand Factors**



Notes: Units measure the percent of the health index difference between each income group and the richest income group that is caused be each factor: product group prices, product group nutrients, product group preferences, and nutrient preferences.

IX Conclusion

We study how and why healthful eating varies by income in the United States. The public health literature has documented that lower-income neighborhoods suffer from lower availability of healthful groceries and that lower-income households eat less healthfully, and some researchers and policymakers have asserted that lack of supply causes unhealthful demand. Our results, like those of Handbury, Rahkovsky, and Schnell (2015), are not consistent with this argument. We find that despite the differences in local supply, low-income households still purchase the great majority of their groceries from grocery stores, supercenters, and club stores, which carry more produce and generally more healthful items than convenience stores, drug stores, and mass merchants. Thus, when a new supermarket enters nearby, this may benefit households by reducing travel costs, but it does not meaningfully change their choice sets or the healthfulness of their purchases. On the other hand, our results in Section IV.B suggest the importance of demand side factors such as information and early-life habits. We also present demand model estimates and a decomposition

of the nutrition-income relationship into the effects of prices, availability, and preferences.

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Online Appendix: Not for Publication

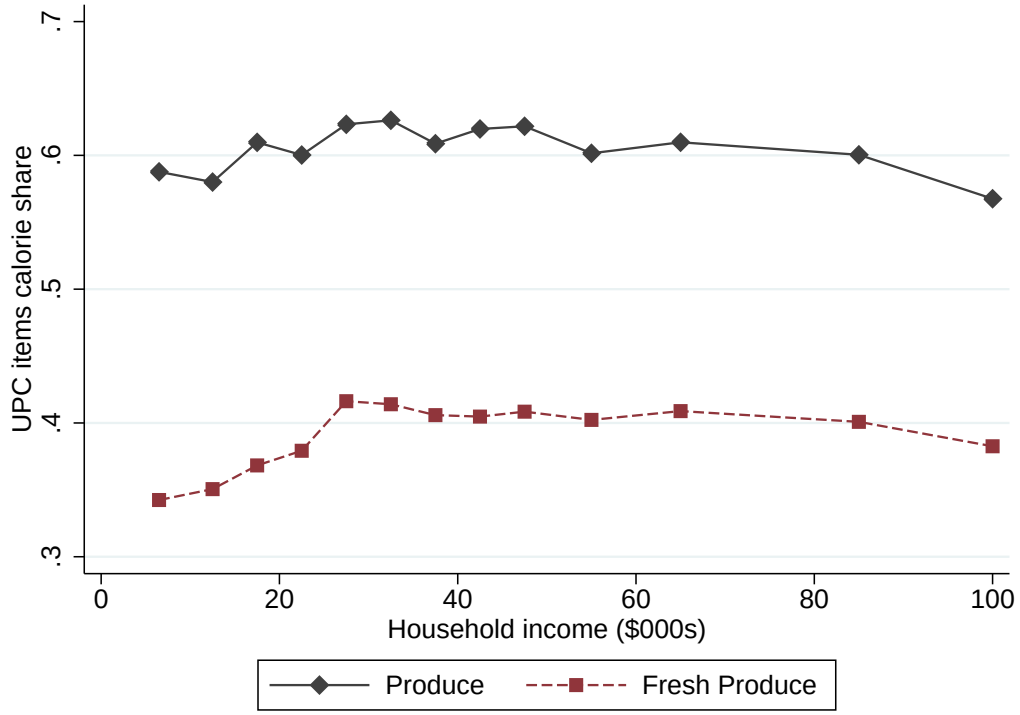
The Geography of Poverty and Nutrition: Food Deserts and Food Choices Across the United States

Hunt Allcott, Rebecca Diamond, and Jean-Pierre Dubé

A Appendix to Data Section

A.A Magnet Calorie Shares

Figure A1: **Calorie Shares from Produce Items with UPC Codes**



Notes: This figure uses the Nielsen Homescan "magnet" subsample for 2004-2006. "Produce" includes fresh, dried, canned, and frozen produce. Shows the share of produce and fresh produce calories coming from items with UPCs, which are the items we observe outside the Magnet subsample.

A.B Health Index

Our raw Health Index $H(\mathbf{x})$ is the sum of good minus bad nutrients, weighting each by its recommended daily intake (RDI): $H(\mathbf{x}) = \sum_k G_k \frac{g_k}{r_k} - (1 - G_k) \frac{g_k}{r_k}$, where g_k is the grams of macronutrient k, r_k is the RDI for a normal adult, and G_k takes value 1 for "good" macronutrients and 0 for "bad" macronutrients. Appendix Table A1 presents the RDI r_k used to construct the Health Index. For example, $H(\mathbf{x})$ would take value 1 for a UPC (say three cups of vegetables) that exactly satisfied the RDI of one "good" macronutrient, or -1 for a UPC that contained the maximum RDI of one "bad" macronutrient.

In the 2004-2013 Homescan data, the mean household-level raw Health Index per 1000 calories is 2.60, and the standard deviation is 0.70. Using these figures, the Health Index reported in the paper is re-normalized to mean 0, standard deviation one across households.

