# Promoting Healthy Diet at a Large Chain Restaurant

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PRELIMINARY AND INCOMPLETE - PLEASE DO NOT CITE

January 31, 2020

**Abstract**

In the US, many public health and social problems–for example obesity–are linked to unhealthy diets. No doubt, people in lower-income and lower-education neighborhoods tend to consume less healthy food. But the underlying reasons remain unclear. Some papers attribute the nutritional inequality to "food desert", others have found evidences that can attribute the mainly to demand factors. In this paper, we examine the nutritional inequality generated from consumer within-category food choices for a meal in a restaurant setting where consumers need to trade off food item characteristics against its price. Using proprietary data from a large national restaurant chain, we show that people in more disadvantaged neighborhoods consume food items that are less healthy but are more sensitive to price promotions. We estimate a random coefficient demand model of consumer preferences on food items and show that consumer price sensitivities differ by demographics and as well as by the calorie content and the healthfulness of the item. With the estimated preferences, we conduct various counterfactual price policies to decrease or remove the differences in food choice healthfulness between the most and least advantaged neighborhoods.

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# 1 Introduction

In the US, many public health and social problems–for example obesity–are linked to unhealthy diets. In theory, body weight depends on food intake, exercise, working style, smoking, and other behavioral factors, but many believe unhealthy diet is one of the reasons why the US obesity rate has doubled in the past three decades.[1] More alarmingly, obesity and nutrition intake demonstrate similar gradient by income and education. Based on the 2011–2014 National Health and Nutrition Examination Survey (NHANES), the Center of Disease Control and Prevention (CDC) finds that obesity among US adults (age-adjusted) was lower in the highest income group (31.2%) than in the medium- and low-income groups (40.8% and 39.0%), and lower among college graduates (27.8%) than among those with some college and those of high school graduates or less (40.6% and 40.0%) (Ogden et al., 2017). Consistently, mounting evidences show that higher socioeconomic status (SES) is correlated with a greater diet variety and higher values in the Healthy Eating Index (HEI) and many other diet-quality measures (see the review article by Darmon and Drewnowski, 2008).

Nutritional inequality, and its potential consequence in public health and social problems, motivates many to explore why. We can classify the existing literature in two branches. One branch views it as a supply problem: because healthy food is less available and/or more expensive in disadvantaged neighborhoods, "food deserts" deprive low-SES people of the opportunity to choose healthy food. As the former First Lady Michelle Obama put it, "it's not that people don't know or don't want to do the right thing; they just have to have access to the foods that they know will make their families healthier" (Curtis, 2011). The food dessert literature, as reviewed by Bitler and Haider (2011), has justified millions of public dollars each year to subsidize grocers, farmers market, and other supply of health food in underserved areas. In the meantime, Currie et al. (2010) show that having a fast food restaurant within 0.1 miles of a school results in a 5.2 percent increase in obesity rates among ninth graders, and having a fast-food restaurant within 0.5 miles of residence leads to a 1.6 percent increase in the probability of pregnant women gaining over 20 kilograms. This evidence posts fast food restaurants as a source of unhealthy food thus a factor contributing to the food dessert problem.

The second branch of the literature attributes most nutritional inequality to the demand side. In a recent paper, Allcott et al. (2018) use scanner and sales data from A.C. Nielson to show that exposing low-income households to the same products and prices available to high-income households can only reduce the nutritional inequality by 9 percent while the remaining 91 percent is due to demand differences. Simply put, low-income households choose to buy relatively unhealthy food even if healthy food is available. This finding challenges the food dessert explanation, implying that policy interventions that aim to supply healthy food to low-SES neighborhoods would likely to be less effective than desired. While Allcott et al. (2018) focus on consumer preferences on cross-

[1] According to the Dietary Guidelines 2015-2020, the typical eating patterns of Americans (as of 2015) do not align with the *Dietary Guidelines*. In particular, most Americans consume fruits, diary and oil less below the recommended levels, but consume added sugar, saturated fat, and sodium more than the recommended limit (https://health.gov/dietaryguidelines/2015/guidelines/chapter-2/current-eating-patterns-in-the-united-states/).

category products in the grocery setting, we focus on consumer substitution within a category of heterogeneous food items with diverse characteristics and healthfulness in the restaurant setting.

In this paper, we look at nutritional inequalities from a different angle. Using proprietary data from a national restaurant chain, we show that people living in disadvantaged neighborhoods do consume less healthy food items but they are also more price sensitive. The point estimates for average price elasticities of demand ranges from -2.28 in the most advantaged neighborhoods to -3.53 in the most disadvantaged neighborhoods in terms of education and income. We estimate a random coefficient discrete choice model using national promotions as key instrumental variables for price. The national promotions are relatively frequent and they apply to standardized food items with varying calorie content and healthfulness. Thus, they provide excellent price variations for identification but are independent of neighborhood-specific demand shocks.

We are not the first to study price sensitivity for food[2], but our findings highlight the socio-economic gradient in price sensitivity, especially when it comes to the choice of healthy and unhealthy food in chain restaurants. We conduct various counterfactual price policies to examine the sets of price policies that could remove the consumption inequality in HEI. One counterfactual simulations suggest that extending the chain's temporary price promotion on three small size healthy food items to the entire sample period can effectively remove the overall HEI inequality between the most and least advantaged neighborhoods in our data. Another counterfactual shows that the existing HEI inequality between the most advantaged neighborhood and other neighborhoods can be removed by cutting price price by \$0.10-\$0.33 on the 22 most healthy food items or raising price by \$0.06-\$0.44 on the 22 least healthy food items.

Our findings complement both branches of the literature. For the supply-side literature, we show that even if the chain restaurant provide equal access and equal price across neighborhoods, it does not solve the nutrition inequality problem. To encourage healthy choices, price on healthy items needs to be disproportionally discounted. For the literature that emphasizes consumer demand, we also find preferences differ for consumers of different SES. Moreover, the higher price elasticities of the consumers in low SES neighborhoods can be harnessed to nudge them towards healthier food using targeted price policies, such subsidies on healthy food or taxes on unhealthy food.

The rest of the paper is organized as follows. In section 2, we describe the data source and data construction and provide summary statistics on the variety of food items offered and the diversity of neighborhood demographics across stores locations. In section 3, we will explore reduced-form evidences of how consumers in different neighborhoods respond to the national discounts. In section 4, we discuss the structural model and estimation. In section 5, we show the structural estimation results and conduct counterfactual price policy experiments.

[2]For example, Bertail and Caillavet (2008) define consumers in six clusters by socio-demographics characteristics. They find that the lowest income cluster with the lowest consumption remains insensitive to economic variables, while the usual price and income policy tools may be effective on the other clusters. Beydoun et al. (2008) use survey data from USDA and define two food price indices. They find that higher fast food price indices (FFPIs) were associated with higher fiber intake, lower saturated fat, and better overall diet quality, while the other food price index (FVPI) was positively associated with improved dietary quality, improved HEI and lower BMI. Contrary to our paper, they find most of these associations are homogenous across income groups.

# 2 Data

## 2.1 Data Description

### Data Sources

Our data comes from a large, national restaurant chain in the US. The data contains the universe of transactions from its chain stores in the New York City marketing area between January 2014 and June 2015. For each transaction, we observe information about the date and store of the transaction,[3] food items ordered and their listed price and discounts. We keep only stand-alone stores and drop those in shopping malls, schools, hospitals, airports and highway service areas. The non stand-alone stores are usually subject to different pricing schemes and often do not participate in national or regional promotions which we will exploit as exogenous sources of price variations. The resulting data includes 811 stores.

The restaurant chain has a rich variety of entrées offerings in terms of nutrition facts and serves the usual drinks, sides, and fruits as other chains. In this paper we focus on a core set of menu items or entrées, around which all meals are centered. The core menu items considered account for over 95% of the sales in the New York City market during the sample period. They are offered in two sizes, small and big. In our study, we focus only on the core menu item and not the accompanying side items and beverages since consumers get the majority of their nutrition intake per meal at the restaurant from these core menu items.

Detailed nutrition facts of each item are available on the restaurant's website. We use two measures to describe the the nutrition content of an item. The first measure is calorie. The second measure is based on the USDA's Healthy Eating Index (HEI), a score that measures the deviation of the menu item's nutrition content from the USDA's recommended daily nutrients intake benchmark. The HEI has sharp non-linearities because it values a balanced diet, so an item's contribution to the HEI depends on the consumer's full diet. We follow Allcott et al. (2018) and construct a modified version of the HEI that is based on the same USDA dietary recommendations but is linear and additively separable in macronutrients. Nutrients are classified into "healthy" and "unhealthy". Healthy nutrients include protein and fiber, while unhealthy nutrients include sugar, saturated fat, sodium and cholesterol.

Each healthy nutrient has a recommended daily in-take (RDI), and each unhealthy nutrient has a maximum RDI. The revised HEI for an item $i$ is then generated from these official recommendations: it is the sum of healthy minus unhealthy nutrients per 1,000 grams , demeaned around its recommended daily intake, and weighting each by the recommended daily intake: $\tilde{H}_i = \sum_c G_c(a_{ic} - r_c)/r_c$, where $a_{nc}$ is the grams of nutrient $c$ per 1,000 calories, $r_c$ is the RDI for nutrient $c$, $G_c$ takes value 1 if the nutrient is classified as "healthy", and -1 if the nutrient is classified as "unhealthy". Table A1 lists the daily recommended levels for nutrients included to calculate HEI. We have 4 unhealthy nutrients and 2 healthy ones, an item that exactly follows the RDI has an HEI of 0.

We use consumer choice patterns to estimate the consumer preferences. As we may expect,

[3] We do not have the exact time stamp of each transaction.

consumer preferences vary by demographic groups. Unfortunately, the data does not provide information on the customer demographics of the customers, so we can only infer the demographic attributes from where the transaction takes place. We will use the demographic variations across stores locations to identify the heterogeneity in consumer preferences. We geocode each store using detailed address and match each store into a census tract. We then collect census tract level demographics data from tabulations of 2015-2017 three-year American Community Survey (ACS), available at the IPUMS.

Summary statistics of product characteristics and neighborhood demographics are provided in Section 2.2 and 3.1.

