Groceries or School Cafeterias: How Households Respond to School Nutrition Mandates

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Abstract

The Healthy, Hunger-Free Kids Act (HHFKA) placed strict nutritional mandates on meals served at U.S. public schools. This policy offers a unique opportunity to study household response to a large, exogenous change in healthiness of food available to their children. Did more healthy school meals lead households to substitute towards them, and away from grocery food purchases? Which households were more responsive to the nutritional mandates? And was there any spillover effect on the nutritional quality of their grocery food purchases? We document a meaningful decrease in the quantity of grocery food in response to the HHFKA, and a small decrease in quality. Consistent with substitution towards school meals, more of the quantity decrease is attributable to items likely to be purchased for children and categories traditionally associated with breakfast and lunch (the meals served at school). The HHFKA attracted even greater participation from financially and time constrained households for whom school meals were already important and were now coupled with the additional benefit of healthier food. These findings have important implications for policy makers and researchers, but also for food manufacturers and retailers.

Keywords:
Nutrition mandates, children, dietary health, nudges, grocery choices, public policy.

INTRODUCTION

Much recent research in marketing and related fields has attempted to answer an important question: "How can we help consumers eat healthier?" One key stream of literature has examined why consumers purchase unhealthy foods. Oft-cited explanations include insufficient access to healthy foods, financial constraints, time constraints, low nutrition literacy, and the importance of taste. Another important stream of literature has examined actions that could stem the tide, including price changes, advertising bans and taxes on unhealthy foods, new forms of nutrition labels and health symbols, package/portion size reduction and product reformulation, and various types of nudges.

A significant challenge faced by researchers seeking to learn about food choices in the marketplace—or what Haws et al. (2022) refer to as "free-living eating" rather than "lab eating"—is that exogenous shocks to the healthiness of food options available to consumers are rare. One such shock occurred in the U.S. at the start of the 2012 school year, when the Healthy, Hunger-Free Kids Act (HHFKA) was implemented. It mandated strict and significantly higher nutrition standards for meals provided by the School Breakfast Program and the National School Lunch Program, substantially improving the healthiness of school meals (Kinderknecht, Harris, and Jones-Smith 2020; Cohen and Schwartz 2020).

Detractors of the policy argued that children would dislike the healthier meals, leading to lower participation and/or more wasted food (Simpson and Baertlein 2012; Yee 2012), while supporters claimed that participation would not decline (Donald 2010). Empirical evidence on whether households shifted towards, or away from, the now-healthier school meals is limited to two sources: year-over-year changes in the number of "meals served" that schools report to the USDA in order to be reimbursed, which show a slight increase in the first year after the HHFKA's nutritional mandates were implemented (USDA 2023), and studies on participation among small regional samples of schools, which find little to no change in participation (e.g., Bergman et al. 2014). However, causal or generalizable evidence is lacking

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for the overall effect of the nutrition mandates on participation, heterogeneity in that effect, or spillover effects on grocery purchases.

Marketers, marketing researchers, and policy makers all have an interest in understanding consumers' response to the HHFKA's stricter nutrition guidelines and, in turn, what that response might say about ways to improve consumers' food choices. Analyzing response to the HHFKA is especially important at this time, because the rules regarding school meal nutrition standards continue to change, weakening or strengthening depending on which political party is in power (Jacobs 2018; Riley 2023).

This paper aims to fill this gap in the literature by (1) studying whether the HHFKA's improved nutrition standards (independent of the act's other changes) resulted in a shift from grocery food purchases towards school meals or vice versa; (2) examining whether the shift changed the healthiness of households' grocery food shopping; and (3) characterizing which types of households shifted the most towards school meals, to learn why certain households may have availed of the healthier food for their kids in school.

We accomplish this by using the NielsenIQ Homescan Panel of household grocery purchases to estimate changes in the quantity and nutritional quality of grocery food purchases that can be attributed to the policy change. We can infer changes in households' school meal participation from the changes in the quantity of their grocery food shopping (see Brown 2021, Handbury and Moshary 2021, and Marcus and Yewell 2022 for similar use of grocery purchase data), and changes in the nutritional quality of grocery food shopping inform us about any spillover effects of the policy change. To identify the effect of the HHFKA, we compare changes in the shopping baskets of households with children (who are treated by the policy) and matched control households without children.

There are several benefits to this approach. First, our data come from a national panel and are therefore much more representative of the US than small, regional samples are. Second, we can measure food quantity and quality at a granular level, versus the monolithic measure of "meals served." Third, our data on demographic and grocery shopping

behavior enable an analysis of the types of households that were most attracted to healthier school meals. And fourth, quantifying the impact of the policy on grocery food purchases is important in its own right, particularly to manufacturers and retailers.

We find that grocery food quantity (measured as total calories per capita) declined by approximately 6% due to the HHFKA mandates, suggesting that there was a small but meaningful shift towards school meals. Consistent with this, the reduction was driven more by food items that are likelier to be purchased by households with kids, and by breakfast and lunch categories (the two meals offered at school) than other categories. We also find the nutritional quality of grocery purchases declined slightly, but that this decline is much smaller than the increased healthiness of school meals.

Finally, we find that the HHFKA attracted even greater participation from households for whom the pre-existing benefits of school meals (time and money savings) were already important and were now coupled with an additional benefit: healthier food for their kids. It had a stronger pull among households with limited time and money, and whose pre-HHFKA grocery food purchases were both smaller and less healthy.

Our study makes important contributions to the growing stream of literature focused on encouraging healthy eating. It is a generalizable, in-market examination of response to a substantial change in the food landscape for families with school-going kids. Compared to studies of nutrition labels, price/tax changes, or package/nutrition changes of individual items, this paper's context is unique in that it provides insight into how consumers respond when meal offerings are made substantially healthier overall. The magnitude of response to this policy change is informative not only for those studying policy interventions, but also for retailers and manufacturers, whose sales are directly affected by substitution to or from school meals.

Our examination of heterogeneity in households' response to the mandates also adds to the policy literature on these mandates, which understandably focuses on poor and under-privileged children. Our work underscores the important role of not just financial constraints

in shaping response to healthier school meals, but also time constraints; information which should be of interest to both policy makers and marketers in the food space.

Our findings should be encouraging to policy makers because (a) making school meals healthier attracted greater participation, rather than turning kids off or merely leaving participation unaffected; (b) for participating kids, any reduction in the healthiness of foods purchased at home was likely dwarfed by the healthiness of school meals; and (c) substitution towards healthier school meals was stronger among busy, low socioeconomic status households that purchased less healthy foods at the grocery store, thus benefiting the kids who most need the healthier food.

THE POLICY CHANGE AND RELATED LITERATURE

Mandated Nutrition Standards Under The HHFKA

The HHFKA was a centerpiece of First Lady Michelle Obama's "Let's Move!" initiative to combat childhood obesity and was signed into law in 2010. This research focuses only on the nutrition standards mandated by section 208; the first major change to nutrition standards for food served through the National School Lunch Program (NSLP) and School Breakfast Program (SBP) since their respective introductions in 1946 and 1966. The new standards required that milk served in schools be either fat-free or 1% fat, that more fruit and vegetables be served, and that unhealthy components such as sodium, sugar, and saturated fat be capped. To combat overeating, portion sizes of meals were reduced as well.[1]

These changes greatly improved the nutritional content of school meals. Measured using the USDA's Healthy Eating Index (HEI), the healthiness of breakfasts served at school increased from 50% of the maximum score to 71%, and the healthiness of lunches served at schools increased from 58% of the maximum score to 82% (Gearan and Fox 2020). Other studies also reported that consumed foods at school were healthier after the implementation

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[1] https://www.federalregister.gov/documents/2016/07/29/2016-17227/national-school-lunch-program-and-school-breakfast-program-nutrition-standards-for-all-foods-sold-in

of the HHFKA's nutrition standards (Bergman et al. 2014; Cullen, Chen, and Dave 2015; Schwartz et al. 2015; Kinderknecht, Harris, and Jones-Smith 2020).

Schools were required to implement the revised nutrition guidelines starting from the 2012-2013 school year. We use one year before and after the change for our analyses. We specify August 2012 as the treatment start date, since August is the most common back-to-school month in the United States. Thus, our data span the period from August 2011 through July 2013. The policy change rollout was announced to schools in advance of its required implementation, and a large majority of schools were reported to be in compliance with these guidelines shortly after implementation began (Au et al. 2020). To the extent that some specific schools implemented changes to food served early (or late), our results would be rendered conservative, as an early (or late) application of the treatment would reduce the difference between the treatment group's pre- and post-treatment outcome variables.

Crucially, our analysis is not contaminated by the two other changes made by the HHFKA: the national roll-out for the Community Eligibility Provision (CEP), which expanded eligibility for free and reduced-price meals, and the nutritional standards for "competitive foods." Both these changes took effect after our analysis period (the 2014-15 school year). So, our analyses cleanly measure consumers' response to only the new nutrition standards.[2]

Related Literature

Impact of HHFKA nutrition mandates on school meal participation

Much of the research on the HHFKA's nutrition standards has focused on their impact on the healthiness of school meals, as previously noted. Research on the impact on school meal participation is quite limited because it is impractical to get generalizable data on changes in participation. Vaudrin et al. (2018) found no change in schools located in four urban, low-income, high-minority cities in New Jersey, nor did Johnson et al. (2016) in six schools in an urban school district in Washington state. Schwartz et al. (2015) reported a reduction

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[2]A handful of states did enact the CEP during the period under study, and we exclude affected counties from these states from our analyses.

in food waste, rather than the increase forecasted by some detractors of the HHFKA. These limited analyses underscore the importance of our first research question – to quantify the causal impact of the HHFKA's nutrition mandates on the quantity of grocery food purchases by households with school-age kids. We follow in the tradition of researchers like Handbury and Moshary (2021) and Marcus and Yewell (2022), who have investigated the impact of the CEP on household demand for groceries and other related outcomes.

Heterogeneity in the impact of HHFKA's nutrition mandates

We found no prior research that has broadly examined heterogeneity in the effect of the HHFKA's nutrition standards on participation. Research has instead focused on lower-income populations. There is, however, substantial research on the drivers of school meal participation and also a large literature that speaks more generally to drivers of the healthiness of households' food choices. The intersection of these literatures reveals three potential sources of heterogeneity in response to the HHFKA nutrition mandates: financial constraints, time constraints, and nutrition literacy.

School meal programs were designed to help children from families that cannot afford healthy meals. In line with this objective, a sizable proportion of program participants were eligible for free or reduced-price meals even pre-HHFKA (63% for lunches and 82% for breakfasts in 2009-2010 according to USDA 2023). More generally, lack of financial resources is a key barrier to healthy eating (e.g., Daniel 2020; Jetter and Cassady 2006; Ma, Ailawadi, and Grewal 2013), and can lead to food insecurity.

Saving time is one of the most-cited reasons for participating in the school lunch program (Farris et al. 2016). Time pressured households also have less healthy diets, relying more on convenience foods and less on in-home food preparation (e.g., Jabs and Devine 2006; Rahkovsky and Jo 2018). Households with a single head or two fully-employed heads have been shown to rely more on food away from home (Ziol-Guest, DeLeire, and Kalil 2006), and children may eat less healthy food when their mothers work long hours (Hawkins, Cole,

and Law 2009).

Households' nutrition literacy is the third key driver. It encompasses both knowledge about nutrition and the skills to make appropriate dietary decisions and is known to influence the quality of food purchases (Spronk et al. 2014). It also affects school meal participation. For example, among households that were not eligible for free or reduced-price lunches, 61.9% of those who sent kids with lunch from home felt that it would be more nutritious than the options available at school (Farris et al. 2016).

Since these drivers influence both school meal participation and healthy eating, it is not clear a priori what effect they would have on response to the improved nutrition mandates of the HHFKA. Financially- and time-constrained households are likely to already have high rates of school meal participation, so their participation may hit a ceiling. Or more of them may participate, attracted by the healthier meals. It is also an empirical question whether the nutritional mandates might attract unconstrained and nutritionally literate households that did not previously participate in school meals, such as the households referenced in Farris et al. (2016) who preferred to pack healthy lunches for their children.

Spillover effects on grocery food quality

We also could not find any research on the impact of the nutrition standards on the healthiness of grocery food purchases. The broader literature on food choice suggests that there is no obvious *a priori* hypothesis about the existence and direction of any spillover effects. There may be no material food quality changes at home because grocery shopping tends to be habitual with mostly automatic decision-making (e.g., Khare and Inman 2006; Machín et al. 2020; Wood and Neal 2009), and household diets seem to not be very malleable (Hut and Oster 2022).

Alternatively, there may be a positive spillover if repeated exposure to healthier food in school as a normal routine makes children more amenable to healthier options and parents more likely to buy them (Maimaran and Fishbach 2014). Children must try less satiating,

calorie-light foods (that may be less palatable) about ten times before developing a taste for them (Birch 1999; Sullivan and Birch 1990). Or there may be a negative spillover if households feel licensed to indulge in less healthy food at home (e.g., Khan and Dhar 2006; Wight et al. 2023), or less obligated to serve healthy food at home, because kids are eating healthier food at school. We test the validity of these propositions with our data, that we describe next.

DATA

We make use of two main data sets for our analysis: the NielsenIQ Consumer Panel and the nutrition label data provided by Label Insight. We match the nutrition label data with individual items (i.e., Universal Product Code or UPC) in the NielsenIQ data, which allows us to measure a household's quantity and quality of grocery food purchases.

Dependent Variables: Grocery Food Quantity and Quality

Our primary measure of food quantity is a household's total calories purchased in a given month, scaled by the number of "adult equivalents" in the household (which is based on the typical calorie needs of different age group(s), following Allcott et al. 2019; Palazzolo and Pattabhiramaiah 2021) and also by the number of days in the month. Hereafter, we will refer to this as calories per capita for simplicity.

Our primary measure of quality is the Nutrient Profile Score (NPS) from the UK's Nutrient Profiling Model (Poon et al. 2018; Dubois et al. 2021). This model assigns a score to each UPC based on the volume of three healthy components (protein, fiber, and fruits/vegetables/nuts) and four unhealthy components (saturated fat, sugar, sodium, and calories) per 100 grams. We calculate the NPS as prescribed by the UK Department of Health (2011), with two modifications due to data limitations. We detail the calculation of both measures in Web Appendix A.

We are able to match 56% of purchased UPCs in NielsenIQ's six food departments to the

nutrition labels in the Label Insight data. The median and mean daily purchase of calories per capita from matched UPCs in our data set are 597 and 686 respectively. These numbers are reasonable given the match rate and a 2,000 calorie daily diet.

In addition to our two primary measures, we also check robustness with total servings and total grocery food expenditure (which covers all food items, not only the matched UPCs) as alternative measures of quantity and an approximation of the USDA's HEI as an alternative measure of quality (see Web Appendix B).

Sample Selection

The NielsenIQ data provide information about whether households include children in one of three age groups: 0-5 years old, 6-12 years old, or 13-17 years old. Children in the US are eligible to begin kindergarten if they turn five years old by the start of a given school year, or shortly thereafter (Ratnam 2020). Given this threshold, we classify a household in our "treatment group" if they have a child in either of the two older age buckets (6-12 or 13-17). Because we cannot be sure whether households with children only in the 0-5 age bucket are treated (some households with children of age 5 will be in school), we exclude such households from our sample. We also exclude households that switch into or out of the treatment group during the time under study (i.e., households whose kids age into the 6-12 group part-way through the period under study, or whose kids age out of the 13-17 group in that window). We classify households without children in our "control group" pool.

As noted previously, the national roll-out of the CEP happened after the period of our analysis. However, six states (IL, KY, MI, NY, OH, WV) and the District of Columbia did enact the CEP during our period of study, so we exclude households in affected counties of these states (using publicly available data from Ruffini 2022). Because we will conduct difference-in-difference analyses, we also retain only those households that were present in the NielsenIQ panel at least during the 2012 calendar year, to ensure that we have data both before and after treatment (recall that the treatment began in August 2012). We also drop

households that move between counties during the period under study, as we will control for county-specific time trends in our model, and location data are only updated at the end of the calendar year.