Table A1: **Health Index Function**

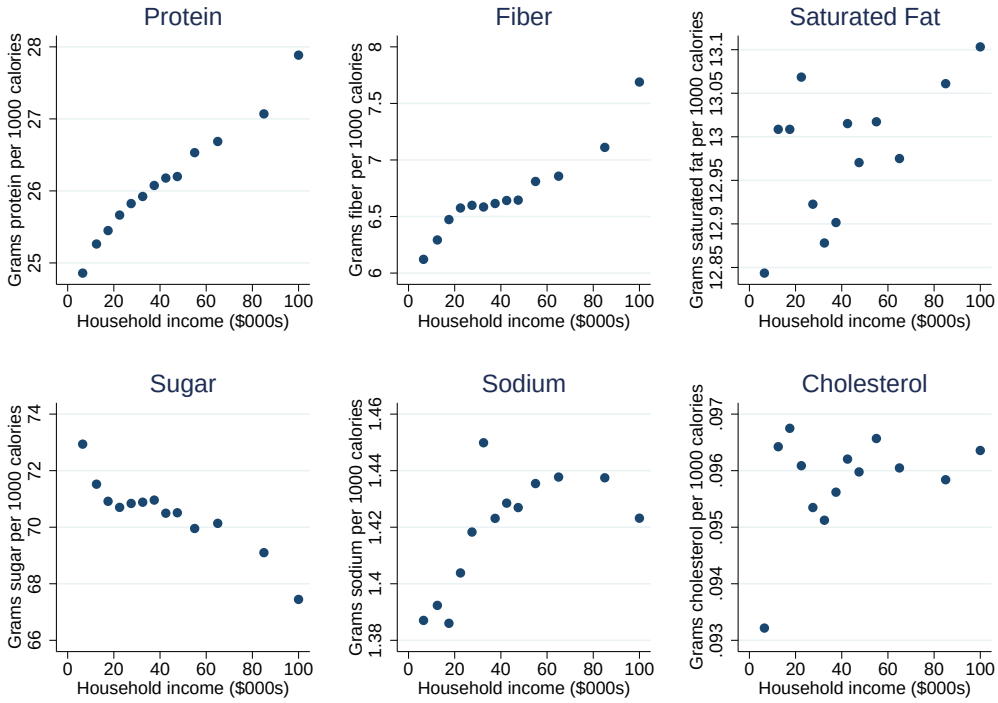
Attribute	Recommendation	Recommended Daily Intake (grams)	Explanation
		Fruits and vegetables	
Fruit	Increase	320	Two cups/day (Food Patterns); 160 g/cup
Vegetables	Increase	390	Three cups/day (Food Patterns); 130 g/cup
		All other items	
Protein	Increase	51	51 grams/day (DRI)
Fiber	Increase	29.5	29.5 grams/day (DRI)
Sugar	Reduce	32.8	45% of 282 calories/day from sugar+sat. fat (Food Patterns)
Saturated fat	Reduce	17.2	55% of 282 calories/day from sugar+sat. fat (Food Patterns)
Sodium	Reduce	2.3	2300 mg/day (Dietary Guidelines)
Cholesterol	Reduce	0.3	300 mg/day (Dietary Guidelines)

Notes: This table presents the Recommended Daily Intakes (RDI) for each attribute. The Health Index $H(\mathbf{x}) = \sum_k G_k \frac{g_k}{r_k} - (1 - G_k) \frac{g_k}{r_k}$, where g_k is the grams of macronutrient k, r_k is the RDI for a normal adult, and G_k takes value 1 for macronutrients recommended to "Increase" and 0 for macronutrients recommended to "Reduce."