**National Promotions** In the sample period, the chain carried out four major national promotions. Since these national promotions apply to all stores in the US and are not specifically targeting the New York market, they are likely to be independent of local demand shocks. The promotion may still be correlated with seasonal demand shocks at the national level, and we will add controls for seasonality when estimating consumer preferences.

The timetable of the four promotions are the following. The first national promotion took place between September 1, 2014 and October 31, 2014, seven small size food items are discounted to $3 each. The discount is applied to one food item each day depending on the day of the week. The second promotion took place between November 15, 2014 and December 31, 2014. Two small size food items are discounted to $2 per day. The third promotion took place between April 1 and April 30, 2015, which applied a uniform price to all big-size items. The last promotion was a discount based on a bundles. It started on November 1, 2014 and remained in effect by the end of our sample period. The deal promotes all small-size food items with a drink and a side. Because the price was set for the bundle, for this promotion, we calculate the overall discount rate by adding up the regular prices of all the items in the bundle, and then use the overall discount rate to back out the discounted price for the food item. There are rich variations in both discount rates and the characteristics of the items discounted which will assist us with identification.

In section 3.2, we will use the first and the second national promotions that target specific items to look at reduced-from evidences of how consumers respond to the discount of more healthy and less healthy items and how the responses differ by neighborhoods.

**Product Availability** The data records the number of food items sold at the store each day, but if the food item records zero sales, it could be that the food item is offered but does not yield any sales, or that the food item is not offered. We do not have external data to verify seasonal offerings of the limited items. To solve this problem, we first look for evidence of the timing when stores changes availabilities, we then assume that the types of food items offered are fixed within a period without availability changes. For the first step, we calculate the number of different food items sold each day at the store. It is natural that the number of food items would fluctuate day-by-day, so we look for cliffs when the number of different food items sold changes sharply. We find that sharp changes usually happen around the turn of calendar months, and therefore we assume that each store can change availabilities by the end of the month and fix the varieties offered during the month. We define that a type food item is available if the item has positive sales at a store in a month.

### 2.2 Summary Statistics

Table 1 shows the summary statistics of the items sold in different stores. The distribution of calories and HEI for 46 big size food items and 45 small size food items are plotted in Figure 1. The figures show a rich variety of food items with different combinations of healthfulness and calories offered. The calorie count of a food item is negatively correlated with its healthfulness. The correlation is -0.32 for small size food items and -0.24 for big size food items (Table 2). Calories are not perfectly collinear with HEI, allowing us to identify consumer preference for healthfulness and calories separately. Figure 1 also shows the sales share of the food items during our sample by the size of the circles.[4] There is not clear pattern what types of food items are consumers' favorite. Top-selling food items spread out on the calories-HEI space, suggesting potential consumer preference heterogeneity. Lighter circles represent more expensive items. The lighter circles are smaller in size, and are usually at or above the fitted line, suggesting that conditional on calories, the healthy items are usually more expensive and sold in lower quantities.

The information in Figure 1 are further examined in Table 2 regarding the correlation of the food item characteristics. In this table, we construct price using the average listed price and we construct the market share of an item by aggregating all quantities sold across all store in the sample period. The denominator for the market share is the total sales of the food items we consider. In Panel A, the correlation among food item characteristics for big size food items are shown in the upper right, and those for small size food items are shown in the bottom left. Conditional on food items of the same size, items with higher calories are less healthy, they are associated with higher prices and lower market shares. The raw correlation between HEI and price is positive but not statistically significant. If we regress average listed price on HEI, calories, and size, the coefficient for HEI is significant, and for each one unit increase in HEI, price increases by 15 cents.

Table 1: Summary of Product Characteristics

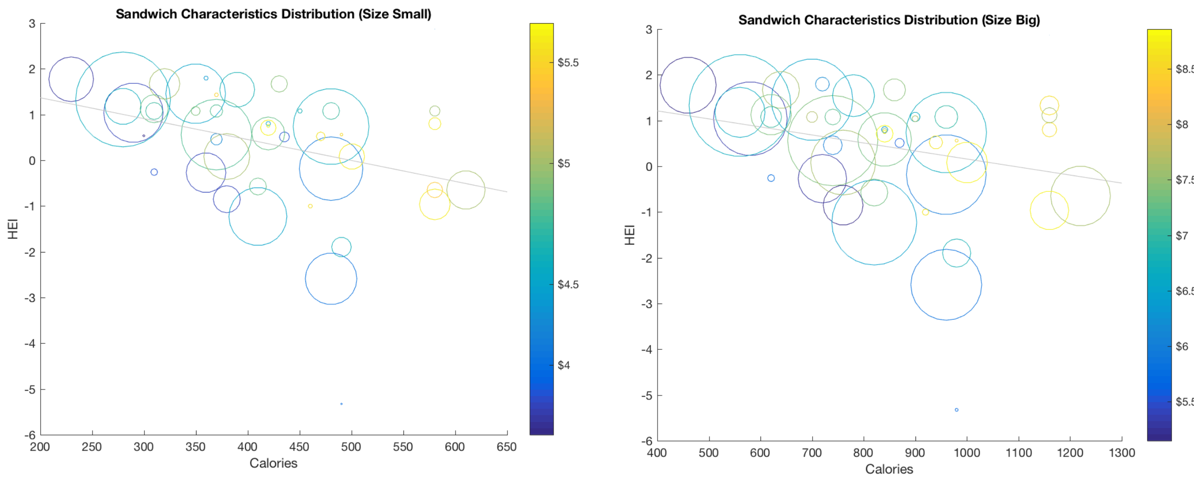
| | Mean | StdDev | p25 | p50 | p75 | N |
|---|---|---|---|---|---|---|
| HEI | 0.40 | 1.35 | -0.26 | 0.74 | 1.12 | 91 |
| Calories | 635.77 | 260.48 | 420 | 580 | 840 | 91 |
| I(Small) | 0.49 | 0.50 | 0 | 0 | 1 | 91 |
| Price | 5.87 | 1.48 | 4.68 | 5.62 | 7.06 | 91 |
| Sales Share | 1.10% | 1.60% | 0.06% | 0.27% | 1.46% | 91 |

*Note*: **1** The unit of observation is at the item level. **2** We construct the sales share of a food item by calculating the total sales of a food item during our sample period as a percentage of total sales of 91 food items we consider during the sample period. **3** Price and sales shares are averages across stores.

[4] We construct the sales share of a food item by calculating the total sales of a food item during our sample period as a percentage of total sales of 91 food items we consider during the sample period. We will use this construction throughout section 2 and section 3. The sales share is distinguished from the market share definition that we will discuss in Section 4.

Figure 1: Distribution of Food Item Characteristics

Panel A: Small Size Food Items　　　　Panel B: Big Size Food Items




*Note:* Panel A and panel B show the scatter plots of the food item calories and the HEI offered by size. The color of the marker shows the average listed price of the item, and the size of the marker shows the relative sales share of the items.

Table 2: Correlations among Food Item Characteristics

Panel A: Small/Big Size Food Items

| | Calories | HEI | Price | Share |
|---|---|---|---|---|
| Calories | | **-0.238** | **0.419** | **-0.270** |
| | | (0.111) | (0.004) | (0.070) |
| HEI | ***-0.315*** | | 0.130 | -0.053 |
| | *(0.035)* | | (0.390) | (0.724) |
| Price | ***0.429*** | *0.102* | | **-0.274** |
| | *(0.003)* | *(0.505)* | | (0.065) |
| Share | ***-0.239*** | *0.037* | *-0.233* | |
| | *(0.115)* | *(0.808)* | *(0.124)* | |

Panel B: All Food Items

| | Calories | HEI | Price |
|---|---|---|---|
| HEI | -0.123 | | |
| | (0.247) | | |
| Price | 0.806 | 0.085 | |
| | (0.000) | (0.421) | |
| Share | -0.011 | -0.012 | -0.026 |
| | (0.921) | (0.908) | (0.806) |

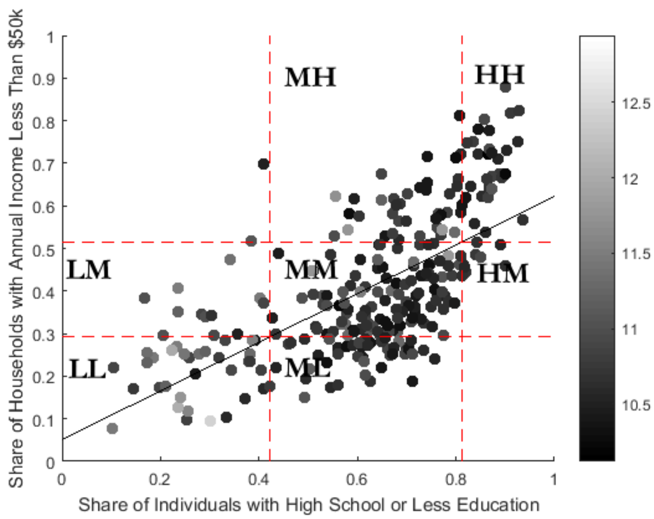
*Note*: **1** p-values are shown in parentheses. The observation is at the item level. **2** In Panel A, the lower left triangle (in italic) shows the correlations among different characteristics for small-size food items and the upper right triangle shows the correlations for big-size food items. **3** Panel B shows the characteristics correlation across all items.

There are also rich demographic variations in the neighborhoods where the stores are located. We will use the demographics variations to identify preference differences for consumers in different neighborhoods. We are particularly interested to study the preference of consumers with disadvantaged social economic backgrounds, we choose our demographic measures to represent the percentage of low education and low income individuals. We define low education as individuals with an education of high school or less. We define low income as households with an annual income with $50,000 or less. For each store, we calculate these measures using the ACS demographics information for the census track where the store locates.

In Figure 2, we plot the distribution of store demographics. Each dot represents a store, and the scatter plot shows the neighborhood composition of low education and low income population.

The figure shows a positive correlation between the percentages of low education and low income population. The grayscale of the marker represents the average wage of people working in the zip code where the store is located. The linear fit between the education and the income measures is represented by the gray line.

Figure 2: Neighborhoods Clustered by Income and Education




*Note:* Each dot in the figure represents a store and its corresponding education and income characteristics of the census track where the store is located. The grayscale of the dot represents the average wage of employees hired in the zip code where the store is located. The solid linear line is the linear fit of income and education. The cutoffs are chosen so that block $LL$ and block $HH$ each contains around 10% of stores.

