The Effect of Online Shopping on the Healthfulness of Grocery Purchases

Katherine Harris-Lagoudakis*

Iowa State University

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Abstract

This paper utilizes novel household panel data to analyze the effect of online grocery shopping on the healthfulness of grocery purchases. In order to obtain a causal estimate of the impact of online grocery shopping on grocery purchases, I utilize variation in the timing that an online shopping service was introduced as a source of exogenous variation in the decision to shop online. Average treatment effects for the treated indicate that the introduction of the online shopping service increases the propensity to shop online by 18.2 pp, on average, in the months immediately following introduction. Analysis of Thrifty Food Plan (TFP) budget shares reveals that the introduction of the online shopping service induces a +5.8, -2.7, and +2.6 percent change in the budget shares for breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated meals, respectively. I also analyze other measures of purchase quality and find a 1.0 percent decrease in the average calorie content per ounce of food purchased (calorie density) but find no evidence for improvements in the nutrient density of purchases nor in the average share of expenditure (calories) allocated towards healthful foods. These insights into consumer purchasing behavior can be utilized to inform food policy aimed at improving the quality of food purchases.

JEL: D12, L81, I12

Keywords: retail, e-commerce, consumer choice, nutrition

1 Introduction

"Plus, since I wasn't at the store I stuck to my list and didn't give into those random, impulse purchases [...]"

- Customer Review of Online Grocery Experience, April 2016

Over the past sixteen years, the rate of adult obesity in the United States has increased thirty-three percent (Hales CM, et al. 2017). Afflicting 30% of adults in 2000 and nearly 40% of adults in 2016, obesity is associated with a number of health conditions (heart disease, stroke, type 2 diabetes and some types of cancer) that can reduce both the quality and length of life (Hales CM, et al. 2017). In response to this growing public health concern, there have been a number of policies and campaigns, implemented within the last ten years, aimed at fighting obesity. Such policies include Michelle Obama's *Let's Move!* campaign to fight childhood obesity, the implementation of soda taxes on sugary beverages and the mandatory disclosure of calories on restaurant menu boards across the United States. In order to better inform public policies designed to combat obesity, it is important to understand the factors that influence consumer decisions over food.

This paper explores how purchasing environments influence consumer choice over groceries. Specifically, I evaluate how shopping for groceries in an online purchasing environment affects the composition and quality of grocery purchases. In order to isolate the effect of an online shopping environment, I utilize grocery scanner data generated from the purchases of 25 thousand households who shop for groceries at a traditional brick and mortar supermarket that also offers an online grocery shopping service. These data provide an attractive setting to study the effect of online grocery shopping for three reasons: first, the panel structure of the data allow for a within household

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E-mail: kaharris@iastate.edu

comparison of purchases across the in-store and online purchasing environments; second, online and in-store purchases are fulfilled by the same retailer, alleviating concerns over differences in product selection and branding; third, the retailer of this study offers products for purchase online at the same prices as those found in the store.

This paper complements existing behavioral research by providing a natural setting in which the validity of theories regarding self-control can be explored. Existing theoretical research suggests that consumers have difficulty exercising self-control due to time inconsistent preferences (Thaler 1981, Laibson 1997), visceral influences (Loewenstein 1996), and/or consumption cues (Laibson 2001). Theories on time inconsistent preferences predict that the decisions consumers make for themselves in the future are better than the decisions they make for themselves in the present. Thus, the time delay between ordering and receiving groceries, that exists when shopping online, could lead to more healthful purchases. Visceral influences and cue theories of consumption indicate that as the level of distraction (noise, congestion, presence of children) and the level of product placement (checkout lanes, end of aisle displays) declines in a shopping environment, a consumers' ability to exercise self-control may increase. If the online shopping experience is less distracting than the in-store shopping experience, households may be able to exercise more self-control over their purchases. The representation of products with pictures has also been theorized to improve the healthfulness of food purchases (Shiv and Fedorikhin 1999; Shiv and Fedorikhin 2002).

This paper contributes to existing empirical research that analyzes how an online purchasing environment, in and of itself, may influence the healthfulness of consumer purchases. Huyghe et al. (2017) utilize panel data for households shopping online and in-store at the same European retailer and find that expenditure shares for unhealthy products are lower in online shopping trips relative to in-store shopping trips. However, Huyghe et al. do not address the endogeneity of the decision to shop online and their data is limited to a four month observation period over a restricted set of product categories (salty snacks, chips, chocolate, candy bars and sweets and chewing gum).[1] Milkman, Rogers, and Bazerman (2010) test whether increased delay in delivery

[1] In order to address these limitations, Huyghe et al. run an experiment that randomizes the purchasing environment each participant experiences and find further evidence to suggest that consumers are less likely to purchase indulgent

improves the healthfulness of grocery purchases utilizing online grocery orders generated from a panel of households. They find that the share of "should" items (vegetables and fruit) in an online grocery order increases the further in advance the order is placed relative to delivery. However, it is possible that the circumstances in which a consumer places an order far in advance of delivery are correlated with product choice; thus, a limitation of their work is that these findings may also not be causal.[2] In contrast, this paper utilizes an event study framework to estimate a causal effect of online grocery shopping on the healthfulness of grocery purchases.

I employ non-parametric, semi-parametric and parametric event study estimation strategies that utilize variation in the time the online grocery service became available, at different store locations, as a source of exogenous variation in the decision to shop online. In order to evaluate changes in the healthfulness of grocery purchases, I begin by evaluating shifts in the allocation of the households' grocery budget. I find that upon the introduction of the online shopping service, households begin to allocate a larger share of their grocery budget toward breakfast/lunch meats and frozen/refrigerated entrees at the expense of sugars/sweets/candies. Specifically, I estimate average treatment effects for the treated (ATT) that indicate a 5.8 and 2.6 percent increase in the average budget shares for breakfast/lunch meats and frozen/refrigerated entrees, respectively. This reallocation of funds comes at the expense of sugars/sweets/candies with estimates indicating a 2.7 percent decrease in the average budget share. I then quantify the impact of shopping online on four different measures of grocery purchase quality: the share of expenditure allocated towards healthful foods, the share of calories allocated towards healthful foods, calories per ounce of food purchased and a nutrient density score. I find a 1.0 percent decrease in the average calorie content per ounce of food purchased but do not find evidence for improvement in any of the other three quality measures.

The biggest limitation of this study is that the data featured in this paper only captures purchases from a specific supermarket retailer. I combat this limitation by analyzing heterogeneous effects of the introduction of the online shopping service in store locations where outside competition is not as prevalent. The idea behind this analysis is that it is more likely that purchases from

items when presented pictures of products.

[2]For example, buying groceries in advance of an event at which you plan to have a specific meal prepared.

the retailer compose the vast majority (if not all) of the households grocery purchases when outside competition is not as prevalent. I find empirical evidence that supports the hypothesis that households in these areas are less likely to exhibit patterns of retailer substitution upon the introduction of the online shopping service. This analysis also reveals that roughly 25, 50 and 24 percent of the main analysis TFP budget share estimates for breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated entrees can be explained by changing retailer substitution patterns upon the introduction of the online shopping service.

The remainder of this paper is structured as follows: Section 2 discusses the ways in which an online shopping environment might influence consumer choice. Section 3 describes the data. Section 4 presents the empirical model and Section 5 discusses the results. Section 6 explores retailer substitution patterns upon the introduction of the online shopping service, Section 7 summarizes robustness checks for the main specification and Section 8 discusses and concludes.

2 Predictions for Online Shopping

Online search functions and product recommendations change the way consumers "browse" when they are online compared to the in-store purchasing environment. While the in-store search path (or browsing experience) is dictated by the physical layout of the products in the store, the online search function generally does not impose a specific search path on the consumer. The online purchasing environment featured in this study, allows customers to search for products either by using the online search bar or by clicking through a hierarchy of product categories; according to the retailer, the search bar is the most popular form of search in the online purchasing environment.

The time and effort that brick and mortar retailers put into product displays and store design suggests that search paths play an important role in nudging customers towards purchases. Laibson (2001) indicates that the placement of products in checkout lanes can be interpreted as a "cue" that increases the marginal utility of consumption when an individual is exposed to it. According to this theory, in the absence of the cue, we would expect to see different consumption decisions being made. For example, the absence of a checkout lane when shopping online is likely to lead to decreased purchases of individual sized packages of candy bars, mints and gum; additionally, if you are less likely to be hungry when shopping online (another form of cue) we may expect to see less hunger driven impulse purchases. Reduced exposure to purchasing cues while searching for groceries online could lead to less unplanned purchasing.

Beyond differences in exposure to purchasing cues, there are many other elements of the online purchasing experience that could influence consumer choice. For example, time delays between the point of purchase and actual receipt of the goods could lead to differences in consumer choice across the two purchasing environments. A multiple selves framework in which our long-term selves value "should" products and our short-term selves value "want" products predicts that shoppers might purchase more healthful foods when shopping online simply because they are receiving the goods further in the future than they would if they were in the store (Schelling 1984, Bazerman et al. 1998, Thaler and Shefrin 1981). Additionally, the valuation of goods that are generally consumed immediately after purchase will likely decrease in the presence of time delays.

It could be difficult for consumers to verify the quality of a product when shopping online due to the inability to physically inspect it. Shiv and Fedorikhin (1999, 2002) suggest that symbolic product representation creates sensory distance, which decreases a product's vividness and makes immediate gratification less important.[3] Hence, in the online shopping environment, households may be less tempted to purchase indulgent products simply because they are represented by pictures rather than by the physical products themselves.

The literature discussed above generates predictions about how online grocery purchases should differ from in-store grocery purchases. Specifically, differences in exposure to purchasing cues, timing and the representation of products suggest that households may be less likely to make unhealthy purchases when shopping online.[4]

[3]Other research on this topic includes: Hoch and Loewenstein (1991), Loewenstein (1996) and Mischel et al. (1972).

[4]There is evidence to suggest that the level of social interaction in a purchasing occasion has influence over purchases. Specifically, in the context of food purchases, when individuals experience lower levels of social interaction, they may be prone to purchase less healthy items because they are less likely to face social judgement upon checkout (Goldfarb et al., 2015). Given the presence and wide-spread use of self-checkout lanes in grocery stores, whether or not online grocery shopping reduces social interaction in a meaningful way is unclear. If online grocery shopping were to reduce social interaction in a meaningful way, the mechanism would work in a competing direction of those men-

3 Purchasing Environment, Data & Summary Statistics

The supermarket chain featured in this study offers grocery products as well as a large variety of general merchandise items. Over the course of two and a half years, the retailer began to introduce an online shopping service which allows customers, for a small convenience fee, to select their groceries online, choose an appointment window with their local store, and pick-up and pay for their groceries at a designated "drive-through."[5] At the time of this study, the retailer offered products for purchase online at the same prices utilized in the store. The wait time to pick up groceries depends on the size of the order and the volume of orders the retailer receives at the time of the order.[6]

Over the time frame of this study, thirty-three store locations introduced the online purchasing service. The service was first introduced in March 2015 and was slowly rolled out to additional stores following the initial introduction of the program. Figure 1 illustrates the proportion of households that had access to the online shopping service over time.[7] In March 2015, roughly

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tioned in the body of the paper; hence, my ability to identify an effect of online grocery shopping on the healthfulness of purchases would be hindered.

[5]The convenience fee varies by the location but is between \$5 to \$10 per online shopping occasion. This convenience fee changed for some stores over the time period of this study.

[6]Unfortunately, I do not have access to the average wait time in my data; however, through personal experience, it seems as if same day pick-up is probable (if you place an order in the morning) and next day pick-up is very likely. There is one idiosyncrasy of the online shopping environment that is worth noting. First, shoppers are not able to use paper coupons when they shop online, but they are allowed to use digital coupons. Paper coupon offerings are primarily composed of the coupons that print when the customer checks out at the store. According to the retailer, they rarely publish paper coupons in their weekly ads and paper coupons are rarely redeemed.

[7]Figure 1 is generated utilizing the data for the households that engage in online shopping over the time frame of my data. I constructed the date the service was available to a given household based on the stores the household visited in the six months prior to any store having the service available (i.e. September 2015-February 2015). After constructing the store footprint for each household in the six months prior to introduction, I then assigned each household an availability date based on the first store (within their pre-online service footprint) that offered the online purchasing service. Roughly three thousand in-store households and three thousand online households did not visit

20% of households have access to the online shopping service. This proportion increases over time as more stores begin to offer the service and by March 2017, all of the households in my sample have access to the online shopping service.

This paper utilizes household level purchasing data at the day, store, universal product code (UPC) level before and after the introduction of the online purchasing service. For the majority of the paper, I utilize the purchasing data generated from the purchases of 25 thousand households that engage in online shopping from September 2014 through March 2017. However, the original data received from the retailer contains the entire purchasing history (over grocery products) for roughly 130 thousand households from September 2014 through March 2017. The original sample of households was constructed based on two criteria: (1) all households that had used the online service in that time frame; and (2) a random sample of households that had not yet used the service but have visited a store that offered the online purchasing service. I limit the households in my sample based on visit and purchase requirements in order to identify households that frequently shop with the retailer.[8] The final household sample consists of 34 thousand households, 25 thousand of which have used the online service and 9 thousand of which have not used the online service (over the time frame of my data). The data also contain detailed product information; including the

a store in the six months prior to introduction that later introduced the online purchasing service. Since I cannot assign these households an availability date according to the definition of availability outlined above, these households have been dropped from the main estimation results of this paper. However, the Online Appendix presents estimation results that include these households by basing the definition of online availability on the entire store footprint of the household. These results illustrate that the main findings of this paper are not sensitive to changes in the definition of online service availability.

[8]First, I drop households that do not visit the retailer at least once every two months (roughly 87,171 households). Next, I drop households that spend less than $20 per month on average (72 households). Additionally, there are small businesses in the data set so I drop "households" who spend more than $1,500 per month on average (2,290 households). I further limit the household sample to the group of households for whom I have demographic information on; this restriction drops 7% of the remaining eligible households from my sample. Additional households were dropped based on the definition of online service availability; these restrictions are discussed in the previous footnote. Sections 2 and 3 of the Online Appendix present results with the household loyalty and complier restrictions, respectively, removed. These results illustrate that my findings are insensitive to the restrictions made on the household sample.

product name, category, nutritional content and product attribute claims made by the manufacturer (i.e. organic, gluten free, etc.). Additionally, I can distinguish, at the household-day-store-UPC level, purchases that were made online from purchases that were made in the store.

Based on United States Department of Agriculture (USDA) classifications, I have assigned products to twenty-four different product categories according to the Thrifty Food Plan (TFP). I then collapse the purchasing data to the household-month level and define an indicator for online service use if the service was used to buy any products in the monthly basket.[9] I evaluate the impact of online service availability on combined (in-store and online) monthly grocery purchases because I am interested in understanding how using the online service impacts *overall* food purchases rather than understanding how online purchases differ from in-store purchases.[10]

Tables 1 and 2 compare the demographics and purchasing patterns of households who eventually adopt the online purchasing service (online households) to households who never adopt the online purchasing service (in-store only households). Comparisons between these two different types of shoppers are made over the time period in which no one had access to the online purchasing service. Table 1 illustrates that households who adopt the online purchasing service are more likely to be married, are more likely to be in a higher income group, are more likely to have children and tend to be younger. Table 2 indicates that the households that eventually adopt the online purchasing service, relative to the households who never adopt the online purchasing service (in-store only households), tend to spend more with the retailer per month ($448 vs. $331) and make more trips to the store each month (7.5 vs. 6.8), prior to online service adoption. Tests of

[9]Note that the data constructed for estimation is unbalanced because not every household visits the store each month. The loyalty restrictions that were placed on the households, discussed in the previous paragraph, require that the household visits the store bi-monthly.