B Appendix to Stylized Facts Section

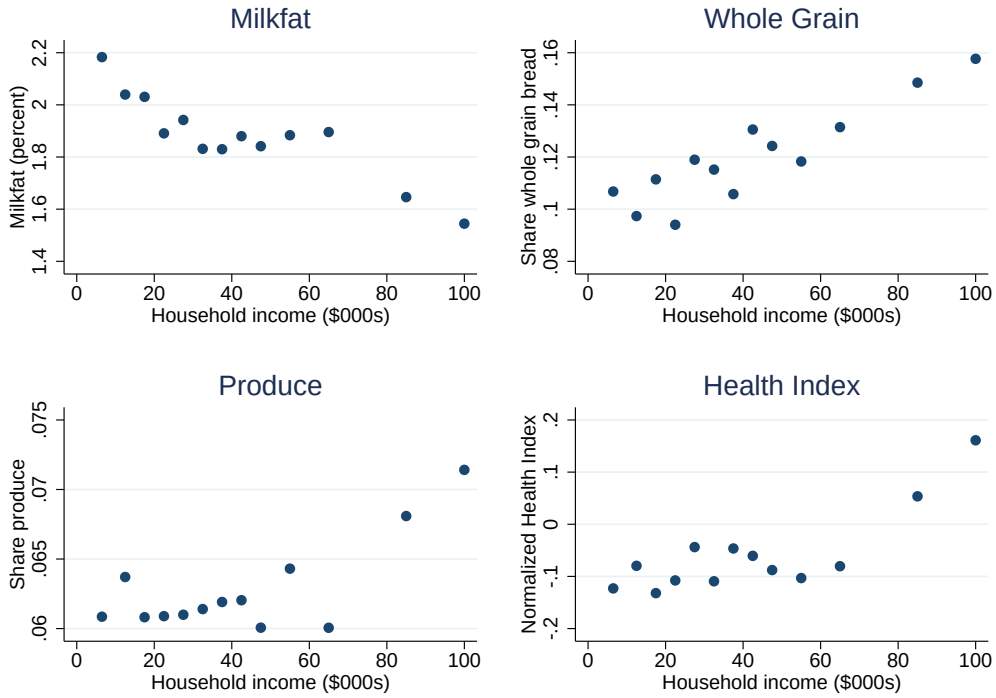
B.A Additional Figures

Figure A2: **Macronutrient Purchases by Household Income**



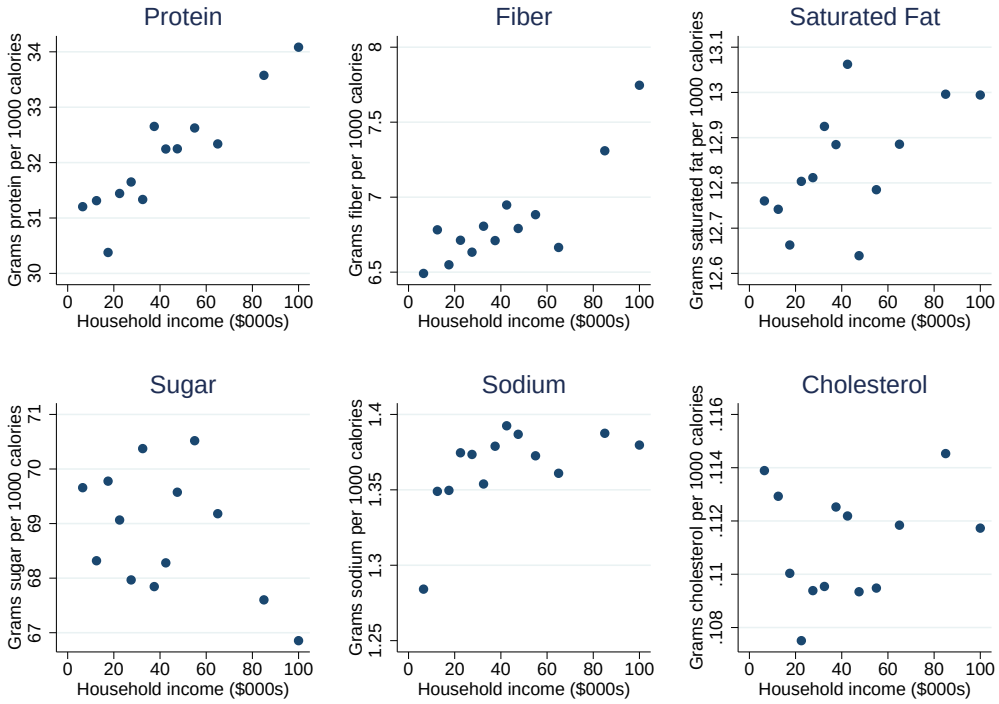
Notes: Presents calorie-weighted average macronutrient contents of purchases using Nielsen Homescan data for 2004-2013. The x-axis presents nominal income bins; household incomes larger than $100,000 are coded as $100,000.

Figure A3: **Magnet Subsample: Healthful Purchases by Household Income**



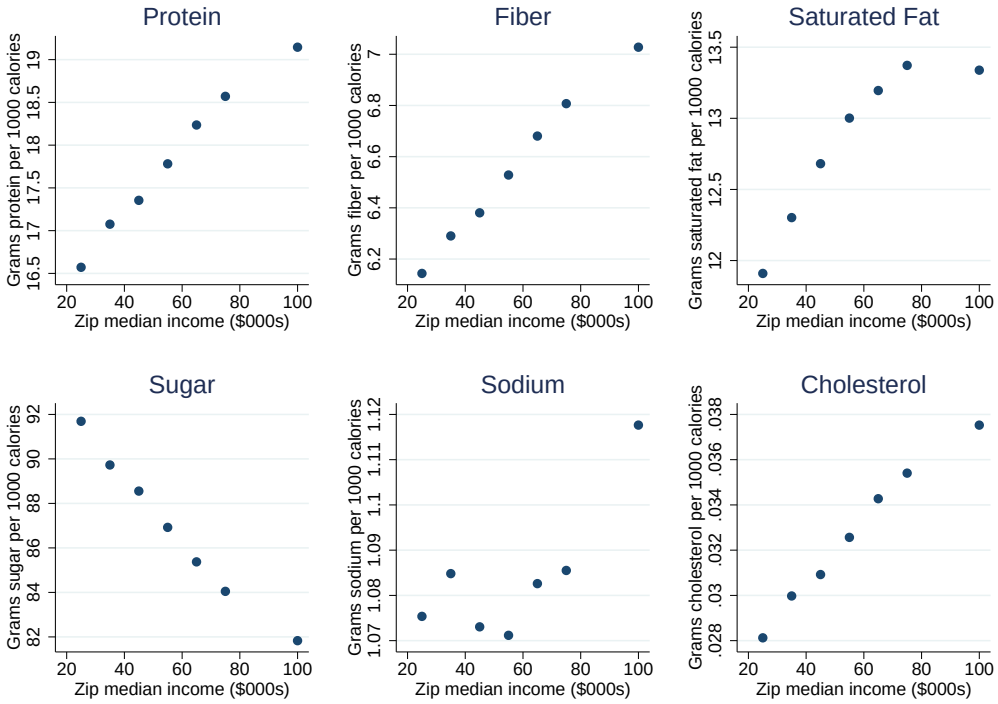
Notes: Nielsen Homescan data, magnet subsample, for 2004-2006. The x-axis presents nominal income bins; household incomes larger than $100,000 are coded as $100,000. This parallels Figure 1, except using the magnet subsample which also records purchases of non-UPC items such as bulk produce. Milkfat is the calorie-weighted average milkfat of milk purchases, whole grain is the calorie-weighted average share of bread, buns, and rolls purchases that are whole grain, produce is the share of calories from fresh, canned, dried, and frozen fruits and vegetables, and Health Index is the average Health Index per 1000 calories across all UPCs purchased. Health Index is normalized to mean zero, standard deviation one across households.