With information on food items and consumer demographics near the store, we examine whether food item choices differ systematically across neighborhoods, in particular, whether consumers in disadvantaged neighborhoods eat less healthy food items. In the first set of analysis, we examine whether consumers differ in their probabilities of choosing the most healthy food items. In column (1)-(3) of Table 3, we regress the sales share of the 10 healthiest food items sold in each store on the neighborhood demographic characteristics. We find that the share of the healthiest food items sold are lower in neighborhoods with higher concentration of low-income and low-education households. Overall, a 10% increase in the share of low-income households reduces the market share for each of the top 10 healthiest food items by 0.04 percentage points, or by 5% compared with the 0.8% market share baseline. The marginal effect of the increase in the percentage of low education population is about the same. Since the local wages seems to play little role on the choice of healthy diet, we will not consider local wage in the following analysis.

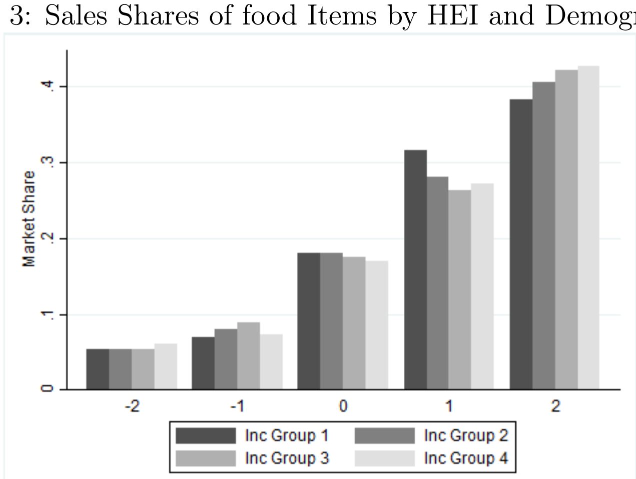
Lastly, we look at the sales share of food items in different HEI brackets consumed in different neighborhoods based on income levels. We group the food items into brackets based on HEI. The least healthy bracket consists of food items with HEI less than -2 and the most healthy bracket is consist of food items with HEI between 1 and 2. We then divide the neighborhoods into four categories based on the percentile of the percentage of low-income population. “Group 1” have the highest percentage of low income households and “Group 4” have the lowest percentage of low income households. The market share of each category of food items are shown in Figure 3. The figure shows that consumers do not differ much in consuming food items that are less healthy. The biggest difference is that the poorer neighborhoods are less likely to consume food items that are the most healthy .

Table 3: Demographics and The Sales Share of (Un)Healthy food items

| | (1)<br>Sales Share of the 10 Healthiest food Items<br>*All* | (2)<br>Sales Share of the 10 Healthiest food Items<br>*Small Size* | (3)<br>Sales Share of the 10 Healthiest food Items<br>*Big Size* | (4)<br>Sales Share of the 10 Lowest Cal food Items<br>*All* |
|---|---|---|---|---|
| Share(HhIncome≤$50k) | -0.00396*** | -0.00349*** | -0.00433*** | -0.00267** |
| | (0.00108) | (0.000819) | (0.00160) | (0.00125) |
| Share(Edu≤HighSchool) | -0.00351** | -0.00409*** | -0.00302 | -0.00833*** |
| | (0.00147) | (0.00101) | (0.00221) | (0.00119) |
| AvgWage (in $1,000) | 0.00000217 | 0.000000490 | 0.00000419 | -0.00000607 |
| | (0.00000722) | (0.00000419) | (0.0000110) | (0.00000476) |
| Constant | 0.0117*** | 0.0102*** | 0.0132*** | 0.0217*** |
| | (0.00104) | (0.000658) | (0.00160) | (0.000771) |
| Number of Observations | 2,108 | 1,028 | 1,080 | 2,379 |

* p<0.10 ** p<0.05 *** p<0.0. Standard errors clustered at the store level.
*Notes*: Observations are at the store-by-item level. The average sales share of each food item in the top 10 healthiest category is 0.8%, and in the top 10 lowest calories category is 1.5%.

Figure 3: Sales Shares of food Items by HEI and Demographics




*Note:* The x-axis represents HEI brackets. "-2" represents $HEI \leq -2$; "-1" represents $HEI \in (-2,-1]$; "0" represents $HEI \in (-1,0]$; "-1" represents $HEI \in (0,1]$; "-1" represents $HEI \in (1,2]$.

# 3 Consumption Patterns

## 3.1 Summary Statistics by Neighborhoods

Summary statistics in Section 2.2 show the importance in both income and education in affecting consumer choices. In this section, we will divide the neighborhoods in to groups based on the percentage of low-income ($\%L_{inc}$) and low-education ($\%L_{edu}$) population and examine the group specific sales pattern. In Figure 2, we plot the distribution of stores in the income and education space. We divide the space into three-by-three cells. The cutoffs are determined by finding two points on the fitted linear line so that the most and the least advantaged groups each have about 10% of the stores.

Most of the stores lie in six cells in the graph, labeled as $LL$, $ML$, $ML$, $MM$, $ML$, $HH$. The first indicator represents whether the neighborhoods have a high percentage of households with low education. The second indicator represents whether the neighborhoods have a high percentage of individuals with low income. The $LL$ is hence the *most advantaged* group and $HH$ is *the least advantaged*. The two cutoffs along the percentage of low-education dimension are 40.62% and 80.34% respectively, and the two cutoffs along the percentage of low-income dimension are 28.32% and 52.56% respectively. The percentage stores in each groups of neighborhood are shown in the Table 4.

Table 4: Sales Weighted Average Calories and HEI of the Food Items Consumed

| | % of | All Items | | Small Items | | Large Items | |
|---|---|---|---|---|---|---|---|
| Block | Stores | Calories | HEI | Calories | HEI | Calories | HEI |
| LL | 10.1% | 604.0 | 0.420 | 381.3 | 0.487 | 773.3 | 0.369 |
| LM | 5.6% | 607.7 | 0.402 | 384.5 | 0.476 | 778.9 | 0.346 |
| ML | 14.6% | 634.1 | 0.362 | 380.2 | 0.451 | 781.1 | 0.311 |
| MM | 42.9% | 635.9 | 0.367 | 383.6 | 0.444 | 783.0 | 0.322 |
| MH | 13.9% | 638.0 | 0.365 | 388.9 | 0.418 | 788.1 | 0.333 |
| HM | 2.8% | 651.2 | 0.386 | 387.7 | 0.431 | 782.5 | 0.364 |
| HH | 10.1% | 651.8 | 0.343 | 392.9 | 0.395 | 792.2 | 0.315 |

*Notes*: LL stands for "L"ow ratio of low-education population and "L"ow ratio of low-income households. $LL$ is hence the *most advantaged* group and $HH$ is *the least advantaged*. The table presents the sales weighted averages of the calories and HEI of the food items consumed. The weights are the total sales of each item during the entire sample period across all scores.

We then calculate the sales weighted average calories and HEI of the food items consumed. Table 4 shows the summary statistics. In general, consumers in more disadvantaged neighborhoods eat items with higher calories and lower healthfulness, the patterns are similar conditional on size. To check statistical significance of the differences, we regress HEI and calories of each item sold in a store on neighborhood indicator using sales as weights. The results are shown in Appendix Table A2. Comparing the $LL$ and $HH$ neighborhoods, for every food item consumed, consumers in $LL$ neighborhoods take in 47.8 more kcal and 0.08 lower HEI, or a 7.9% increase in calories and 18.3% decrease in healthfulness.

We also examine whether consumers have paid less per 100 kcal in more disadvantaged neighborhoods. The summary statistics are shown in Appendix Table A3 and its regression version in Appendix Table A4. The table showed that the price paid for each food item is higher in more disadvantaged groups but the price paid for each 100 kcal is slightly lower for small size food items. We then examine the average price per food item in different groups of neighborhoods by regressing the daily price consumers paid for the food items in each store on neighborhood dummies. We add food item fixed effects to control for price differences driven by item availabilities. Using $LL$ neighborhood as the baseline group, we find no statistically differences in prices paid except for the $HH$ neighborhood. Consumers in $HH$ neighborhoods pay on average \$0.12 less per item than consumers in $LL$ neighborhoods. We examine the availabilities and the price of the healthy food items options by neighborhoods.

### 3.2 Consumer Response to National Promotions

Before estimating the full discrete choice model, we examine the reduced form evidences of how consumers in different neighborhoods respond to promotions. We will focus on two promotions in detail.

During the first promotion period, one small size food item is discounted each day, and the discounted items is different depending on the day of the week. During three of the seven days in a week, food items on the healthy choice menu are discounted. We will use data from the days when healthy choices are discounted to examine whether and by how much consumers increase their purchase of these healthy items and how the healthy item discounts raise the average HEI.

We keep data from two months before the promotion and one and a half months during the promotion. To focus on the response to the discounts on healthy items, we only keep dates during the promotion period when the healthy items are discounted. In the first set of regressions, we check the changes in sales and market share of the items sold by neighborhood demographics. We regress quantity and market share of each item on the indicator of the promotion period, promotion items and their interactions.[5] The indicator for promotion items is only turned positive on the day it is discounted. To check differential response in different neighborhoods, we added the cross products with neighborhood demographics–the percentage of low income and low education households. The regression results are shown in Table 5. The cross product term of the discount period and the discount term shows a substantial increase in both sales and market share. As a reference, the average market share of the discounted healthy items before the discount period is 3.73%, so both quantity and market share. For every 10% increase in share of low-income population, the sales of the promoted items increase by an additional 3.5%, and the market share will increase by another 0.2 percentage points. Similarly, with every 10% increase in the low-education population, the sales of the promoted items increase by an additional 2.6%. Overall, the promotion almost doubled the item sales, and the sales increase is higher in neighborhoods with higher concentration of poorer households.

[5]The market share constructed in this section is the food item's market share at a given store during a single day among the items sold in store.