This leaves 47,468 households, of which 8,292 are classified as treatment households. We further trim our sample to exclude households that are not reliably reporting their food purchases or that may be small business owners making very large purchases. We do this by identifying the 5th and 99th percentile of calories per capita in the treatment group pool and excluding households in both the treatment and control group pools below the 5th percentile value and above the 99th percentile value.[3] We use a stricter cut-off at the low end of calories than at the high end because it appears that under-reporting is more common than outliers at the high end of the distribution. These screens bring our sample to 43,220 households, of which 7,795 are treatment households. The full set of screens, along with the number of households excluded by each, are summarized in Table 1.[4]

Table 1: Sample Screens and Resulting Sample Size

	Control	Pct Loss	Treat	Pct Loss	Total HH
		-		-	81,364
Remove "Switchers"	62,420	-	15,287	-	77,707
Remove HH not present pre or post	47,446	-24%	9,486	-38%	56,932
Remove CEP eligible counties	41,750	-9%	8,468	-7%	50,218
Remove Control HH with kids<6y.o.	40,231	-2%	8,468	-	48,699
Remove households that move	39,176	-2%	8,292	-1%	47,468
Quantity Screens	35,425	-6%	7,795	-3%	43,220
Coarsened Exact Matching	27,148	-13%	7,645	-1%	34,793

Each row details how many households remain after implementing a given screen. E.g., after removing households that switch between treatment and control ("switchers"), 77,707 households remain, of which 15,287 are classified as "treatment" households.

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[3]The 5th percentile is 178 daily calories per capita, while the 99th percentile is 1,556 daily calories per capita. Recall that our match rate is 56%, making the 178 to 1,556 calorie range loosely equivalent to 318 to 2,779 calories per adult, per day—a fairly conservative screen.

[4]In Web Appendix B we show that our analyses are robust to dropping these screens altogether and to using additional, stricter screens.

Identification Strategy

Using households without children as the control group presents a challenge to our identification strategy because households without children may differ from households with children on both observable and unobservable dimensions. We employ Coarsened Exact Matching (Iacus, King, and Porro 2012) for our analyses, matching the control group to the treatment group on key demographic and behavioral variables (e.g., Yan, Miller, and Skiera 2022). The demographic variables are the number of adult household heads, their age, education level, and employment, and the behavioral variables for the two key dimensions of households' pre-HHFKA grocery food shopping: their average pre-treatment quantity (calories per adult equivalent per day) and quality (NPS).

We provide a breakdown of the demographic differences between treatment and control group households before and after matching in Web Appendix A. After matching, the treatment and control groups are well balanced on all the matching variables. 150 treatment households and 8,277 control households that could not be matched are dropped, leaving 7,645 treatment households and 27,148 matched control households for our analyses. We also show results where we don't match on these variables at all in Web Appendix A for comparison.

In addition to matching, we verify that the parallel trends assumption holds. While we do find some differences in the pre-treatment shopping baskets of treatment and control households, these differences appear to be a statistical artifact of different seasonal patterns in the purchases of households with and without school-aged children. Households with school-aged children purchase relatively fewer grocery calories per capita during the summer months and around the winter holidays. This seasonal pattern manifests both before and after treatment. We follow O'Neill et al. (2016) to formally control for these differences in seasonality, and once that is done the parallel trends assumption holds. Complete details are shown in Web Appendix A.

RESULTS: IMPACT OF THE HHFKA ON THE AVERAGE HOUSEHOLD

Grocery Food Quantity and Quality

We begin by estimating the average response to the HHFKA treatment, using a difference-in-difference (DiD) model of the form:

$$DV_{ht} = \beta(I[TreatGroup]_h \times I[TreatPer]_t) + \delta_h + \lambda_{ct} + \epsilon_{ht} \tag{1}$$

Here, DV_{ht} denotes the dependent variable of interest (calories per capita and NPS) for household h during month t. We include strict controls for unobservables through fixed effects. Apart from household fixed effects, we include county $\times$ month fixed effects for the 24 months under study ($\lambda_{ct}, t = 1, ..., 24$). These control for any time-varying differences at the county level in the demand for groceries. The household fixed effects subsume the treatment group dummy $I[TreatGroup]_h$ which is standard in the traditional DiD model, while the county $\times$ month fixed effects subsume the treatment period dummy $I[TreatPer]_t$. The parameter β estimates the effect of the HHFKA on each of our dependent measures.

We use the natural logarithm of the calories DV in equation 1 so the estimate (when it is small) can be interpreted as approximate percentage changes in the DV.[5] We cluster standard errors at the household level to account for within-household error dependence.

We find that the average household decreased the calories per capita of food purchased at grocery stores by 6.4% in response to the HHFKA's mandated nutrition standards (Table 2). We also find a small reduction (-0.093) in the nutritional quality of food purchased at the grocery store (Table 2). To put the magnitude of the NPS reduction in perspective, a 1-point reduction corresponds to (for example) an additional 4.5 grams of sugar per 100 grams of food (UK Department of Health 2011). A reduction of 0.093 points, then, corresponds to 0.42 grams of sugar per 100 grams of food, or about 1.7 extra grams of sugar per day on a 2,000 calorie diet. This may be concerning, as some of the nutrition gains at school may be

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[5]We cannot log transform the nutritional quality DV as it can take both positive and negative values.

offset in part by less healthy choices at home.

Table 2: Mean Effects of HHFKA on Household Food Purchases

	(1) Ln Calories	(2) NPS
β	−0.064***	−0.093***
	(0.009)	(0.031)
Adjusted R-Sq	0.400	0.402
Sample Size	735,543	728,042

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We next delve into how the composition of shopping baskets changed, in terms of the quantity and quality of different types of foods. These analyses serve two purposes. First, they provide additional evidence that the reduction in grocery food purchases is likely attributable to substitution towards school meals. Second, they provide some context for how concerned we should be about the observed reduction in grocery food quality.

Quantity and Quality of Different Foods Groups in the Grocery Basket

To address our first purpose, we categorize the grocery foods into two pairs of groups relevant to the topic of study: breakfast and lunch categories versus others, and "kid-friendly" UPCs versus others. Because school meals are a potential substitute for breakfast or lunch, we should expect these foods to show the greatest reduction. We include the following categories from the NielsenIQ data in "Breakfast and Lunch": eggs, milk, yogurt, bagels, breakfast cakes, breakfast food, frozen breakfast food, cereal, doughnuts, breakfast sausage and bacon, fresh bread, and lunch meat. These categories are each strongly associated with breakfast or lunch. We consolidate all other food categories into a broad "other" category, to compare the relative change in breakfast and lunch categories to the change observed for all other foods.

Additionally, we categorize individual UPCs of all foods into "kid-friendly" and "not kid-friendly" buckets. "Kid-friendly" UPCs are those purchased considerably more frequently by households with children than other households. Importantly, kid-friendly UPCs are not purchased *only* by treatment households, which would have rendered our control group insufficient for these supplemental analyses. Appendix A contains a description of our classification method along with evidence of its face validity.

Because households do not purchase in every category every month, category-level quantities have a relatively large number of zeros, and dependent variables should not be logged in the presence of zeros (Chen and Roth, 2024). For these analyses, therefore, we construct household-quarter level measures of category calories per capita and NPS.[6] We then use these dependent variables in a modified version of equation 1 (again taking the natural log of calories, and using quarter as the measure of time instead of month) to obtain average treatment effects in each group.

Table 3 shows that the average quantity treatment effect for "kid-friendly" UPCs is more than four times the effect for other UPCs (9.5% versus 2.1%). The fact that the quantity reduction is so much stronger for foods likely to be purchased for children provides more confidence that the reduction in grocery food reflects HHFKA-induced substitution towards school meals. Also consistent with a substitution towards school meals, we find that treatment households reduced their calories per capita more for categories associated with breakfast and lunch (7.3%), the two meals that can be served at schools, than for other categories (5.5%).[7]

Table 4 presents the corresponding treatment effects for grocery quality. We find that the reduction in grocery quality is strongly driven by kid-friendly UPCs, just as quantity was. In fact, we do not find a statistically significant change in the quality of UPCs that are not kid-friendly. When comparing by category, we don't find a statistically significant

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[6]Please see Web Appendix C for additional details and robustness tests.

[7]Since these foods are eaten by more than just kids, may be consumed outside of breakfast and lunch, and other foods might be eaten during breakfast and lunch, there is likely some measurement error in our classification here. As a result, we would not expect differences between these category effects to be large.

Table 3: ATE for Quantity by Target Audience and Food Group

Target Audience	% of Cal#	Est.	Food Group	% of Cal#	Est.
Kid-Friendly UPCs	29%	-0.095***	Breakfast/Lunch	21%	-0.073***
		(0.010)			(0.010)
All other UPCs	71%	-0.021***	All other categories	79%	-0.055***
		(0.008)			(0.008)

Percentage of calories from corresponding group in the average treatment household's shopping basket.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

change in the nutritional quality of either breakfast and lunch UPCs, or other UPCs, though the estimated effect size for each is still negative and economically small, just as the ATE for the full grocery basket was (-0.093). This is suggestive of households continuing their habit-driven shopping at least in categories that are less affected by substitution towards school meals.

Table 4: ATE for Quality by Target Audience and Food Group

Target Audience	Avg. NPS#	Est.	Food Class	Avg. NPS#	Est.
Kid-Friendly	-6.9	-0.122**	Breakfast, Lunch	-4.1	-0.054
		(0.054)			(0.047)
Not Kid-Friendly	-5.7	0.001	All other food, bev	-7.2	-0.038
		(0.102)			(0.035)

Average NPS from corresponding group in the average treatment household's shopping basket.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 also presents the average quality for each group measured as the purchase incidence weighted average NPS. We note that Kid-Friendly UPCs are on average somewhat less healthy than others while breakfast and lunch categories are more healthy than others. The reduction in quality of the overall shopping basket may be because the more-healthy products are substituted away to school meals, due to other mechanisms like licensing, or from a combination of both. Our data don't allow us to definitively say which plays a larger role, though we explore whether there are more granular, category-level changes in Web

Appendix C.

To further contextualize the magnitude of the reduction in grocery quality, we conduct a set of calculations to examine how large it is relative to the healthiness of school meals. This also enables an assessment of whether the children who substitute towards school meals are better off, nutritionally.

Comparison of Higher School Meal Quality With Reduced Grocery Quality

The nutritional composition of school meals has been examined in detail by Gearan and Fox (2020), who report the USDA's Healthy Eating Index (HEI) at the component level (e.g., fruit, vegetables, dairy, etc.) for both school breakfasts and lunches.[8] In this section, we compare the reported HEI of these components to corresponding HEI scores for the reduction in nutritional content of groceries.

The general idea behind these calculations is easiest to see with an example. Say that a household purchases 100 fewer calories and 5 fewer grams of saturated fat per day due to the nutrition mandates. We would like to compare the nutritional content of those calories with the calories that presumably replaced them—those coming from school meals. For a given component of the HEI, j, such as saturated fat, we calculate the average household's percentage reduction in that component. We then use that value, along with the 6.4% reduction in the average household's calories purchased, to calculate the quantity of component j per 1,000 calories *not purchased due to the nutrition mandate*, and the corresponding component-level HEI score.

Not all components of the HEI can be measured using the NielsenIQ data, but six can be: cups of fruit and vegetables, cups of dairy, ounces of "protein foods" (e.g., meat, eggs, beans), ounces of seafood and plant "protein foods" (a subset of all "protein foods"), mg of sodium, and grams of saturated fat. These measures make up 50% of the points in the HEI's 100-point scale.

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[8]The scores are only provided for the 2014-2015 school year, so we use those.

In Table 5, we report the HEI score reported by Gearan and Fox (2020) for each of these four components for (i) school breakfast and (ii) lunches in the first two columns, and the HEI score calculated from the NielsenIQ data for the (iii) groceries not purchased due to the nutrition mandates in the third column.[9] We report the corresponding quantities per 1,000 calories in columns four through six (e.g., the groceries not purchased by households in our panel contained 15 grams of saturated fat per 1,000 calories, reported in column 6, corresponding to an HEI score of 31, reported in column 3). Details of these calculations are provided in Web Appendix D.

Table 5: Healthiness of school meals v.s. the groceries they were substituted for

	HEI Score[#]			Quantity per 1,000 Calories		
	School Breakfast	School Lunch	Grocery Food[##]	School Breakfast	School Lunch	Grocery Food[##]
Fruit and Veg (cups)	52	88	39	0.84	1.66	0.37
Dairy (cups)	99	99	49	1.29	1.29	0.64
Protein Foods (oz)	32	90	78	0.80	2.26	1.94
Seafood, Plant (oz)	13	46	68	0.11	0.37	0.54
Sodium (mg)	93	27	20	1,165	1,757	1,817
Saturated Fat (g)	83	96	31	10.4	9.2	15.0
HEI (overall)	70	76	42			

[#]Higher HEI scores reflect higher quality. For example, the 1,165 mg of sodium per 1,000 calories in school breakfasts is higher quality (HEI score of 93), than the 1,757 mg of sodium per 1,000 calories in school lunches (HEI score of 27).

[##] This is the grocery food not purchased due to treatment. For example, the groceries not purchased due to treatment had, on average, 0.37 cups of fruit and vegetables per 1,000 calories. In comparison, school breakfasts had 0.84 cups and school lunches had 1.66 cups.

Table 5 shows that school meals were much lower in sodium and saturated fat and higher in fruit, vegetables, and dairy compared to the food estimated to be removed from grocery baskets. The HEI scores for these components were considerably better in school meals than in the grocery foods substituted for those meals. The improvement for saturated fat is particularly large; grocery food contained about 50% more saturated fat than school

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[9]Gearan and Fox (2020) report an HEI score for "empty calories", which includes saturated fat and added sugar, but we lack complete data on added sugars. We report their empty calories HEI score for saturated fat in Table 5.

meals, and had a much lower HEI score (31, versus 83 and 96 for school breakfasts and lunches). School breakfasts were lower in protein foods, however. We also compute the overall HEI for school breakfasts, lunches, and groceries not purchased, scaled for the subset of measures available to us. Overall, school breakfasts (70 on the HEI) and lunches (76 on the HEI) were considerably healthier than the calories households did not purchase due to the nutrition mandates (42 on the HEI). It is therefore fair to say that healthiness of school meals post-treatment dwarfs the reduction in healthiness of grocery food purchases along these dimensions.

WHICH HOUSEHOLDS ARE CHANGING THEIR GROCERY FOOD SHOPPING?

We now examine *which* households changed their shopping baskets in response to the HH-FKA's updated nutritional standards. Health policy research has often been evaluative; e.g., seeking to measure the extent to which the HHFKA improved the healthiness of school meals, especially for low-income students. Our goal is more prospective. We leverage the unique shock to the food landscape afforded by the HHFKA to examine who changed their behavior so that we can learn what types of consumers might be more amenable to changing the composition of food they eat in the future, and why they might do so. Our analysis of heterogeneity in response focuses on the three literature-based drivers of school meal participation and healthy eating that we highlighted previously – time constraints, financial constraints, and nutrition literacy. We conduct the heterogeneity analysis in two ways – by introducing moderators into the DiD model of equation (1) and by estimating a causal forest model. Neither model found meaningful heterogeneity in the quality effect linked to the observed variables, so we focus our attention on quantity, but we discuss heterogeneity in the quality effect in Web Appendix E.

Measures for Analyses

We compile household-level indicators of these three drivers from the demographic and pre-treatment purchase data in NielsenIQ, and a few regional socioeconomic measures from other sources. The variables are discussed below and their definitions are provided in Table 6.

Time constraints: Several demographics in the NielsenIQ data are likely to be associated with time pressure: being a single parent, being fully employed, and having more children (e.g., Ailawadi, Neslin, and Gedenk 2001; Bronnenberg, Klein, and Xu 2023). The propensity to buy more frozen prepared meals (frozen food other than desserts and unprepared meat) pre-treatment is also indicative of time pressure.

Financial constraints: Household income is the most commonly used measure of a household's financial capacity. However, whether a household is eligible for free or reduced-price school meals is a measure of financial constraints that is more closely related to our context. We identify each household's eligibility based on their income and household size using the 2011 Federal Guidelines.[10] We also use a county-level measure of school meal eligibility: the percentage of households eligible for free or reduced-price meals in 2011 (from the online data accompanying Ruffini 2022).[11] In addition, we use the propensity to buy more store brands, which are generally priced substantially below national brands, as a behavioral indicator of financial constraints.