Figure A4: **Magnet Subsample: Macronutrient Purchases by Household Income**



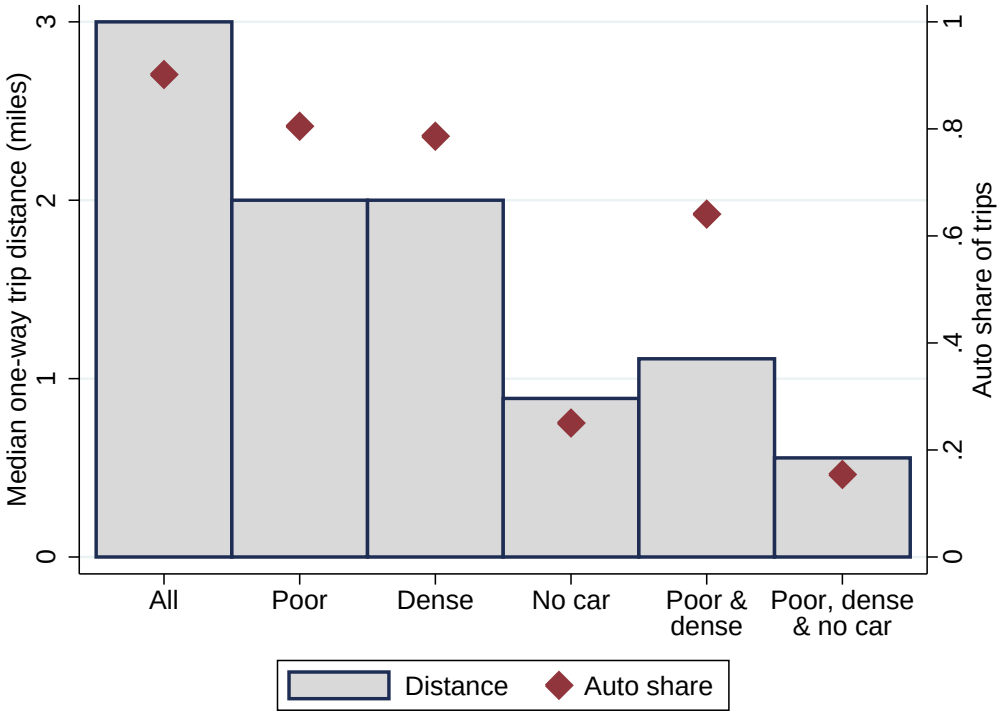
Notes: Presents calorie-weighted average macronutrient contents of purchases using Nielsen Homescan data, magnet subsample, for 2004-2006. The x-axis presents nominal income bins; household incomes larger than $100,000 are coded as $100,000. This parallels Figure A2, except using the magnet subsample which also records purchases of non-UPC items such as bulk produce.

Figure A5: **Store Average Healthfulness by Zip Code Median Income**



Notes: Using Nielsen RMS data for year 2012, we constructed calorie-weighted mean macronutrient content across all UPCs offered in each store. This figure presents the means of these variables within categories of zip code median income. This parallels Figure 2 in the text.