Table 5: Sales Responses to the Promotion of Healthy Choices by Neighborhoods

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Log(Q) | Share | Log(Q) | Share |
| DsctPeriod | 0.0123*** | -0.000461*** | 0.0123*** | -0.000461*** |
| | (0.00250) | (0.0000902) | (0.00250) | (0.0000902) |
| DsctPeriod×DsctItems | 0.855*** | 0.0513*** | 0.855*** | 0.0513*** |
| | (0.0211) | (0.00126) | (0.0211) | (0.00126) |
| DsctPeriod×% $L_{inc}$ | -0.0375*** | -0.000285 | | |
| | (0.0119) | (0.000448) | | |
| DsctPeriod×DsctItems×% $L_{inc}$ | 0.353*** | 0.0222*** | | |
| | (0.131) | (0.00765) | | |
| DsctPeriod×% $L_{edu}$ | | | 0.0236** | 0.000357 |
| | | | (0.0119) | (0.000400) |
| DsctPeriod×DsctItems×% $L_{edu}$ | | | 0.261** | 0.000592 |
| | | | (0.131) | (0.00841) |
| Date(normalized) | -0.0440*** | 0.000302*** | -0.0441*** | 0.000302*** |
| | (0.00307) | (0.000110) | (0.00307) | (0.000110) |
| Constant | 0.397*** | 0.0183*** | 0.397*** | 0.0183*** |
| | (0.00176) | (0.0000540) | (0.00176) | (0.0000541) |
| N | 1,214,068 | 1,214,068 | 1,214,068 | 1,214,068 |

* p<0.10 ** p<0.05 *** p<0.0. Standard errors clustered at the item-store level.

*Notes*: **1** An observation is an item-store-day period. **2** Share represents the sales of the food item as a percentage of total sales of all food items sold in all stores during the time period.

Has the discount raised the average healthfulness of the consumer food item consumption? We look at the changes in the food item characteristics consumers consume during the promotional period in Table 6. We regress sales and market share on the indicator of discount period and its interactions with the item characteristics, including healthfulness, calories content, and size. In addition, we add the triple interactions with the neighborhood demographics to capture differential response in different neighborhoods. The results are reported in Table 6. Although the coefficient of the interaction between the discount period and the healthfulness is not significant, the sales for healthy items increase in neighborhoods with poorer consumers. The relative market share of the healthy items also increase for neighborhoods with higher percentage of low income households. Since the discount is on small size items, it we can see that the small size items are sold better overall, and the increase is stronger in poorer neighborhoods. The direction of the impact is similar looking at neighborhoods with higher concentration of low education individuals.

Table 6: Average Food Item Characteristics Consumed during the Promotion of Healthy Choices

| | (1) Log(Q) | (2) Share | (3) Log(Q) | (4) Share |
|---|---|---|---|---|
| DsctPeriod | -0.0241*** | -0.000995*** | -0.0241*** | -0.000997*** |
| | (0.00412) | (0.000160) | (0.00412) | (0.000160) |
| DsctPeriod×HEI | 0.00142 | 0.0000461 | 0.00151 | 0.0000485 |
| | (0.00227) | (0.0000824) | (0.00227) | (0.0000825) |
| DsctPeriod×(100)kcal | 0.0101*** | 0.000254*** | 0.0102*** | 0.000256*** |
| | (0.00150) | (0.0000545) | (0.00150) | (0.0000545) |
| DsctPeriod×SizeSmall | 0.107*** | 0.00310*** | 0.107*** | 0.00311*** |
| | (0.00665) | (0.000260) | (0.00665) | (0.000260) |
| DsctPeriod×%$L_{inc}$ | -0.0839*** | -0.00170 | | |
| | (0.0243) | (0.00109) | | |
| DsctPeriod×%$L_{inc}$×HEI | 0.0395*** | 0.00114** | | |
| | (0.0145) | (0.000547) | | |
| DsctPeriod×%$L_{inc}$×(100)kcal | 0.0183* | 0.000642* | | |
| | (0.00984) | (0.000388) | | |
| DsctPeriod×%$L_{inc}$×SizeSmall | 0.112** | 0.00387** | | |
| | (0.0436) | (0.00188) | | |
| DsctPeriod×%$L_{edu}$ | | | -0.0352 | -0.000746 |
| | | | (0.0239) | (0.00102) |
| DsctPeriod×%$L_{edu}$×HEI | | | 0.0406*** | 0.000435 |
| | | | (0.0151) | (0.000547) |
| DsctPeriod×%$L_{edu}$×(100)kcal | | | 0.0273*** | 0.000765** |
| | | | (0.00927) | (0.000345) |
| DsctPeriod×%$L_{edu}$×SizeSmall | | | 0.133*** | 0.00231 |
| | | | (0.0422) | (0.00171) |
| Date(normalized) | -0.0438*** | 0.000318*** | -0.0438*** | 0.000317*** |
| | (0.00307) | (0.000111) | (0.00307) | (0.000111) |
| Constant | 0.397*** | 0.0183*** | 0.397*** | 0.0183*** |
| | (0.00181) | (0.0000592) | (0.00182) | (0.0000592) |
| N | 1,214,068 | 1,214,068 | 1,214,068 | 1,214,068 |

* p<0.10 ** p<0.05 *** p<0.0. Standard errors clustered at the item-store level.
*Notes*: **1** An observation is an item-store-day period. **2** Share represents the sales of the food item as a percentage of total sales of all food items sold in all stores during the time period.

The reduced-from evidence shows that price discounts are effective in raising the sales of healthy items among poorer households and is even more effective than richer neighborhoods. The stronger response in poorer neighborhoods can be driven by their preference for healthy items and their sensitivity for price. Without structurally estimate the consumer preference, we cannot tell apart which is driving consumers in poorer neighborhoods to respond more strongly. It is also interesting from the policy perspective when stores or governments design price incentives to promote healthy eating. This motivates us to model and estimates the consumer preference in more details which allows us to conduct counterfactuals of different price experiments.

To provide more evidence on consumer response to promotion of less healthy items, we replicate the above analysis for a one-and-a-half month time period when two small size less healthy items are discounted. The healthy index for these two items are -0.18 and -0.27 respectively, less healthy than the median item. The consumer response from different neighborhoods in terms of sales of the discounted an undiscounted items are represented in Table 7. The results show that both sales and relative share of the discounted items both more than doubled during the discount period. Neighborhoods with higher concentration of low-income households and low-education individuals responded even more strongly. The effect of the discounts on the average characteristics of the items consumed is reported in Table 8. The table shows a decrease in consumption healthfulness during the discount period of less healthy items, and the reduction in average healthfulness is greater in poorer neighborhoods. Combined with the evidence of the promotion of healthy items, we expect that price elasticities of demand play a major role in consumer choices.

Table 7: Sales Responses to the Promotion of Less Healthy Item

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Log(Q) | Share | Log(Q) | Share |
| DsctPeriod | -0.0186*** | -0.00228*** | -0.0186*** | -0.00228*** |
| | (0.00145) | (0.0000577) | (0.00145) | (0.0000577) |
| DsctPeriod×DsctItems | 1.112*** | 0.0552*** | 1.112*** | 0.0553*** |
| | (0.0222) | (0.00155) | (0.0220) | (0.00154) |
| DsctPeriod×%$L_{inc}$ | -0.0208** | -0.00188*** | | |
| | (0.00997) | (0.000410) | | |
| DsctPeriod×DsctItems×%$L_{inc}$ | 0.559*** | 0.0383*** | | |
| | (0.143) | (0.00995) | | |
| DsctPeriod×%$L_{edu}$ | | | -0.00496 | -0.00176*** |
| | | | (0.00845) | (0.000307) |
| DsctPeriod×DsctItems×%$L_{edu}$ | | | 0.576*** | 0.0419*** |
| | | | (0.123) | (0.00790) |
| Date(normalized) | -0.00110*** | -0.000000659 | -0.00110*** | -0.000000648 |
| | (0.0000208) | (0.000000770) | (0.0000208) | (0.000000770) |
| Constant | 0.402*** | 0.0213*** | 0.402*** | 0.0213*** |
| | (0.00167) | (0.0000654) | (0.00167) | (0.0000654) |
| N | 1,567,797 | 1,567,797 | 1,567,797 | 1,567,797 |

* $p<0.10$ ** $p<0.05$ *** $p<0.0$. Standard errors clustered at the item-store level.

*Notes*: **1** An observation is an item-store-day period. **2** Share represents the sales of the food item as a percentage of total sales of all food items sold in all stores during the time period. The average share of the discounted items outside the discount period is 1.71%.

Table 8: Average Food Item Characteristics Consumed during the Promotion of Less Healthy Items

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Log(Q) | Share | Log(Q) | Share |
| DsctPeriod | -0.00824** | -0.00296*** | -0.00825** | -0.00296*** |
| | (0.00359) | (0.000153) | (0.00359) | (0.000153) |
| DsctPeriod×HEI | -0.0411*** | -0.00146*** | -0.0411*** | -0.00147*** |
| | (0.00219) | (0.0000935) | (0.00219) | (0.0000938) |
| DsctPeriod×(100)kcal | -0.00486*** | 0.0000953 | -0.00487*** | 0.0000938 |
| | (0.00170) | (0.0000699) | (0.00170) | (0.0000701) |
| DsctPeriod×SizeSmall | 0.0757*** | 0.00619*** | 0.0756*** | 0.00618*** |
| | (0.00740) | (0.000384) | (0.00741) | (0.000385) |
| DsctPeriod×%$L_{inc}$ | -0.000951 | -0.00149 | | |
| | (0.0229) | (0.00103) | | |
| DsctPeriod×%$L_{inc}$×HEI | -0.0246* | -0.000973 | | |
| | (0.0146) | (0.000626) | | |
| DsctPeriod×%$L_{inc}$×(100)kcal | -0.00791 | -0.000321 | | |
| | (0.0112) | (0.000459) | | |
| DsctPeriod×%$L_{inc}$×SizeSmall | 0.0157 | 0.00293 | | |
| | (0.0484) | (0.00256) | | |
| DsctPeriod×%$L_{edu}$ | | | 0.00160 | -0.00214*** |
| | | | (0.0188) | (0.000755) |
| DsctPeriod×%$L_{edu}$×HEI | | | -0.0225* | -0.00116*** |
| | | | (0.0116) | (0.000450) |
| DsctPeriod×%$L_{edu}$×(100)kcal | | | 0.00277 | -0.0000398 |
| | | | (0.00910) | (0.000340) |
| DsctPeriod×%$L_{edu}$×SizeSmall | | | 0.0385 | 0.00455** |
| | | | (0.0393) | (0.00194) |
| Date(normalized) | -0.00111*** | -0.00000130* | -0.00111*** | -0.00000131* |
| | (0.0000208) | (0.000000771) | (0.0000208) | (0.000000771) |
| Constant | 0.402*** | 0.0213*** | 0.402*** | 0.0213*** |
| | (0.00188) | (0.0000763) | (0.00188) | (0.0000763) |
| N | 1,567,797 | 1,567,797 | 1,567,797 | 1,567,797 |

* p<0.10 ** p<0.05 *** p<0.0. Standard errors clustered at the item-store level.