Nutrition Literacy: We use the education level of the household as an indicator of preference for and knowledge of nutrition (e.g., Allcott et al. 2019; Ma et al. 2011; Hawkins, Cole, and Law 2009). While education is an imperfect proxy for nutrition knowledge, Allcott et al. (2019) find that education is actually more strongly correlated with the healthiness of households' shopping baskets than nutrition knowledge is. As a behavioral measure, we also use the household's pre-treatment propensity to buy snacks and desserts (which are known to be poor on nutritive value).

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[10] https://www.federalregister.gov/documents/2011/03/25/2011-6948/child-nutrition-programs-income-eligibility-guidelines

[11] Income is highly correlated with household eligibility so we only include the latter in our model.

Pre-Treatment Grocery Food Purchases: The quantity (i.e., calories per capita) and quality (NPS) of grocery food purchased by a household before the HHFKA treatment are likely to reflect a combination of these drivers. Specifically, low pre-treatment quantity may reflect time pressure as households who have less time are likely to buy less food to prepare at home and rely more on outsourcing meals (e.g., fast food, school meals). Among low-income households, it may also reflect food insecurity due to financial constraints. Low pre-treatment quality may reflect time pressure because busy households buy more convenient, prepared foods that are generally less healthy; it may reflect financial constraints because healthy foods tend to be more expensive; and of course, it may reflect nutrition literacy.

Finally, because the political environment surrounding the HHFKA was divisive, we also include a measure of whether a county voted for Romney or Obama in the 2012 U.S. Presidential election, collected from the MIT Election Data and Science Lab (2018). Doing so helps us explore the role played by political inclination in influencing school meal participation.

Table 6: Model Variables and Definitions

Demographics	
Multiple Kids	More than one school-aged child (42% of treat HH)
Single Head	Only one household head (12% of HH)
Two Heads Employed	Female & male head employed > 30 hours per week (21% of HH)
Free Meal Eligibility	Household is eligible for free meals (10.3% of treat HH)
RP Meal Eligibility	Household is eligible for reduced-price meal (10.9% of treat HH)
No College	Household doesn't have college degree (35.1% of HH)
County-Level Measures	
Republican Vote	Romney vote percent in 2012 Election (mean = 50%, SD = 14%)
Cty Meal Eligibility	Pct of students eligible for free meals (mean = 36%, SD = 14%)
Shopping Basket Measures	
Grocery Quantity	Average Pre-Treat Cal per Capita (mean = 660, SD = 301)
Grocery Quality	Average Pre-Treat NPS (mean = -5.7 , SD = 2.3)
Pct Frozen Meals	Pct spending on frozen prepared meals (mean=8%, SD=5%)
Pct Store Brands	Pct spending on store brands (mean=18%, SD=10%)
Pct Snacks, Desserts	Pct spending on snacks & desserts (mean=21%, SD=7%)

Difference-in-Difference Analysis of Heterogeneity

We return to the DiD model in equation 1 and interact the DiD term with the variables in Table 6. Estimates for these interactions are shown in the columns for "Model 1" in Table 7. All continuous variables are standardized for ease of interpretation and standard errors are clustered at the household level as before.

In general, behavioral variables are stronger predictors of HHFKA response than demographics, a common pattern that has been documented in many other domains in marketing. A prime example is the strength of previous recency, frequency, and monetary value of purchases as predictive measures of customer response to new retail policies and new channels.

Time constraints are associated with more negative response to treatment, i.e., bigger shifts from grocery to school meals. Households with multiple children have an additional 4.1% reduction in grocery quantity, a substantial effect which is about 64% as large as the average treatment effect of -0.064. Having multiple children (relative to only one) increases the time burden in the form of care and food preparation, and it also increases the amount of time saved by switching to school meals and away from preparing food at home. Households with a greater reliance on frozen prepared meals also have stronger response to treatment: a one standard deviation increase in this variable is associated with an additional 1.7% reduction in grocery quantity, which is 27% as large as the average effect. Households that relied less on the grocery store for their calories also responded more strongly to treatment, with a one standard deviation decrease in pre-treatment quantity being associated with a 1.9% additional reduction in post-treatment grocery quantity, 30% of the size of the ATE.

Financial constraints are also associated with a more negative treatment effect. A household's eligibility for free school meals is associated with an additional 5.4% reduction in grocery quantity, which is 85% as large as the average effect.

While neither of our two indicators of nutrition literacy have a significant moderating influence, we do find that households with the least healthy shopping baskets have a stronger response to treatment than others. Specifically, we find that the relationship between treat-

ment effect and pre-treatment shopping basket *quantity* is larger for households who also purchase lower *quality* groceries pre-treatment. Households that are one standard deviation below the mean on both shopping basket quantity and quality reduce their grocery quantity post-treatment by 3.4% more than the average household, a magnitude that is 53% as large as the average treatment effect. We explore the relationship between quantity and quality in additional detail in Web Appendix E.

Recall that household pre-treatment shopping basket quantity and quality are likely to be driven by a mix of the three drivers studied. To provide additional context for these relationships, we ran separate regressions of pre-treatment quantity and quality on household demographics. The results, reported in Appendix B, support our reasoning. Demographics have a significant association with pre-treatment purchases even if they don't directly predict response to treatment. Busier households bought significantly lower grocery quantity and quality prior to treatment, which in turn were associated with stronger treatment response. Similarly, lower-income households purchased lower quality groceries. Finally, less-educated households purchased lower quality groceries as well (a pattern associated with a stronger response to treatment), though they also purchased higher quantities of groceries (which is associated with a weaker response to treatment); this mixed relationship between education and pre-treatment shopping basket variables is consistent with our finding no direct relationship between education and treatment response.

Overall, this analysis suggests that the households most drawn to the healthier meals made available by the HHFKA were those who were likely accustomed to outsourcing meals, financially constrained, and purchased less healthy food for the home. These households gravitated towards school meals, which now served as a healthy alternative to food at home, but also as a time saving alternative to preparing food for one's own children.

One might expect that these households were already participating in the school meal programs, and that they might not have much room to further substitute away from the grocery store towards school meals. Instead, we find evidence consistent with greater substitution

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Table 7: Heterogeneous Treatment Effects

Variable	Model 1: DiD			Model 2: Causal Forest		
	Estimate	SE	RelEff[#]	Estimate	SE	RelEff[#]
Time Constraints Variables						
Multiple Kids	-0.041**	0.012	63%	-0.041**	0.019	81%
Single Head	0.019	0.020	30%	-0.001	0.017	3%
Two Heads Employed	-0.007	0.014	11%	0.003	0.014	6%
Pct Frozen Meals[##]	-0.017**	0.007	27%	-0.012**	0.006	24%
Financial Constraints Variables						
Eligible for R.P. Meal	-0.028	0.020	44%	0.000	0.019	0%
Eligible for Free Meal	-0.054**	0.025	85%	-0.020	0.027	41%
Cty Meal Eligibility[##]	-0.011	0.010	18%	-0.011	0.042	22%
Pct Store Brands[##]	0.007	0.006	11%	-0.003	0.006	6%
Nutrition Knowledge Variables						
No College: Household	-0.009	0.013	14%	0.012	0.012	23%
Pct Snacks and Dessert[##]	0.011	0.008	17%	-0.004	0.007	7%
Pre-treatment Grocery Food Purchases						
Grocery Quantity (Cal)[##]	0.019*	0.010	30%	0.020***	0.006	40%
Grocery Quality (NPS)[##]	0.013	0.011	21%	-0.006	0.006	11%
Quantity x Quality	0.015**	0.007	24%	0.009*	0.005	18%
Political Leaning						
Republican Vote[##]	-0.005	0.009	7%	-0.036	0.043	72%

\# Size of effect relative to ATE; -0.064 for DiD, -0.050 for Causal Forest.

\#\# Variables standardized, coefficient represents change in DV with a 1 SD change in the variable.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

towards school meals by such households. This is encouraging from a welfare perspective because these are the households that may need the most help achieving a healthy diet. It is also encouraging to find evidence that more of the financially constrained households were drawn towards the now healthier school meals even without the cost of meals being reduced.

Causal Forest Based Analysis of Heterogeneity in Treatment Effects

We also conduct a causal forest based analysis as a robustness check for our heterogeneous DiD results and to see whether it reveals additional sources of heterogeneity. The logic behind the causal forest is to construct, for each treated household, a weighted set of matched control households with similar covariates to obtain individual treatment effects. Unlike traditional matching methods, the causal forest method is both non-parametric and resilient to model misspecification (Wager and Athey 2018). The dependent variable for the causal forest is the difference between the natural log of post-treatment and the natural log of pre-treatment calories.

We provide relevant diagnostics linked to our causal forest construction in Appendix C and estimation specifics in Web Appendix E. The average treatment effect for quantity using the causal forest is -0.050 (SE = 0.006), substantively consistent with our DiD based estimate of -0.064 (the 95% confidence intervals for the two estimates overlap).[12] The average treatment effect for quality is almost identical to the DiD based estimate at -0.095 (SE = .019).

The second model in Table 7 examines heterogeneity in individual treatment effects by regressing doubly robust scores for each household on the variables of interest (Chernozhukov et al. 2018). A comparison between the two models in the Table shows that there is remarkable consistency between the two sets of estimates, except that eligibility for free meals is not statistically significant in the causal forest analysis.[13]

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[12]The difference between ATE estimates for calories, though not statistically significant, is likely due to differences in the weights assigned to treated and control units by the coarsened exact matching approach (used for our DiD analysis) and the causal forest.

[13]Regressing the estimated individual treatment effects rather than doubly robust scores on these variables, as

DISCUSSION

In this paper, we have studied the impact of the HHFKA's nutrition standards on the grocery food purchases of a large national sample of households. We have examined whether there was substitution away from or towards grocery stores, whether there were any desirable or undesirable changes in the quality of grocery food purchases, and which types of households gravitated most towards the now-healthier school meals. Our findings linked to these three research questions are supported across several robustness checks (that are detailed in the Web Appendix). They have important implications for marketers, marketing researchers, and policy researchers, which we discuss below.

Substitution away from grocery stores. We find that the HHFKA's improved nutrition mandates alone resulted in a substantial substitution away from grocery food purchases (a 6% reduction in calories, and a 4% reduction in spending). This demonstrates that making the food available for consumption healthier, all else equal, can increase its demand. The magnitude of the effect is quite comparable to that of the CEP, which expanded eligibility for free and reduced-priced meals. Handbury and Moshary (2021) and Marcus and Yewell (2022) found that the CEP led to an average reduction in grocery food spending of 6.6% and 5% respectively.

From a policy perspective, this finding suggests a significant win. The revised nutrition standards not only made school meals healthier, it made them more popular, even in the absence of expanded eligibility for free or reduced-price meals. Interestingly, while opponents of the HHFKA had predicted a decrease in school meal consumption due to increased nutrition standards (Yee 2012), even proponents had not forecasted an increase, instead typically arguing that participation would hold steady. For marketing researchers, our finding suggests that, at least in the medium-run, any negative influence of lay-theories such as healthy

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has been done in some previous research, does result in more statistically significant coefficients than the ones shown here. However, recent advances in the causal forest method underscore the importance of debiasing the individual treatment effects (to avoid possible contamination due to regularization bias) so that is the approach we have adopted here.

food being less tasty is more than offset by the positive influence of sustained provision of healthy food, especially in an environment where one's peers are also eating it.

Both retailers and manufacturers were affected by the HHFKA's nutrition mandates, which exerted pressure on grocery sales. The 4.4% reduction in spending among households with kids translates to a roughly 1.4% revenue loss for grocery retailers due to the HHFKA's nutrition mandates.[14] This is a meaningful loss in light of the slim net margins in grocery retail. When faced with similar pressure from the CEP, retailers responded by reducing prices in affected regions (Handbury and Moshary 2021). Here, however, competitive pressure does not come from school meal price reductions, but from major changes to the composition of school meal offerings. Thus, major changes to the composition of what is offered at the grocery store may be needed to bring back sales lost due to the higher nutrition standards, as opposed to the more commonly observed incremental changes to product lines. Relatedly, the school meal program is itself a large revenue source for manufacturers whose products fit the nutritional requirements of the HHFKA. Kraft Heinz is reformulating its Lunchables products to meet the requirements so that they can be part of the school meal program (Newman 2023).

There are similar recent examples of marketers responding to policy interventions, sometimes, though not always, in ways that can further benefit consumers. Recent research shows that firms have responded to nutrition or warning labels by reformulating their foods to be healthier (Alé-Chilet and Moshary 2022; Lim et al. 2020; Barahona, Otero, and Otero 2023) though the Nutrition Labeling and Education Act-standardized labeling reduced the nutritional quality of food at the grocery store (Moorman, Ferraro, and Huber 2012). Other research shows that some firms also respond to such labels by changing prices, increasing them for labeled products and decreasing them for unlabeled products (Pachali et al. 2023), and to soda taxes by reducing their promotion frequency and depth (Keller, Guyt, and Grewal 2023). Our findings on which households responded most strongly to the nutrition

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[14]These households make up 27.5% of the population but spend about 25% more on groceries than other households; see Web Appendix B.

mandates, to be discussed next, shed additional light on how manufacturers and retailers might respond to competitive pressure from mandated nutrition standards in ways that could be positive both for their firms and for customers.

Who Substitutes and Why. The profile of households that substituted more towards school meals provides a signal of what types of households might not be currently well-served by the options available at the grocery store. These households might be open to changing what they eat in other ways going forward, should suitable options become available. Time pressured households, who relied less on the grocery stores for their food needs and bought more frozen prepared foods, responded more strongly to treatment. This should be of particular interest to retailers and manufacturers, as well as to those in the policy space. Its implications contrast with recent efforts to promote healthier eating by steering consumers away from pre-made meals and towards more nutritious options that require greater preparation (Belahsen 2014; Lin and Guthrie 2012; Matsumoto et al. 2021). These initiatives have been promoted by the USDA and received coverage by the Mayo Clinic and in various media outlets.

Our findings suggest that, instead of summarily discouraging households from relying on convenience food, making healthy and convenient foods more readily available may be a more productive goal. This would also be in line with previous research that finds "convenience enhancements" are more effective at encouraging healthy eating than a battery of alternative nudges (Cadario and Chandon 2020). It is also in line with a recent push by some states to allow SNAP to be used for the purchase of hot meals, because SNAP recipients often face barriers to cooking healthy meals at home, including not only time constraints, but also a lack of cooking equipment and storage space (USDA 2021).

The fact that those who substituted most were also previously buying less healthy food underscores the distinction between buying unhealthy food and *preferring* unhealthy food. Households may want to provide healthy meals for their children but may not have the knowledge, money, or time to do so at home (recall that lower education, lower income,

and time constraints were all associated with lower pre-treatment grocery quality). Their greater level of substitution towards school meals is encouraging, as they had the most to gain from eating healthier meals. It also suggests that these households' tendency to purchase less healthy foods at the grocery store is not fait accompli. The fact that financially constrained households also gravitated more strongly towards the now-healthier school meals is interesting, given that the CEP had not yet reduced the price of meals for these households in the period under study.

It is notable that financially- and time-constrained households would be expected to already have higher levels of participation before the nutrition standards were changed. Yet, they gravitated more strongly towards school meals due to the change. The fact that substitution towards the healthier school meals was not more uniform across households is a positive finding. The HHFKA represents an expensive undertaking by the federal government to improve the nutritiousness of the food served to children. While their goal is to provide healthy food to all kids, the emphasis is rightly on food insecure, under-privileged children for whom the school meals may be the healthiest they eat. Households with the financial, time, and cognitive resources to provide healthy meals from and at home substituted at a lower rate into the healthier school meals, suggesting that the government's resources are spent more on helping the sub-populations that need them the most.

Small Impact on Grocery Food Quality. Our finding that there is a small reduction in the nutritional quality of grocery food likely attributable to the policy change also provides food for thought. On the positive side, our calculations suggest that this decline is dwarfed by the gains that children receive by substituting towards school meals. Clearly, however, there is no evidence of a positive spillover: it does not appear that exposure to healthier meals at school led kids and/or their parents to become more open to healthy foods at home, at least during the first year of implementation.