Figure A6: **Median Shopping Trip Distances by Household Income**

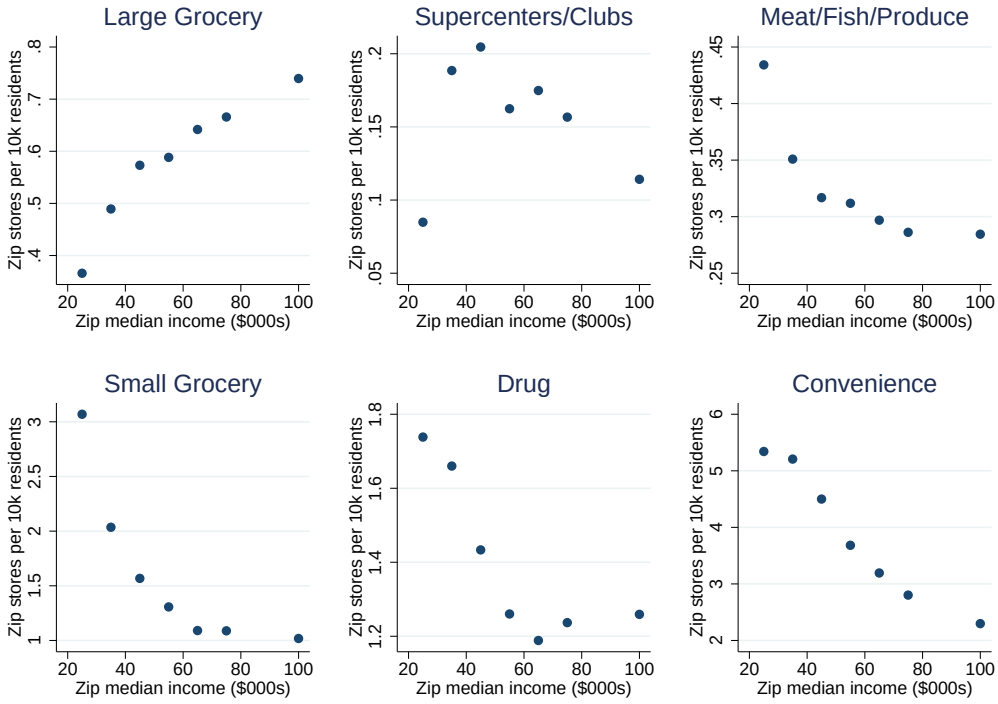


Notes: Data are from the 2009 National Household Travel Survey. Bars represent the mean one-way trip distance for trips beginning or ending in "buying goods: groceries/clothing/hardware store." "Poor" means household income less than $30,000, "Dense" means Census tract population density greater than 4,000 people per square mile, and "No car" means that the household does not own a car.

B.B Low-income neighborhoods have relatively more unhealthful store types

Using the Zip Code Business Patterns data for 2012, Appendix Figure A7 plots the average count of stores by channel type for zip codes by median income category. Zip codes vary substantially in area and population, so this figure normalizes store counts per 10,000 residents; the mean zip code has 12,000 residents. Lower-income zip codes have more stores per capita of all channel types, with two exceptions. First, the concentration of large grocery stores per capita is sharply monotonically increasing in median income, consistent with Powell *et al.* (2007). Second, the concentration of supercenters and club stores takes an inverted-U shape, with many fewer per capita in the very lowest-income zip codes.

Figure A7: **Store Counts by Zip Code Median Income**



Notes: Population-weighted mean store counts by zip code income category from Zip Code Business Patterns, averaged over 2004-2013. Large (small) grocers are defined as those with 50 or more (fewer than 50) employees.

C Appendix to Reduced Form Section

C.A Entry by All Retailers

To complement the event study estimates in the body of the paper, we present alternative specifications that measure entry using the Zip Code Business Patterns (ZBP) data.

Panel A of Appendix Table A2 shows that the Zip Code Business Patterns data date openings of specific supercenters in the correct year 50 to 80 percent of the time, although they are sometimes recorded a year later and sometimes in a broader "general merchandise" NAICS code (452) instead of the specific "supercenter and club store" NAICS code (452910).

Table A2: **Zip Code Business Patterns Accuracy Check with Known Entry Dates**

	(1)	(2)
Dependent variable is count of channel type:	Supercenter	General Merchandise
Panel A: Difference Estimator		
Supercenter Chain 1:		
2-year lead	0.00478	0.00629
	(0.00622)	(0.0166)
1-year lead	0.0375	0.0577
	(0.00978)***	(0.0164)***
Entry year	0.562	0.821
	(0.0199)***	(0.0210)***
1-year lag	0.208	0.0821
	(0.0169)***	(0.0191)***
2-year lag	0.0777	0.0133
	(0.0127)***	(0.0145)
Supercenter Chain 2:		
2-year lead	0.0158	-0.0172
	(0.0298)	(0.0421)
1-year lead	0.0133	-0.0451
	(0.0222)	(0.0462)
Entry year	0.0621	0.480
	(0.0327)*	(0.0623)***
1-year lag	0.172	0.0701
	(0.0413)***	(0.0594)
2-year lag	0.133	0.0918
	(0.0514)***	(0.0599)
Observations	264,734	264,734
Panel B: Fixed Effects Estimator		
Post entry: chain 1	0.902	0.932
	(0.0138)***	(0.0227)***
Post entry: chain 2	0.667	0.665
	(0.0365)***	(0.0659)***
Observations	297,966	297,966

Notes: Data are at the zip code-by-year level. All regressions include year indicators; fixed effects regressions have zip code fixed effects. Robust standard errors, clustered by zip code, in parentheses. *, **, ***: Statistically significant with 10, 5, and 1 percent confidence, respectively.

The entry event study regression is analogous to Equation (1). Define S_{zt} and G_{zt}, respectively, as the count of supercenters/club stores and large (at least 50 employee) grocery stores in zip code z in year t. Using household-by-year data and now denoting μ_{dt} as Census division-by-year indicators, the regression is:

$$Y_{izt} = \tau_S S_{zt} + \tau_G G_{zt} + \mu_{dt} + \phi_{ic} + \varepsilon_{izt} \tag{20}$$

Standard errors are again clustered by household.

Appendix Table A3 presents results. The structure is similar to that of Table 3: Panel A presents effects on expenditure shares, while Panel B presents effects on healthful eating. Estimates for all zip codes and for food deserts are on the left and right, respectively.