[10]For example, suppose households use the online service only to buy healthy foods; if I were to analyze orders, I would find that online orders are much healthier than in-store orders. However, analysis at the order level ignores the fact that the same household may be supplementing all of their healthy online purchases with unhealthy in-store purchases that could perfectly balance their grocery purchases (in-store and online) to where they were before the household began shopping online. Hence, in this hypothetical scenario, online service use has had no impact on consumer choice; it has only impacted how the consumer chooses to purchase the various items in their basket.

the equivalence of means between the two groups reveal that online adoption households allocate a larger percentage of their grocery spending towards non-whole grains ; while in-store only households allocate a larger proportion of their budgets towards grains, dark-green vegetables, beans, dairy products (whole, reduced fat and cheese), poultry, breakfast/lunch meats and eggs; in contrast, non-adopters allocate more of their budget towards other vegetables, red meat products, fish, fats/condiments, coffee/tea, soft drinks, sugars/sweets/candies and frozen/refrigerated entrees.[11] In the analysis that follows, I restrict the majority of my attention to the subset of households that eventually use the online purchasing service (i.e. the online households).[12] The pre-existing differences between early online adopters and non-adopters suggest that the results of this paper will not be representative of the effect of online shopping for the general population of shoppers; however, the results of this paper are representative of the effect of online shopping for early adopters of the online purchasing service.[13]

Since I am evaluating the effect of online shopping on the combined (in-store and online) monthly purchases of these households, it is useful to understand the intensity with which households shop online in a month in which the purchasing service is used. Figure 2 presents the distribution of the proportion of sales that occur online in a month in which a household uses the online shopping service at least once. Interestingly, the distribution appears rather bimodal with a mass of online purchasing months clustered around 10-30 percent of sales occurring online and another

[11]There are no statistically significant or economically significant differences among the two household types in the budget shares of potato products, orange vegetables, whole fruits, fruit juices, nuts/seeds and soups.

[12]Section 3 of the Online Appendix presents and discusses estimates of the main analysis with all households (compliers and non-compliers) included in the data; given the nature of the estimation strategy (presented below) the two-stage least squares estimates that incorporate all households are remarkably similar to those which include only the online households. The in-store households (households that do not adopt the online purchasing service over the time frame of my data) are also utilized in the robustness checks in order to verify that the timing of online service introduction is uncorrelated with other factors within the store that might influence grocery purchases.

[13]It would be possible, theoretically, to make the results general utilizing the Heckman selection method (Heckman 1979). However, in order to employ this method I would need an instrument that induces people to shop online and is orthogonal to their grocery purchases.

cluster of purchasing observations around 100 percent of sales occurring online. Conditional on using the online purchasing service in a given month, forty percent of sales occur online in that month, on average.[14]

3.1 Purchase Quality Measures

In order to better understand the implications that online shopping may have for consumer health, I construct four different measures of purchase quality: monetary budget allocations over healthy foods, caloric budget allocations over healthy foods, the mean calorie content per ounce of food purchased and a nutrient density score (NDS).

The first two types of diet quality measures, expenditure and caloric budget shares allocated toward healthful foods, are based on the USDA's Thrifty Food Plan (TFP).[15] The TFP assigns products to twenty-four product categories (whole grains, whole fruits, dark-green vegetables etc.).[16] TFP product categories have been frequently used to measure the quality of food purchases in related literature; this literature includes, but is not limited to, Volpe et al. (2013), Handbury et al. (2015), Oster (2018), Hastings et al. (2019) and Hut (2018).[17]

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[14]The standard deviation for the proportion of sales that occur online, in an online purchasing month, is 0.287. Section 4 of the Online Appendix further documents the correlation between online shopping intensity and budget share allocations, as well as the pattern of service usage for online households.

[15]The TFP is one of four types of food plans developed by the USDA; the TFP was specifically developed in order to illustrate how a nutritious diet can be achieved with minimal resources (Carlson et al. 2006). As such, the TFP serves as the basis for maximum Supplemental Nutrition Assistance Program (SNAP or food stamp) benefits that a household can receive in a given month (Carlson et al. 2006).

[16]The process of mapping individual UPCs to the TFP product categories is discussed in detail in the online appendix. Thank you to Emily Oster and Stefan Hut for sharing their data "key" that maps UPCs to TFP product categories.

[17]Often these papers will also construct an expenditure score utilizing the TFP product categories. I am unable to construct the expenditure score in this paper because I do not have demographic information for the members of a household. Another popular measure of purchase healthfulness are nutrient indices. Following the literature, I have also analyzed changes in nutrient indices. However, one shortcoming of the nutrient index is that it does not penalize

Utilizing the TFP product classifications, I construct both the monetary and caloric budget share allocations for products that are classified as healthful. Specifically, following Volpe et al. (2013), Handbury et al. (2015) and Hastings et al. (2019), I classify the following TFP product categories as healthful product categories: whole-grains, potato products, beans, whole fruits, fruit juice, low fat dairy products, poultry, fish, nuts, eggs, unsweetened coffee/tea, dark-green, orange and other vegetables; while, the remaining product categories (non-whole grains, whole dairy products, cheese, red meat, breakfast/lunch meats, fats and condiments, soft drinks, sugars/sweets, soups and prepared entrees) are classified as unhealthful product categories. The third measure of purchase quality, calories per ounce, provides insight into the caloric density of the grocery bundle purchased; while the fourth measure, the nutrient density score, is a measure of the nutrient density of the calories purchased from the retailer. The nutrient density score increases in healthful nutrients and decreases in unhealthful nutrients; hence, for this measure, a higher number corresponds to a more healthful basket. The online appendix discusses the nutrition facts data utilized to construct these measures of purchase quality and also goes into further detail on how these measures were constructed.

Table 3 illustrates the relationship between the budget share allocations and the purchase quality measures. Specifically, Table 3 presents means for product category budget share allocations, healthful calorie share allocations, calories per ounce and nutrient density score by each quartile of the expenditure share allocated towards healthful foods. As the share of expenditure towards healthful product categories increases, the mean calorie share allocated towards healthful product categories also increases, while the caloric density of the grocery bundle purchased (measured by calories per ounce) generally declines and the nutrient density score increases.

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sugar content and snacks/sweets (sugars, sweets and candies in the TFP product classifications) is one of the product categories that experiences the biggest declines in expenditure and caloric budget shares. Details of nutrient index construction and the results are discussed in the online appendix.

4 Methodology

The gradual introduction of the online service lends itself nicely to an event study framework, where the treatment group are households that have the service available to them in year-month, m, and the control group is the set of households for whom the service is not yet available in year-month, m. I restrict the time periods of my data so that there is always a control group of households who have not yet received access to the online shopping service.[18] Explicitly, I only use data prior to October 2016, the month in which the last group received access to the online shopping service.

Section 6, of the Online Appendix, compares the demographics and pre-online service shopping patterns of the households assigned to different dates of availability; this analysis reveals that there are differences between the households who received access to the online purchasing service earlier compared to those that received access later. This analysis provides evidence that the timing that the online service became available was not randomly assigned across households/locations. Moreover, the decision to offer the online service at a given store location was strategically made by the retailer according to: (1) the proximity of the store to the corporate headquarters, (2) existing store infrastructure and (3) reasons that are potentially unknown to the researcher.[19] In order to correct for this form of endogeneity, I employ a household fixed effects model.

The identifying assumption in the household fixed effects model is that the timing of online service availability is unpredictable conditional on unit characteristics. In other words, conditional on time-invariant household characteristics and preferences, households may be unable to predict when the online service will be made available to them. I also include year-month fixed effects to control for any common changes in household demand for foods across time (e.g. retailer-wide

[18]Borusyak & Jaravel (2017) show that event study estimates suffer from under identification and negative weighting when all units or groups are treated.

[19]The first location chosen to pilot this service was close to the corporate headquarters, where it was presumably easiest to manage. Additionally, the ability of a location to provide this service is highly dependent on the existing infrastructure of the store. In order to effectively implement this program a location needs to have a designated space to stage groceries for customer pickup and a convenient entrance for employees to exit and re-enter when delivering groceries to customers' cars.

product promotions, seasonal dietary behavior, the release of press related to dietary guidelines, etc.). With the inclusion of year-month fixed effects, the identifying assumption is as follows: conditional on time-invariant household characteristics and preferences as well as year-month fixed effects, the time that the online service was made available to a particular household is independent of any other factors that might influence their demand for food products (e.g. retailer-wide product promotions, seasonal dietary behavior, the release of press related to dietary guidelines, the household's decision to begin a diet, store and/or region specific promotions, etc.).

In the subsections that follow, I discuss multiple approaches to testing the assumption that timing of online availability was truly random conditional on household and year-month fixed effects. These subsections are informed by the most recent applied econometrics literature which has shown that difference-in-differences and event study designs in which all units are treated suffer from underidentification; furthermore, underidentification can lead to misleading estimates of the average treatment effect on the treated (ATT) if not properly addressed (Boruskak & Jaravel, 2017; Abraham and Sun, 2018; Goodman-Bacon, 2018).[20]

4.1 Non-Parametric Event Study Estimates

In order to test the identifying assumption, researchers often employ a non-parametric event-study analysis and then evaluate whether outcomes began to change prior to the time of treatment. If there is no indication of anticipatory behavior, researchers use this as evidence to support the argument that the timing of treatment is truly random. Given the structure of my data, the non-parametric event-study analysis takes the following form:

$$y_{it} = \alpha + \sum_{s=-25}^{s=-2} \beta_s 1\{r = s\} + \sum_{s=0}^{s=18} \beta_s 1\{r = s\} + \gamma_i + \gamma_t + \epsilon_{it} \tag{1}$$

where y_{it} represents the outcome of interest, y, for household, i, at time, t. $1\{r = s\}$ is an indicator for being s periods away from the online service becoming available, γ_i represents the household fixed effect, which controls for time invariant household specific preferences and

[20]There are a plethora of papers on this topic; the ones listed here are the papers that have been most heavily utilized to help inform the analysis below.

characteristics, and γ_t is a year-month fixed effect.[21] Additionally, I follow the standard practice of omitting the time period immediately prior to treatment, $r = -1$.

As previously alluded to, a multicollinearity issue arises in the specification presented above. Specifically, because all units are treated, we are unable to separately identify the effects of relative time to treatment from calendar time in specifications that contain household fixed effects.[22] In order to break the multicollinearity between relative time and calendar time Borusyak and Jaravel (2017) suggest two options: (1) do not include two periods of pre-treatment relative time or (2) do not include household fixed effects.[23] Given the identifying assumptions discussed in the previous section, I modify the non-parametric event study by omitting an additional pre-treatment time period as follows:

$$y_{it} = \alpha + \sum_{s=-24}^{s=-2} \beta_s 1\{r = s\} + \sum_{s=0}^{s=18} \beta_s 1\{r = s\} + \gamma_i + \gamma_t + \epsilon_{it} \tag{2}$$

Estimation of equation (2) provides a visual representation of any pre-treatment trends that could exist and also allows me to conduct an F-test for the joint significance of the pre-treatment coefficients (e.g. $\beta_s = 0$ for all $s < 0$). According to Borsyak and Jaravel (2017), this F-test only has power to detect non-linear pre-treatment trends; however, there is no reason to expect pre-trends to be exactly linear.[24] The results of the F-tests uniformly reject the null hypothesis that all pre-treatment coefficients are equal to zero. These results indicate the presence of pre-treatment trends and imply that semi-parametric and parametric event study designs may be more appropriate in this setting.

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[21]Note that the household fixed effect controls for time invariant household specific preferences/characteristics while the year-month fixed effect controls for common preference shocks over time.

[22]We would also be unable to separately identify the effects of relative time to treatment from calendar time in specifications that contained treatment-cohort fixed effects.

[23]Borusyak and Jaravel also go on to explain that which option the researcher should choose depends on the source of "randomness" in the timing of treatment (e.g. unpredictable conditional on unit fixed effects vs. truly randomized assignment of treatment timing).

[24]Borusyak and Jaravel (2017) also state that the F-test is invariant to which two pre-treatment periods are omitted (or essentially restricted to zero).

Figure 3 provides a visualization of the β_s estimates for the product categories of non-whole grains and sugars/sweets/candies. These two product categories are highlighted in order to motivate the semi-parametric and parametric analyses that follow; the β_s estimates for all TFP product categories are illustrated in the online appendix. It is important to note that as you get further from the time of treatment, there is less data available (and less treatment cohorts available) to contribute to our estimates. As illustrated by Figure 1, the minimum number of leads before treatment that exist in the data for any cohort is 6 months. Hence, evaluating pre-treatment trends prior to 6 months before treatment can be misleading for two related reasons: (1) the data has less support over these relative time periods and (2) there is a different mix of treatment cohorts contributing to these estimates. Lastly, fitting trend lines through all twenty-four pre-treatment estimates can be misleading. The product category of non-whole grains provides the best example of this. When a trend line is fitted through all twenty-four pre-treatment estimates, it looks very flat and supports the argument for no anticipatory behavior. However, when you look more closely at the 6 months prior to treatment, there is a clear downward trend in the coefficients. For these reasons, Figure 4 takes a closer look at the estimated coefficients for seven months prior to online introduction and the seven months following introduction.

Figure 4 indicates that there is not a clear trend break around the time of treatment for the product category of non-whole grains. In contrast, there is a distinct trend break for the sugars/sweets/candies product category. Due to the existence of pre-trends, I now turn to semi-parametric and parametric event-study approaches in order to better understand and appropriately account for these pre-trends.

4.2 Semi-Parametric Event Study Estimates

Given the results and discussion of the non-parametric event study specification, I now estimate a semi-parametric event study specification which focuses, more directly, on the trends occurring in the 6 months prior to online service introduction. The non-parametric event study is modified as follows:

$$y_{it} = \alpha + \beta_{<-6}1\{r < -6\} + \sum_{s=-6}^{s=-2} \beta_s 1\{r = s\} + \sum_{s=0}^{s=18} \beta_s 1\{r = s\} + \gamma_i + \gamma_t + \epsilon_{it} \qquad (3)$$

In order for the estimate of $\beta_{<-6}$ to be an accurate representation of the ATT more than six periods prior to treatment, one of either of these two things must be true: (1) that all pre-treatment effects more than 6 months prior to online service introduction are homogenous (e.g. $\beta_s = \beta_{s\prime}$ for all $s < -6$ and $s\prime < -6$) or (2) that the weights implicitly assigned to each β_s for all $s < -6$, by the ordinary least squares procedure, in order to construct the estimate of $\beta_{<-6}$ are randomly assigned (Abraham Sun, 2018; Borusyak and Jaravel, 2017).

The online appendix tests for homogenous pre-treatment effects for all $\beta_{s<-6}$ and discusses the results in more detail. Ultimately I find evidence that $\beta_{s<-6}$ are homogenous for some but not all outcomes. When homogeneity does not hold, estimates of $\beta_{<-6}$ are not an accurate representation of the ATT more than six periods prior to treatment; however, we are not particularly interested in $\beta_{<-6}$ and the failure of homogeneity among the β_s, when $s < -6$, seems to have very little practical relevance for estimates of β_s, when $s > -6$, in this setting. However, estimates of $\beta_{<-6}$, when homogeneity among the $\beta_{s<-6}$ estimates does not hold, does have implications for the parametric specification presented shortly. These implications will become clearer when the parametric event study specification is presented and will be carefully discussed when the event study graphs are presented.

Visual representation of the β_s coefficients in the semi-parametric approach suggest linear pre-trends. In order to to produce event study estimates that directly account for these pre-trends, I now turn to a parametric event study specification.

4.3 Parametric Event Study Estimates

Modeling the trend in relative time directly allows for the identification of the treatment effect relative to the pre-existing relative time trend modeled. In other words, the identification assumption becomes the following: conditional on the controls, the timing of online service availability is uncorrelated with any deviation of the outcome from the modeled relative time trend. Note, we must also assume that there are no factors that affect the outcome, conditional on the controls, that occur simultaneously with the introduction of the online shopping service that would lead households to deviate from the modeled relative time trend (e.g. households don't also decide to go on a diet the same time that the online service is introduced).