Our research has a few limitations owing mainly to the nature of our data. First, we proxy for a household's opportunity to receive treatment as a function of the presence of school-aged

kids in the household. We do not directly observe household/student-level food provided at school, as no comprehensive database that records such information at the household level currently exists (as far as we know). Access to such data would enable an alternative means of validating our estimates. However, the types of UPCs driving the estimated treatment effect ("kid-friendly" UPCs, those associated with breakfast and lunch) and the robustness of the effect strongly suggest that households' reduction in grocery purchases does reflect substitution towards school meals. Second, we use observable proxies for time constraints and nutrition knowledge, which are less easily measured by demographics than financial constraints. Moreover, even income may represent more than one driver; scarcity of time and money can tax the bandwidth of low-income households (Mullainathan and Shafir 2013). Third, we do not observe household food purchases from sources other than the grocery store. It is conceivable that the HHFKA's nutrition standards also had an impact on (for example) food purchased at fast food restaurants.

Our findings are especially timely as the school meal program continues to undergo changes. The landscape of school meal programs continues to fluctuate, as political factions have actively pursued measures to either fortify or relax the regulations governing school meals since the enactment of the HHFKA. The previous administration aimed to weaken the nutritional guidelines, while the USDA has recently announced even more rigorous nutrition standards for school meals (Riley 2023). In the future, Republicans hope to eliminate the CEP (Thakker 2023). Understanding the implications of these policies is crucial for retailers and for manufacturers whose products are sold in their stores, in addition to being crucial for those in the policy space.

In sum, this paper leverages a unique opportunity afforded by the HHFKA to shine a light on the types of households that change their shopping basket in response to an essential food option (school breakfasts and lunches) becoming markedly healthier, and documents how their shopping basket changes. Our findings add to a valuable knowledge base that marketers and nutrition policy advocates can utilize in efforts to encourage households to

adopt healthier diets.

REFERENCES

Ailawadi, Kusum L., Scott A. Neslin, and Karen Gedenk (2001), "Pursuing the Value-Conscious Consumer: Store Brands Versus National Brand Promotions," *Journal of Marketing*, 65 (1), 71–89 Publisher: SAGE Publications Sage CA: Los Angeles, CA.

Allcott, Hunt, Rebecca Diamond, Jean-Pierre Dubé, Jessie Handbury, Ilya Rahkovsky, and Molly Schnell (2019), "Food deserts and the causes of nutritional inequality," *The Quarterly Journal of Economics*, 134 (4), 1793–1844 Publisher: Oxford University Press.

Alé-Chilet, Jorge and Sarah Moshary (2022), "Beyond consumer switching: Supply Responses to Food Packaging and Advertising Regulations," *Marketing Science*, 41 (2), 243–270 Publisher: INFORMS.

Athey, Susan and Stefan Wager (2019), "Estimating Treatment Effects with Causal Forests: An Application," *Observational Studies*, 5.

Au, Lauren E., Lorrene D. Ritchie, Klara Gurzo, Lilly A. Nhan, Gail Woodward-Lopez, Janice Kao, Patricia M. Guenther, Marisa Tsai, and Wendi Gosliner (2020), "Post–Healthy, Hunger-Free Kids Act Adherence to Select School Nutrition Standards by Region and Poverty Level: the Healthy Communities Study," *Journal of Nutrition Education and Behavior*, 52 (3), 249–258 Publisher: Elsevier.

Barahona, Nano, Cristóbal Otero, and Sebastián Otero (2023), "Equilibrium effects of food labeling policies," *Econometrica*, 91 (3), 839–868.

Bergman, Ethan A, Tim Englund, Katie Weigt Taylor, Tracee Watkins, Stephen Schepman, and Keith Rushing (2014), "School Lunch Before and After Implementation of the Healthy Hunger-Free Kids Act," *The Journal of Child Nutrition & Management*, 38 (2), 1–12.

Birch, Leann L. (1999), "Development of Food Preferences," *Annual Review of Nutrition*, 19, 41 Publisher: Annual Reviews, Inc.

Bronnenberg, Bart J, Tobias J Klein, and Yan Xu (2023), "Consumer Time Nudges and Grocery Shopping Behavior," *Management Science*.

Brown, Alyssa (2021), "Who Takes Up a Free Lunch? Food Spending and the Summer Food Service Program.," *Food Spending and the Summer Food Service Program.(November 2, 2021)*.

Chen, Jiafeng and Jonathan Roth (2024), "Logs with zeros? Some problems and solutions," *The Quarterly Journal of Economics*, 139 (2), 891–936.

Chen, Yixing, Shrihari Sridhar, and Vikas Mittal (2021), "Treatment Effect Heterogeneity in Randomized Field Experiments: A Methodological Comparison and Public Policy Implications," *Journal of Public Policy & Marketing*, 40 (4), 457–462.

Chernozhukov, Victor, Denis Chetverikov, Mert Demirer, Esther Duflo, Christian Hansen, Whitney Newey, and James Robins (2018), "Double/Debiased Machine Learning for Treatment and Structural Parameters," *The Econometrics Journal*, 21 (1), C1–C68.

Cohen, Juliana and Marlene B Schwartz (2020), "Documented Success and Future Potential of the Healthy, Hunger-Free Kids Act," *Journal of the Academy of Nutrition and Dietetics*, 120 (3), 359.

Cullen, Karen W, Tzu-An Chen, and Jayna M Dave (2015), "Changes in Foods Selected and Consumed After Implementation of the New National School Lunch Program - Meal Patterns in Southeast Texas," *Preventive medicine reports*, 2, 440–443.

Daniel, Caitlin (2020), "Is healthy Eating Too Expensive?: How Low-Income Parents Evaluate the Cost of Food," *Social Science & Medicine*, 248, 112823.

Donald, Maria "Congresswoman Linda Sánchez Applauds Passage of the Healthy, Hunger-Free Kids Act," (2010) https://lindasanchez.house.gov/media-center/press-releases/congresswoman-linda-s-nchez-applauds-passage-healthy-hunger-free-kids.

Dubois, Pierre, Paulo Albuquerque, Olivier Allais, Céline Bonnet, Patrice Bertail, Pierre Combris, Saadi Lahlou, Natalie Rigal, Bernard Ruffieux, and Pierre Chandon (2021), "Effects of front-of-pack labels on the nutritional quality of supermarket food purchases: evidence from a large-scale randomized controlled trial," *Journal of the Academy of Marketing Science*, 49 (1), 119–138.

Farris, Alisha R., Sarah Misyak, Kiyah J. Duffey, Naama Atzaba-Poria, Kathy Hosig, George C. Davis, and E. Serrano (2016), "Elementary Parent Perceptions of Packing Lunches and the National School Lunch Program," *Journal of Child Nutrition and Management*, 40 (1), 1–10.

Gearan, Elizabeth C and Mary Kay Fox (2020), "Updated Nutrition Standards Have Significantly Improved the Nutritional Quality of School Lunches and Breakfasts," *Journal of the Academy of Nutrition and Dietetics*, 120 (3), 363–370.

Handbury, Jessie and Sarah Moshary "School Food Policy Affects Everyone: Retail Responses to the National School Lunch Program," Technical report, National Bureau of Economic Research (2021).

Hawkins, S. Sherburne, Tim J. Cole, and Catherine Law (2009), "Examining the Relationship Between Maternal Employment and Health Behaviours in 5-year-old British Children," *Journal of Epidemiology & Community Health*, 63 (12), 999–1004 Publisher: BMJ Publishing Group Ltd.

Haws, Kelly L., Peggy J. Liu, Brent McFerran, and Pierre Chandon (2022), "Examining Eating: Bridging the Gap Between "Lab Eating" and "Free-Living Eating"," *Journal of the Association for Consumer Research*, 7 (4), 403–418 Publisher: The University of Chicago Press Chicago, IL.

Hut, Stefan and Emily Oster (2022), "Changes in Household Diet: Determinants and Predictability," *Journal of Public Economics*, 208, 104620.

Iacus, Stefano M., Gary King, and Giuseppe Porro (2012), "Causal Inference without Balance Checking: Coarsened Exact Matching," *Political Analysis*, 20 (1), 1–24 Publisher: Cambridge University Press.

Imbens, Guido W and Donald B Rubin (2015), *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction* Cambridge University Press, https://doi.org/10.1017/CBO9781139025751.

Jabs, Jennifer and Carol M. Devine (2006), "Time Scarcity and Food Choices: an Overview," *Appetite*, 47 (2), 196–204 Publisher: Elsevier.

Jacobs, Julia "Trump Administration Rolls Back Obama-Era Rules for School Lunches," (2018) https://www.nytimes.com/2018/12/08/us/trump-school-lunch-usda.html.

Jetter, Karen M. and Diana L. Cassady (2006), "The Availability and Cost of Healthier Food Alternatives," *American Journal of Preventive Medicine*, 30 (1), 38–44 Publisher: Elsevier.

Johnson, Donna B., Mary Podrabsky, Anita Rocha, and Jennifer J. Otten (2016), "Effect of the Healthy Hunger-Free Kids Act on the Nutritional Quality of Meals Selected by Students and School Lunch Participation Rates," *JAMA pediatrics*, 170 (1), e153918–e153918 Publisher: American Medical Association.

Keller, Kristopher, Jonne Guyt, and Rajdeep Grewal (2023), "Soda Taxes and Marketing Conduct," *Journal of Marketing Research*.

Khan, Uzma and Ravi Dhar (2006), "Licensing Effect in Consumer Choice," *Journal of Marketing Research*, 43 (2), 259–266 Publisher: SAGE Publications Sage CA: Los Angeles, CA.

Khare, Adwait and J. Jeffrey Inman (2006), "Habitual Behavior in American Eating Patterns: The Role of Meal Occasions," *Journal of Consumer Research*, 32 (4), 567–575 Publisher: The University of Chicago Press.

Kinderknecht, Kelsey, Cristen Harris, and Jessica Jones-Smith (2020), "Association of the Healthy, Hunger-Free Kids Act with Dietary Quality Among Children in the US National School Lunch Program," *Journal of the American Medical Association*, 324 (4), 359–368 Publisher: American Medical Association.

Li, Fan, Kari Lock Morgan, and Alan M Zaslavsky (2018), "Balancing covariates via propensity score weighting," *Journal of the American Statistical Association*, 113 (521), 390–400.

Lim, Joon Ho, Rishika Rishika, Ramkumar Janakiraman, and P.K. Kannan (2020), "Competitive Effects of Front-of-Package Nutrition Labeling Adoption on Nutritional Quality: Evidence from Facts Up Front–Style Labels," *Journal of Marketing*, 84 (6), 3–21 http://journals.sagepub.com/doi/10.1177/0022242920942563.

Ma, Yu, Kusum L. Ailawadi, Dinesh K. Gauri, and Dhruv Grewal (2011), "An Empirical Investigation of the Impact of Gasoline Prices on Grocery Shopping Behavior," *Journal of Marketing*, 75 (2), 18–35 Publisher: SAGE Publications Sage CA: Los Angeles, CA.

Ma, Yu, Kusum L. Ailawadi, and Dhruv Grewal (2013), "Soda Versus Cereal and Sugar Versus Fat: Drivers of Healthful Food Intake and the Impact of Diabetes Diagnosis," *Journal of Marketing*, 77 (3), 101–120 Publisher: SAGE Publications Sage CA: Los Angeles, CA.

Machín, Leandro, María Rosa Curutchet, Vanessa Gugliucci, Agustina Vitola, Tobias Otterbring, Marcela de Alcantara, and Gastón Ares (2020), "The Habitual Nature of Food Purchases at the Supermarket: Implications for Policy Making," *Appetite*, 155, 104844.

Maimaran, Michal and Ayelet Fishbach (2014), "If it's Useful and You Know it, Do You Eat? Preschoolers Refrain from Instrumental Food," *Journal of Consumer Research*, 41 (3), 642–655 Publisher: University of Chicago Press.

Marcus, Michelle and Katherine G Yewell (2022), "The Effect of Free School Meals on Household Food Purchases: Evidence from the Community Eligibility Provision," *Journal of Health Economics*, 84, 102646.

MIT Election Data and Science Lab "County Presidential Election Returns 2000-2020," (2018) https://doi.org/10.7910/DVN/VOQCHQ.

Moorman, Christine, Rosellina Ferraro, and Joel Huber (2012), "Unintended Nutrition Consequences: Firm Responses to the Nutrition Labeling and Education Act," *Marketing Science*, 31 (5), 717–737 Publisher: INFORMS.

Mullainathan, Sendhil and Eldar Shafir (2013), *Scarcity: Why having too little means so much* Macmillan.

Newman, Jesse "Kraft Heinz Sees a \$25 Billion Opportunity—in Schools," (2023) https://www.wsj.com/business/hospitality/kraft-heinz-sees-a-25-billion-opportunity-it-starts-with-lunchables-372fb82f.

O'Neill, Stephen, Noémi Kreif, Richard Grieve, Matthew Sutton, and Jasjeet S. Sekhon (2016), "Estimating Causal Effects: Considering Three Alternatives to Difference-in-Differences Estimation," *Health Services and Outcomes Research Methodology*, 16 (1), 1–21 Publisher: Springer.

Pachali, Max J, Marco JW Kotschedoff, Arjen Van Lin, Bart J Bronnenberg, and Erica Van Herpen

(2023), "How do nutritional warning labels affect prices?," *Journal of Marketing Research*, 60 (1), 92–109.

Palazzolo, Mike and Adithya Pattabhiramaiah (2021), "The Minimum Wage and Consumer Nutrition," *Journal of Marketing Research*, 58 (5), 845–869.

Poon, Theresa, Marie-Eve Labonte, Christine Mulligan, Mavra Ahmed, Kacie M. Dickinson, and Mary R. L'Abbé (2018), "Comparison of Nutrient Profiling Models for Assessing the Nutritional Quality of Foods: A Validation Study," *British Journal of Nutrition*, 120 (5), 567–582.

Rahkovsky, Ilya and Young Jo "USDA ERS - Higher Incomes and Greater Time Constraints Lead to Purchasing More Convenience Foods," (2018) https://www.ers.usda.gov/amber-waves/2018/june/higher-incomes-and-greater-time-constraints-lead-to-purchasing-more-convenience-foods/.

Riley, Laura "USDA Announces Rigorous New School Nutrition Standards," (2023) https://www.washingtonpost.com/business/2023/02/03/school-meals-dietary-guidelines/?itid=ap_laurareiley.

Ruffini, Krista (2022), "Universal Access to Free School Meals and Student Achievement: Evidence from the Community Eligibility Provision," *Journal of Human Resources*, 57 (3), 776–820.

Schwartz, Marlene B., Kathryn E. Henderson, Margaret Read, Nicole Danna, and Jeannette R. Ickovics (2015), "New School Meal Regulations Increase Fruit Consumption and do not Increase Total Plate Waste," *Childhood Obesity*, 11 (3), 242–247.

Simpson, Ian and Lisa Baertlein (2012), "More Fruits, Veggies in U.S. School Lunch Rules," *Reuters* https://www.reuters.com/article/us-school-food-idUSTRE80O1KV20120125.

Spronk, Inge, Charina Kullen, Catriona Burdon, and Helen O'Connor (2014), "Relationship between nutrition knowledge and dietary intake," *British journal of nutrition*, 111 (10), 1713–1726 Publisher: Cambridge University Press.

Sullivan, Susan A and Leann L Birch (1990), "Pass the Sugar, Pass the Salt: Experience Dictates Preference.," *Developmental Psychology*, 26 (4), 546.

Thakker, Prem "Republicans Declare Banning Universal Free School Meals a 2024 Priority," (2023) https://newrepublic.com/post/173668/republicans-declare-banning-universal-free-school-meals-2024-priority.

UK Department of Health "Nutrient Profiling Technical Guidance," (2011) https://assets.publishing.service.gov.uk/media/5a7cdac7e5274a2c9a484867/dh_123492.pdf.

USDA "BARRIERS THAT CONSTRAIN THE ADEQUACY OF SUPPLEMENTAL NUTRITION ASSISTANCE PROGRAM SNAP ALLOTMENTS SUMMARY," Technical report, USDA (2021) https://fns-prod.azureedge.us/sites/default/files/resource-files/SNAP-Barriers-Summary.pdf.

USDA "National Level Annual Summary Tables," (2023) https://www.fns.usda.gov/pd/child-nutrition-tables.

Vaudrin, Nicole, Kristen Lloyd, Michael J. Yedidia, Michael Todd, and Punam Ohri-Vachaspati (2018), "Impact of the 2010 US Healthy, Hunger-Free Kids Act on School Breakfast and Lunch Participation Rates Between 2008 and 2015," *American journal of public health*, 108 (1), 84–86 Publisher: American Public Health Association.