Columns 1 and 2 confirm that the ZBP data contain meaningful information. Column 1 shows that conditional on household fixed effects, a larger count of large grocery stores and/or a smaller count of supercenters and club stores in the zip code are both strongly positively associated with higher expenditure share at chain groceries. Column 2 shows the opposite: fewer grocery stores and more supercenters are strongly positively associated with higher expenditures at supercenters and club stores. Columns 3 presents effects on combined expenditure shares for all grocery stores, supercenters, and club stores. Columns 4-6 and 7-9 present estimates for the low-income and food desert subsamples. As in Table 3, effects of entry on expenditures are larger in food deserts. Also as in Appendix Table 3, we see that entry by a large grocery retailer substantially diverts sales from other supermarkets. Appendix Table A4 shows that most of this diversion is from other mass merchants; there is no statistically significant diversion from drug and convenience stores.

The bottom panel shows no statistically significant effect of the number of large grocers and supercenters/clubs on healthful eating. The standard errors are tighter than in Appendix Table 3. For low-income households, we can bound the effect of supercenter/club store entry on produce calorie shares at about 0.025 percentage points, or about 1/23 of the difference between the lowest- vs. highest-income households. Similarly, we can bound the effects on mean Health Index per 1000 calories at about 0.02 standard deviations, or about 1/11 of the difference between the lowest- and highest-income quartiles. Appendix Table A4 shows that under all alternative definitions of "food deserts," entry by large grocers, supermarkets, and club stores does not affect produce calorie share or Health Index.

One reason to prefer the earlier regressions with specific known retailers is that we have high confidence that entry dates are correctly measured. We can also imagine using the true supercenter entry dates as an instrument for ZBP data, which are measured with error. Panel B of Appendix Table A2 shows that the "first stages" of such a regression have coefficients around 0.9 and 0.66 for two different supercenter chains. If the average retailer in ZBP is measured with equal or perhaps somewhat more error than the less well-measured supercenter chain, this suggests that our bounds in the paragraph above should be increased by 50 to 100 percent due to measurement error. Even after this adjustment, however, our results in Tables 3 and A3 suggest that differences in supply, as measured by entry or exit of a large grocery retailer, explain at most only a small share of the differences in nutritional decisions between low- and high-income households.

Table A3: **Effects of Supermarket Entry Using Zip Code Business Patterns**

Panel A: Effects of Retailer Entry on Expenditure Shares

	(1)	(2)	(3)	(4)	(5)	(6)	(4)	(5)	(6)
Sample:	All Zip Codes			Income<$25,000			"Food Desert" Zip Codes		
Expend. shares	Chain	Super/	Grocery/	Chain	Super/	Grocery/	Chain	Super/	Grocery/
at store type:	Grocers	Club	Super/Club	Grocers	Club	Super/Club	Grocers	Club	Super/Club
Large grocers	0.341	-0.393	-0.121	-0.0862	-0.358	-0.428	0.335	-0.348	-0.213
	(0.128)***	(0.0961)***	(0.0853)	(0.288)	(0.201)*	(0.224)*	(0.461)	(0.378)	(0.278)
Supers/clubs	-2.144	3.433	0.755	-2.811	4.002	0.739	-4.234	5.514	0.513
	(0.290)***	(0.271)***	(0.172)***	(0.675)***	(0.629)***	(0.456)	(1.039)***	(1.185)***	(0.551)
Observations	543896	543896	543896	86940	86940	86940	131703	131703	131703
Dep. var. mean	58	25	87	56	22	85	53	27	87

Panel B: Effects of Retailer Entry on Healthful Eating

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Full Sample		Income<$25,000		"Food Desert" Zip Codes	
	Share	Health	Share	Health	Share	Health
Dependent variable:	Produce	Index	Produce	Index	Produce	Index
Large grocers	-0.00160	0.0000827	-0.00172	0.00302	0.0840	0.000960
	(0.0156)	(0.00653)	(0.0298)	(0.0128)	(0.0660)	(0.0167)
Supercenters/clubs	-0.0223	0.00493	0.0372	0.0335	-0.000362	0.0189
	(0.0284)	(0.0108)	(0.0677)	(0.0250)	(0.0772)	(0.0268)
Observations	543,896	543,892	86,940	86,939	131,703	131,702
Dependent var. mean	4.2	0.00	3.9	-0.12	4.13	-0.056

Notes: Data are at the household-by-year level. "Food Desert" zip codes are those with no grocery stores with 50 or more employees, supercenters, or club stores in 2003. Expenditure shares are in units of percentage points. Share Produce is the share of calories from fresh, canned, dried, and frozen fruits and vegetables, in units of percentage points. Health Index is the average Health Index per 1000 calories purchased. Health Index is normalized to mean zero, standard deviation one across households. Reported independent variables are the count of stores by channel type in the household's zip code; regressions also include Census division-by-year indicators and household-by-Census tract fixed effects. Robust standard errors, clustered by household, in parentheses. *, **, ***: Statistically significant with 10, 5, and 1 percent confidence, respectively.