*Notes*: **1** An observation is an item-store-day period. **2** Share represents the sales of the food item as a percentage of total sales of all food items sold in all stores during the time period.

# 4 Model and Estimation

## 4.1 Model

Our baseline model follows the typical random coefficient discrete choice framework, and we estimate the model using aggregate data at product-store-time level. We define the indirect utility received by individual $i$ consuming food item $j$ in store $m$ at time $t$ as,

$$U_{ijmt} = \delta_{jmt} + \sigma V_i W_{jmt} + \epsilon_{ijmt} \tag{1}$$

$$where\ \delta_{jmt} = (\beta_o + X_{jmt}\beta_p)p_{jmt} + \mu_j + \eta_m + \phi_{qtr,t} + \xi_{jmt} \tag{2}$$

$$and\ \sigma V_i W_{jmt} = \sigma_p v_{pi} p_{jmt} + \sigma_c v_{ci} C_j + \sigma_h v_{hi} H_j + \sigma_s v_{si} S_j \tag{3}$$

where $p_{jmt}$ is the price paid by the customer, $C_j$ and $H_j$ are continuous measures of the item's total calories and healthy index respectively. $S_j$ equals to one for small size food items. Consumers in different neighborhoods may We allow the consumer's price sensitivities to vary conditional on the characteristics of the food item she chooses, hence we included the cross product which is represented by the cross product term vector$X_{jmt} = [C_j, H_j, S_j, C_j \times S_j, H_j \times S_j]$. The cross product terms capture whether consumers $\xi_{jmt}$ is the time varying store-specific unobserved quality shock that may be correlated with $p_{jmt}$. We allow random coefficients on price, calories, healthfulness, and size to vary by individual to capture consumer preference heterogeneity. We assume $v_{pi}$, $v_{ci}$, $v_{hi}$, and $v_{si}$ follow standard normal distribution and are independent with each other. We add food item fixed effects to control for the consumer common taste for each item which would also captures any item-specific constant unobserved quality differences. We also added store fixed effects and quarter fixed effects to account for potential heterogeneity in the consumer's valuation of the store food item choice compared with outside choices.

A consumer chooses item $j$ when $U_{ijmt} > U_{ij'mt}$ for $\forall\ j' \neq j$. Assuming $\epsilon_{ijmt} \sim i.i.d. TIEV$, we can write the market share for product $j$ as,

$$s_{jmt} = \int_V \frac{exp(\delta_{jmt} + \Sigma V_i W_{jmt} + \epsilon_{ijmt})}{1 + \sum_{j'=1}^{J_{mt}} exp(\delta_{jmt} + \Sigma V W_{jmt} + \epsilon_{ijmt})} d\Phi_V$$

where $\Phi_V$ is the joint probability distribution of $V$ the sample.

**Data Setup for the Estimation** We define market as the neighborhood that each store is located. Because demographics in two nearby stores could be different, we do not group the stores into larger geographic area as a single market. We then need to decide the time unit. During some of the discount periods, the item each day discounts is different, bundling the discounts together will attenuate the price variations we can use. But keeping the time unit at the day level causes two problem, the first one is zero market share problem. The finer we define the time unit, the more likely the sampling error will lead to zeros which causes problems for inverse mapping in the logit model. The second problem is the computation burden. The nested fixed point would calculate the inverse mapping from the market shares to the mean values market by market. Even with parallel processing, the computation is still expensive. So we chose the intermediate ground, we define the time unit based on the change in the market (store) conditions. When the market does not experience a changes in the price of any products offered or a change in availability of products, we group the consecutive days into a single time period. This left us with 810 markets with an average of 33 time periods per market. An average period lasts 15 days.

We approximate the market size for each store-day. We calculate the mean and standard deviation of the total sales for each store. we then drop store-days with sales outside 2.36 standard deviation from the mean. This drops days with unusual low sales or sales spikes. We then fix the market size at 2.36 standard deviations above the mean. In the appendix, we will discuss a few different ways to construct the market size. We test the multinomial logit model without random coefficients based on different market size definitions and we find that our estimates are robust. Among the 811 stores, some stores adopted the new payment record system too late in the data set and we only observed a short time period on them. To reliably estimate the fixed effects in the linear model, we dropped the stores with 30 time periods or less. We are left with 287 stores for the estimation but have kept 85% of all observations.

## 4.2 Estimation

We estimate the random coefficient multinomial logit model using the nested fixed-point method discussed in BLP (Berry et al., 1995). We will discuss the departures from the classic BLP estimation strategy below.

#### Instruments

We need to instrument for prices that could be correlated with local demand shocks. The first set of instruments comes from the national promotions. During our sample period, there are three main discount periods when uniform prices are automatically applied to promoted items. Since the national promotions are independent of local demand shocks, we treat it as exogenous. We construct the second set of instruments as the Hausman-type instruments–average price of the same item paid by consumers in other stores in the area. This would capture any cost shocks common to the area.

To identify substitution patterns governed by the model of random coefficients, we need to use the variation in the product characteristics relative to those of other products in the same market. As suggested in construct Gandhi and Houde (2016), we construct difference instruments. Denote $d_{j,k} = X_j - X_k$, where $X_j$ is the variable that we allow for random coefficient.[6] The first set of instruments capture how different other products in the market are for product $j$ and the second set of instruments capture the number of other products that lies within a given bound $\chi$ which we construct as the mean standard deviation of $X$ within a market. And the third set of instruments

[6] Since the difference instruments are constructed using product characteristics in each market, we drop the time and store subscript for convenience

capture the mean characteristics of substitutable products close to product $j$.

$$IV_j^{d_1} = \sum_{j' \neq j} (X_j - X_{j'})^2,\ IV_j^{d_2} = \sum_{j' \neq j} (|X_j - X_{j'}| < \kappa)$$
$$IV_j^{d_3} = \sum_{j'=j} (|X_j^k - X_{j'}^k| < \kappa^k)(X_j^k - X_{j'}^k)^2$$

Similarly, we can construct higher order polynomials using the following equation,

$$IV_j^{d_4} = \sum_{j'=j} (X_j^k - X_{j'}^k)(X_j^l - X_{j'}^l)$$
$$IV_j^{d_5} = \sum_{j'=j} (|X_j^k - X_{j'}^k| < \kappa^k)(X_j^l - X_{j'}^l)^2$$

where $X^k$ and $X^l$ are two different variables. The fourth set of instrument capture the correlation in characteristics differences between two different characteristics. The fifth set of instruments capture the sum squared difference in characteristics $l$ for products similar to $j$ in characteristics $k$. In our setting, this could capture, for example, the mean difference in healthfulness between product $j$ and other products that have similar prices as product $j$.

As shown in equation (3), we allow consumer preference to differ on item price, calories, healthfulness, and size. The first three variables are continuous, the construction of $IV^{d1} - IV^{d_4}$ yield to

Since price is endogenous, we cannot construct difference instruments directly based on price. Instead, we first project price on all linear parameter instruments to predict price, denoted as $\hat{p}$. The price projection follows the following equation,

$$\hat{p} = Z(Z'Z)^{-1}Z \cdot p.$$

We then construct the difference instruments using $\hat{p}$. We have conducted Monte Carlo on the performance of difference instruments, and they outperform market mean characteristics and high order polynomials as instruments for random coefficients.

**Estimation by Neighborhoods**

In the model specification, we have not allowed price coefficients to vary by demographic characteristics. Instead, we will estimate the model described by equation (1) in each of the six neighborhood groups we discussed in Section 3.2. We choose this approach for two reasons. The first reason is due to computation constraint. As discussed in the data section, in order to take full advantage of the price variations, some markets are defined at the length of a day. In addition, because there exists cross-store variation in prices and neighborhood demographics, we treat each store as a market. This results in 29,574 markets with a median of 51 products in each market and a total of 1,509,259 observations at the product-store-time level. The inverse contraction mapping is computationally costly to solve. The second reason is due to identification. To identify the heterogeneous preference by different demographics, we will need micro-BLP moments to assist identification Petrin (2002). However, we only have demographics information at the census track level and we cannot obtain information on the demographics conditional on the purchase of specific items. This makes the identification of higher order random coefficients based on demographics challenging. In this paper, we will estimate the consumer preference in neighborhoods with similar demographics and compare across groups to draw conclusions on the consumer preference based on demographics.

Because we estimate the model for groups of stores located in areas with similar demographics, we expect the random coefficient to be small since the consumers could be relatively homogenous within the groups of stores.

**Zeros in Observed Market Shares**

The observed sales are realizations of a binomial draw according to the product purchase probabilities, when the number of consumers in the market is large enough, the realized market share coverages to the true purchase probabilities. However, when the number of consumers in the market is small and the purchase probabilities for certain products are small, we can have observed zeros in the markets. We define each market as a store-time. The number of days in each time period depends on the frequency of price fluctuations and the adjustment of product availabilities. For example, during promotion period when a different item is discounted everyday, the length of time of a day. When a market is consist of a single store-day, we are likely to run into zero market share problems. In the data used for estimation, 455 thousand of our 1.5 million

In the contraction mapping step, we map observed market shares to mean values of the product. We cannot do the inversion with zeros in the observed market shares. We have considered three ways to deal with the zeros. The way is to simply drop the observations with zero market shares, the second way is to assume one unit is sold when the observed quantity is zero. The third way to proposed by Gandhi et al. (2017) that uses identification method in conditional moment inequalities settings discussed in Andrews and Shi (2013). We used Monte Carlo to test the performance of the three methods. Dropping the zeros causes the estimates to deviate from the true parameters by a large margin. Since zeros contain information of consumer responding to market conditions that is used for identification, dropping them underestimates the consumer price sensitivity. We also replicate the Gandhi et al. (2017), the method does not perform well when random coefficients are small which is likely to be the case in our setting since we estimate each group of neighborhoods with similar demographics.