Wager, Stefan and Susan Athey (2018), "Estimation and Inference of Heterogeneous Treatment Effects Using Random Forests," *Journal of the American Statistical Association*, 113 (523), 1228–1242.

Wight, Kelley Gullo, Peggy J Liu, Lingrui Zhou, and Gavan J Fitzsimons (2023), "EXPRESS: Sharing Food Can Backfire: When Healthy Choices for Children Lead Parents to Make Unhealthy Choices for Themselves," *Journal of Marketing Research*, page 00222437231184830.

Wood, Wendy and David T Neal (2009), "The Habitual Consumer," *Journal of Consumer Psychology*, 19 (4), 579–592.

Yan, Shunyao, Klaus M Miller, and Bernd Skiera (2022), "How Does the Adoption of Ad Blockers Affect News Consumption?," *Journal of Marketing Research*, 59 (5), 1002–1018.

Yee, Vivian (2012), "No Appetite for Good-for-You School Lunches," *The New York Times* https://www.nytimes.com/2012/10/06/nyregion/healthier-school-lunches-face-student-rejection.html.

Ziol-Guest, Kathleen M, Thomas DeLeire, and Ariel Kalil (2006), "The Allocation of Food Expenditure in Married and Single-Parent Families," *Journal of Consumer Affairs*, 40 (2), 347–371.

APPENDICES

Appendix A: Classification of "Kid-Friendly" UPCs

To identify kid-friendly UPCs, we consider UPCs that have at least 30 purchases in total, so that we can be confident we have sufficient data upon which to base the "kid-friendly" label. We calculate the percentage of each UPC's total purchases that are made by households with school-aged kids (i.e., treatment households) versus by control households. We label as "kid-friendly" the UPCs that fall above the 75th percentile in the distribution of this percentage for treatment households. All other UPCs, including those that are purchased less than 30 times in total, are included in the "All Other UPCs" group. Consequently, some UPCs that are targeted at children but infrequently purchased are classified as not "kid-friendly," making our estimate of the difference between these two groups of UPCs more conservative. This cut-off translates to a purchase rate of kid-friendly UPCs that is about twice as big for treatment households as for control households. Kid-friendly UPCs are critically not UPCs purchased only by treatment households, which would render our control group insufficient for these supplemental analyses. These UPCs make up 38% of treatment household calories and 25% of control household calories.

Our approach—using a reasonable numerical cut-off, as opposed to relying on researcher intuition to identify "kid-friendly" UPCs—has pros and cons. It avoids researcher bias, but also necessarily means some UPCs will actually be UPCs geared towards parents of children, rather than children themselves. Nonetheless, the measure of being "kid-friendly" should be strongly correlated with UPCs purchased *for children*; sufficient for our goal of illustrating that UPCs for children are a strong driver of the reduction in calories we observe.

As a test of the face validity of our classification procedure, we examined the cereal category, in which products are largely well-known and kid-friendly UPCs are easy to identify by name. It suggests our classification method has strong face validity. The ten cereals most frequently labeled as "kid-friendly UPCs" are kid-branded cereals: Berry Colossal Crunch,

Marshmallow Mateys, Frosted Flakes, Cinnamon Toast Crunch, Frosted Mini Wheats, Life, Cocoa Puffs, Lucky Charms, Apple Jacks, and Cocoa Pops. The categories with the highest and lowest shares of "kid-friendly" UPCs also show face validity. The top five categories, for example, are Baby Food (36%), Breakfast Food (34%), Dry Mixes (Tortillas, pasta, and rice; 31%), Gum (31%), and Pizza (30%). The bottom five categories are Yeast (11%), Nuts (16%), Coffee (17%), Canned Sea Food (17%), and Canned Fruit (19%).

Appendix B: Association of Demographics With Pre-Treatment Quantity and Quality

We present here the results from regressions of treatment household h's (i) pre-treatment quantity (calories per capita), and (ii) pre-treatment quality (NPS) on the demographic and socio-economic variables from Table 7 in the paper. Both dependent variables are standardized to easily compare coefficient magnitudes. We see a negative relationship between pre-treatment shopping basket quantity and quality and the variables associated with time constraints, suggesting that time constraints reduce households' reliance on the grocery store, and impede the healthiness of their purchases. Income has a negative relationship with the quality of groceries. Finally, less educated households purchased less healthy groceries pre-treatment, but relied more on the grocery store for their calories (i.e., consumed a higher quantity of calories).

Table 8: Relationship between shopping basket and other variables

	Std PreTreat Cal		Std PreTreat NPS	
	Est.	SE	Est.	SE
Multiple Kids	-0.145***	0.023	-0.095***	0.022
Single Head	-0.040	0.036	-0.139***	0.035
Two Heads Employed	-0.214***	0.028	-0.083***	0.027
HH Eligibility: Reduced Price Meal	-0.005	0.037	-0.095***	0.035
HH Eligibility: Free Meal	0.009	0.038	-0.210***	0.037
County Eligibility: Free or RP	-0.011	0.011	-0.041***	0.011
No College: Household	0.065***	0.024	-0.196***	0.023
Romney Vote	0.082***	0.011	-0.052***	0.011

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix C: Causal Forest Diagnostics

Following the approach outlined by Imbens and Rubin (2015), we evaluate the balance of observables between the treatment and control group using the standardized absolute mean differences metric. As shown in Figure 1, our matched treated and control households are largely indistinguishable based on their observed characteristics.

Figure 1: Covariate Balance
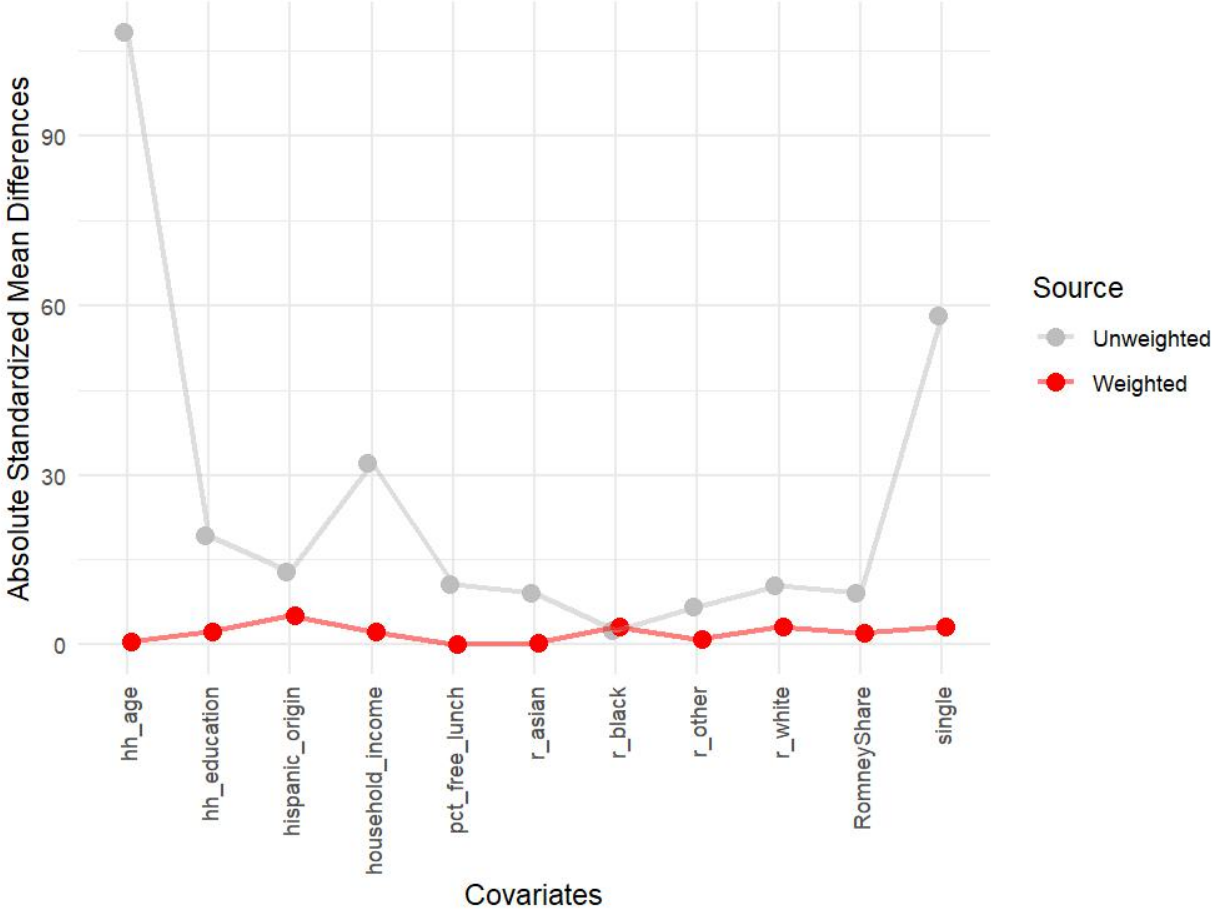
We ensure that our forest is well calibrated using the recommended metrics. A coefficient of 1 for the 'mean.forest.prediction' measure suggests that the mean forest prediction is correct, while a coefficient of 1 for 'differential.forest.prediction' additionally suggests that the heterogeneity estimates from the forest are well calibrated. The mean forest prediction of our model for shopping basket quantity is 1.01 (p<0.01) and the differential forest prediction

metric takes a value of 0.75 (p<0.05), confirming our model's ability to successfully uncover heterogeneous treatment effects (Athey and Wager 2019). We show the distribution of treatment effects for quantity across households in Figure 2. A full description of the data and estimation approach can be found in Web Appendix E.

Figure 2: Heterogeneous Treatment Effects
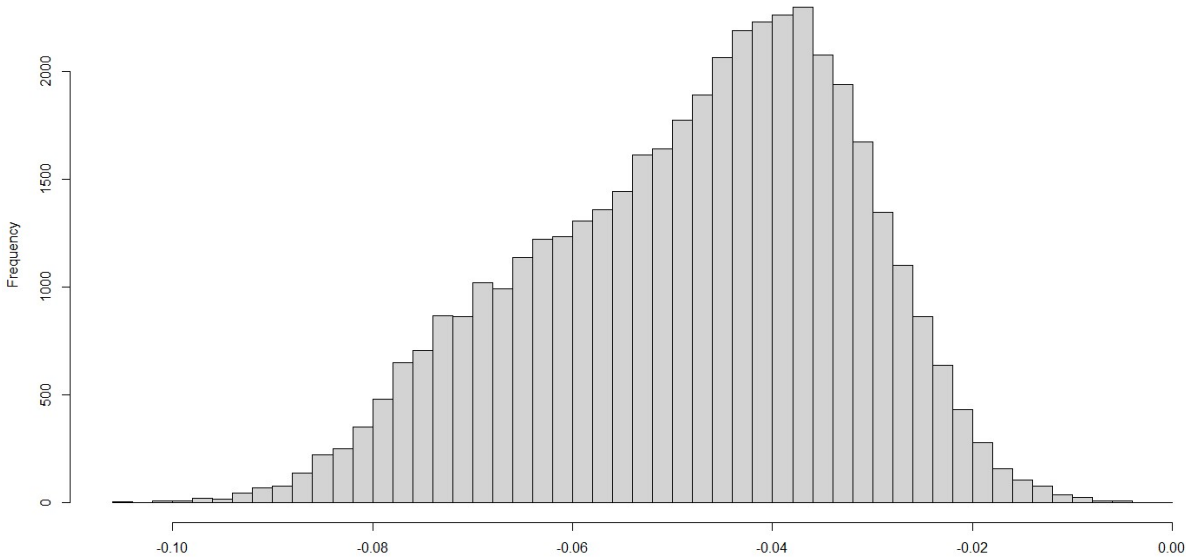
WEB APPENDIX TO "SCHOOL NUTRITION MANDATES AND THE HOUSEHOLD GROCERY BASKET"

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WEB APPENDIX A: METHODOLOGICAL DETAILS FOR THE AVERAGE TREATMENT EFFECT

Calculation of Variables

Calculation of Adult Equivalents

The NielsenIQ data contain a variable for total household size (which may include household heads, children, and other adults living in the household), specific ages for some members of the household, and a variable indicating whether or not there are children in each of three age groups: 0 to 5 years old, 6 to 12 years old, and 13 to 17 years old.

We first count how many children in each age group are explicitly accounted for with listed ages. Then, using the variable for whether or not there are children in each age group, we check whether there are children in any age group not previously specified by the explicitly listed ages. If so, we assume there is one child in that age group. In the cases where it is still ambiguous whether one or more member is an adult or a child, we assume they are adults. We treat each child in the 0 to 5 age group as having 50% of the caloric needs of an adult, i.e. half an adult equivalent; each child in the 6 to 12 age group as 0.75 adult equivalents; and each child in the 13 to 17 age group as a full adult equivalent. These are approximations for the age group based on caloric needs reported by the National Institutes of Health.[15]

We also conduct a robustness check in which we assume all members for whom age is ambiguous are children whose age is a weighted average of all other children in the home. Our model estimates in this robustness check are nearly identical to those presented in the paper: the main effect of the HHFKA nutrition mandates on calories per adult equivalent is -0.065 with a standard error of 0.009.

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[15]https://www.nhlbi.nih.gov/health/educational/wecan/downloads/calreqtips.pdf

Calculation of NPS

We use AOAC fiber (based on the classification scheme developed by the Association of Analytical Chemists), instead of NSP or non-starch polysaccharide fiber (AOAC fiber is inclusive of NSP fiber). Additionally, because we cannot identify the precise proportion of each UPC attributable to fruits, vegetables, or nuts, we simplify the formula for Nutrient Profile Score and assume all fruits, vegetables, nuts, and juices are "pure" (scoring a 5/5), and all other UPCs are scored a 0/5 on this dimension.

We then calculate a weighted average score for each household h's shopping basket in each month t, based on the Nutrient Profile Score for each of the UPCs purchased by these households. To aid interpretation and for better directional consistency with the USDA's HEI, we reverse the sign of the NPS in our calculations such that less healthy baskets have lower (as opposed to higher) scores. Scores lie between -40 and 15. We designate the resulting variable $HindexNPS_{ht}$. In our sample, the median and mean values for $HindexNPS_{ht}$ are -5.2 and -5.7 respectively.

Coarsened Exact Matching Details

Treatment and control group households differ with respect to a few key demographics. Households without children are typically older, less likely to have two heads of the household, less likely to be college-educated, less likely to be fully employed, and have lower incomes. We use a coarsened exact matching (CEM) approach to balance treatment and control households along these dimensions. The CEM algorithm coarsens the variables fed to it, reducing the number of levels for a given variable to make it easier to match. Households are then matched on the reduced number of levels across each variable, with weights applied to match the control group (in aggregate) to the treatment group. We match on the variables and levels listed in Table WA1.

After matching, the treatment and control group are well-balanced on these variables. Table WA2 presents summary statistics for the treatment group, control group prior to

matching, and the matched control group (designated Matched Control) below.

Table WA1: Matched Variables

Variable	Description
Household Heads	Two Heads
	One Head
Female Head Employment	Fully Employed (>35 hours)
	Less than fully employed
Male Head Employment	Fully Employed (>35 hours)
	Less than fully employed
Female Head Education	College Degree
	No College Degree
Male Head Education	College Degree
	No College Degree
Oldest HH Head Age	65+ years old
	55-64 years old
	40-54 years old
	45-49 years old
	< 45 years old
HH Pre-Treatment Calories	Quartile 1 (Calories<424)
	Quartile 2 (424<=Calories<615)
	Quartile 3 (615<=Calories<832)
	Quartile 4 (832<=Calories)
HH Pre-Treatment NPS	Quartile 1 (NPS<-6.99)
	Quartile 2 (-6.99<=NPS<-5.56)
	Quartile 3 (-5.56<=NPS<-4.21)
	Quartile 4 (-4.21<=NPS)

Table WA2: Matched Variables

Shopping Basket	Treat	Control	Matched Control
Calories	652	784	663
NPS	-5.7	-5.3	-5.7
Demographics	**Treat**	**Control**	**Matched Control**
M + F Adult HH	88%	61%	86%
Median M age	45-49	55-64	45-49
Median F age	40-44	55-64	40-44
Male College	29%	21%	30%
Female College	39%	25%	39%
Male Employed	75.0%	35%	74.0%
Female Employed	37.0%	33%	39.0%
Median Inc	$60-70k	$50-60k	$60-70k

Note that in Table WA2, the median household income is similar between the treatment and control group despite not explicitly matching on it, likely because we match on employment and education.