The event study estimates from the parametric event study specification capture deviations from the relative time trend modeled. I utilize both the non-parametric event study and the semi-parametric event study to inform the appropriate relative time trend to model. Note that because all units are treated, modeling a relative time trend that is based on all relative time periods introduces multicollinearity between relative time to treatment and calendar time. Additionally, utilizing all pre-treatment relative time periods to model a relative time trend could be misleading for the reasons discussed in the non-parametric event study results. Subsequently, I model a linear relative time trend over seven periods of pre-treatment time (with all relative time periods $r < -6$ pooled into one time period, $r = -7$). This approach is comparable to modeling a linear pre-trend through the semi-parametric event study estimates.

Parametric event study estimates are generated utilizing the following event study specification:

$$y_{it} = \alpha + \delta r + \sum_{s=0}^{s=18} \beta_s 1\{r = s\} + \gamma_i + \gamma_t + \epsilon_{it} \tag{4}$$

where r indexes relative time to treatment.

4.4 Summary Measures

In order to easily compare and summarize results from the different specifications discussed in the previous subsections, I construct summary measures of the average treatment effect for the treated (ATT) over the first three months of treatment and the first six months of treatment, respectively. These summary measures are constructed similar in spirit to Abraham & Sun (2018). Each measure is defined as follows:

$$ATT_{3months} = \frac{\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2}{3} \tag{5}$$

$$ATT_{6months} = \frac{\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3 + \hat{\beta}_4 + \hat{\beta}_5}{6} \tag{6}$$

Note that a standard difference-in-difference estimate is simply a weighted average of post-treatment event-study estimates (Boruskak & Jaravel, 2017; Abraham and Sun, 2018; Goodman-Bacon, 2018). Hence, these summary measures can be thought of as standard panel difference-in-difference estimates over data that only contain 3 (or 6) post-treatment months.

5 Results

Due to the large number of product categories and outcomes analyzed by this paper, I have chosen to first present and discuss the $ATT_{3months}$ and $ATT_{6months}$ generated by each of the event study specifications discussed above. After reviewing these summary measures and determining which outcomes are of particular interest, I will then present the event study graphs for the product categories and outcomes with notable changes. The event study graphs for all outcomes have been made available in the online appendix.

5.1 Summary Measures

Thrifty Food Plan Budget Shares

Tables 4, 5 and 6 present the $ATT_{3months}$ and $ATT_{6months}$ for each of the TFP product category budget shares and event study specifications outlined above. Of the twenty-four product categories, there are nine product categories which produce ATT estimates that are of particular interest; these categories are: non-whole grains, dark-green vegetables, whole fruits, whole milk products, breakfast/lunch meats, fats/condiments, coffee/tea, sugars/sweets/candies, and frozen/refrigerated entrees. Of these nine, there are four product categories which consistently produce $ATT_{3months}$ and $ATT_{6months}$ that are statistically significant across all event study specifications: dark-green vegetables (+0.035 pp), breakfast/lunch meats (+0.134 pp), sugars/sweets/candies (-0.361 pp) and frozen/refrigerated entrees (+0.171 pp).[25] Furthermore, there are four product categories (non-whole grains, whole fruits, fats/condiments, and coffee/tea) that generally illustrate significant estimates of $ATT_{3months}$ and $ATT_{6months}$ in the non-parametric and semi-parametric specifications;

[25]The value provided in parenthesis is the average of all of the six ATT estimates presented in Tables 4, 5 and 6.

however, the results for these product categories are not robust to the parametric specification with seven pre-periods. In contrast, the final product category of interest, whole milk products, yields statistically insignificant estimates of $ATT_{3months}$ and $ATT_{6months}$ in the non-parametric and semi-parametric specifications, but estimates of $ATT_{3months}$ and $ATT_{6months}$ generated from the parametric specification with seven pre-periods are statistically significant and positive (+0.044 pp and +0.063 pp, respectively).

Thrifty Food Plan Calorie Shares

Tables 7, 8 and 9 present the $ATT_{3months}$ and $ATT_{6months}$ estimates for each of the TFP product category calorie shares and event study specifications outlined above. Of the twenty-four product categories, there are seven product categories with ATT estimates that are of particular interest; these categories are: whole fruits, whole milk products, low-fat milk products, fish products, breakfast/lunch meats, sugars/sweets/candies, and frozen/refrigerated entrees. Of these seven, there are three product categories which consistently produce $ATT_{3months}$ and $ATT_{6months}$ that are statistically significant across all event study specifications: breakfast/lunch meats (+0.027 pp), sugars/sweets/candies (-0.321 pp) and frozen/refrigerated entrees (+0.172 pp).[26] Furthermore, there are two product categories (low-fat milk products, fish products) that generally illustrate significant estimates of $ATT_{3months}$ and $ATT_{6months}$ in the non-parametric and semi-parametric specifications; however, the results for these product categories are not robust to the parametric specification with seven pre-periods. In contrast, the final product categories of interest, whole fruits and whole milk products, yields statistically insignificant estimates of $ATT_{3months}$ and $ATT_{6months}$ in the non-parametric and semi-parametric specifications, but estimates of $ATT_{3months}$ (for whole grains) and $ATT_{6months}$ (for whole fruit and whole grains) generated from the parametric specification are statistically significant.

Aggregate Measures of Healthfulness

Table 10 presents each of the $ATT_{3months}$ and $ATT_{6months}$ estimates for the aggregate health outcome measures discussed in section 3. The only outcome measure which consistently produces $ATT_{3months}$ and $ATT_{6months}$ that are statistically significant across all event study specifications

[26]The value provided in parenthesis is the average of all of the six ATT estimates presented in Tables 7, 8 and 9.

is calories per ounce (-0.43 calories per ounce).[27] Furthermore, the TFP healthy budget share outcome illustrates significant estimates of $ATT_{3months}$ and $ATT_{6months}$ in the non-parametric and semi-parametric specifications; however, the results are not robust to the parametric specification. Results for the TFP healthy calorie share and nutrient density score are generally statistically insignificant across all specifications.

5.2 Event Study Figures

In this sub-section I will present and discuss the event study figures for the non-parametric and semi-parametric event study specifications. The estimated trend lines from the parametric event study specifications will also be presented and discussed alongside the non-parametric and semi-parametric event study specifications. Recall, that the parametric event study estimates capture deviations from the estimated pre-trend in the outcome variable; as a result, it is imperative that the estimated linear pre-trends fit the pre-treatment event study estimates well.

In the event study figures presented in the body of this paper I focus on event study estimates that occur seven periods prior and seven periods post-treatment. This bandwidth of relative time periods was selected for four reasons: (1) the identifying assumption is most likely to be valid in the time periods immediately surrounding treatment (2) per the discussion in the non-parametric methodology section, these time periods have better support of the data, (3) the estimated parametric trend line is intended to fit the 7 seven periods leading up to to treatment, and (4) looking at all periods before and after treatment is aesthetically unpleasant. Event study graphs with all relative time periods are available in the online appendix.

Thrifty Food Plan Budget Shares

Figure 5 illustrates the non-parametric event study estimates that occur seven periods prior and seven periods post-treatment alongside the parametric time trend, which has been normalized to zero in the period immediately preceding treatment, estimated in equation (4). In contrast, Figure 6 illustrates the semi-parametric event study estimates that occur seven periods prior and seven periods post-treatment alongside the estimated parametric time trend. These figures are nearly

[27] The value provided in parenthesis is the average of all six ATT estimates presented in Table 10.

identical; the minor differences that exist between the two figures almost exclusively occur in the estimate of β_{-7} in the non-parametric approach vs. $\beta_{<-6}$ in the semi-parametric approach. The striking similarities between these graphs suggests that the homogeneity and/or random weight condition needed for the semi-parametric approach is not very restrictive in this setting.

In general, the estimated parametric time trend tends to fit the pre-treatment event-study estimates quite well. The only product categories which exhibit relatively minor deviations in the pre-treatment event-study estimates from the estimated trend line are those of dark green vegetables and fats/condiments. In the case of these two categories, the estimated trend line is downward sloping; however, the event study estimates that occur roughly three to four periods prior to treatment exhibit an upward trend. If we were to change the parametric approach to model the upward trend in pre-treatment event study estimates in the four periods prior to treatment, this would likely lead to the following changes in results: (1) the estimated $ATT_{3months}$ and $ATT_{6months}$ for dark green vegetables would no longer be statistically significant and (2) the estimated $ATT_{3months}$ and $ATT_{6months}$ for fats/condiments might be statistically significant and negative in sign. The relevance of this for the main finding of this paper is minor for reasons provided in the discussion; however, it is worth noting.

The product categories of breakfast/lunch meats, sugar/sweets/candies and frozen/refrigerated entrees illustrate fairly distinct deviations from the estimated parametric trend line. Of these three product categories, the results for sugar/sweets/candies is particularly salient for its lack of pre-trend and distinct jump upon treatment. In contrast, the product categories of dark green vegetables and coffee/tea illustrate more minor deviations from the estimated trend line. Specifically, it looks as if the event study estimate occurring three periods after treatment drives the significance of $ATT_{3months}$ and $ATT_{6months}$ for dark green vegetables, while the estimates of $ATT_{3months}$ and $ATT_{6months}$ for coffee/tea in the parametric specification are only significant at the ten percent significance level. Lastly, the lack of deviation of the event study estimates from the estimated parametric trend line suggest that we should not expect to see statistically significant estimates of $ATT_{3months}$ and $ATT_{6months}$ in the parametric specification for the product categories of: non-whole grains, whole fruits, whole milk products and fats/condiments; this is pretty consistent with the summary measure findings discussed previously.

Thrifty Food Plan Calorie Shares

Figure 7 illustrates the non-parametric event study estimates that occur seven periods prior and seven periods post-treatment alongside the parametric time trend, which has been normalized to zero in the period immediately preceding treatment, estimated in equation (4). Figure 8 illustrates the semi-parametric event study estimates that occur seven periods prior and seven periods post-treatment alongside the estimated parametric time trend. Again, these figures are nearly identical; the differences that exist between the two figures pretty much exclusively occur in the estimate of β_{-7} in the non-parametric approach vs. $\beta_{<-6}$ in the semi-parametric approach.

In general, the estimated parametric time trend tends to fit the pre-treatment event-study estimates quite well. The only product categories which exhibit concerning deviations in the pre-treatment event-study estimates from the estimated trend line are those for whole fruit and whole milk products. In these product categories, the non-parametric event study estimates appear to have a trend that is flatter than the parametric trend estimated. Intuition for why the parametric trend line is estimated with such a steep slope is best illustrated by the semi-parametric event study estimate for $\beta_{<-6}$; specifically, for both categories, $\hat{\beta}_{<-6}$ is much larger in magnitude than the non-parametric estimate of $\hat{\beta}_{-7}$ (whole fruits: 0.025 vs. 0.004) and (whole milk: 0.09 vs. 0.01). As a result, when the estimated pre-trend is larger than it should be, small deviations become amplified; this finding helps to explain why the summary measures for whole fruit and whole milk products were statistically insignificant in the non-parametric and semi-parametric approaches but significant in the parametric approach.

The product categories of breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated entrees illustrate fairly distinct deviations from the estimated parametric trend line; note that although the event study estimates for sugars/sweets/candies don't appear to have distinct deviations from the trend line, the scale on the graph for this product category covers a much larger range than all of the other product categories. Of these three product categories, the results for sugar/sweets/candies are once again particularly salient for the lack of pre-trend and distinct jump upon treatment. Fish products illustrate more minor deviations from the estimated trend line; estimates of $ATT_{3months}$ and $ATT_{6months}$ for fish average at -0.026 percentage points, across the three different specifications, and are statistically significant in the non-parametric and semi-parametric specifications but are not statistically significant the parametric specification. Lastly, the lack of deviation of the event study estimates from the estimated parametric trend line suggest that we should not expect to see statistically significant estimates of $ATT_{3months}$ and $ATT_{6months}$ in the parametric specification for low-fat milk products; this is consistent with the summary measure findings discussed previously.

Summary Healthfulness Measures

Figure 9 illustrates the non-parametric event study estimates that occur seven periods prior and seven periods pos-treatment alongside the parametric time trend, which has been normalized to zero in the period immediately preceding treatment, estimated in equation (4). Figure 10 illustrates the semi-parametric event study estimates that occur seven periods prior and seven periods pos-treatment alongside the estimated parametric time trend. In general, the estimated parametric time trend tends fits both sets of pre-treatment event-study estimates quite well. There are minor differences between the semi-parametric estimate of $\beta_{<-6}$ compared to the non-parametric estimate of β_{-7}; however, these differences don't seem to be pulling the trend line in any meaningful way for these outcomes.

The only healthfulness measure which illustrates distinct deviations from the estimated parametric trend line is that of calories per ounce. In contrast, the TFP healthy budget share and healthy calorie share measures closely follow the estimated pre-trend while the nutrient density score measure appears to have no real pre-trend and no deviation from zero post treatment. All of these results are consistent with the summary measure findings discussed previously.

5.3 Summary of Results & Discussion

There are three product categories which illustrate distinct and consistent changes in the allocation of dollars spent and calories purchased from the retailer: breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated entrees. Summarizing these results relative to their pre-online service mean, I have found a +5.8, -2.7 and a +2.6 percent change in the budget shares of breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated entrees, respectively.[28] I have also identi-

[28]The percent change utilizes the mean of the ATT estimates relative to the average TFP budget share allocation of online households before the online shopping service was introduced. For example, the percent change for breakfast/lunch meats is equal to $\frac{0.134}{2.32}x100$.

fied an +8.3, -1.6 and +3.0 percent change in the calorie shares of breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated entrees, respectively.[29]

While these changes may seem very small in magnitude, I would like to remind the reader that these estimates indicate the change in budget/calorie allocation after the *introduction* of the online service which does not necessarily translate into adoption by all households in the periods immediately following introduction. In fact, estimates of $ATT_{3months}$ and $ATT_{6months}$ indicate that the probability of having a month in which the household engages in online shopping in the 3 (6) months following introduction increases by 17.5 (19.0) percentage points, on avereage. This implies that if one is interested in the average effect of engaging in online shopping in a given month, the average effect of the introduction of the online shopping service should be scaled by the proportion of the households that actually shop online upon introduction; in this case that amounts to multiplying each of the $ATT_{3months}$ and $ATT_{6months}$ by roughly 5 (or $\frac{1}{0.18}$). Even after re-scaling these estimates to account for adoption rates that are less than unity, the average household in this sample only makes 40% of their purchases online in an "online" month and the online appendix illustrates that the amount with which budget shares change is correlated, fairly linearly, with online shopping intensity.

Despite finding changes in the budget and calorie allocations across TFP product categories, the summary measures of healthfulness generally do not illustrate any change upon the introduction of the online shopping service. For the TFP healthy budget and calorie shares this is perhaps unsurprising given that breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated entrees are all classified as unhealthful product categories. The lack of change in the nutrient density score could also be explained by the reallocation of expenditure/calorie purchases being made primarily among products that are classified as unhealthy. However, it also is worth mentioning that due to recent changes in nutrition labeling laws, further discussed in the online appendix, the nutrient density score measure presented in this paper is not penalized for the sugar content of purchases which could also, in part, explain a lack of change in the NDS score. In contrast, changes in the calorie density of the basket (measured by calories per ounce) are quite striking. The difference in

[29]The percent change utilizes the mean of the ATT estimates relative to the average TFP calorie share allocation of online households before the online shopping service was introduced.

the calories per ounce outcome, relative to the other healthfulness measures, could be partly due to increased purchases of water and diet beverages which are not accounted for in the TFP product categories and which would "wash" out in the NDS measure because they contribute no calories nor nutrients to this measure.

The fact that the magnitudes for the TFP product category allocations are small and that most of the healthfulness measures exhibit no change should not be surprising. In general, what I believe we can learn from this exercise is that purchasing cues and the shopping environment itself can influence your decision to purchase of a handful of items, but the extent to which these items influence measures of the healthfulness of your purchases is limited. What really matters for how healthy purchases are is what consumers *intend* to buy, not what they bought impulsively. However, it is still worth noting that the estimates presented above support the prediction that the online shopping environment reduces the incidence of sugar/sweet/candy purchases from this retailer. Furthermore, if households do not change their food purchasing patterns outside of the retailer of study upon the adoption of the online shopping service, then the estimated changes in the caloric content of food purchased suggest that online shopping could contribute to slow but gradual improvements in consumer health through weight loss. The next section further explores the role that retailer substitution patterns may play in these estimates.