In the estimation results presented in the next section, we use the plus one method. Intuitively, the estimation bias of plus one method is serious if we observe a zero share for a product whose true share should be far away from zero. The plus one method is less of a problem if the true share is close to zero. Hence, we check whether the products that often have observed zero shares are also less popular. We have 20,750 unique store-product combinations, and we calculate the number of times each store-product experience zero shares, and the mean market share of the product when the share is not zero. For products with small market shares (excluding zeros), they are also more likely to have observed zero shares. 11,878 store-products have more than 10 time periods with observed zero shares. They account for 94% of all observations with zero shares. We check the market share of these store-products when their shares are positive, the mean share is 0.5%, the median is 0.4%, and the 90th percentile is 0.8%, confirming our speculations that these products are likely to have low true market shares when we observe zeros.

# 5 Results

## 5.1 Results from the Full Random Coefficient Model

The estimation results from the full model are presented in Table 9. Note that the random coefficients are all statistically insignificant, and the point estimates are very small. The small random coefficients are due to two reasons. The first reason is because we have estimated the consumer preference model using stores in neighborhoods with similar demographics, so the heterogeneity in taste could be small. The second reason is that we have allowed the price coefficient to vary by product characteristics and added product fixed effects in the model that captures some degrees of heterogeneity in taste. All cross products between price and product characteristics are large and statistically significant, suggesting substantial heterogeneity in price sensitivities.

We have estimated versions of the model dropping product fixed effects, this results in statistically significant and meaningful magnitudes of estimates for the random coefficient on product characteristics. In addition, removing the cross product with price will results in statistically significant price coefficients. Both of these makes sense since the random coefficients would capture the remaining substitution pattern in the two modified models. We choose the full model adding the product fixed effects and the cross-product between price and the product characteristics since it generates the best for data. With the alternative models, the residual variance $\hat{\xi}^2$ are almost twice as large as the full model.

### Price Elasticities of Demand

Based on the estimates from the full model, we calculate the own price elasticity of demand for every observation in the data. The equations for own- and cross-elasticities are the following,

$$\eta_j = \frac{\partial s_j}{\partial p_j} \cdot \frac{p_j}{s_j} = \frac{p_j}{s_j} \int_v (\beta_o + X_j \beta_p + \sigma_p v_{pi}) s_{ij}(v)(1 - s_{ij}(v)) d\Phi_v \tag{4}$$

$$\eta_{jj'} = \frac{\partial s_j}{\partial p_{j'}} \cdot \frac{p_{j'}}{s_j} = \frac{p_{j'}}{s_j} \int_v (\beta_o + X_j \beta_p + \sigma_p v_{pi}) s_{ij}(v) s_{ij'}(v) d\Phi_v \tag{5}$$

The results of own price elasticities are reported in Table 10.

Table 10 reveals large heterogeneity in consumer preference. Comparing the neighborhood with the lowest ratio ($LL$) with the highest ratio ($HH$) of low-education and low-income population, the mean estimate of the elasticities in $HH$ neighborhoods is more than one a half time that of the $LL$

neighborhoods. Holding the education constant, we can compare differences in own price elasticities among neighborhoods with different level of low-income households, i.e. we can compare between neighborhoods within the following sets $(LL, LM)$ and $(ML, MM, MH)$. The elasticity estimates show that conditional on neighborhoods with similar education statistics, price elasticities rise linearly with the concentration of low-income households. Similarly, we can compare neighborhoods with similar income conditions but different education attainment—comparing within the sets of $(LL, ML)$, $(LM, MM)$ and $(MH, HH)$. When the neighborhoods have relatively few low-income households, the increase in the percentage of low-education population slightly raise the price elasticities. In neighborhoods with similarly high ratios of households with a relative high concentration of low-income households, education does not make a difference in consumer price sensitivities. In the current version of the paper, we have not produced the standard error of the elasticity estimates. We will obtain the standard errors by bootstrap.

Table 9: Full-model Estimates

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | LL | LM | ML | MM | MH | HH |
| **Random Coefficients** | | | | | | |
| Price | 0.02 | 6.44E-07 | 2.30E-06 | 2.12E-06 | 3.91E-03 | 0.001 |
| | (0.156) | (0.284) | (0.147) | (0.169) | (0.250) | (0.160) |
| HEI | 4.54E-06 | 1.50E-06 | 0.3530 | 2.57E-08 | 0.1770 | 1.65E-06 |
| | (0.219) | (0.264) | (0.176) | (0.412) | (0.243) | (0.214) |
| (100)kcal | 0.02*** | 0.017 | 3.39E-07 | 1.68E-03 | 3.43E-07 | 4.95E-06 |
| | (0.078) | (0.19) | (0.134) | (0.240) | (0.101) | (0.161) |
| SizeSm | 0.376 | 1.73E-07 | 3.25E-06 | 1.34E-08 | 4.77E-06 | 0.150 |
| | (0.763) | (0.662) | (0.537) | (0.585) | (0.442) | (0.357) |
| **Linear Coefficients** | | | | | | |
| Price | -1.213*** | -1.408*** | -1.007*** | -1.242*** | -0.938*** | -0.808*** |
| | (0.109) | (0.115) | (0.074) | (0.106) | (0.101) | (0.113) |
| Price×(100)kcal | 0.121*** | 0.138*** | 0.100*** | 0.124*** | 0.077*** | 0.063*** |
| | (0.013) | (0.014) | (0.009) | (0.013) | (0.012) | (0.014) |
| Price×HEI | 0.163*** | 0.181*** | 0.031** | 0.144*** | 0.092*** | -0.043*** |
| | (0.024) | (0.025) | (0.015) | (0.024) | (0.022) | (0.020) |
| Price×SizeSm | 0.331*** | 0.532*** | 0.029 | -0.551*** | -0.933*** | -1.030*** |
| | (0.162) | (0.199) | (0.112) | (0.162) | (0.156) | (0.183) |
| Price×(100)kcal×SizeSm | -0.108*** | -0.164*** | -0.091*** | 0.039*** | 0.069*** | 0.089*** |
| | (0.031) | (0.04) | (0.022) | (0.031) | (0.03) | (0.036) |
| Price×HEI×SizeSm | -0.011 | -0.028 | 0.123*** | 0.074*** | 0.218*** | 0.228*** |
| | (0.032) | (0.037) | (0.022) | (0.031) | (0.031) | (0.030) |
| Weekday Ratio | 0.038*** | 0.034*** | -0.031*** | -0.034*** | -0.021*** | -0.040*** |
| | (0.005) | (0.008) | (0.003) | (0.004) | (0.004) | (0.005) |
| Constant | -0.680** | 0.925*** | 0.682*** | -0.277 | 1.079*** | -0.040 |
| | (0.339) | (0.344) | (0.175) | (0.232) | (0.225) | (0.263) |
| Objective Function | 952.69 | 469.91 | 1344.07 | 1333.66 | 1358.72 | 1191.44 |
| Residual Variance | 0.4682 | 0.4804 | 0.4261 | 0.4771 | 0.4952 | 0.5603 |
| N | 137,681 | 87,310 | 227,227 | 185,729 | 197,623 | 149,692 |

* $p<0.10$ ** $p<0.05$ *** $p<0.0$.

*Notes*: **1** The indicator for neighborhood LL represents (L)ow in low-education population and (L)ow in low-income households. **2** Due to large number of stores in the MM sample, we estimated the parameters by randomly drawing one third of the stores from the entire sample.

Table 10: Own Price Elasticities of Demand

| | (1) LL | (2) LM | (3) ML | (4) MM | (5) MH | (6) HH |
|---|---|---|---|---|---|---|
| Mean | -2.28 | -2.82 | -2.57 | -2.85 | -3.50 | -3.53 |
| Std Dev | 1.62 | 1.88 | 1.69 | 2.00 | 1.98 | 1.80 |
| 25th percentile | -3.33 | -4.01 | -3.73 | -4.57 | -5.00 | -5.05 |
| 50th percentile | -2.37 | -2.89 | -2.60 | -2.57 | -2.80 | -3.46 |
| 75th percentile | -1.49 | -1.83 | -1.44 | -1.59 | -2.04 | -2.10 |
| N | 137,681 | 87,310 | 227,227 | 185,729 | 197,623 | 149,692 |

*Notes*: We calculate the elasticities of demand for each item-store-time period during our sample. The above numbers show the distribution of the elasticities within each neighborhood.

### Preference for Product Healthfulness, Calories, and Size

Because we have added the product fixed effects in the estimation, we cannot separately identify consumer preference for product characteristics that are fixed over time. But we are interested in the heterogeneity of consumer preference on these dimensions. In order to get a sense of it, we calculate the marginal effect of product fixed effects on the probability of purchase. More specifically, we change one product's fixed effect from its estimated value to the mean value of all product fixed effects one at a time and we assess the average change in the product's purchase probability. This way, we get the fixed effects for each product in term of purchase probabilities. We then regress product "fixed effects" on product characteristics. We do it for each neighborhood and compare the outcomes.

Table 11: Unpacking Item "Fix Effects"

| | (1) LL | (2) LM | (3) ML | (4) MM | (5) MH | (6) HH |
|---|---|---|---|---|---|---|
| SizeSm | 0.525*** | 0.681*** | 0.365*** | 0.654*** | 0.303*** | 0.0972*** |
| | (0.0689) | (0.0849) | (0.0397) | (0.0706) | (0.0381) | (0.0258) |
| HEI | 0.0592*** | 0.0762*** | 0.0165*** | 0.0733*** | 0.0420*** | -0.0300*** |
| | (0.00781) | (0.00934) | (0.00419) | (0.00803) | (0.00401) | (0.00284) |
| (100)kcal | 0.144*** | 0.185*** | 0.104*** | 0.187*** | 0.0896*** | 0.0438*** |
| | (0.0115) | (0.0137) | (0.00619) | (0.0118) | (0.00594) | (0.00418) |
| HEI×SizeSm | -0.0575*** | -0.0755*** | -0.0154** | -0.0700*** | -0.0401*** | 0.0314*** |
| | (0.0108) | (0.0134) | (0.00624) | (0.0111) | (0.00599) | (0.00408) |
| (100)kcal×SizeSm | -0.141*** | -0.184*** | -0.103*** | -0.181*** | -0.0872*** | -0.0417*** |
| | (0.0158) | (0.0196) | (0.00912) | (0.0162) | (0.00874) | (0.00595) |
| Constant | -0.550*** | -0.697*** | -0.382*** | -0.695*** | -0.325*** | -0.118*** |
| 75th percentile | (0.0502) | (0.0599) | (0.0272) | (0.0516) | (0.0261) | (0.0182) |
| N | 90 | 87 | 89 | 89 | 89 | 88 |
| Adjusted $R^2$ | 0.702 | 0.739 | 0.8126 | 0.797 | 0.817 | 0.855 |

* p<0.10 ** p<0.05 *** p<0.0.