Because households' employment and food choice decisions may differ *because* of the decision to have children (e.g., working less, rather than paying for childcare), we conduct robustness checks in which we (i) do not match at all, (ii) match only on our primary demographics but not shopping basket variables, (iii) do not match on employment, and (iv) add household income to our matching variables (Table WA3).

The treatment effects for shopping basket quantity and quality are quite robust to different matching approaches. The treatment effect for quality (NPS) is non-significant when not matching on shopping basket variables, but this remains consistent with our conclusion that any negative impact on healthiness is small and of little concern.

Table WA3: Effect of Nutrition Standards: Alternate Matching Approaches

	Households		Ln Calories		NPS	
	Treat	Control	Est.	SE	Est.	SE
Main Specification	7,645	27,148	-0.064***	0.009	-0.093***	0.031
Removing Basket Variables	7,795	35,376	-0.043***	0.008	-0.039	0.028
Remove Employment	7,763	28,580	-0.054***	0.009	-0.116***	0.030
Add Income	6,827	19,948	-0.057***	0.009	-0.115***	0.033

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Parallel Trends

We first plot the raw data for the treatment control group for the school year prior to treatment, and the school year to which treatment was applied. Figures WA1 and WA2 show a clear divergence for calories and a smaller divergence for NPS.

Figure WA1: Calories per capita
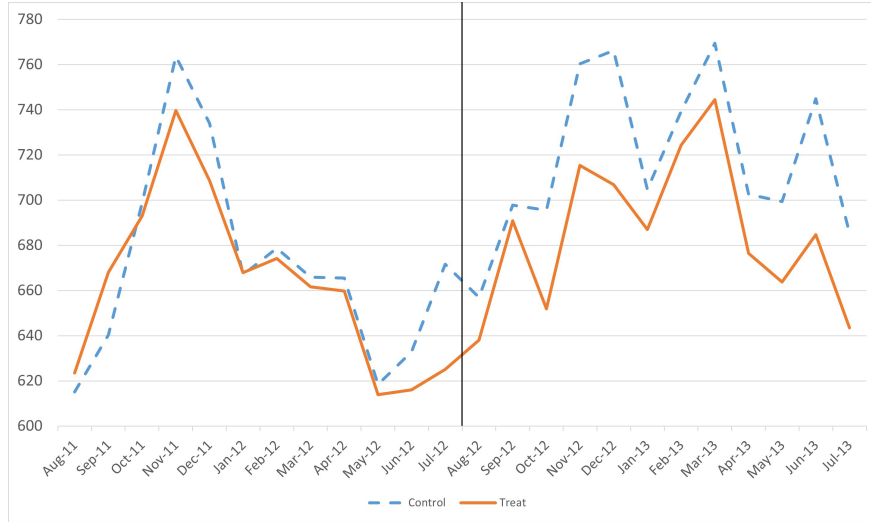
Figure WA2: Nutrient Profile Score
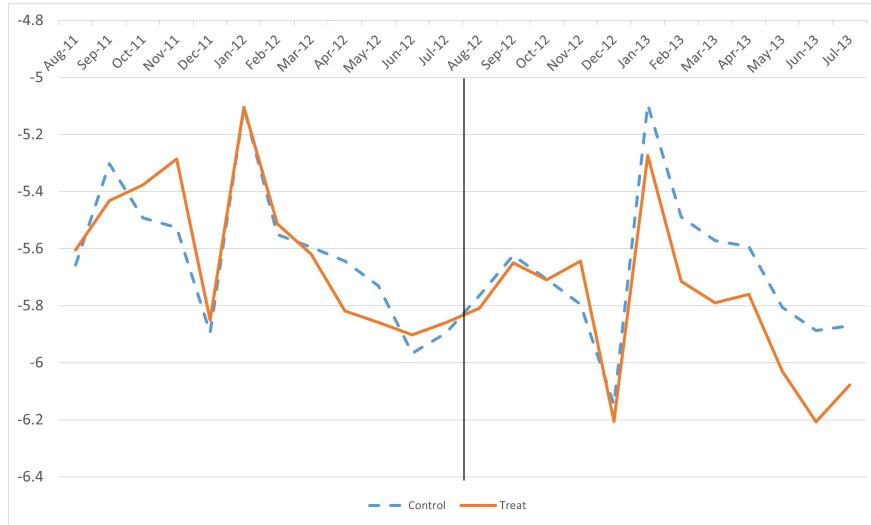
Next, we test whether the parallel trends assumption holds for our dependent variables with the following regression:

$$\text{DV}_{ht} = \delta_h + \lambda_{ct} + \omega_t I[TreatGroup]_h \times I[t] + \epsilon_{ht} \qquad (2)$$

We include the same fixed effects from our original regression, plus treatment group $\times$ month fixed effects (For t=1,...,24), the parameters for which (ω_t) semi-parametrically test

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whether the "trends" in our DVs for households with school-aged children differ from those for our control group.

Table WA4: Test of Parallel Trends

	Ln Calories		NPS	
Month	Est.	SE	Est.	SE
(t-12) Aug	0.000	-	0.000	-
(t-11) Sept	0.038	0.027	-0.188**	0.087
(t-10) Oct	-0.042*	0.024	0.086	0.091
(t-9) Nov	-0.049**	0.023	0.196**	0.092
(t-8) Dec	-0.044*	0.026	0.082	0.093
(t-7) Jan	-0.003	0.025	-0.089	0.088
(t-6) Feb	-0.001	0.024	-0.037	0.088
(t-5) Mar	-0.020	0.024	-0.060	0.093
(t-4) Apr	-0.032	0.023	-0.265***	0.091
(t-3) May	-0.015	0.024	-0.188**	0.092
(t-2) Jun	-0.057**	0.026	-0.037	0.091
(t-1) Jul	-0.104***	0.025	-0.054	0.090

$^*\ p < 0.10,\ ^{**}\ p < 0.05,\ ^{***}\ p < 0.01$

We find that ω_t is at times significantly different from zero during the pre-treatment period (Table WA4). However, these differences are not due to a difference in the overall *trend* of the two groups, but due to different seasonal patterns. In particular, households with school-aged children purchase relatively fewer calories from grocery stores during the summer and around the winter holidays. This is perhaps consistent with higher travel during the summers and a higher tendency to eat-out during the holiday season. Critically, we observe this seasonal pattern both before and after treatment.

To illustrate this, we re-estimate the model from equation 2 using two years of pre-treatment data, to demonstrate that these seasonal patterns are long-running seasonal trends and not an idiosyncratic feature of the year prior to treatment. Estimates for ω_t for each month, pre- and post-treatment, are presented in Table WA5. They are also plotted in Figure WA3 for calories and Figure WA4 for Nutrient Profile Score.

For both calories and nutrient profile score, a clear annual pattern emerges prior to treatment. For calories, this pattern repeats in the year of treatment, but at a lower overall level, consistent with the previously established strong treatment effect. For the nutrient profiling score, there is also evidence of a decline during the year of treatment, though a weaker and less consistent one; not unsurprising given the relatively small effect of treatment on nutrition.

Table WA5: Test of Parallel Trends, Two-Year Pre-Treatment Window

Month	Ln Calories			Nutrient Profile Score		
	t-2	t-1	treat year	t-2	t-1	treat year
Aug	0.000	0.007	-0.062**	0.000	-0.035	-0.161*
	-	0.027	0.028	-	0.100	0.097
Sept	0.029	0.043	0.001	0.018	-0.227**	-0.105
	0.029	0.031	0.027	0.109	0.105	0.097
Oct	-0.002	-0.037	-0.112***	-0.187*	0.050	-0.104
	0.025	0.026	0.028	0.104	0.100	0.100
Nov	-0.066**	-0.043	-0.081***	0.071	0.161	-0.062
	0.026	0.028	0.029	0.092	0.102	0.104
Dec	-0.050*	-0.038	-0.102***	-0.049	0.043	-0.151
	0.029	0.029	0.030	0.108	0.106	0.108
Jan	0.004	0.003	-0.056**	-0.220**	-0.120	-0.308***
	0.029	0.028	0.028	0.104	0.106	0.103
Feb	0.016	0.005	-0.062**	-0.137	-0.067	-0.318***
	0.029	0.027	0.030	0.114	0.100	0.102
Mar	0.022	-0.014	-0.089***	-0.123	-0.094	-0.201*
	0.027	0.027	0.031	0.095	0.100	0.106
Apr	-0.024	-0.026	-0.083***	-0.131	-0.297***	-0.195*
	0.029	0.026	0.030	0.108	0.097	0.103
May	0.030	-0.009	-0.102***	-0.144	-0.223***	-0.312***
	0.029	0.028	0.030	0.096	0.101	0.103
Jun	-0.036	-0.051*	-0.174***	-0.111	-0.071	-0.339***
	0.028	0.028	0.029	0.104	0.098	0.108
Jul	-0.050*	-0.098***	-0.149***	-0.010	-0.087	-0.254**
	0.028	0.028	0.030	0.098	0.100	0.105

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure WA3: ω_t by Month and Year, Calories
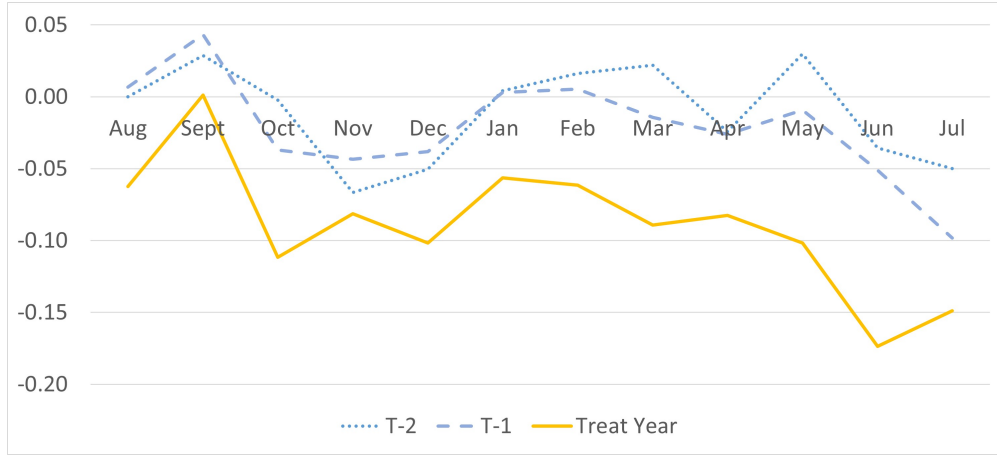
Figure WA4: ω_t by Month and Year, Nutrient Profile Score
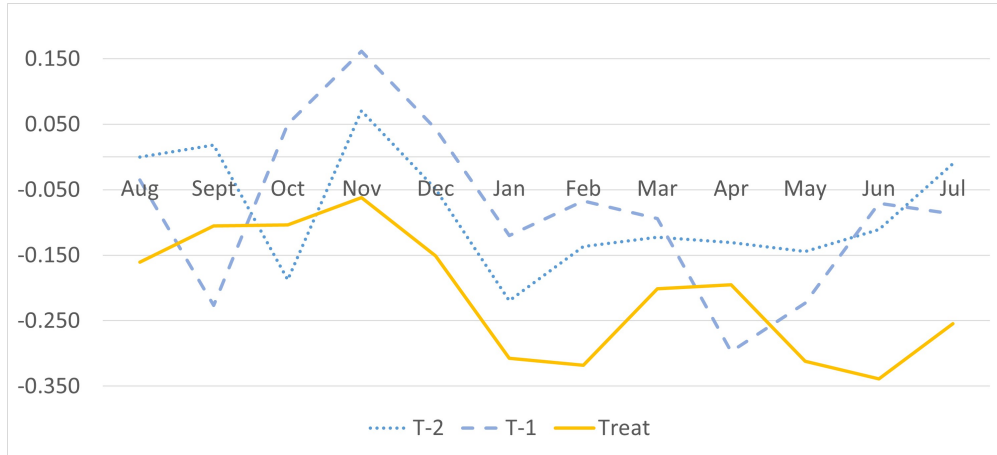
To more formally demonstrate that the significant differences from Table WA5 are driven only by differences in seasonality, as opposed to a genuine difference in *trend*, we follow the approach from O'Neill et al. (2016). Specifically, we incorporate a linear trend variable for the treatment group, and month-of-the-year dummy variables interacted with the treatment group. The parameters on the month-of-the-year variables capture differences in seasonality between the treatment and control group. Our approach differs from that in O'Neill et al. (2016) only in that they utilize a parametric control for seasonality, while we use the non-parametric monthly dummies.

$$DV_{ht} = \beta DID + \delta_h + \lambda_{ct} + \theta_m I([Month]_t = m) \times I[TreatGroup]_h$$
$$+ \mu LinearPreTrend_t \times I[TreatGroup]_h + \epsilon_{ht}$$

(3)

These parameters are estimated using both years of pre-treatment data and the year of treatment data, ensuring that we are controlling only for seasonality that exists both before and after treatment. Once these differences in seasonality (measured by θ_m) are controlled for, the linear trend variable tests (via μ) whether there is a difference between the groups with respect to their *trend* during the pre-treatment period.

Table WA6: Parallel Trends Seasonality Correction

	Ln Calories		NPS	
	Est.	SE	Est.	SE
Linear Trend (μ)	-0.0005	0.0008	0.0010	0.0027
	Ln Calories		NPS	
	Est.	SE	Est.	SE
Dif-in-dif (β)	-0.065***	0.012	-0.136***	0.041
	Seasonality variables			
	Ln Calories		NPS	
	Est.	SE	Est.	SE
Jan ($\theta_{m=1}$)	0.045***	0.016	-0.159***	0.059
Feb ($\theta_{m=2}$)	0.048***	0.016	-0.116*	0.061
Mar ($\theta_{m=3}$)	0.034**	0.016	-0.089	0.062
Apr ($\theta_{m=4}$)	0.018	0.016	-0.176***	0.055
May ($\theta_{m=5}$)	0.035**	0.016	-0.183***	0.058
June ($\theta_{m=6}$)	-0.022	0.016	-0.119	0.059
July ($\theta_{m=7}$)	-0.038**	0.017	-0.073	0.060
Aug ($\theta_{m=8}$)	0.043**	0.017	-0.015	0.060
Sep ($\theta_{m=9}$)	0.090***	0.016	-0.045	0.058
Oct ($\theta_{m=10}$)	0.007	0.015	-0.009	0.055
Nov ($\theta_{m=11}$)	0.003	0.016	0.106*	0.061
Dec (reference)	-	-	-	-

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Our results (Table WA6) show that once this difference in seasonality is controlled for, the parallel trends assumption clearly holds: the linear trend variable is not close to significant for either calories (p=0.51) or nutrient profile score (p=0.85). We also include the

term corresponding to the two-way interaction between the treatment group and the post-treatment window (the coefficient on which represents the DiD estimate) and confirm that the effect is still statistically significant after factoring in seasonality.

WEB APPENDIX B: ROBUSTNESS CHECKS FOR AVERAGE TREATMENT EFFECT

Alternative Sample Selection Screens

We also test to ensure that our findings are robust to both removing our primary quantity screens, as well as enacting a stricter set of sample screens. The stronger screens are primarily designed to weed out households that may not be reporting their purchases to NielsenIQ regularly, as observations that appear to be low due to under-reporting seem to be more common than outliers at the high end.

We test two stricter quantity screens that enact stricter lower bounds for a household's average pre-treatment calories purchased per month. Our screen in the main analysis is the 5th percentile of treatment households' calories purchased per adult equivalent; our stricter screens here are the 10th and 20th percentile (250 and 360 calories per adult, per month respectively).

Our results with these alternate sets of matching variables and quantity screens, along with our primary results reported in the paper (for reference) are shown in Table WA7. The treatment effect for shopping basket quantity (calories) is very robust; we get roughly the same estimate using no matching and no quantity screens (-0.058) as we do with our primary sets of sample screens and matching variables (-0.064). The treatment effect for shopping basket quality (NPS) is also fairly robust.