6 Online Shopping & Retailer Substitution Patterns

If consumers change retailer substitution patterns differentially across product categories when shopping online, then consumer "crowd-in" (or "crowd-out") could explain the changes we observe in grocery basket composition as well as the documented changes in purchase quality measures. For example, suppose that the households in this study, prior to using the online shopping service, purchased produce at other grocery stores (health food grocery stores, etc.) and/or a farmers market. Further suppose that after transitioning to the online shopping service, these households stopped buying produce from other retailers and began purchasing more produce with the retailer in this study. In this hypothetical scenario, we would expect to see the budget share for fruits and vegetables increase, but these shifts are the result of changing retailer substitution patterns rather than a change in the relative amount of fruits and vegetables purchased.

Similar to Pozzi (2013), the households studied in this paper also exhibit increases in monthly grocery expenditure when they begin using the online shopping service.[30] Following the estimation strategy outlined in section 4, but with expenditures instead of budget shares as the outcome variable, summary ATT measures indicate that households spend \$8.96 more per month (roughly a 2% increase over average pre-online service expenditures), upon the introduction of the online shopping service.[31]

I explore whether changing retailer substitution patterns after online adoption can explain the documented changes in grocery purchases by analyzing heterogeneous outcomes by the level of local competition faced by the store location. This strategy exploits variation in the level of outside competition a given store location faces. The idea, in the extreme case, is that store locations that face no outside competition should capture the entirety of a household's grocery purchases both before and after the introduction of the online shopping service. Hence, for these store locations, the introduction of the online shopping service should not affect a household's retailer substitution patterns because no other retailers exist in the area. I begin my competition analysis by identifying stores that are likely to capture the entirety of a household's grocery purchases.

Utilizing information on the local competition facing each store location, I identify store locations that do not compete with all of the retailers major competitors. Using this information, I split store locations (and as a result online shoppers) into two groups: those whose online service availability was determined by a store location that does not compete with at least one major competitor and those whose online service availability was determined by a store location that competes with all major competitors.

[30]Pozzi (2013) documents that online grocery services can lead consumers to divert their grocery business away from other retailers, toward the online shopping service provider. Pozzi finds evidence that households living in areas with higher levels of retailer competition increase monthly expenditures with the online retailer at a higher rate than households living in areas with relatively lower levels of outside competition.

[31]Note that these figures are conditional on arrival to the store in a given month. In other words, this number is telling us how much more a household spends *when they shop with the retailer* after the introduction of the online shopping service compared to what they spent *when they shopped with the retailer* before the introduction of the online shopping service. Months of no shopping with the retailer, e.g. \$0 months, have not been imputed into the data.

6.1 Empirical Strategy

I modify the non-parametric, semi-parametric and parametric event study regressions to allow for heterogeneous effects according the the level of local competition faced by a store location. Similar in spirit to Abraham & Sun (2018), the event study specifications are modified in the following manner:

Non-Parametric:

$$\begin{aligned} y_{it} = \alpha + \sum_{s=-24}^{s=-2} \beta_s 1\{r=s\} + \sum_{s=-24}^{s=-2} \beta_{s,low} 1\{r=s\} 1\{lowcomp_i\} + \sum_{s=0}^{s=18} \beta_s 1\{r=s\} \\ + \sum_{s=0}^{s=18} \beta_{s,low} 1\{r=s\} 1\{lowcomp_i\} + \gamma_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{7}$$

Semi-Parametric:

$$\begin{aligned} y_{it} = \alpha + \beta_{<-6} 1\{r<-6\} + \beta_{<-6,low} 1\{r<-6\} 1\{lowcomp_i\} + \sum_{s=-6}^{s=-2} \beta_s 1\{r=s\} \\ + \sum_{s=-6}^{s=-2} \beta_{s,low} 1\{r=s\} 1\{lowcomp_i\} + \sum_{s=0}^{s=18} \beta_s 1\{r=s\} \\ + \sum_{s=0}^{s=18} \beta_{s,low} 1\{r=s\} 1\{lowcomp_i\} + \gamma_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{8}$$

Parametric:

$$y_{it} = \alpha + \delta r + \delta r 1\{lowcomp_i\} + \sum_{s=0}^{s=18} \beta_s 1\{r=s\} + \sum_{s=0}^{s=18} \beta_{s,low} 1\{r=s\} 1\{lowcomp_i\} + \gamma_i + \gamma_t + \epsilon_{it} \tag{9}$$

where $1\{lowcomp_i\}$ is an indicator variable that takes the value one when the store that determines household i's online availability is located in an area where at least one major competitor does not exist.

The $ATT_{3months}$ and $ATT_{6months}$ summary measures are constructed as presented in equations (5) and (6) with a minor modification. Specifically, $\hat{\beta}_s = \hat{\beta}_s$ when evaluating the effects for households that have all major competitors present, while $\hat{\beta}_s = \hat{\beta}_s + \hat{\beta}_{s,low}$ when evaluating the effects for households that are missing at least one major competitor.

6.2 Results

Similar to the previous results discussion, I will first present and discuss the summary measures and then present the event study figures.

Summary Measures

Tables 11, 12 and 13 contain the estimates of $ATT_{3months}$ and $ATT_{6months}$ for each of the event study specifications specified above and by whether or not the store that determined household i's online availability is in an area where all major competitors are present (high competition areas) or in an area where at least one major competitor is not present (low competition areas).

Table 11 illustrates that the high competition group estimates of $ATT_{3months}$ and $ATT_{6months}$ for total expenditure are statistically significant across all event study specifications; the ATT estimates range from \$10.89 to \$15.41. In contrast, the total expenditure results for the low competition group are statistically significant in the non-parametric and semi-parametric specifications, ranging from \$8.08 to \$9.37, but are not statistically significant and drastically differ in the parametric specification where $ATT_{3months} = \$1.05$ and $ATT_{6months} = -\$1.52$.

Tables 12 and 13 compare TFP budget share outcomes for the two groups of households; these tables focus specifically on the TFP budget shares that exhibit consistent and significant changes upon online introduction for at least one competition regime. The online appendix contains these estimates for all twenty-four product categories by the two groups of households. Tables12 and 13 present results for the product categories of non-whole grains, dark-green vegetables, whole fruits, breakfast/lunch meats, fats/condiments, coffee/tea, sugars/sweets/candies and frozen/refrigerated entrees. Of these eight categories, the product categories which produce significant ATT estimates across all specifications and under both competition regimes are: breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated entrees. Comparisons of the ATT estimates across the two competition regimes indicate that the magnitude of the effect of the introduction of the online shopping service is subdued in areas where at least one major competitor is missing. The means of the ATT estimates when all major competitors are present are +0.17 pp, -0.58 pp and +0.22 pp for breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated entrees, respectively, compared to when at least one major competitor is missing: +0.10 pp, -0.18 pp, +0.13 pp. In contrast, the results for dark green vegetables and fats/condiments are statistically significant (across all specifications) for the group of households that have all major competitors present (+0.05 pp and -0.05 pp) but are not statistically significant when at least one major competitor is missing (+0.02 pp and -0.01 pp). The remaining three product categories, non-whole grains, whole fruits and coffee/tea, are statistically significant in the non-parametric and semi-parametric approach for the group of households that are missing at least one major competitor but these results are not robust to the parametric specification.

These summary results provide preliminary evidence to suggest that changes in TFP budget allocations still persist even when there is no robust evidence of retailer substitution upon the introduction of the online shopping service. In order to get a deeper understanding of the summary ATT measures, the next subsection presents the non-parametric and semi-parametric event study figures under each competition regime.

Event Study Figures

Figure 11 illustrates the non-parametric and semi-parametric event study estimates that occur seven periods prior and seven periods post-treatment alongside the parametric time trend, which has been normalized to zero in the period immediately preceding treatment, by the presence and absence of major competitors for the outcome of total expenditure. Figure 11 illustrates that in both levels of outside competition (presence of all major competitors vs. absence of at least one), the differences that exist between the non-parametric and semi-parametric figures exclusively occur in the estimate of β_{-7} in the non-parametric approach vs. $\beta_{<-6}$ in the semi-parametric approach. In the case where are all major competitors are present, the estimate of $\beta_{<-6}$ is distinctly larger in magnitude than β_{-7}. As a result the estimated parametric pre-trend looks a bit too negatively sloped when imposed over the non-parametric event study estimates; the implication of this is that the parametric estimates of $ATT_{3months}$ and $ATT_{6months}$ are likely a little larger in magnitude than they should be; the parametric ATT estimates are about \$15 vs. roughly \$12 in the non-parametric and semi-parametric approaches. Regardless, there is a significant jump in total expenditure around the time that the online service is introduced for the group of households that have all major competitors present. In contrast, for the group of households where at least one major competitor is missing, there is no clear change in the total expenditure outcome. The event study estimates for the periods prior to treatment and the periods immediately following treatment all hover around \$7 to \$12. This helps to explain why the ATT estimates are positive and fairly large in the non-parametric and semi-parametric specifications but are not significant and close to zero in the parametric specification.

Figures 12-14 illustrate the non-parametric and semi-parametric event study results, alongside the parametric trend line, for the TFP product categories of breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated entrees. For these product categories, the differences between the non-parametric and semi-parametric figures are negligible; estimates of $\beta_{<-6}$ vs. β_{-7} are slightly different but their differences are small and importantly the estimate of $\beta_{<-6}$ doesn't seem to have influence over the parametric trend line estimated. For the outcomes of breakfast/lunch meats and frozen/refrigerated entrees budget shares, Figures 12 and 14, the event study estimates across the different competition regimes illustrate fairly similar patterns of change but at different magnitudes. The post-treatment event study estimates when all major competitors are present for breakfast/lunch meats and for frozen/refrigerated entrees hover around +0.20 pp, while the post-treatment event study estimates when at least one major competitor is missing hover around +0.10 pp. In contrast, the outcome of sugars/sweets/candies budget shares, Figure 13, illustrates results that are less mirrored across the two competition regimes. In the case where are all major competitors are present, there is a clear jump in the budget share for sugars/sweets/candies around the time that the online service is introduced. In contrast, for the group of households where at least one major competitor is missing, there is a much smaller and nuanced change present in the sugars/sweets/candies budget share; the coefficients on the event study estimates for the periods prior to treatment are all positive but not statistically significant while the first five event study estimates immediately after treatment are all negative with one estimate, β_1, being statistically significant. The fading of the effect as you get further from treatment and the statistical significance of β_1 is likely the reason that the estimates of $ATT_{3months}$ are consistently negative and statistically significant, while the $ATT_{6months}$ tend to be closer to zero and not statistically significant for the group of households that are missing at least one major competitor.

Figures 15 and 16 illustrate the non-parametric and semi-parametric event study results, alongside the parametric trend line, for the TFP product categories of dark green vegetables and fats/condiments. These figures reflect the summary ATT findings quite well. Specifically, the product category of dark green vegetables illustrates a small jump upon the introduction of the online shopping service for households where all major competitors are present but does not illustrate a distinct change when at least one major competitor is missing.[32] The fats/condiments estimates, presented in Figure 16, illustrate a handful of statistically signifiant post treatment event study estimates, that are small in magnitude, for the group of households that have all major competitors present; in contrast, the group of households that are missing at least one major competitor exhibit no change upon treatment.

Figures 17-19 illustrate the non-parametric and semi-parametric event study results, alongside the parametric trend line, for the TFP product categories of non-whole grains, whole fruit and coffee/tea. In the case of non-whole grains, Figure 17, the estimated parametric trend line fits the event study estimates well and helps to explain why the ATT results were not robust to the parametric specification. The results for coffee/tea and whole fruits exhibit minor deviations from the parametric trend line estimated. Specifically, for coffee/tea both competition regimes exhibit minor deviations from the estimated parametric trend line in the two periods immediately following online introduction; for whole fruits only the households that have at least one major competitor missing exhibit deviations from the estimated parametric trend line. The results for these product categories align well with the summary ATT estimates discussed previously.

Summary and Discussion

Analyzing heterogenous results according the competitive environment surrounding the store location has revealed a number of important findings. First, households who gain access to the online shopping service from a store location where at least one major competitor is missing do not exhibit robust or distinct changes in total monthly expenditures upon the introduction of the online shopping service; this finding is in stark contrast to the households that gain access from a store location that has all major competitors present where ATT estimates indicate a \$10-\$15 per month increase in expenditure. This finding is relevant for two reasons: first, this finding

[32]It is worth noting that the event study estimates of $\beta_{<-6}$ vs. β_{-7} are quite different for the group of households that have all major competitors present; specifically, $\beta_{<-6}$ is greater than β_{-7} which is likely leading to a steeper slope for the parametric trend line. Ultimately, this just means that the parametric ATT estimates are likely a bit larger than they should be (0.07 pp in the parametric approach vs. 0.04 pp in the non-parametric/semi-parametric approaches).

illustrates that the online shopping service may be used as a means to build retailer loyalty in geographic regions where outside competition is abundant and second, this finding supports the hypothesis that households located in regions where at least one major competitor is missing do not change retailer substitution patterns upon the introduction of the online shopping service.

Analysis of the heterogenous effects on TFP budget shares, by the two competition regimes, further illustrate the role that retailer substitution patterns may play in the estimates presented in section 5. Mean ATT estimates of the effect of online introduction on the budget shares of breakfast/lunch meats, sugars/sweets/candies and frozen/refrigerated entrees for the group of households where at least one major competitor is missing are +0.102 pp, -0.181 pp and +0.127 pp, respectively; in contrast, the analysis in section 5 produced mean ATT estimates of +0.134 pp, -0.361 pp and +0.17 pp. Comparisons of these estimates suggest that roughly 25%, 50% and 24% of the magnitude of the main estimates could be due to retailer substitution patterns, respectively.[33] Furthermore, it seems that all of the changes identified in the dark green vegetables product category in the main analysis can be explained by households crowding their dark green vegetable purchases into the retailer of study, at the expense of major competitors.

7 Robustness Check Summary

This section summarizes further robustness checks performed. I first test whether the timing of the introduction of the online shopping service was correlated with other changes that may be influencing grocery purchases; this test also provides some assurance against multiple hypothesis testing. Then, despite assurances from the retailer, I verify that the main results of the paper are not driven by differences in product offerings across the two purchasing environments.

In order to test whether or not there are other changes influencing demand that occur simultaneously with the introduction of the online purchasing service, I perform an event study analysis that estimates the effect of the availability of the online purchasing service for the subset of households that never adopt the online service (i.e. in-store only households). Section 9, of the Online

[33]These percentages are calculated in the following manner: $1 - \frac{A\bar{T}T_{lowcomp}}{A\bar{T}T_{main}}$. This implicitly assumes that $\frac{A\bar{T}T_{lowcomp}}{A\bar{T}T_{main}}$ is the proportion of the main estimate that cannot be explained by changing retailer substitution patterns.

Appendix, presents and discusses the results of this robustness check in further detail. In summary, I find no evidence to suggest that online service availability has any significant effect on the budget share allocations of households who never use the online purchasing service; this finding provides evidence that the timing of the introduction of the online service was uncorrelated with other factors (e.g. store level and/or regional promotions) that might also influence demand.

Despite assurances from the retailer that the grocery products available online were the same as those available in the store, I verify that limited online product offerings are not responsible for the main results of this paper. In Section 10, of the Online Appendix, I show that by January 2016 the UPCs purchased online account for the vast majority of purchases made in the store. Hence, a conservative date by which online product offerings were representative of in-store product offerings is January 2016. I then test whether limited product offerings are driving the results of the previous analysis by evaluating heterogeneous effects according to the timing of treatment (e.g. treatment prior to 2016 and treatment post 2016). The results of these regressions, presented and discussed in Section 10 of the Online Appendix, provide evidence that limited online product offerings cannot explain the main results of this paper.

The results of these robustness checks provide evidence that the timing of the introduction of the online service is uncorrelated with other factors that could influence household demand and that the main results of this paper are robust to tests of whether or not online product offerings are representative of in-store product offerings.