*Notes*: The outcome variable in each regression is the marginal effect of the item fixed effects–the contribution of the item fixed effects on the probability of purchase. The differences in the number of observations is due to the differences in item availabilities in each sets of stores. We normalized calories by the size (weight) of the food item.

Results are shown in Table 11. We use the interactive term with size to allow differential preference when consumers eat the large size food items and the small size ones. Overall, consumers care about healthfulness and calories when they choose large size items, but they are insensitive to these characteristics when they choose small size food items. When interpreting the coefficients, we need to keep in mind that these are residual effects that already conditioned on consumer preference for price. Comparing neighborhoods with different demographics, we see a sharp contrast between the neighborhoods with high percentage of both low income and low education individuals ($HH$). Consumers in $HH$ neighborhoods have the least preference for small size food items and their preference for healthfulness is negative. Conditional on price, consumers in $HH$ neighborhoods also care less about calories. Also, for neighborhoods with similar income conditions, that is, comparing within the following three pairs of neighborhoods ($LL, ML$), ($LM, MM$) and ($MH, HH$), the neighborhoods that have a lower fraction of individuals with low education in general have greater preference for healthfulness, small size, and calories. In terms of magnitude, the outcome are in probabilities, so for one unit increase in healthy index, the probability of purchase increases by 6 percentage points in the best off neighborhoods, and probability of purchase decreases by 3 percentage points in the worst off neighborhoods.

## 5.2 Counterfactual Price Experiments

Reduced form evidences show that consumers in more advantaged neighborhoods choose healthier food items and consume less calories per meal from food items. In this section, we will explore the contribution of heterogeneity in consumer taste preference and price taste to explain the consumption inequality in healthfulness. In particular, we will construct counterfactuals in which we set equal prices across products and neighborhoods. We will then discuss price experiments that can equalize the HEI consumed by consumers in different neighborhoods.

### Equalizing Prices across Items and Neighborhoods

Consumers in disadvantaged neighborhoods are choose less healthy food items. This could be driven by consumer heterogeneity in price elasticities of demand or by consumer differential taste for calories and healthfulness of the food. Estimates from the structural model show that consumers in more disadvantaged neighborhoods are much more price sensitive. Given that healthier food items are slightly pricier and usually contain less calories (Table 2), we expect consumers in more disadvantaged neighborhoods to choose less healthy food items. Estimates for consumer taste preferences, shown in Table 11, reveals that consumers in most neighborhoods have similar taste for food item healthfulness, but the most disadvantaged neighborhoods have a distaste for healthfulness, which also contributes to their choice of less healthy food items. We will conduct two counterfactual experiments that remove the price differences. In the first experiment, we will set the price per calories the same, and in the second experiment, we will set the price per food item the same.

In the first experiment, we set price per calories the same across all food items. We use average listed price per 100kcal across all stores during the sample period \$1.04 per 100 kcal. We then assume that the store charges the price according to this pricing rule during the sample period and simulate the in-sample market shares. In Table 12, we show the quantity weighted average characteristics of the food items chosen by consumers in different neighborhoods. With prices on per 100 calories equal, consumers in all neighborhoods opt for food items with lower calories and are more likely to buy small size food items. Due to the consumer choice of lower calories and the positive correlation between calories and HEI, consumers choose much healthier food items.

Comparing across neighborhoods, setting the price per 100kcal equal almost closes the gap in the overall average food item healthy index between the $LL$ and $HH$ from 0.9 (Table 4) to 0.2. And consumers in less well-off neighborhoods achieve an average healthy index that's even higher than the most advantaged neighborhood. The key contributing factor of this pattern is the heterogeneity in consumer price elasticities. Since consumers in poorer neighborhoods are more price sensitive, if prices per 100 calories are the same across all items, consumers in poorer neighborhoods would choose food items with lower calories, often times more healthy. Also, from Table 11, we can see that the preference for food item healthfulness in $LM$, $MM$, $MH$ neighborhoods are similar as consumers in $LL$ neighborhoods, so consumers in these neighborhoods end up choosing even healthier food items than $LL$. Lastly, since consumers in group $ML$ has the second lowest taste for HEI, and they are not as price sensitive as the $LL$ group, they are less incentivized than the $LL$ group to eat items with lower calories, so they end up consuming food items with the lowest average HEI. The implications for small size and large size items are also different. While consumers in worse-off neighborhoods choose healthier food items when they choose small ones, they eat less healthy food items when choosing big ones.

Table 12: Equalizing Price per Calorie among All Food Items in All Neighborhoods

| | All Items | | Small Items | | Large Items | |
|---|---|---|---|---|---|---|
| Block | Calories | HEI | Calories | HEI | Calories | HEI |
| $LL$ | 543.20 | 0.79 | 338.64 | 0.89 | 787.48 | 0.67 |
| $LM$ | 513.81 | 0.82 | 338.53 | 0.88 | 779.97 | 0.73 |
| $ML$ | 565.43 | 0.66 | 335.14 | 0.88 | 794.71 | 0.44 |
| $MM$ | 535.62 | 0.82 | 325.53 | 0.98 | 802.88 | 0.61 |
| $MH$ | 484.00 | 0.85 | 330.95 | 0.93 | 739.26 | 0.72 |
| $HH$ | 499.41 | 0.77 | 329.83 | 0.95 | 751.55 | 0.50 |

*Notes*: The LL stands for "L"ow ratio of low-education population and "L"ow ratio of low-income households. Compared with Table 4, group $HM$ is removed since we do not have enough number of stores to reliably estimate the preference in this neighborhoods. The table presents the sales weighted averages of the calories and HEI of the food items consumed. The weights are the total simulated sales of each item during the entire sample period across all scores.

In the above exercise, we see that the consumer price preference still plays a major role since when modeling consumer preference, we allow consumers to care about both overall price and price per calories. What about equalizing prices per item? In the following counterfactual, we equalize the price of the food items with the same sizes to be the same. We set the small food items to their overall sample mean of \$4.8 each and the big food items to its overall average mean of \$6.8 each. The resulting sales weighted average HEI and calories of the food items chosen are shown in

Table 13. The consequence of making prices the same is that consumers in worse off neighborhoods have stronger incentive to increase calories consumed per item–eating higher calories per food item means getting more calories per dollar spent or paying less for per calorie. This actually worsens the consumption inequality in healthfulness. With consumers in $HH$ neighborhoods who do not care about food item healthfulness but care about paying less money per calorie, they will choose items with much lower HEI than the rich neighborhoods. Sales weighted average calories increase and average HEI declines from the most to the least advantaged neighborhoods, and the prediction is similar for both big and small size food items.

Table 13: Equalizing Price per Item among All Food Items in All Neighborhoods

| | All Items | | Small Items | | Large Items | |
|---|---|---|---|---|---|---|
| Block | Calories | HEI | Calories | HEI | Calories | HEI |
| $LL$ | 611.3 | 0.477 | 395.7 | 0.519 | 779.3 | 0.445 |
| $LM$ | 605.9 | 0.443 | 406.0 | 0.448 | 785.9 | 0.438 |
| $ML$ | 647.4 | 0.374 | 399.1 | 0.475 | 789.7 | 0.316 |
| $MM$ | 653.8 | 0.434 | 404.9 | 0.477 | 790.3 | 0.411 |
| $MH$ | 656.7 | 0.397 | 413.4 | 0.415 | 799.7 | 0.386 |
| $HH$ | 676.2 | 0.330 | 416.4 | 0.403 | 808.9 | 0.292 |

*Notes*: LL stands for "L"ow ratio of low-education population and "L"ow ratio of low-income households. $LL$ is hence the *most advantaged* group and $HH$ is *the least advantaged*. The table presents the sales weighted averages of the calories and HEI of the food items consumed. The weights are the total simulated sales of each item during the entire sample period across all scores.

### Expanding the Existing National Promotions on Healthy Food Items

In this section, we examine the price experiments that try to remove the inequality in average HEI in chosen food items across different neighborhoods. In the reduced-from analysis of national promotions, we see that price incentives are strong for consumers to switch into discounted items. The structural estimates also reveal that consumers in more disadvantaged neighborhoods are much more price sensitive, suggesting price cuts on healthy items could be very effective in removing consumption inequality in HEI.

We first examine the effectiveness of the existing promotions carried out by the chain that promotes the food items on the healthy choice menu. With the structural model, we can extend the limited-time national promotion on healthy items to the entire sample period in the $HH$ neighborhoods and see how consumers would have chosen during the sample period. The results are shown in Table 14 under "Counterfactual 1". The existing national promotion promoted three small items on the healthy choice menu, so we can see the effect of the promotion fell mainly on small items. The average HEI consumed by consumers on small items rose from 0.395 to 0.563, surpassing the average HEI in $LL$ neighborhoods on small items. It drive up the overall average HEI consumed by $HH$ neighborhoods to the level similar to the $LL$ neighborhood.

Table 14: Price Experiments in the most disadvantaged ($HH$) neighborhoods

| | All Items | | Small Items | | Large Items | |
|---|---|---|---|---|---|---|
| | Calories | HEI | Calories | HEI | Calories | HEI |
| Current statistics: | | | | | | |
| $LL$ | 604.0 | 0.420 | 381.3 | 0.487 | 773.3 | 0.369 |
| $HH$ | 651.8 | 0.343 | 392.9 | 0.395 | 792.2 | 0.315 |
| Counterfactual 1: extend existing promotion on healthy items | | | | | | |
| $HH$ | 625.0 | 0.417 | 378.2 | 0.563 | 792.4 | 0.318 |
| Counterfactual2: expand existing promotion on healthy items | | | | | | |
| $HH$ | 623.2 | 0.511 | 378.2 | 0.563 | 762.8 | 0.482 |

*Notes*: LL stands for "L"ow ratio of low-education population and "L"ow ratio of low-income households. $LL$ is hence the *most advantaged* group and $HH$ is *the least advantaged*. The table presents the sales weighted averages of the calories and HEI of the food items consumed. The weights are the total simulated sales of each item during the entire sample period across all scores.