Table A4: **Effects of Supermarket Entry Using Zip Code Business Patterns**

Panel A: Effects on Expenditure Shares at Other Store Types

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Full Sample		Income<$25,000		"Food Desert" Zip Codes	
Expenditure shares at store type:	Convenience/ Drug Stores	Other Mass Merchants	Convenience/ Drug Stores	Other Mass Merchants	Convenience/ Drug Stores	Other Mass Merchants
Large grocers	0.00750	0.154	0.00649	0.378	0.0360	0.200
	(0.0343)	(0.0599)**	(0.0775)	(0.179)**	(0.117)	(0.176)
Supercenters/clubs	0.0173	-0.826	-0.108	-0.729	0.251	-0.752
	(0.0632)	(0.123)***	(0.183)	(0.316)**	(0.177)	(0.363)**
Observations	543896	543896	86940	86940	131703	131703
Dependent var. mean	2.8	5.8	3.7	7.3	2.6	6.1

Panel B: Effects on Healthful Eating Using Alternative Food Desert Definitions

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	<1000 Produce UPCs		No Medium Groceries		Three-Mile Radius	
Dependent variable:	Share Produce	Health Index	Share Produce	Health Index	Share Produce	Health Index
Large grocers	0.0114	-0.0277	-0.0122	-0.0103	0.0768	-0.0122
	(0.109)	(0.0312)	(0.0876)	(0.0254)	(0.0620)	(0.0187)
Supercenters/clubs	0.145	0.0141	0.0327	-0.00954	0.0322	0.0250
	(0.108)	(0.0381)	(0.0984)	(0.0327)	(0.101)	(0.0338)
Observations	63180	63180	77989	77989	100379	100379
Dependent var. mean	4.1	-0.06	4.1	-0.046	4.1	-0.08

Notes: Data are at the household-by-year level. Parallels Table A3, except Panel A presents effects on expenditure shares at alternative channel types, and Panel B uses alternative definitions of a "food desert." In Panel B, columns 1 and 2 limit the sample to zip codes with fewer than 1000 produce UPCs available in 2003, as predicted by applying RMS data from Table 2 to Zip Code Business Patterns data; columns 3 and 4 also exclude any zip codes with grocery stores employing between 10 and 49 employees in 2003; columns 5 and 6 define a zip code as a food desert only if all zip codes with centroids within three miles have no supermarkets with 50 or more employees, supercenters, or club stores in 2003. Expenditure shares are in units of percentage points. Share Produce is the share of calories from fresh, canned, dried, and frozen fruits and vegetables, in units of percentage points. Health Index is the average Health Index per 1000 calories purchased. Health Index is normalized to mean zero, standard deviation one across households. Reported independent variables are the count of stores by channel type in the household's zip code; regressions also include Census division-by-year indicators and household-by-Census tract fixed effects. Robust standard errors, clustered by household, in parentheses. *, **, ***: Statistically significant with 10, 5, and 1 percent confidence, respectively.

C.B Additional Reduced Form Section Table and Figure

Table A5: **Effects of Supermarket Entry**

Panel A: Effects on Expenditure Shares at Other Store Types

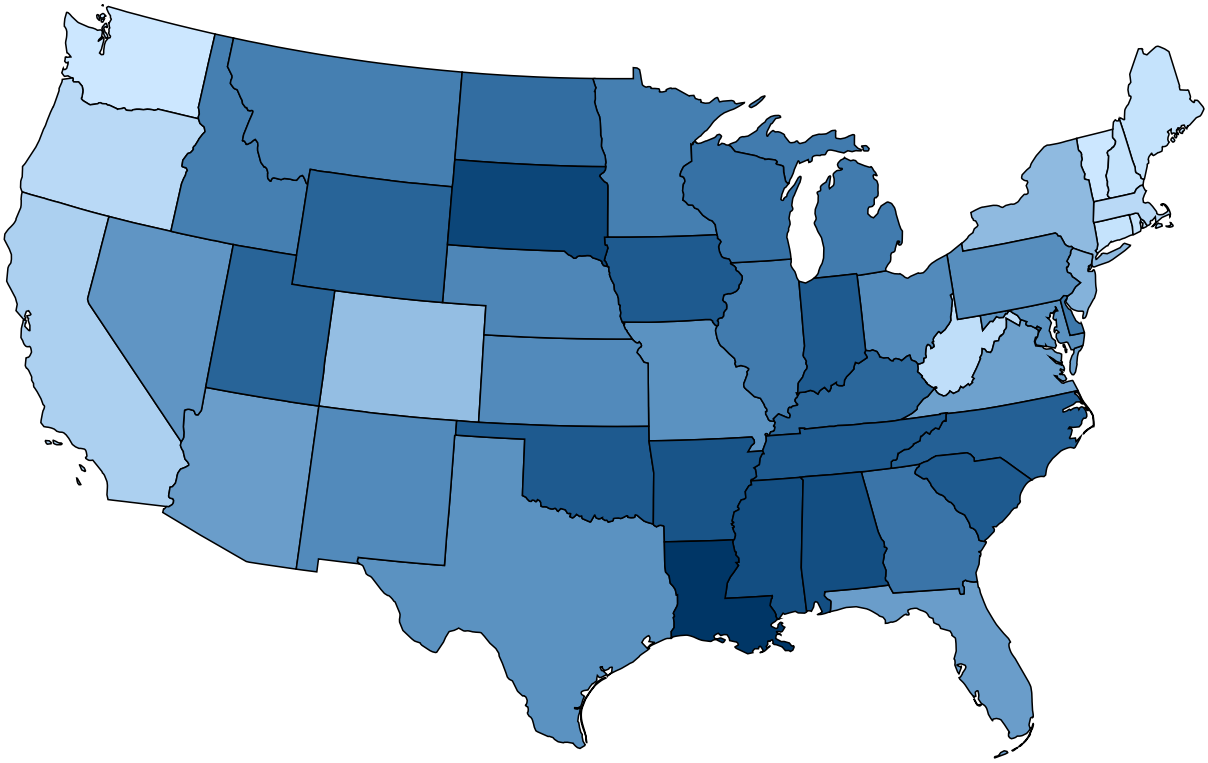
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Full Sample		Income<$25,000		"Food Desert" Zip Codes	
Expenditure shares at store type:	Conv/ Drug Stores	Other Mass Merchants	Conv/ Drug Stores	Other Mass Merchants	Conv/ Drug Stores	Other Mass Merchants
Post entry: 0-10 minutes	-0.0652	-0.609	-0.166	-0.679	-0.221	-0.806
	(0.0635)	(0.116)***	(0.192)	(0.316)**	(0.170)	(0.279)***
Post entry: 10-15 minutes	-0.0996	-0.113	-0.128	0.108	-0.272	-0.335
	(0.0437)**	(0.0807)	(0.145)	(0.236)	(0.112)**	(0.195)*
Observations	2,168,142	2,168,142	346,046	346,046	523,198	523,198
Dependent var. mean	2.9	5.9	3.8	7.5	2.7	6.2