8 Discussion & Conclusion

This paper analyzes the effect of online grocery shopping on the quality of grocery purchases. I find that households allocate a significantly larger share of their total grocery expenditures toward breakfast/lunch meats and frozen/refrigerated entrees at the expense of sugars/sweets/candies when shopping online. In addition, I find that the calorie density of grocery purchases is lower in the months in which households engage in online shopping but do not find evidence of improvement in the allocation of expenditure (or calories) across healthful product categories nor in the nutrient density of purchases. The findings of this paper illustrate that consumer choice is sensitive to variation in purchasing environments, but the extent to which purchases change along measures of healthfulness is limited. Differences in exposure to purchasing cues, time delays between order and receipt of the goods and the representation of products with pictures are all potential mechanisms that could contribute to small changes grocery purchases.

Online grocery purchases amounted to $20.5 billion dollars in sales and represented 4.3 percent of all groceries purchased in 2016 (Nielsen & FMI, 2017). Over the past couple years, as brick and mortar retailers begin to offer online grocery services and web based retailers (Amazon, etc.) have also entered the online grocery market, online grocery shopping has become more and more commonplace. Due to increasing accessibility and consumer adoption of online grocery services, it is projected that within the next five to ten years, 20 percent of all grocery purchases will be conducted online (Nielsen & FMI, 2017). Given the large projected growth in the online grocery business, my results have immediate implications for policy as well as for online, in-store and blended retailers.

The findings of this paper suggest that elements of the purchasing environment can contribute to impulsive purchases of sugars/sweets/candies. Hence, policies interested in reducing these purchases could do so by reducing exposure to purchasing cues for these products when designing school cafeterias and/or in the design of nutrition of assistance programs. Changing the level of purchasing cues that exist in a purchasing environment, for example, is probably a relatively cheap policy to implement, is unlikely to lead to worse quality outcomes and may even slightly improve the composition of purchases. The negative consequence of such a policy is the potential for lost revenue if consumers aren't successfully "nudged" toward another product.

My findings also have implications that extend beyond food policy. A retailer interested in boosting online purchases might do so by replicating purchasing cues, that currently exist in the in-store shopping experience, in their web design. For example, the retailer could incorporate "check-out lane" pop-ups or more sophisticated product recommendation banners into their web design. On the other hand, a traditional brick and mortar retailer interested in boosting in-store sales may also be able to do so by increasing the level of purchasing cues that exist in their in-store shopping environment. Lastly, heterogenous results for the effect of online shopping on total expenditure indicate that retailers will see larger returns on investment in online shopping services (development, marketing, promotions, etc.) in regions where outside competition is more prominent.

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10 Figures

Figure 1: Online Shopping Service Availability

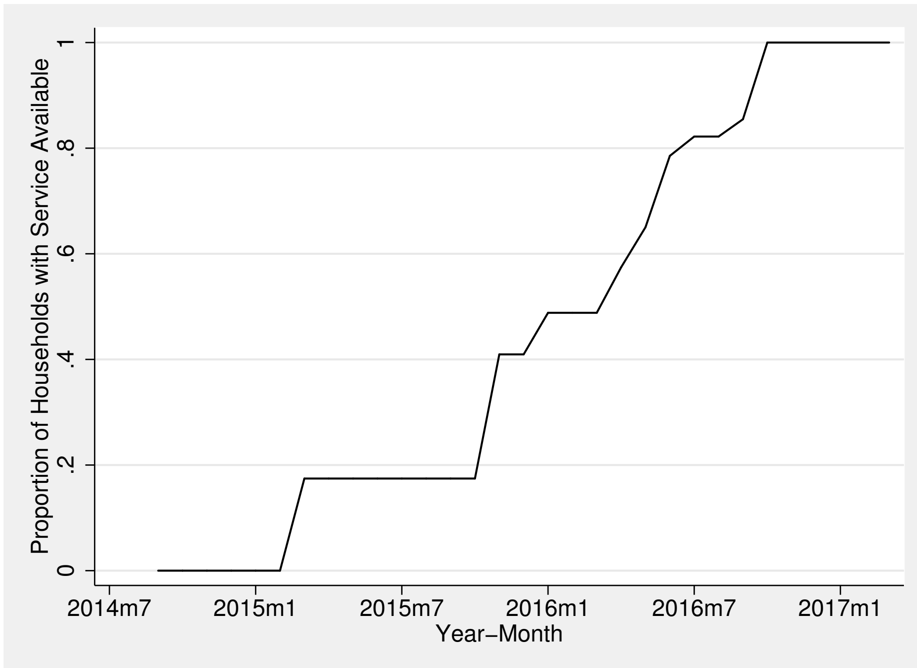


Figure 1 illustrates the proportion of households who have access to the online purchasing service over time.

Figure 2: Distribution for the Share of Expenditure Online | Online Month

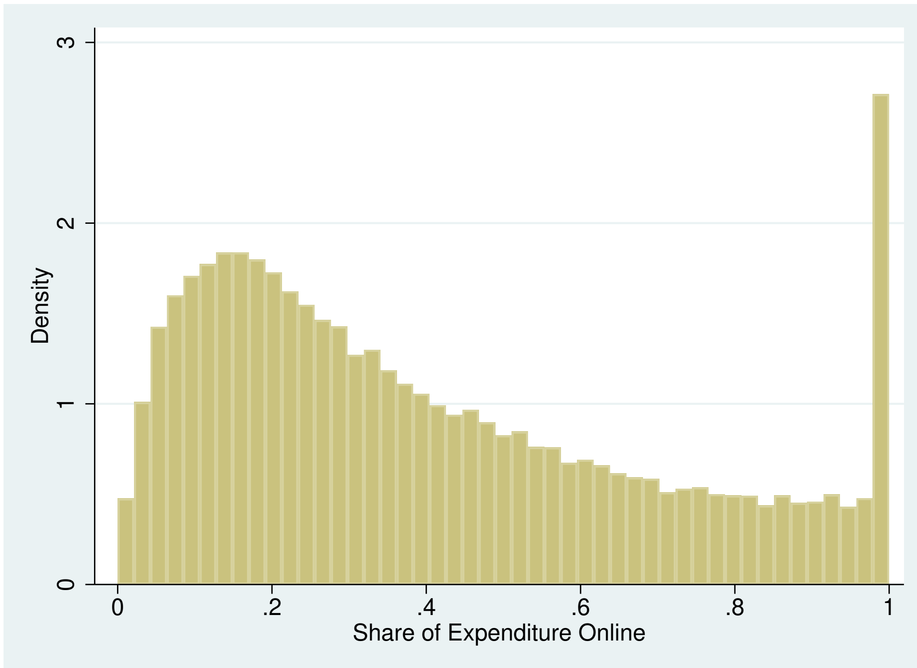


Figure 2 illustrates the distribution of the proportion of sales being made online conditional on the household using the online service at least once in the month. The average proportion of sales occurring online, in an online month, is 0.409 with a standard deviation of 0.287.

Figure 3: Non-Parametric Results: Non-Whole Grains and Sugars/Sweets/Candies

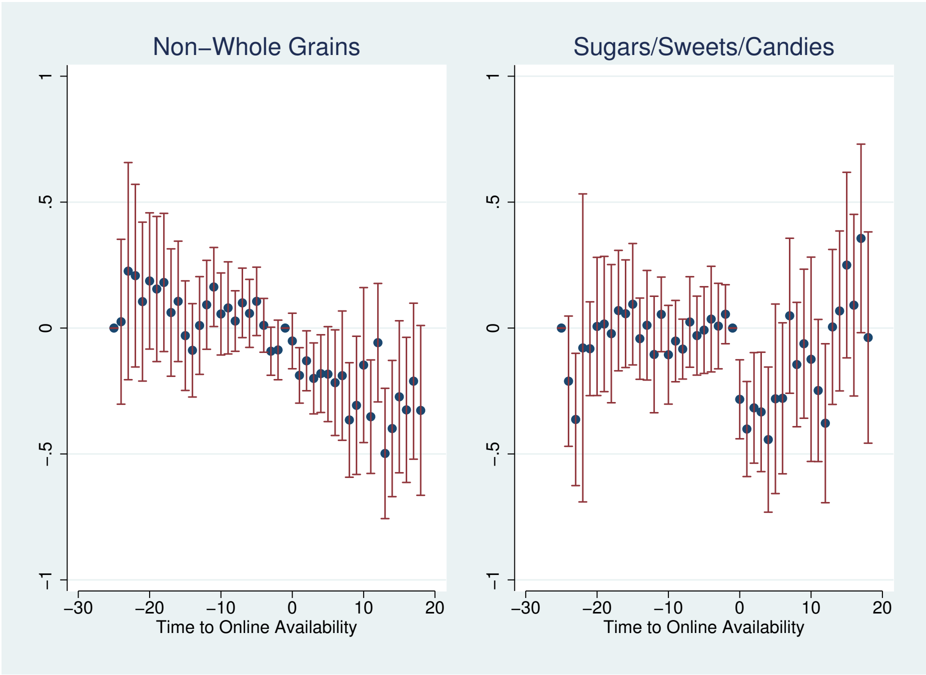


Figure 4: Non-Parametric Results: Non-Whole Grains and Sugars/Sweets/Candies

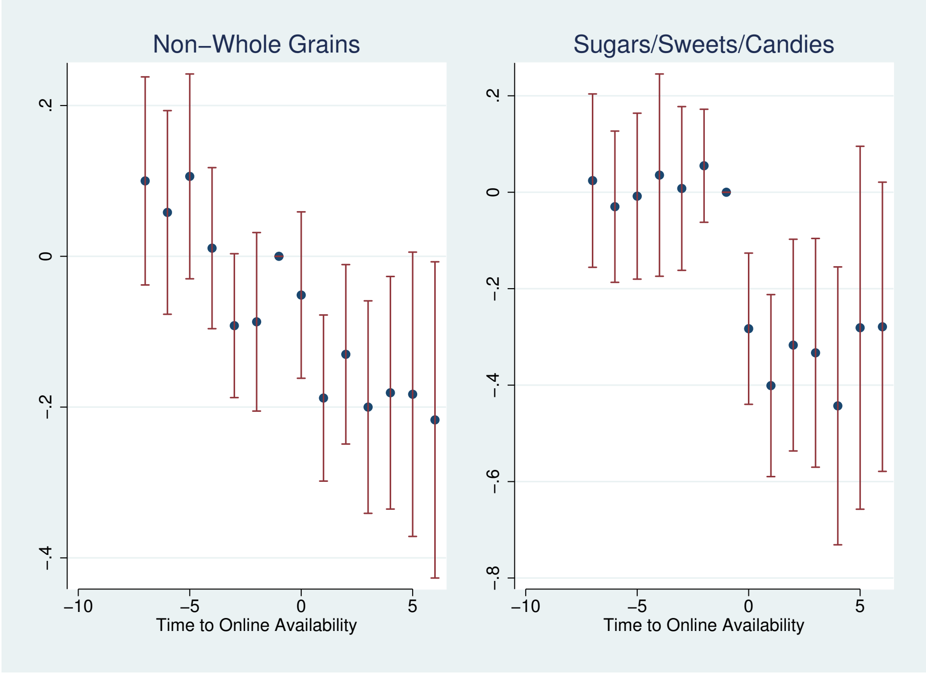


Figure 5: Non-Parametric Event Study Estimates with Parametric Trend Line
TFP Budget Shares

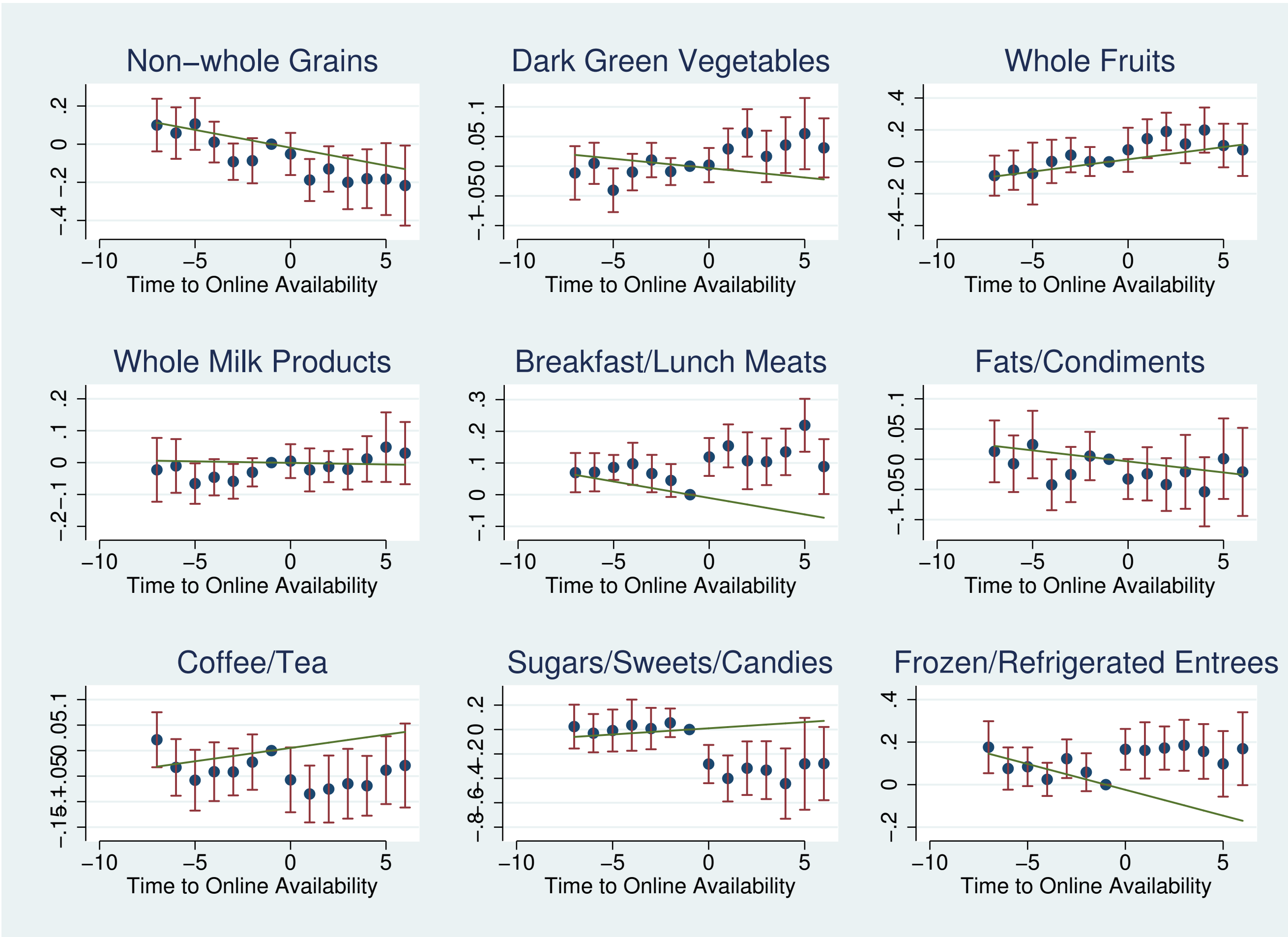


Figure 6: Semi-Parametric Event Study Estimates with Parametric Trend Line
TFP Budget Shares