Table WA7: Effect of Nutrition Standards: Alternate Sample Screens

	Households		Ln Calories		NPS	
	Treat	Control	Est.	SE	Est.	SE
No Qty Screens or Matching	8,389	39,265	-0.058***	0.006	-0.039**	0.020
Main Specification	7,645	27,148	-0.064***	0.009	-0.093***	0.031
Alternate Samples						
10th pct Quantity Screen	7,479	26,323	-0.057***	0.009	-0.090***	0.031
20th pct Quantity Screen	6,594	25,316	-0.052***	0.009	-0.064**	0.031

$^{*}\ p < 0.10,\ ^{**}\ p < 0.05,\ ^{***}\ p < 0.01$

Other Measures: Servings, Healthy Eating Index, Spending

Alternate Dependent Variables

We test an alternate dependent variable for shopping basket quantity: total servings, as reported on each UPC's nutrition label. Our estimate of the average treatment effect using this measure (-0.061, SE=0.007) is nearly identical to our estimate using calories (-0.064, SE=0.009).

We use the Nutrient Profile Score as our primary measure of shopping basket nutrition because we possess nearly all the data necessarily to calculate it precisely. Another measure is the Healthy Eating Index used by the USDA to evaluate the nutritional composition of diets, and often used in research for school meals. The HEI is more difficult to calculate because of its components, which are presented in Figure WA5 below. Nonetheless, we construct a measure that approximates the HEI, following Palazzolo and Pattabhiramaiah (2021).

We do not have data on whole grains, fatty acids, or refined grains. Because the primary distinction between whole grains and refined grains is that refined grains have fiber stripped out, we include fiber as a substitute for these two measures. We also cannot easily distinguish between "whole fruit" and other forms of fruit, between "total vegetables" and "greens and beans", or between "total protein foods" and "seafood and plant proteins". We therefore

Figure WA5: Formula for calculating the Healthy Eating Index

HEI-2015[1] Components and Scoring Standards

Component	Maximum points	Standard for maximum score	Standard for minimum score of zero
Adequacy:			
Total Fruits[2]	5	≥0.8 cup equivalent per 1,000 kcal	No Fruit
Whole Fruits[3]	5	≥0.4 cup equivalent per 1,000 kcal	No Whole Fruit
Total Vegetables[4]	5	≥1.1 cup equivalent per 1,000 kcal	No Vegetables
Greens and Beans[4]	5	≥0.2 cup equivalent per 1,000 kcal	No Dark-Green Vegetables or Legumes
Whole Grains	10	≥1.5 ounce equivalent per 1,000 kcal	No Whole Grains
Dairy[5]	10	≥1.3 cup equivalent per 1,000 kcal	No Dairy
Total Protein Foods[4]	5	≥2.5 ounce equivalent per 1,000 kcal	No Protein Foods
Seafood and Plant Proteins[4,6]	5	≥0.8 ounce equivalent per 1,000 kcal	No Seafood or Plant Proteins
Fatty Acids[7]	10	(PUFAs + MUFAs) / SFAs ≥2.5	(PUFAs + MUFAs)/SFAs ≤1.2
Moderation:			
Refined Grains	10	≤1.8 ounce equivalent per 1,000 kcal	≥4.3 ounce equivalent per 1,000 kcal
Sodium	10	≤1.1 grams per 1,000 kcal	≥2.0 grams per 1,000 kcal
Added Sugars	10	≤6.5% of energy	≥26% of energy
Saturated Fats	10	≤8% of energy	≥16% of energy

[1] Intakes between the minimum and maximum standards are scored proportionately.
[2] Includes 100% fruit juice.
[3] Includes all forms except juice.
[4] Includes legumes (beans and peas).
[5] Includes all milk products, such as fluid milk, yogurt, and cheese, and fortified soy beverages.
[6] Includes seafood; nuts, seeds, soy products (other than beverages), and legumes (beans and peas).
[7] Ratio of poly- and mono-unsaturated fatty acids (PUFAs and MUFAs) to saturated fatty acids (SFAs).

Sourced from the USDA's official website.
https://www.fns.usda.gov/cnpp/how-hei-scored

treat all fruit as equivalent, all vegetables as equivalent, and all protein as equivalent. We calculate component-specific scores and then take the average across components for our HEI measure.

We make two modifications in the Palazzolo and Pattabhiramaiah (2021) measure of HEI for improved validity. First, while we cannot explicitly view added sugars for most UPCs, we do not merely use total sugars as a substitute. Instead, we do our best to modify total sugars by removing sugars that are likely not to be added sugars. Specifically, we calculate each product group's ratio of added sugars to total sugars using the UPCs we can observe

added sugar for. Then, for any product group with an added sugar ratio below 15%, we treat all sugars as "not added" and remove them from the calculation of our HEI measure. The product groups for which sugar content is screened out in this way are fairly consistent with expectations. Examples include Cheese, (non-flavored) Milk, Flour, Pasta, Canned Vegetables, Vegetables and grains, Fresh Produce, and Frozen Vegetables.

Second, while the measure used by Palazzolo and Pattabhiramaiah (2021) was unbounded, we bound our measure, in line with the HEI-2015 (which is bounded between 0 and 100). Specifically, we bound each component-specific score at twice the 99th percentile score for that component. The unbounded measure has a few extreme outliers. While the median score of this measure is -1.5, and the 1st and 99th percentiles are -11.1 and 3.8 respectively, scores as low as -19,063 and as high as 75 for the unconstrained measure exist in the data. The correlation of our bounded HEI measure with the NPS measure is 0.41 while it is only 0.04 for the unbounded HEI measure.

Our estimate of the average treatment effect on the HEI is not significant (-0.016, SE=0.021). While this differs from our estimate using the NPS (which is significant though small), the overall conclusion remains that any change in the quality of grocery food is small.

Grocery Spending and Retailer Revenue

We also measure the impact of the HHFKA's nutrition mandates on another DV: grocery spending. We find a 4.4% reduction in spending on groceries (Est = -0.044, SE = 0.004). Given that households with school-aged children made up roughly 32% of overall grocery spending among households in the NielsenIQ data in 2011 (after incorporating projection factors to scale spending to be representative of the national level), this 4.4% reduction among these households translates to roughly a 1.4% reduction in grocery revenue for retailers. While this may seem small, a 1.4% reduction in revenue is actually quite large for an industry with notoriously small margins; e.g., margins were 2.5% in 2022.[16]

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[16]https://www.dunnhumby.com/about-us/news/americans-believe-grocery-store-profits-are-14-times-higher-than-reality-and-inflation-is-twice-as-high-as-actual-dunnhumby-finds/

Alternative Fixed Effects Levels

Our results are robust to using either state or zip-code fixed effects instead of county fixed effects:

Table WA8: Effect of Nutrition Standards: Fixed Effects Levels

	Ln Calories		NPS	
	Est.	SE	Est.	SE
State-Level Fixed Effects	-0.056***	0.010	-0.088**	0.037
Main Specification (County)	-0.064***	0.009	-0.093***	0.031
Zip Code Level Fixed Effects	-0.064***	0.010	-0.061*	0.033

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

WEB APPENDIX C: CHANGES TO THE COMPOSITION OF THE SHOPPING BASKET

Category-Specific Average Treatment Effects

To provide more context for the changes to households' shopping baskets in response to mandated nutrition standards, we examine average treatment effects on quantity and quality for six categories: breakfast and lunch, beverages, fruit and vegetables, snacks and desserts, prepared meals, and unprepared meals (a category for all other foods, which require preparation). The NielsenIQ data has three layers of categorization (department, product group, and product module). We group categories based primarily on their product group, except in instances where the group contains modules that clearly belong elsewhere. For example, one product group in the Frozen Food department combines frozen fruit and desserts; we categorize frozen fruit under "fruit and vegetables" and desserts under "snacks and desserts." We provide a full breakdown of how we categorize product groups (or modules) at the end of this web appendix. The six categories are mutually exclusive, where breakfast and lunch categories supersede others; any UPC that is included in breakfast or lunch is only classified there even if it might also fit in another category (e.g., prepared meals).

We estimate treatment effects for each category. Because households do not purchase in every category every month, category-level quantities have a relatively large number of zeros, and dependent variables should not be logged in the presence of zeros (Chen and Roth 2024). For these analyses, therefore, we make two modifications. First, we construct household-quarter level measures of category calories per capita and NPS.[17] For five of the six categories, fewer than 5% of observations still have a zero observation; for beverages, 9% of observations are still zero. Second, we exclude households that didn't purchase in a category during any quarter (i.e., that have a zero observation in their data at the household-quarter

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[17] To ensure that combining our observations in this way does not dramatically skew our estimates, we also check the treatment effects for our main DVs (overall quantity and quality) using the same approach, and find estimates that are quite similar to our main analysis (-0.057 for quantity and -0.062 for quality).

level) and separately model the decision to purchase in a category at all.

Table WA9: Category-Specific Treatment Effects

Category	Ln Calories	Purchase	NPS	Pct of Cal	Avg NPS
Breakfast and Lunch	-0.073***	-0.002	-0.054	21%	-3.5
	(0.010)	(0.002)	(0.047)		
Unprepared Meals	-0.056***	-0.002	-0.061	31%	-9.4
	(0.011)	(0.002)	(0.060)		
Prepared Meals	-0.054***	0.001	-0.157***	10%	-5.0
	(0.011)	(0.003)	(0.047)		
Fruit and Vegetables	-0.052***	0.000	-0.047	7%	2.9
	(0.016)	(0.002)	(0.046)		
Snacks	-0.042***	-0.001	-0.094**	25%	-14.4
	(0.009)	(0.001)	(0.045)		
Beverages	-0.026*	-0.003	0.101	7%	-3.2
	(0.014)	(0.003)	(0.089)		

Standard Errors in Parentheses. *** = p<.01, ** = p<.05, * = p<.10

We present the treatment effects for calories purchased, the decision to purchase in a category, and the NPS of purchases in a category in Table WA9. We also provide the proportion of the average household's shopping basket belonging to each category, and the average NPS of each category. We sort categories by the size of their treatment effect for ease of reference. There are, broadly speaking, not many large differences, nor additional substantive insights to be drawn at this level of category disaggregation. There is some potential evidence of licensing in the significant reduction in NPS for snacks, but (as was demonstrated by our analysis comparing the nutritional content of school meals non-purchased groceries), these effect sizes are still economically small.

Average Treatment Effects for Breakfast and Lunch Subcategories

Next, we further decompose breakfast and lunch into subcategories at the product group level defined by NielsenIQ. For these analyses, we construct household-period observations (a single observation per household pre- and post-treatment), because subcategories account

for a very small proportion of foods purchased—e.g., eggs and yogurt each account for about 1% of all purchases—resulting in many zero observations at even the quarterly level. The average treatment effects are presented in Table WA10, along with the percentage of the average household's calories belonging to a subcategory, the average percentage of households purchasing in the subcategory per period (pre/post-treatment), and the subcategory's average NPS.

The largest reduction in calories comes from the subcategories explicitly labeled as "breakfast foods" by NielsenIQ, plus milk. This is intuitive, as these are the UPCs most strongly associated with breakfast, and the small uptick seen in "meals served" by the USDA after the HHFKA's rollout was driven more by school breakfasts than lunches. There do not appear to be meaningful changes to the NPS of subcategories, with the largest change being a significant positive effect for bread and baked goods, which accounts for 0.8% of calories purchased.

We caution that attempting to draw meaningful comparison between some categories at the highly disaggregated level is challenging, given how infrequently some of the categories are purchased. Nonetheless, we provide this additional detail for completeness.

Alternative Definitions of Breakfast and Lunch

We have taken a conservative approach to categorizing UPCs as "breakfast and lunch," including only UPCs that are strongly associated with the two meals in the United States, and categorizing other foods that are less strongly associated with those meals elsewhere. For example, soda may be consumed at lunch but is also commonly consumed at other times of the day, so we do not include it in "breakfast and lunch". Our approach assigns 21% of calories purchased to the "breakfast and lunch" category. Two previous papers that analyze breakfast and lunch (Handbury and Moshary 2021; Marcus and Yewell 2022) have used much broader definitions. For example, one or both of them include snacks, fruit and vegetables, coffee, butter, and many other categories in breakfast and lunch.

Table WA10: Breakfast and Lunch Subcategory Treatment Effects

Category	Ln Calories	Purchase (0/1)	NPS	Pct Cal	Purch Pct	Avg NPS
Breakfast Food-Frozen	-0.144***	-0.044***	-0.012	0.7%	53%	-7.2
	(0.033)	(0.010)	(0.149)			
Milk#	-0.084***	-0.002	0.023	4.7%	94%	-0.8
	(0.017)	(0.005)	(0.054)			
Breakfast Food-Dry	-0.074***	-0.023***	0.087	2.1%	73%	-14.1
	(0.025)	(0.009)	(0.076)			
Cereal	-0.048***	0.000	0.053	5.3%	93%	-7.1
	(0.017)	(0.006)	(0.093)			
Eggs	-0.046*	-0.001	0.004	0.7%	61%	0.4
	(0.024)	(0.009)	(0.010)			
Bread & Baked Goods (L##)	-0.046**	-0.010	0.105*	3.2%	91%	-0.8
	(0.018)	(0.006)	(0.055)			
Packaged Meat (L###)	-0.038*	0.002	0.094	0.7%	79%	-13.1
	(0.023)	(0.009)	(0.156)			
Bread & Baked Goods (B##)	-0.032	-0.010	0.457*	0.8%	55%	-10.5
	(0.031)	(0.010)	(0.266)			
Yogurt	-0.031	-0.010	-0.026	0.9%	78%	0.1
	(0.025)	(0.008)	(0.051)			
Table Syrups, Molasses	-0.009	-0.039***	-0.082	0.4%	47%	-13.1
	(0.032)	(0.011)	(0.196)			
Packaged Meat (B###)	-0.002	-0.023***	0.022	1.2%	76%	-20.6
	(0.023)	(0.009)	(0.124)			

Standard Errors in Parentheses. *** = p<.01, ** = p<.05, * = p<.10

Includes shelf-stable, canned, and powdered milk from "Packaged Milk and Modifiers"

(B=Breakfast) Bagels, Breakfast Cakes, Doughnuts, (L=Lunch) Fresh Bread

(B=Breakfast) Breakfast Sausages & Bacon, (L=Lunch) Lunch Meat

Marcus and Yewell (2022) assign individual UPCs to "breakfast and lunch" and report the number of UPCs from each product group. E.g., they note that 72,099 UPCs from "bread and baked goods" are assigned to lunch, and 15,774 to breakfast. However, they do not include further detail into the specific UPCs that fall within their broadly defined food categories, preventing a perfect replication based on their classification scheme.

On the other hand, Handbury and Moshary (2021) base their classification on NielsenIQ product modules. Using their definition, and household-quarter level observations, we find a 5.7% reduction in breakfast and lunch quantity (Est = -0.057, SE=0.008) but a 6.7% reduction in other foods (Est=-0.067, SE=0.010). The primary difference between their definition of "breakfast and lunch" and ours is the inclusion of snacks (e.g., frozen baked goods, desserts, cookies) and beverages (e.g., juice, soft drinks), which have two of the smallest treatment effects (based on our analyses above), leading to the smaller effect size for their definition of "breakfast and lunch UPCs."