Panel B: Effects on Healthful Eating Using Alternative Food Desert Definitions

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	<1000 Produce UPCs		No Medium Groceries		Three-Mile Radius	
Dependent variable:	Share Produce	Health Index	Share Produce	Health Index	Share Produce	Health Index
Post entry: 0-10 minutes	0.153	-0.0269	0.0827	-0.0348	0.173	0.0128
	(0.193)	(0.0458)	(0.144)	(0.0354)	(0.177)	(0.0415)
Post entry: 10-15 minutes	0.0171	0.00183	0.0281	0.00655	0.104	0.0382
	(0.0641)	(0.0194)	(0.0570)	(0.0188)	(0.0742)	(0.0191)**
Observations	251,974	251,961	309,070	309,056	397,387	397,367
Dependent var. mean	4.2	-0.059	4.2	-0.42	4.2	-0.075

Notes: Data are at the household-by-quarter level. Parallels Table 3, except Panel A presents effects on expenditure shares at alternative channel types, and Panel B uses alternative definitions of a "food desert." In Panel B, columns 1 and 2 limit the sample to zip codes with fewer than 1000 produce UPCs available in 2003, as predicted by applying RMS data from Table 2 to Zip Code Business Patterns data; columns 3 and 4 also exclude any zip codes with grocery stores employing between 10 and 49 employees in 2003; columns 5 and 6 define a zip code as a food desert only if all zip codes with centroids within three miles have no supermarkets with 50 or more employees, supercenters, or club stores in 2003. Expenditure shares are in units of percentage points. Share Produce is the share of calories from fresh, canned, dried, and frozen fruits and vegetables, in units of percentage points. Health Index is the average Health Index per 1000 calories purchased. Health Index is normalized to mean zero, standard deviation one across households. Reported independent variables are indicators for whether a specific retailer has entered within a 0-10 or 10-15 minute drive from the household's Census tract centroid; regressions also include Census division-by-quarter of sample indicators and household-by-Census tract fixed effects. Robust standard errors, clustered by household, in parentheses. *, **, ***: Statistically significant with 10, 5, and 1 percent confidence, respectively.

Figure A8: **Average Health Index of Homescan Purchases by State**



Notes: Calorie-weighted average Health Index of purchases by state, using 2004-2013 Homescan data.

D Appendix to Demand Model Estimates

Table A6: Preferences for Nutrients by Household Income

Income	Carbs	Fat	Saturated Fat	Fiber	Protein	Sugar	Sodium	Cholesterol	Fruit	Vegetables
Inc$\leq 25K$	1.07	11.28	-2.62	-6.62	3.71	2.89	-8.01	-410.00	0.04	-0.74
	[0.092]	[0.318]	[0.160]	[0.217]	[0.190]	[0.126]	[0.218]	[16.227]	[0.028]	[0.024]
$25K < Inc \leq 50K$	1.17	11.22	-2.49	-6.49	3.18	2.72	-8.45	-328.43	0.08	-0.71
	[0.104]	[0.220]	[0.111]	[0.130]	[0.126]	[0.033]	[0.167]	[10.746]	[0.021]	[0.017]
$50K < Inc \leq 75K$	1.72	12.89	-3.09	-6.58	3.48	2.77	-9.18	-328.46	0.13	-0.83
	[0.133]	[0.278]	[0.139]	[0.171]	[0.161]	[0.044]	[0.207]	[13.214]	[0.030]	[0.023]
$75K < Inc$	3.42	17.96	-3.20	-7.74	5.54	2.82	-10.32	-501.49	0.21	-1.24
	[0.117]	[0.249]	[0.128]	[0.157]	[0.151]	[0.039]	[0.184]	[13.519]	[0.024]	[0.023]

Notes: Standard errors are clustered by household. Magnitudes represent willingness to pay in dollars for 1 kilogram of nutrient. A given nutrient can enter through multiple preference parameters, such as saturated fat is both valued as fat and satuarted fat. Fiber and sugar are also carbohydrates. To get total willingnges to pay for these nutrients, the point estimates need to summed across the relavant nutrients. Value of fruit and vegetables accounts for value over and beyond macronutient characteristics of the fruit and vegetables.