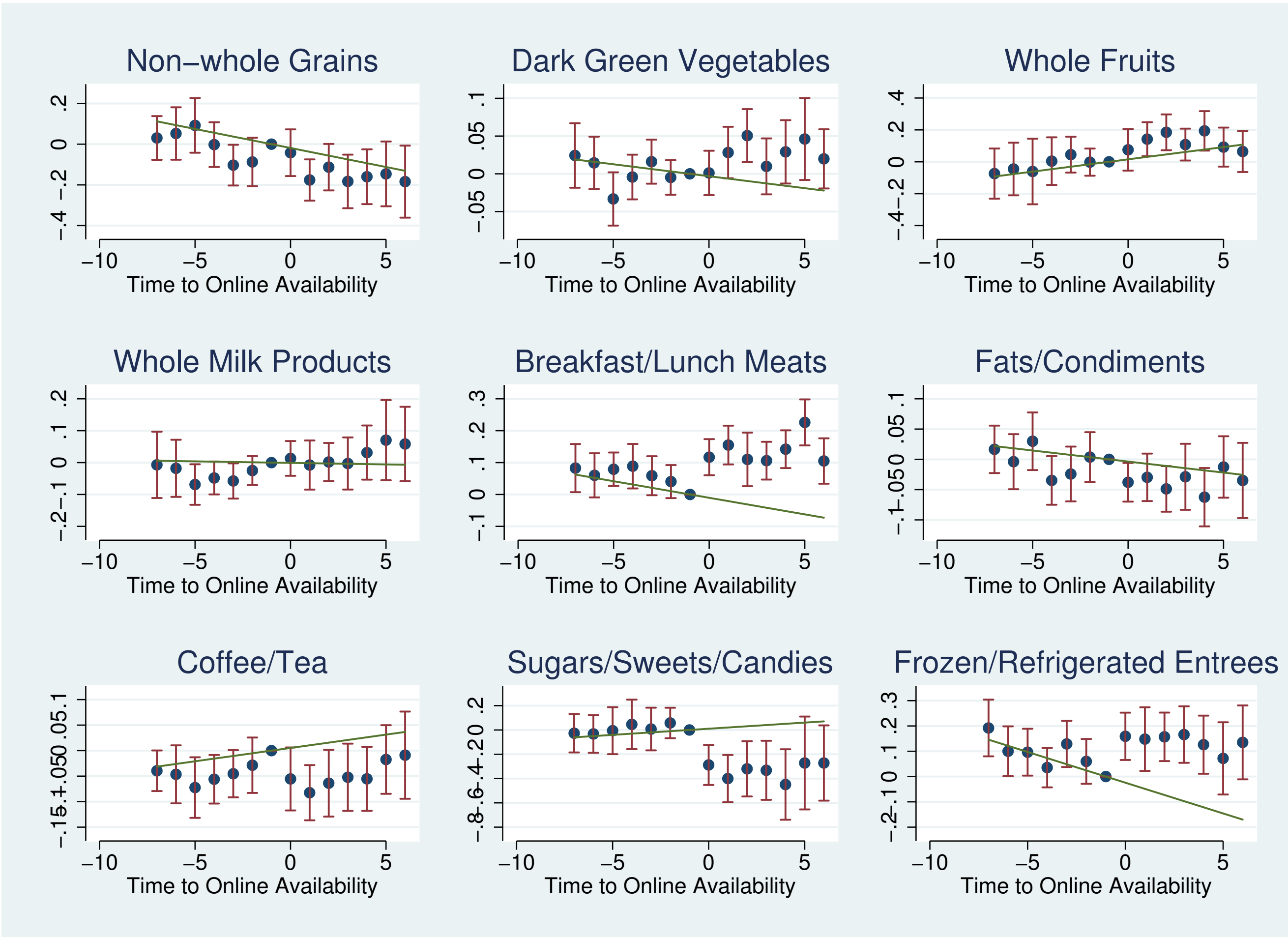


Figure 7: Non-Parametric Event Study Estimates with Parametric Trend Line
TFP Calorie Shares

Figure 8: Semi-Parametric Event Study Estimates with Parametric Trend Line
TFP Calorie Shares

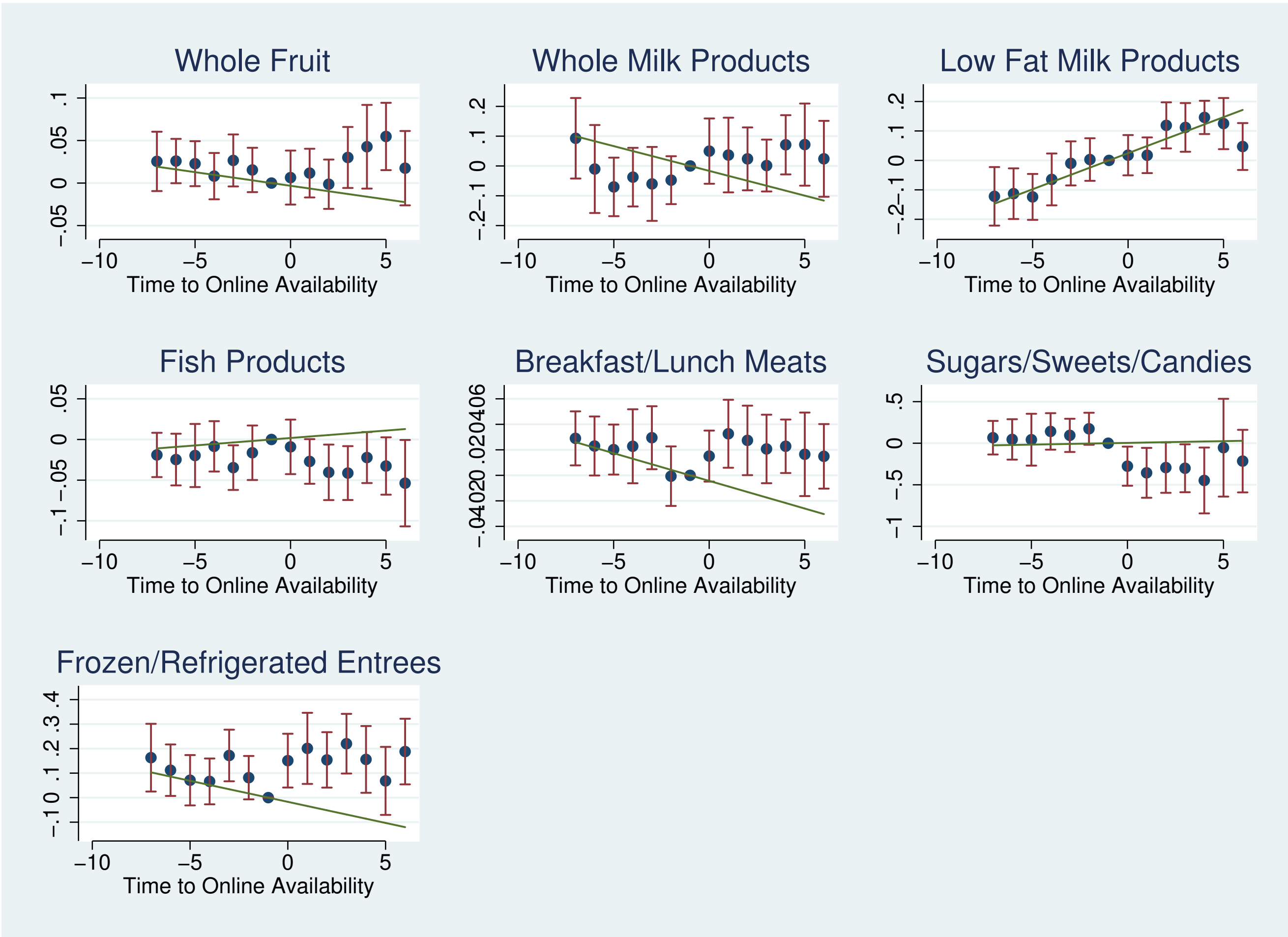


Figure 9: Non-Parametric Event Study Estimates with Parametric Trend Line
Healthfulness Measures

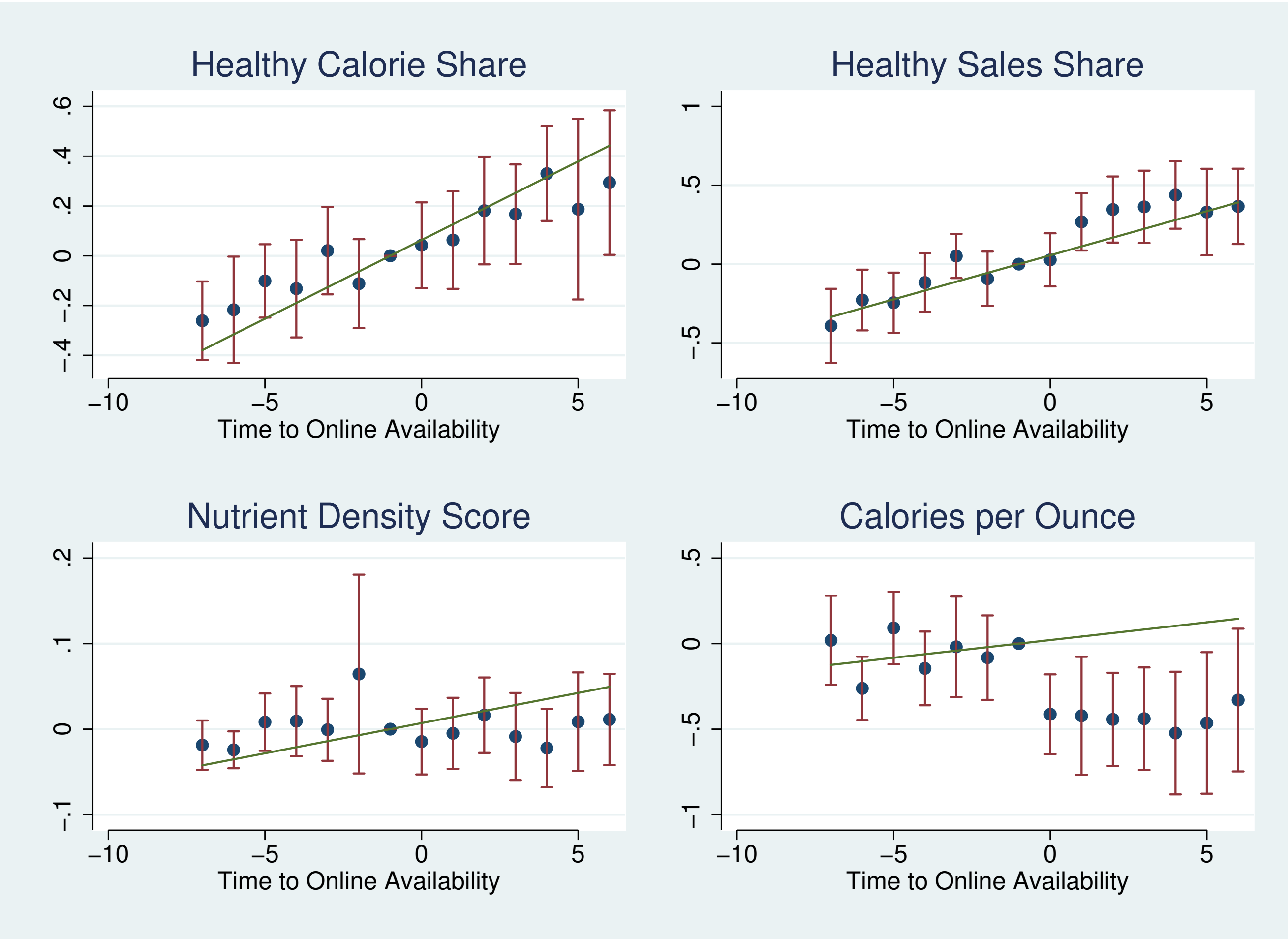


Figure 10: Semi-Parametric Event Study Estimates with Parametric Trend Line
Healthfulness Measures