For the three small food items on the healthy choice menu, they also have the big food items versions with the same HEI. We also examine the counterfactual in which the store expand the promotions to these three large healthy food items. We find a substantial increase in the average HEI consumed. The national promotion on the small food items changes their price from an average of \$4.2 to a uniform of \$3, about a 29% discount. Similarly, we discount the corresponding three large items by 25% from an average price of \$6.0 dollars to a uniform price of \$4.5. The results are shown under "Counterfactual 2" in Table 14. The promotion results in an increase in HEI consumed in large food items from 0.32 to 0.48 in $HH$ neighborhoods, also surpassing the level of the $LL$ neighborhoods. Overall, it leads the average HEI consumed in all food items from 0.34 to 0.51.

In the next counterfactual exercise, we cut price on the food items with HEI higher than 1.1, a set of 22 food items that are are the most healthy among all. We experiment with different discount amounts so that the gap in average HEI between $LL$ neighborhoods and other neighborhoods are closed. The results are shown in Table 15.

Table 15: Discounting Top Healthy Food Items

| | Amount | All Items | | Small Items | | Large Items | |
|---|---|---|---|---|---|---|---|
| Group | Discounted | Calories | HEI | Calories | HEI | Calories | HEI |
| $LL$ | \$0.0 | 604.0 | 0.420 | 381.3 | 0.487 | 773.3 | 0.369 |
| $LM$ | \$0.10 | 603.5 | 0.419 | 382.9 | 0.498 | 777.3 | 0.357 |
| $ML$ | \$0.33 | 619.5 | 0.419 | 374.4 | 0.527 | 774.5 | 0.350 |
| $MM$ | \$0.17 | 618.0 | 0.420 | 380.7 | 0.495 | 778.7 | 0.369 |
| $MH$ | \$0.27 | 623.6 | 0.419 | 381.6 | 0.503 | 783.2 | 0.364 |
| $HH$ | \$0.32 | 633.0 | 0.419 | 383.0 | 0.506 | 784.3 | 0.366 |

*Notes*: LL stands for "L"ow ratio of low-education population and "L"ow ratio of low-income households. $LL$ is hence the *most advantaged* group and $HH$ is *the least advantaged*. The table presents the sales weighted averages of the calories and HEI of the food items consumed. The weights are the total simulated sales of each item during the entire sample period across all scores.

### Raising Prices on the Most Unhealthy Food Items

While discounting the healthy food items can promote healthy eating, raising prices on the less healthy food items can also shift consumers towards healthier food items. We simulate the price experiment of discounting the top 22 food items with the lowest HEI–items with HEI of -0.265 or lower. The results are shown in Table 16. The price experiments involve raising price between \$0.06 and \$0.44 in different neighborhoods. The least advantaged neighborhoods, $HH$, needs the highest raise on the unhealthy items of \$0.44, while the much better off neighborhood $LM$ only need a price increase of 4 cents

Table 16: Discounting Top Healthy Food Items

| | Amount | All Items | | Small Items | | Large Items | |
|---|---|---|---|---|---|---|---|
| Group | Raised | Calories | HEI | Calories | HEI | Calories | HEI |
| $LL$ | \$0.0 | 604.0 | 0.420 | 381.3 | 0.487 | 773.3 | 0.369 |
| $LM$ | \$0.06 | 607.6 | 0.419 | 383.9 | 0.499 | 779.2 | 0.358 |
| $ML$ | \$0.35 | 636.7 | 0.420 | 375.7 | 0.582 | 783.1 | 0.329 |
| $MM$ | \$0.13 | 627.9 | 0.420 | 383.5 | 0.500 | 782.0 | 0.370 |
| $MH$ | \$0.18 | 637.6 | 0.419 | 385.5 | 0.518 | 787.3 | 0.361 |
| $HH$ | \$0.44 | 653.4 | 0.421 | 386.1 | 0.573 | 791.9 | 0.341 |

*Notes*: LL stands for "L"ow ratio of low-education population and "L"ow ratio of low-income households. $LL$ is hence the *most advantaged* group and $HH$ is *the least advantaged*. The table presents the sales weighted averages of the calories and HEI of the food items consumed. The weights are the total simulated sales of each item during the entire sample period across all scores.

## 6 Conclusions

To be completed...

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# Appendix

Table A1: Recommended Nutrients Intake

| Nutrient | $G_c$ | Recommended daily intake ($g$) | Explanation |
|---|---|---|---|
| Protein | + | 51 | 51 grams/day (RDI) |
| Fiber | + | 29.5 | 29.5 grams/day (RDI) |
| Sugar | − | 32.8 | 45% of 282 calories/day from sugar+sat. fat |
| Saturated fat | − | 17.2 | 55% of 282 calories/day from sugar+sat. fat |
| Sodium | − | 2.3 | 2300 mg/day (Dietary Guidelines) |
| Cholesterol | − | 0.3 | 300 mg/day (Dietary Guidelines) |

*Note: DRI is short for “Recommended Daily Intake.” From Allcott et al., (2018).*

Table A2: Sales Weighted Average Calories and HEI of the Food Items Consumed

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | HEI | HEI | HEI | Calories | Calories | Calories |
| | All | Small | Large | All | Small | Large |
| LM | -0.0174 | -0.0110 | -0.0228 | 3.638 | 3.172 | 5.575 |
| | (0.0238) | (0.0283) | (0.0260) | (5.726) | (2.561) | (4.328) |
| ML | -0.0573** | -0.0352 | -0.0580** | 30.00*** | -1.093 | 7.776** |
| | (0.0223) | (0.0233) | (0.0254) | (4.577) | (2.270) | (3.755) |
| MM | -0.0528** | -0.0422* | -0.0472** | 31.88*** | 2.312 | 9.734*** |
| | (0.0211) | (0.0227) | (0.0238) | (4.429) | (2.137) | (3.544) |
| MH | -0.0547** | -0.0689*** | -0.0356 | 33.91*** | 7.636*** | 14.81*** |
| | (0.0239) | (0.0249) | (0.0273) | (5.933) | (2.334) | (3.933) |
| HH | -0.0765*** | -0.0914*** | -0.0539* | 47.79*** | 11.63*** | 18.91*** |
| | (0.0249) | (0.0242) | (0.0285) | (4.699) | (2.299) | (3.967) |
| HM | -0.0332 | -0.0553** | -0.00465 | 47.19*** | 6.374** | 9.173 |
| | (0.0299) | (0.0263) | (0.0356) | (9.092) | (2.632) | (5.587) |
| Constant | 0.420*** | 0.487*** | 0.369*** | 604.0*** | 381.3*** | 773.3*** |
| | (0.0186) | (0.0214) | (0.0205) | (3.694) | (2.049) | (3.318) |
| N | 1054260 | 484037 | 570223 | 1054260 | 484037 | 570223 |

Table A3: Sales Weighted Average Price Paid for Food Items

| | All Items | | Small Items | | Large Items | |
|---|---|---|---|---|---|---|
| Block | Price Paid per 100kCal | Price Paid | Price Paid per 100kCal | Price Paid | Price Paid per 100kCal | Price Paid |
| LL | 1.00 | 5.47 | 1.18 | 4.25 | 0.87 | 6.40 |
| LM | 1.01 | 5.51 | 1.20 | 4.36 | 0.86 | 6.39 |
| ML | 0.98 | 5.64 | 1.17 | 4.21 | 0.87 | 6.48 |
| MM | 0.97 | 5.62 | 1.16 | 4.20 | 0.86 | 6.45 |
| MH | 0.96 | 5.60 | 1.13 | 4.18 | 0.86 | 6.46 |
| HM | 0.97 | 5.79 | 1.15 | 4.24 | 0.87 | 6.56 |
| HH | 0.94 | 5.60 | 1.10 | 4.11 | 0.85 | 6.41 |

*Notes*: The LL stands for "L"ow ratio of low-education population and "L"ow ratio of low-income households. The $LL$ is hence the *most advantaged* group and $HH$ is *the least advantaged*. The weights are the total sales of each item during the entire sample period across all scores.

Table A4: Sales Weighted Average Calories and HEI of the Food Items Consumed

| | (1) All Paid Price | (2) Small Paid Price | (3) Large Paid Price | (4) All Paid Price per 100kcal | (5) Small Paid Price per 100kcal | (6) Large Paid Price per 100kcal |
|---|---|---|---|---|---|---|
| LM | 0.0423 | 0.117* | -0.00648 | 0.00540 | 0.0204 | -0.00737 |
| | (0.0422) | (0.0619) | (0.0462) | (0.00947) | (0.0175) | (0.00748) |
| ML | 0.176*** | -0.0403 | 0.0798** | -0.0227*** | -0.00777 | 0.000172 |
| | (0.0367) | (0.0452) | (0.0365) | (0.00860) | (0.0140) | (0.00539) |
| MM | 0.155*** | -0.0434 | 0.0539 | -0.0304*** | -0.0200 | -0.00552 |
| | (0.0385) | (0.0520) | (0.0349) | (0.00919) | (0.0163) | (0.00528) |
| MH | 0.133*** | -0.0682 | 0.0617 | -0.0412*** | -0.0446*** | -0.0117** |
| | (0.0431) | (0.0460) | (0.0387) | (0.00965) | (0.0153) | (0.00586) |
| HH | 0.135*** | -0.133*** | 0.0139 | -0.0659*** | -0.0752*** | -0.0227*** |
| | (0.0462) | (0.0492) | (0.0532) | (0.0102) | (0.0152) | (0.00765) |
| HM | 0.316*** | -0.00723 | 0.157** | -0.0366* | -0.0256 | 0.00364 |
| | (0.0839) | (0.114) | (0.0661) | (0.0191) | (0.0329) | (0.0104) |
| Constant | 5.469*** | 4.247*** | 6.398*** | 1.002*** | 1.177*** | 0.869*** |
| | (0.0287) | (0.0388) | (0.0309) | (0.00768) | (0.0125) | (0.00467) |
| N | 1054260 | 484037 | 570223 | 1054260 | 484037 | 570223 |