Table WA11: Categorization of UPCS

Department	Product Group (Modules)	Categorization
DAIRY	BUTTER AND MARGARINE	Unprepared Meals
DAIRY	DOUGH PRODUCTS	Unprepared Meals
DAIRY	COT CHEESE, SOUR CREAM, TOPPINGS	Unprepared Meals
DAIRY	YEAST	Unprepared Meals
DAIRY	CHEESE	Snacks
DAIRY	EGGS	Breakfast & Lunch
DAIRY	MILK	Breakfast & Lunch
DAIRY	YOGURT	Breakfast & Lunch
DAIRY	PUDDING, DESSERTS-DAIRY	Snacks
DAIRY	SNACKS, SPREADS, DIPS-DAIRY	Snacks
DRY GROCERY	BREAD AND BAKED GOODS	Various (See below)

Table WA11: Categorization of UPCS

Department	Product Group (Modules)	Categorization
	Buns, Rolls	Prepared Meal
	Bagels, Breakfast Cakes, Doughnuts	Breakfast & Lunch
	Bread - Fresh	Breakfast & Lunch
	Remaining (Cake, muffins, etc)	Snacks
DRY GROCERY	BAKING MIXES	Unprepared Meals
DRY GROCERY	BAKING SUPPLIES	Unprepared Meals
DRY GROCERY	FLOUR	Unprepared Meals
DRY GROCERY	SHORTENING, OIL	Unprepared Meals
DRY GROCERY	CARBONATED BEVERAGES	Beverage
DRY GROCERY	COFFEE	Beverage
DRY GROCERY	JUICE, DRINKS - CANNED, BOTTLED	Beverage
DRY GROCERY	PACKAGED MILK AND MODIFIERS	Beverage
DRY GROCERY	SOFT DRINKS-NON-CARBONATED	Beverage
DRY GROCERY	TEA	Beverage
DRY GROCERY	BREAKFAST FOOD	Breakfast & Lunch
DRY GROCERY	CEREAL	Breakfast & Lunch
DRY GROCERY	PREPARED FOOD-DRY MIXES	Prepared Meals
DRY GROCERY	PREPARED FOOD-READY-TO-SERVE	Prepared Meals
DRY GROCERY	SEAFOOD - CANNED	Unprepared Meals
DRY GROCERY	SOUP	Unprepared Meals
DRY GROCERY	PASTA	Unprepared Meals
DRY GROCERY	FRUIT - CANNED	Fruit & Vegetable
DRY GROCERY	FRUIT - DRIED	Fruit & Vegetable
DRY GROCERY	VEGETABLES - CANNED	Fruit & Vegetable

Table WA11: Categorization of UPCS

Department	Product Group (Modules)	Categorization
DRY GROCERY	VEGETABLES AND GRAINS - DRIED	Fruit & Vegetable
DRY GROCERY	NUTS	Fruit & Vegetable
DRY GROCERY	CANDY	Snacks
DRY GROCERY	COOKIES	Snacks
DRY GROCERY	CRACKERS	Snacks
DRY GROCERY	DESSERTS, GELATINS, SYRUP	Snacks
DRY GROCERY	GUM	Snacks
DRY GROCERY	SNACKS	Snacks
DRY GROCERY	CONDIMENTS, GRAVIES, AND SAUCES	Unprepared Meals
DRY GROCERY	JAMS, JELLIES, SPREADS	Unprepared Meals
DRY GROCERY	PICKLES, OLIVES, AND RELISH	Unprepared Meals
DRY GROCERY	SALAD DRESSINGS, MAYO, TOPPINGS	Unprepared Meals
DRY GROCERY	SPICES, SEASONING, EXTRACTS	Unprepared Meals
DRY GROCERY	SUGAR, SWEETENERS	Unprepared Meals
DRY GROCERY	TABLE SYRUPS, MOLASSES	Unprepared Meals
FRESH PRODUCE	FRESH PRODUCE	Fruit & Vegetable
FROZEN FOODS	BREAKFAST FOODS-FROZEN	Breakfast & Lunch
FROZEN FOODS	BAKED GOODS-FROZEN	Snacks
FROZEN FOODS	DESSERTS/FRUITS/TOPPINGS	Various (See below)
	Frozen Fruits	Fruit & Vegetable
	All others	Snacks
FROZEN FOODS	ICE CREAM, NOVELTIES	Snacks
FROZEN FOODS	JUICES, DRINKS-FROZEN	Beverage
FROZEN FOODS	PIZZA/SNACKS/HORS DOEURVES	Various (See below)

Table WA11: Categorization of UPCS

Department	Product Group (Modules)	Categorization
	Frozen Pizza	Prepared Meals
	Frozen Pizza Crust	Unprepared Meals
	Frozen hors d'oeuvres	Snacks
FROZEN FOODS	PREPARED FOODS-FROZEN	Prepared Meals
FROZEN FOODS	UNPREP MEAT/POULTRY/SEAFOOD	Unprepared Meals
FROZEN FOODS	VEGETABLES-FROZEN	Fruit & Vegetable
PACKAGED MEAT	FRESH MEAT	Unprepared Meals
PACKAGED MEAT	PACKAGED MEATS	Various (See below)
	Breakfast Sausages & Bacon	Breakfast & Lunch
	Lunch Meat	Breakfast & Lunch
	All other meats	Unprepared Meals
DELI	DRESSINGS/SALADS/PREP FOODS	Various (See below)
	Fruit/Salad/Fruit Salad	Fruit & Vegetable
	Chili/Entree/Sandwich/Pizza	Prepared Meal
	Cracklins	Snacks
	Gelatin Salad	Snacks
	Other	Unprepared Meal

WEB APPENDIX D: COMPARING GROCERIES TO SCHOOL NUTRITIONAL CONTENT

In the main text of this paper, we compare the (post-HHFKA) nutritional composition of school meals to the nutritional composition of foods not purchased at the grocery store due to the HHFKA (i.e., the nutritional composition of the 6.4% reduction in calories). Here, we explain our calculations.

We illustrate these calculations with an example: If a household buys 100 fewer calories and 5 fewer grams of saturated fat daily due to nutrition mandates, we compare these with the calories from school meals. Changes in saturated fat could result from both the switch to school meals and adjustments in home food purchases.

We cannot simply compare the nutritional composition before and after the policy because we need to account for non-causal changes using a control group. Thus, we estimate the quantities of interest. While the percentage change in calories is calculated through our primary regression, we also need to determine the change in components of the Healthy Eating Index.

To do this, we first estimate the change in each component's volume per 1,000 calories using the regression in equation 1. For each month and each household, we calculate their quantity of each component j (e.g., grams of saturated fat) per 1,000 calories purchased and use that as a dependent variable in our difference-in-difference specification. We refer to the estimated change in component j's volume per 1,000 calories due to treatment—i.e., the ATE—as λ_j.

After estimating the causal change in each nutritional component per 1,000 calories, we can determine what the treatment group's post-treatment volume per 1,000 calories would be without non-causal trends, which will differ slightly from the observed data. Call the treatment group's observed pre-treatment volume per 1,000 calories for component j, $VolKCal_j^{Pre}$, and the estimated post-treatment value $Vol\hat{K}Cal_j^{Post}$. We estimate

$Vol\hat{K}Cal_j^{Post}$ as:

$$Vol\hat{K}Cal_j^{Post} = VolKCal_j^{Pre}(1 + \lambda_j) \tag{4}$$

We have the nutritional volume per 1,000 calories for HEI component j before and after the treatment. We now need to determine the volume per 1,000 calories for the calories not purchased post-treatment. For example, if a household stopped purchasing 50 calories per day per person, what would be the nutritional composition of those calories? We can now solve this algebraically using the available data. Define the value of interest as $Vol\hat{K}Cal_j^{NotPurch}$. Then, the following must hold:

$$VolKCal_j^{Pre} = Vol\hat{K}Cal_j^{Post}(1 - \pi) + Vol\hat{K}Cal_j^{NotPurch}(\pi) \tag{5}$$

To see this, define Cal^{Pre} as the calories purchased prior to treatment, Cal^{Post} as the calories purchased post-treatment, and π as the percentage reduction in calories due to treatment (previously estimated to be 6.4%). Further define the absolute volume of component j purchased pre-treatment as V_j^{Pre} and the volume purchased post-treatment as V_j^{Post}. Given that $Cal^{Post} = Cal^{Pre}(1 - \pi)$, Equation 5 becomes:

$$
\begin{aligned}
\frac{1000 \times V_j^{Pre}}{Cal_j^{Pre}} &= \frac{1000 \times V_j^{Post}}{Cal_j^{Post}}(1 - \pi) + \frac{1000 \times (V_j^{Pre} - V_j^{Post})}{Cal_j^{Pre} - Cal_j^{Post}}(\pi) \\
\frac{V_j^{Pre}}{Cal_j^{Pre}} &= \frac{V_j^{Post}}{Cal_j^{Post}}(1 - \pi) + \frac{(V_j^{Pre} - V_j^{Post})}{Cal_j^{Pre} - Cal_j^{Post}}(\pi) \\
\frac{V_j^{Pre}}{Cal_j^{Pre}} &= \frac{V_j^{Post}}{Cal_j^{Pre}}\frac{(1 - \pi)}{(1 - \pi)} + \frac{(V_j^{Pre} - V_j^{Post})}{Cal_j^{Pre}}\frac{\pi}{\pi} \\
\frac{V_j^{Pre}}{Cal_j^{Pre}} &= \frac{V_j^{Pre}}{Cal_j^{Pre}}
\end{aligned}
\tag{6}
$$

Consequently, the Pre-Treatment volume per 1,000 calories for component j is a simple weighted average of the Post-Treatment volume per 1,000 calories for groceries purchased (weighted at 93.6%, since $\pi = 0.064$) and groceries not purchased (weighted at

6.4%). Refer to the volume of component j per 1,000 calories for groceries not purchased as $Vol\hat{K}Cal_j^{NotPurch}$. We can estimate $Vol\hat{K}Cal_j^{NotPurch}$ using the formula from equation 5:

$$VolKCal_j^{Pre} = Vol\hat{K}Cal_j^{Post}(0.936) + Vol\hat{K}Cal_j^{NotPurch}(0.064) \tag{7}$$

For each component j, we report the pre-treatment volume per 1,000 calories $VolKCal_j^{Pre}$ (column 1), the percentage change λ_j (column 2), the estimated post-treatment volume per 1,000 calories $Vol\hat{K}Cal_j^{Post}$ (column 3), and the estimated volume per 1,000 calories for groceries not purchased $Vol\hat{K}Cal_j^{NotPurch}$ (column 4) in Table WA14. The largest percentage changes were a reduction in dairy, an increase in sodium, and a decrease in saturated in fat (the latter of which was a positive change). Note that there were only small differences between pre- and post-treatment nutritional compositions, consistent with the small Average Treatment Effect (ATE) for the NPS.

For Dairy, before treatment, households bought 0.57 cups of dairy per 1,000 calories. After treatment, this declined by 1% to 0.56 cups per 1,000 calories. Using these values, we estimate the nutritional composition of the calories not purchased post-treatment to be 0.65 cups per 1,000 calories. This volume is higher than both the pre-treatment and post-treatment volumes because the purchased volume decreased post-treatment. Note also that these numbers fit our equation above: $0.57 = (0.936 \times 0.56) + (0.64 \times 0.65)$. The values presented in column 4 of this table are the values presented in Table 5 in the paper.

Table WA12: Calculating Nutritional Composition of Groceries Not Purchased

	Prior/kCal	Pct Change	Post/kCal	Lost Food
Fruit and Veg (Cups)	0.37	0.00%	0.37	0.37
Dairy (Cups)	0.57	-1.00%	0.56	0.65
Protein Foods	1.94	0.00%	1.94	1.94
Seafood and Plant Protein Foods	0.50	-0.63%	0.50	0.54
Sodium (mg)	2,323	1.49%	2,357	1,817
Saturated Fat (g)	13.3	-0.92%	13.14	15.0

WEB APPENDIX E: HETEROGENEITY ROBUSTNESS CHECKS AND ADDITIONAL DETAILS

Robustness Checks for Heterogeneous DiD

Heterogeneity in the Quantity DV: Quantity and Quality Interaction

In our primary specification, we estimate our model by interacting households' standardized pre-treatment calories per capita and NPS. In this web appendix, we further explore this relationship in a more informative manner, providing some additional details. Specifically, we separate households into terciles along each variable, then form nine groups (3 × 3) of households based on their terciles. We then re-estimate our heterogeneous DiD model in two ways. First, we interact group dummy variables for these groups (other than the group belonging to the lowest tercile for both calories and NPS) with the DiD variable, replacing the standardized terms. This allows us to compare households from higher terciles to those in the lowest tercile for both pre-treatment quantity and quality. Second, we interact the group dummy variables for all groups with the DiD variable, allowing us to determine whether each group's treatment effect is significantly different from zero (rather than significantly different from the treatment effect for households in the lowest terciles).

We report the results in Tables WA13 and WA14. The largest treatment effects are, as previously reported, those for households with the lowest pre-treatment grocery quantity *and* quality. The treatment effect for the households in the lowest tercile for both calories and NPS is -0.122, nearly double the ATE. The impact of nutritional quality can be seen mainly among low-quantity households; households that relied less on the grocery store prior to treatment but who purchased healthy foods from the grocery store did not respond much to treatment.

Table WA13: Quantity Treatment Effect: Differences Between Quantity and Quality Terciles

	Cal Tercile	NPS Tercile	Est	SE
DID	Low	Low	-0.122***	0.040
Difference vs lowest terciles	Low	Medium	0.054	0.051
Difference vs lowest terciles	Low	High	0.095*	0.054
Difference vs lowest terciles	Medium	Low	0.086*	0.048
Difference vs lowest terciles	Medium	Medium	0.077	0.047
Difference vs lowest terciles	Medium	High	0.093**	0.046
Difference vs lowest terciles	High	Low	0.117***	0.044
Difference vs lowest terciles	High	Medium	0.096***	0.047
Difference vs lowest terciles	High	High	0.121***	0.045

*** = p<.01, ** = p<.05, * = p<.10

Table WA14: Quantity Treatment Effect: by Quantity and Quality Terciles

	Low NPS	Medium NPS	High NPS
Low Calories	-0.122***	-0.068*	-0.027
	(0.040)	(0.035)	(0.038)
Medium Calories	-0.035	-0.045	-0.029
	(0.031)	(0.027)	(0.027)
High Calories	-0.005	-0.026	0.000
	(0.025)	(0.029)	(0.022)

*** = p<.01, ** = p<.05, * = p<.10

Heterogeneity in the Quality DV

We did not find evidence of heterogeneity in the treatment effect for the quality DV in our analysis using the causal forest. While the DiD approach did find some statistically significant effects, they remain economically small, just as the ATE was. We nonetheless discuss the results here for completeness.

We again find that the largest effects are for the shopping basket variables, though this time the percentage of spending snacks and desserts is most predictive of stronger treatment

effects. While there are a few statistically significant effects, and some may seem numerically large relative to the estimated ATE of -0.091 (for example, the effect size for the percentage of spending on snacks and desserts is -0.205), the effect size is still very small relative to the range of the measure (-40 to 15).

The range of statistically significant effect sizes was -0.205 to 0.164. Given that we know the ATE was dwarfed by the healthiness of school meals, these results do not appear to be concerning; it seems unlikely that there was a particular set of households that reduced the quality of food at home by a non-trivial amount.

Estimation of Causal Forest and Corresponding Treatment Effects

Our causal forest is estimated following the conventional three step procedure. We estimate a model that predicts treatment, a model that predicts the dependent variable, and a model of the treatment effect. We estimate our causal forest model using the variables specified in Table WA15. All variables are included in the estimation of the second and third model. For estimation of the propensities scores W in the first model, we do not use all variables because of the overlap requirement; i.e., that propensity scores should not be close to zero or one. For example, it is extremely unlikely that a single person above the age of 55 will have school-aged children. We do not include the shopping basket variables in the selection model, because "selection" in this case is the decision to have children, which pre-dates the shopping basket choices. A household cannot select into treatment based on these variables. The variables included in W are shown in Table WA15.

We estimate 5,000-tree forests for the first two stages and a 10,000-tree forest for the final (causal) forest. The forest is then used to generate doubly-robust scores (following Chernozhukov et al. 2018; Chen, Sridhar, and Mittal 2021), which are then regressed on the variables of interest (specified in Table 7 of the main text) using the overlap-weighted approach recommended by Li, Morgan, and Zaslavsky (2018) in the event of poor overlap.

Table WA15: Variables in Causal Forest

Variable	Description	W
AvgPreCal	Avg pre-treatment calories per capita	
AvgPreNPM	Avg pre-treatment NPS	
HH Pct Frozen	Pre-treat pct spending on frozen prepared meals	
HH Pct StoreBr	Pre-treat pct spending on store brands	
HH Pct Snacks	Pre-treat pct spending on "snacks"	
marital status	NielsenIQ Variable	
household income	NielsenIQ Variable	Yes
fe/male head age	NielsenIQ Variable	Yes*
fe/male employment	NielsenIQ Variable	
fe/male education	NielsenIQ Variable	Yes*
Race	NielsenIQ variable, dummies for White, Black, Asian, and "other"	Yes
Hispanic origin	NielsenIQ Variable	Yes
red state	State voted for Romney in 2012 Presidential election	Yes
Romney Share	County's vote share for Romney in 2012 Presidential election (MIT Election Data Lab)	Yes
pct free lunch	Proportion of household's county eligible for a free meal, from Ruffini (2022)	Yes
single	Single head (versus two heads)	Yes

*We include a combined household-level measure, rather than gender-specific measures