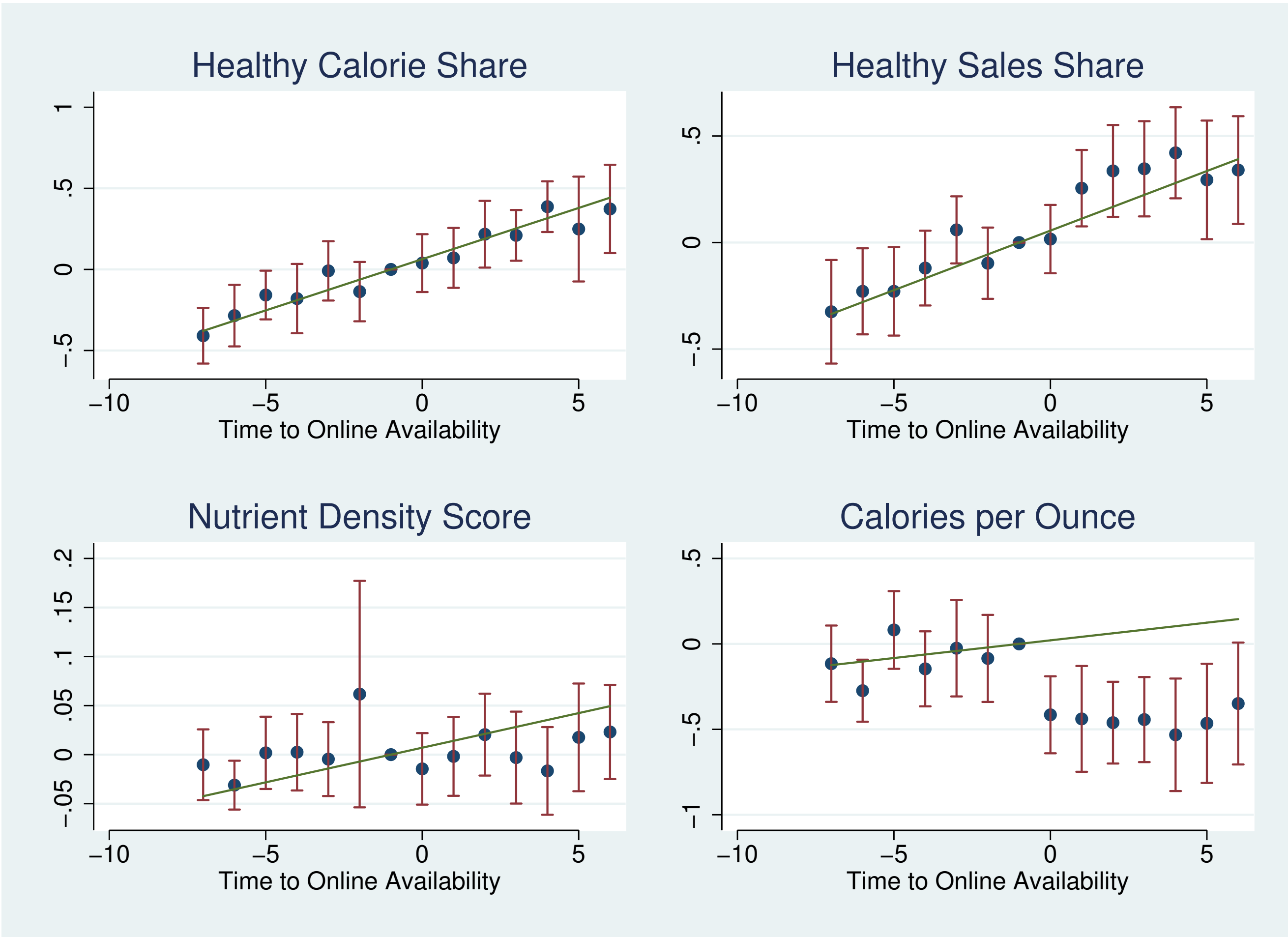


Figure 11: Total Expenditure Event Study Estimates with Parametric Trend Line

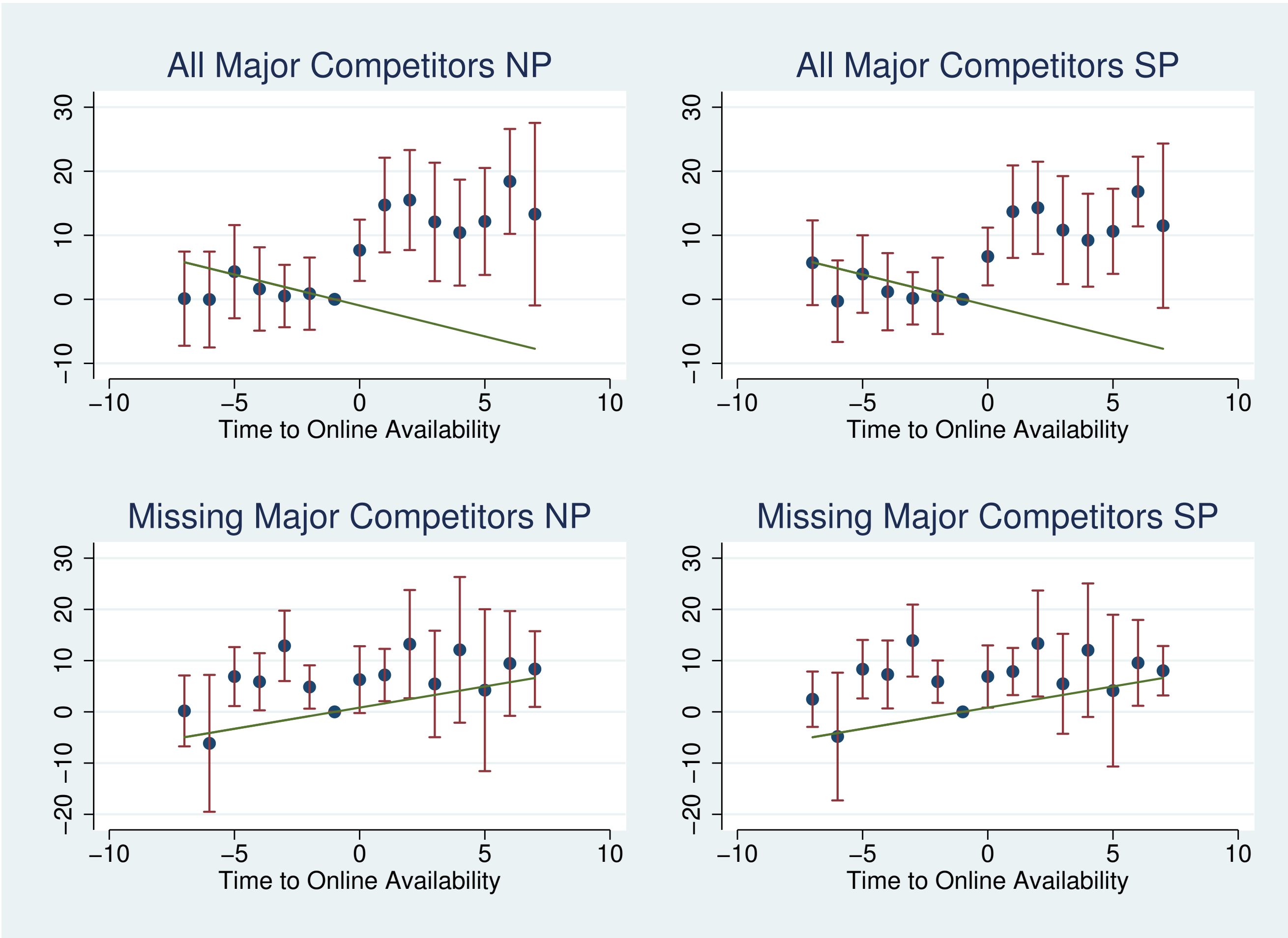


Figure 12: Breakfast/Lunch Meats Event Study Estimates with Parametric Trend Line

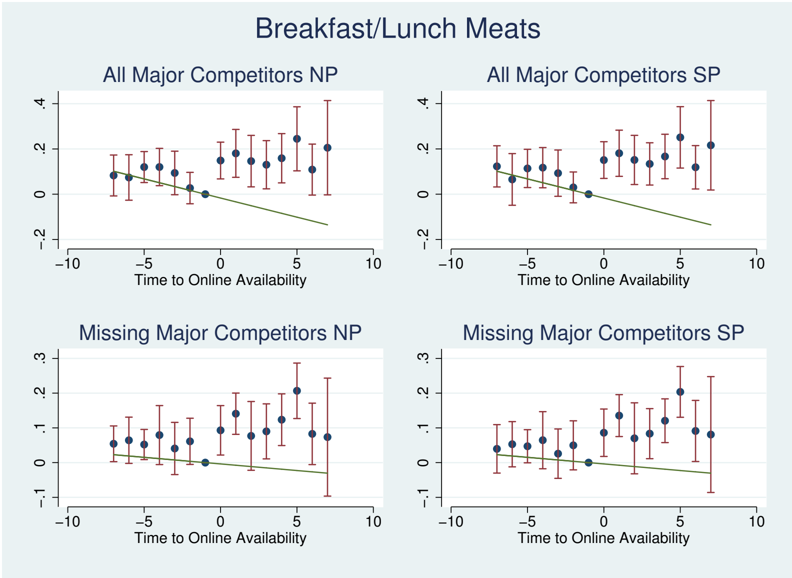


Figure 13: Sugars/Sweets/Candies Event Study Estimates with Parametric Trend Line

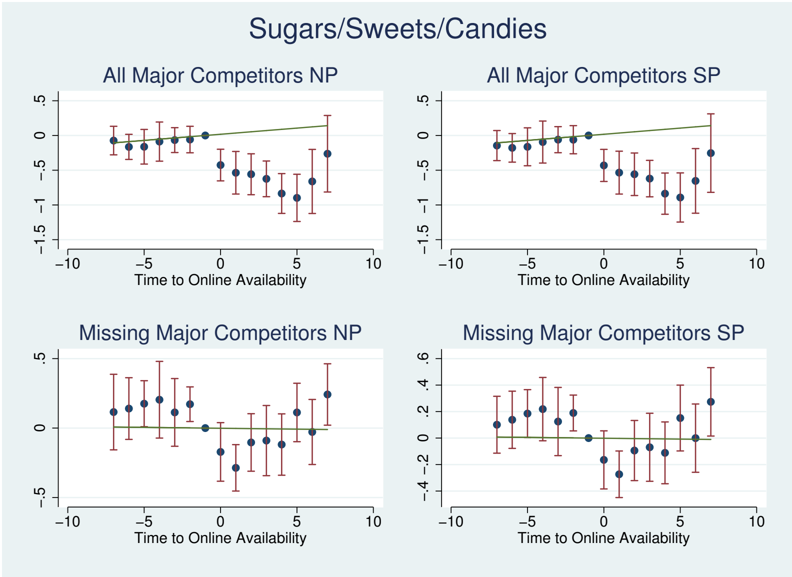


Figure 14: Frozen/Refrigerated Entrees Event Study Estimates with Parametric Trend Line

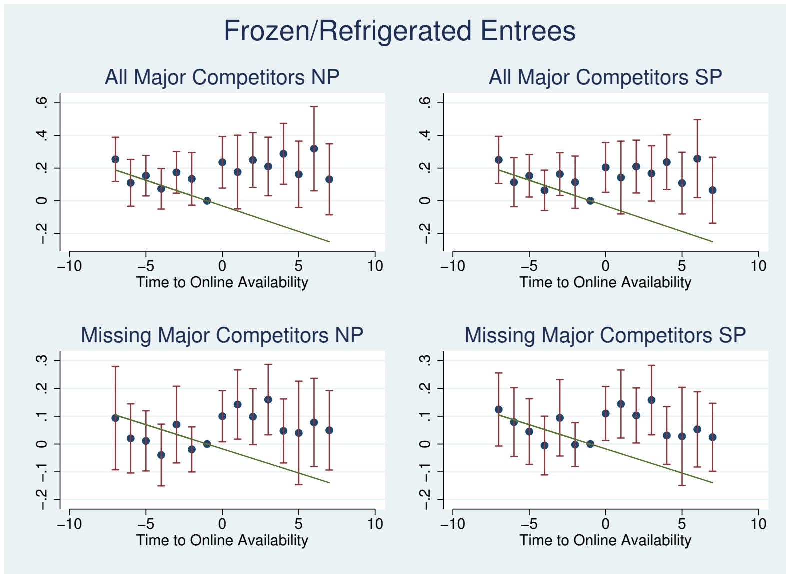


Figure 15: Dark Green Vegetables Event Study Estimates with Parametric Trend Line

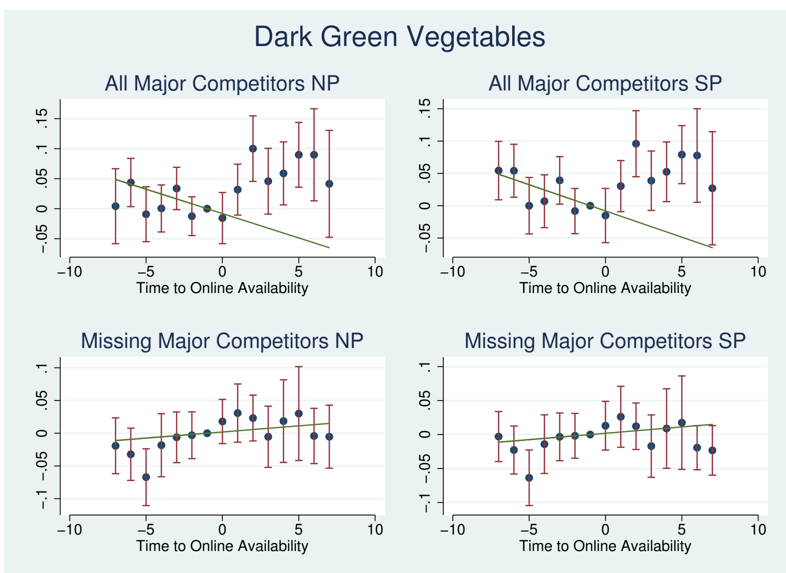


Figure 16: Fats/Condiments Event Study Estimates with Parametric Trend Line

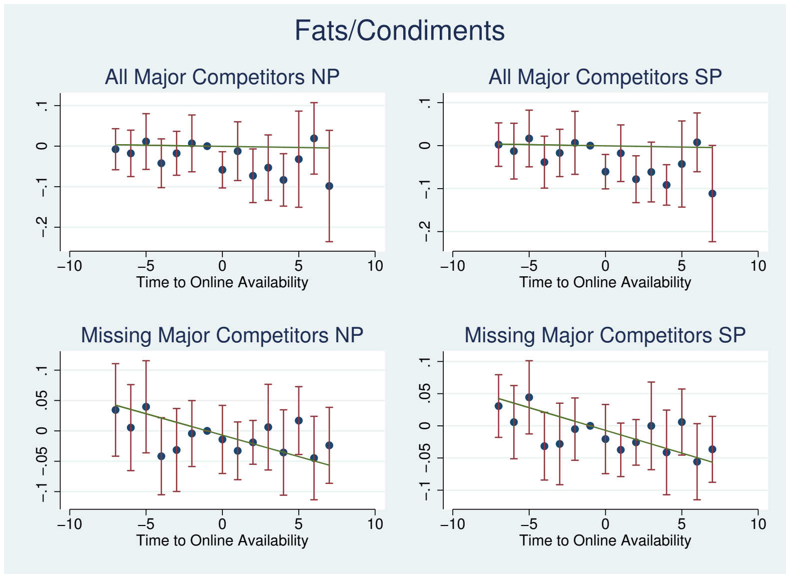


Figure 17: Non Whole Grains Event Study Estimates with Parametric Trend Line

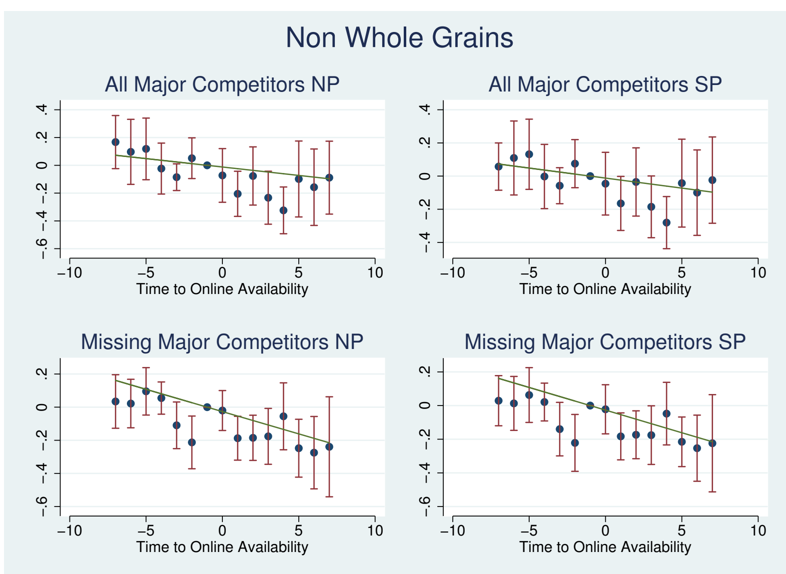


Figure 18: Coffee/Tea Event Study Estimates with Parametric Trend Line

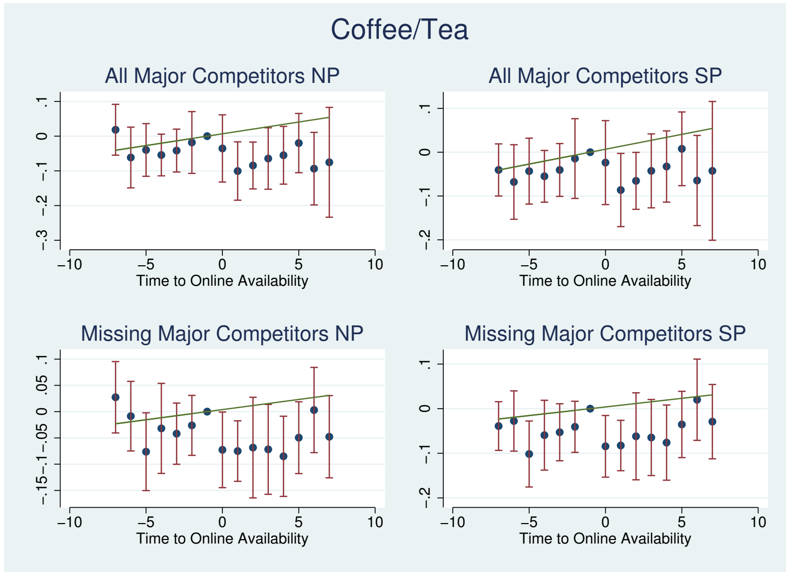
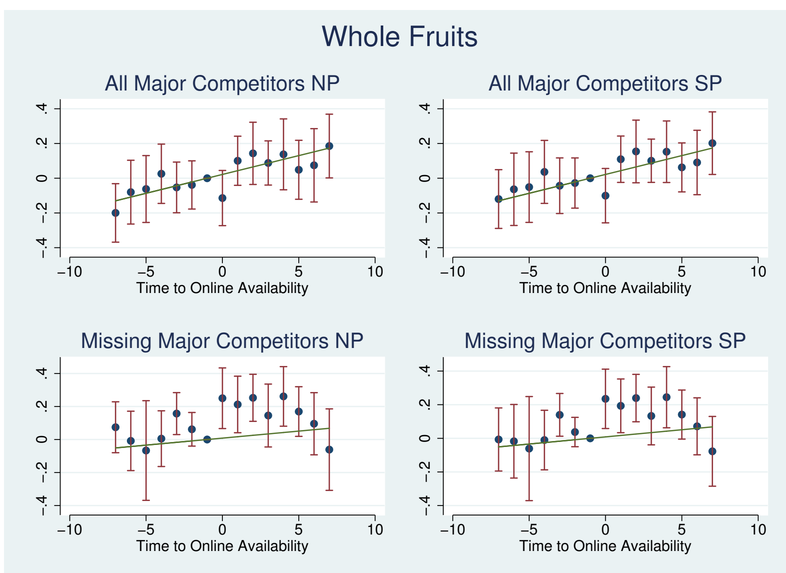


Figure 19: Whole Fruits Event Study Estimates with Parametric Trend Line



11 Tables

Table 1: Household Demographics

Household Demographics	All Households	In-Store Only Households	Online Adoption Households
1{Married}	0.68	0.67	0.69
Household Size	All	In-Store	Online
1{1 Person}	0.10	0.12	0.10
1{2 People}	0.22	0.22	0.22
1{3 People}	0.24	0.22	0.25
1{4 People}	0.17	0.17	0.17
1{5+ People}	0.26	0.26	0.27
Household Income	All	In-Store	Online
1{0-29K}	0.11	0.14	0.10
1{30-50K}	0.16	0.17	0.16
1{51-79K}	0.30	0.28	0.31
1{80-99K}	0.15	0.15	0.15
1{100-149K}	0.12	0.12	0.12
1{150K}	0.16	0.14	0.16
Number of Children	All	In-Store	Online
1{0 Children}	0.43	0.49	0.41
1{1 Child}	0.33	0.31	0.33
1{2 Children}	0.14	0.13	0.15
1{3 Children}	0.07	0.06	0.08
1{4+ Children}	0.03	0.02	0.04
Household Head Age	All	In-Store	Online
1{18-25}	0.02	0.02	0.02
1{26-35}	0.22	0.14	0.25
1{36-45}	0.28	0.20	0.32
1{46-55}	0.20	0.24	0.19
1{56-55}	0.16	0.21	0.14
1{66+}	0.11	0.18	0.08
Household Count	34,797	9,777	25,020

Table 2: Monthly Purchasing Patterns

Time Period	Before & After Online Introduction	Before Online Introduction	
Household Population	All Households	In-Store Only Households	Online Adoption Households
Monthly Shopping Habits	**All**	**In-Store**	**Online**
Grocery Expenditure ($)	437	331	448
TFP Expenditure ($)	422	320	434
Items Purchased	176	135	178
Visits to Store	7.7	6.8	7.5
Share of Sales Online	0.02	0.00	0.00
Observations	855,022	56,973	147,246
Share of TFP Expenditure	**All**	**In-Store**	**Online**
All whole-grain products	1.4	1.4	1.5
Non-whole grains	16.1	15.2	16.1
All potato products	1.6	1.6	1.6
Dark-green vegetables	1.6	1.5	1.6
Orange vegetables	0.5	0.6	0.6
Canned and dry beans	0.3	0.3	0.4
Other vegetables	5.1	5.2	5.0
Whole fruits	8.7	7.7	7.7
Fruit juices	1.3	1.4	1.4
Whole milk dairy products	3.1	3.0	3.1
Low fat dairy products	3.2	3.1	3.5
All cheese	6.5	6.1	6.7
Beef, pork, veal, lamb and game	9.2	9.6	9.3
Chicken, turkey, and game birds	2.8	2.6	2.8
Fish and fish products	1.3	1.4	1.2
Breakfast/lunch meats	2.6	2.2	2.3
Nuts, nut butters, and seeds	3.2	3.2	3.2
Eggs and egg mixtures	1.1	1.0	1.1
Fats and condiments	2.1	2.3	2.2
Coffee and tea	2.1	2.3	2.1
Soft drinks and ades	4.1	4.0	3.6
Sugars/sweets/candies	13.0	14.3	13.4
Soups	2.7	3.0	3.0
Frozen/refrigerated entrees	6.4	6.9	6.7
Observations	850,128	56,589	146,437

Table 3: Means by Healthy Sales Share Quartiles

	Least Healthy			Most Healthy	
Quartile	1	2	3	4	
Healthy Sales Share	17.60	28.87	36.53	50.76	
Healthy Calorie Share	9.06	13.81	17.21	23.82	
Nutrient Density Score	0.64	0.66	0.71	0.90	
Calories per Ounce	46.26	44.65	44.50	43.74	
TFP Budget Shares	1	2	3	4	Healthy Product Category
All whole-grain products	0.85	1.31	1.63	2.00	X
Non-whole grains	18.82	16.90	15.48	12.21	
All potato products	1.31	1.62	1.65	1.78	X
Dark-green vegetables	0.72	1.30	1.75	2.55	X
Orange vegetables	0.33	0.53	0.65	0.86	X
Canned and dry beans	0.20	0.31	0.39	0.49	X
Other vegetables	2.41	4.15	5.45	8.19	X
Whole fruits	3.51	6.18	8.30	12.90	X
Fruit juices	0.93	1.36	1.53	1.80	X
Whole milk dairy products	3.45	3.17	3.01	2.71	
Low fat and skim dairy products	1.81	2.99	3.79	4.82	X
All cheese	6.57	6.90	6.82	5.90	
Beef, pork, veal, lamb and game	11.13	10.53	9.25	6.66	
Chicken, turkey, and game birds	1.40	2.48	3.09	3.96	X
Fish and fish products	0.52	0.95	1.33	2.14	X
Breakfast/lunch meats	3.00	2.47	2.15	1.55	
Nuts, nut butters, and seeds	1.83	2.83	3.50	4.63	X
Eggs and egg mixtures	0.73	0.98	1.11	1.36	X
Fats and condiments	2.26	2.40	2.35	2.02	
Coffee and tea	1.05	1.90	2.38	3.28	X
Soft drinks and ades	6.14	3.85	2.93	2.03	
Sugars, sweets, and candies	18.26	14.23	12.41	9.59	
Soups	3.26	3.24	3.07	2.56	
Frozen/refrigerated entrees	9.52	7.45	6.00	4.01	
Observations					
Healthy Sales Share	50,756	50,790	50,746	50,734	
TFP Sales Shares	50,756	50,790	50,746	50,734	
Healthy Calorie Share	48,998	49,262	49,161	48,613	
Nutrient Density Score	49,025	49,371	49,268	49,271	
Calories per Ounce	49,130	49,377	49,277	49,344	

Table 4: Thrifty Food Plan Budget Shares

Average Treatment Effect for the Treated: 3 and 6 Months Post-Treatment

	Non-Parametric		Semi-Parametric		Parametric with 7 Pre-Periods	
Product Category	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
All whole-grain products	-0.005	0.000	-0.003	0.004	0.011	0.017
	(0.015)	(0.016)	(0.014)	(0.014)	(0.018)	(0.019)
	[0.35]	[0.03]	[0.23]	[0.26]	[0.65]	[0.90]
Non-whole grains	-0.123	-0.155	-0.110	-0.137	-0.020	-0.019
	(0.047)	(0.056)	(0.045)	(0.049)	(0.052)	(0.061)
	[2.61]	[2.79]	[2.44]	[2.78]	[0.38]	[0.32]
All potato products	0.008	0.027	0.007	0.023	-0.006	0.004
	(0.016)	(0.018)	(0.015)	(0.016)	(0.015)	(0.017)
	[0.47]	[1.53]	[0.46]	[1.48]	[0.41]	[0.25]
Dark-green vegetables	0.029	0.032	0.027	0.028	0.044	0.050
	(0.014)	(0.017)	(0.013)	(0.015)	(0.016)	(0.022)
	[2.14]	[1.90]	[2.10]	[1.84]	[2.81]	[2.26]
Orange vegetables	-0.003	0.006	-0.003	0.006	-0.010	-0.003
	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.010)
	[0.34]	[0.67]	[0.40]	[0.67]	[1.35]	[0.33]
Canned and dry beans, lentils, and peas (legumes)	-0.002	-0.002	-0.002	-0.003	-0.001	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
	[0.27]	[0.30]	[0.34]	[0.46]	[0.14]	[0.13]
Other vegetables	0.011	-0.001	0.014	0.002	0.011	-0.008
	(0.035)	(0.035)	(0.035)	(0.033)	(0.033)	(0.042)
	[0.31]	[0.04]	[0.40]	[0.07]	[0.32]	[0.19]
Whole fruits	0.136	0.137	0.134	0.133	0.075	0.049
	(0.056)	(0.052)	(0.049)	(0.042)	(0.067)	(0.075)
	[2.45]	[2.62]	[2.74]	[3.15]	[1.12]	[0.65]

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
T statistics in brackets

Table 5: Thrifty Food Plan Budget Shares

Average Treatment Effect for the Treated: 3 and 6 Months Post-Treatment

	Non-Parametric		Semi-Parametric		Parametric with 7 Pre-Periods	
Product Category	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Fruit juices	0.011	0.007	0.012	0.008	-0.004	-0.009
	(0.017)	(0.015)	(0.016)	(0.014)	(0.017)	(0.019)
	[0.63]	[0.42]	[0.72]	[0.58]	[0.21]	[0.48]
Whole milk products: milk, yoghurt, cream	-0.010	0.001	0.002	0.018	0.044	0.063
	(0.023)	(0.028)	(0.027)	(0.035)	(0.022)	(0.026)
	[0.45]	[0.04]	[0.09]	[0.51]	[2.03]	[2.46]
Low fat and skim milk and lowfat yoghurt	0.047	0.043	0.036	0.026	0.021	-0.006
	(0.030)	(0.027)	(0.031)	(0.028)	(0.025)	(0.024)
	[1.57]	[1.60]	[1.17]	[0.92]	[0.84]	[0.25]
All cheese	0.010	-0.002	0.006	-0.011	0.023	0.019
	(0.045)	(0.042)	(0.042)	(0.037)	(0.034)	(0.034)
	[0.23]	[0.05]	[0.14]	[0.29]	[0.69]	[0.57]
Beef, pork, veal, lamb and game	0.029	0.014	0.034	0.021	-0.004	-0.028
	(0.054)	(0.061)	(0.049)	(0.051)	(0.055)	(0.063)
	[0.54]	[0.22]	[0.70]	[0.41]	[0.08]	[0.44]
Chicken, turkey, and game birds	0.031	0.063	0.025	0.051	0.020	0.041
	(0.028)	(0.028)	(0.026)	(0.026)	(0.037)	(0.035)
	[1.12]	[2.20]	[0.93]	[1.96]	[0.55]	[1.18]
Fish and fish products	-0.005	-0.002	0.002	0.011	-0.003	0.004
	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.023)
	[0.25]	[0.09]	[0.11]	[0.58]	[0.17]	[0.17]
Bacon, sausages, and luncheon meats	0.127	0.140	0.127	0.143	0.120	0.150
	(0.033)	(0.032)	(0.030)	(0.026)	(0.032)	(0.035)
	[3.86]	[4.33]	[4.27]	[5.40]	[3.73]	[4.26]

Robust standard errors in parentheses

Standard errors clustered at the store-availability level

T statistics in brackets

Table 6: Thrifty Food Plan Budget Shares

Average Treatment Effect for the Treated: 3 and 6 Months Post-Treatment

	Non-Parametric		Semi-Parametric		Parametric with 7 Pre-Periods	
Product Category	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Nuts, nut butters, and seeds	0.023	0.036	0.015	0.024	-0.036	-0.041
	(0.026)	(0.029)	(0.026)	(0.027)	(0.026)	(0.032)
	[0.87]	[1.24]	[0.60]	[0.89]	[1.39]	[1.29]
Eggs and egg mixtures	0.005	0.015	0.007	0.020	-0.019	-0.016
	(0.016)	(0.018)	(0.016)	(0.017)	(0.019)	(0.023)
	[0.29]	[0.84]	[0.45]	[1.16]	[1.04]	[0.67]
Fats and condiments	-0.033	-0.029	-0.039	-0.037	-0.017	-0.009
	(0.015)	(0.020)	(0.013)	(0.016)	(0.015)	(0.021)
	[2.15]	[1.44]	[2.99]	[2.33]	[1.12]	[0.41]
Coffee and tea	-0.073	-0.065	-0.067	-0.054	-0.049	-0.042
	(0.025)	(0.024)	(0.024)	(0.023)	(0.027)	(0.025)
	[2.96]	[2.73]	[2.86]	[2.34]	[1.83]	[1.66]
Soft drinks, soda, fruit drinks, and ades	-0.021	-0.042	-0.014	-0.035	0.018	0.003
	(0.042)	(0.046)	(0.040)	(0.042)	(0.038)	(0.047)
	[0.49]	[0.93]	[0.36]	[0.83]	[0.46]	[0.07]
Sugars, sweets, and candies	-0.334	-0.343	-0.336	-0.343	-0.394	-0.417
	(0.085)	(0.111)	(0.089)	(0.115)	(0.069)	(0.095)
	[3.93]	[3.10]	[3.76]	[2.99]	[5.72]	[4.38]
Soups: ready to serve, condensed, and dry soups	-0.022	-0.030	-0.024	-0.031	-0.015	-0.018
	(0.019)	(0.022)	(0.019)	(0.022)	(0.014)	(0.018)
	[1.15]	[1.36]	[1.27]	[1.42]	[1.07]	[0.99]
Frozen or refrigerated entrees (pizza, fish sticks, frozen meals)	0.166	0.156	0.154	0.138	0.196	0.218
	(0.046)	(0.051)	(0.043)	(0.046)	(0.049)	(0.054)
	[3.61]	[3.04]	[3.59]	[2.97]	[3.96]	[4.06]

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
T statistics in brackets

Table 7: Thrifty Food Plan Calorie Shares

Average Treatment Effect for the Treated: 3 and 6 Months Post-Treatment

	Non-Parametric		Semi-Parametric		Parametric with 7 Pre-Periods	
Product Category	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Whole-grains	-0.018	-0.006	-0.006	0.015	0.004	0.008
	(0.034)	(0.036)	(0.028)	(0.026)	(0.039)	(0.041)
	[0.53]	[0.18]	[0.21]	[0.57]	[0.10]	[0.19]
Non-whole grains	-0.006	-0.083	0.015	-0.050	0.141	0.121
	(0.099)	(0.115)	(0.089)	(0.096)	(0.109)	(0.135)
	[0.06]	[0.72]	[0.16]	[0.52]	[1.29]	[0.89]
Potato products	0.018	0.030	0.014	0.022	-0.020	-0.025
	(0.019)	(0.023)	(0.017)	(0.020)	(0.016)	(0.021)
	[0.94]	[1.28]	[0.83]	[1.13]	[1.23]	[1.20]
Dark-green Vegetables	0.002	0.002	0.001	0.000	0.003	0.002
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
	[0.55]	[0.31]	[0.28]	[0.05]	[0.68]	[0.39]
Orange Vegetables	-0.004	-0.003	-0.006	-0.004	-0.006	-0.005
	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)
	[0.84]	[0.45]	[1.15]	[0.83]	[1.71]	[1.08]
Beans, lentils, and peas (legumes)	-0.004	-0.003	-0.006	-0.007	0.004	0.008
	(0.013)	(0.015)	(0.013)	(0.015)	(0.011)	(0.013)
	[0.34]	[0.23]	[0.47]	[0.45]	[0.35]	[0.58]
Other vegetables	0.000	-0.002	0.001	0.000	0.003	0.001
	(0.007)	(0.006)	(0.007)	(0.005)	(0.007)	(0.008)
	[0.02]	[0.31]	[0.14]	[0.04]	[0.47]	[0.14]
Whole fruits	0.007	0.027	0.006	0.024	0.004	0.027
	(0.013)	(0.014)	(0.013)	(0.015)	(0.011)	(0.013)
	[0.58]	[1.96]	[0.42]	[1.58]	[0.34]	[2.10]

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
T statistics in brackets

Table 8: Thrifty Food Plan Calorie Shares

Average Treatment Effect for the Treated: 3 and 6 Months Post-Treatment

	Non-Parametric		Semi-Parametric		Parametric with 7 Pre-Periods	
Product Category	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Fruit juices	0.022	0.022	0.022	0.023	0.012	0.012
	(0.024)	(0.024)	(0.023)	(0.022)	(0.021)	(0.024)
	[0.91]	[0.93]	[0.92]	[1.03]	[0.57]	[0.50]
Whole milk products	0.023	0.030	0.037	0.042	0.151	0.189
	(0.047)	(0.044)	(0.052)	(0.044)	(0.046)	(0.047)
	[0.49]	[0.69]	[0.71]	[0.96]	[3.26]	[4.05]
Low fat milk products	0.053	0.092	0.051	0.090	-0.007	-0.004
	(0.034)	(0.037)	(0.029)	(0.028)	(0.027)	(0.031)
	[1.58]	[2.49]	[1.78]	[3.18]	[0.25]	[0.14]
All cheese	-0.011	-0.036	-0.012	-0.039	0.007	-0.024
	(0.052)	(0.054)	(0.050)	(0.049)	(0.044)	(0.048)
	[0.21]	[0.67]	[0.25]	[0.80]	[0.17]	[0.50]
Beef, pork, veal, lamb and game	0.006	0.006	0.005	0.004	0.004	0.005
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
	[1.60]	[1.41]	[1.61]	[1.32]	[1.36]	[1.38]
Poultry	-0.003	-0.003	-0.003	-0.003	-0.001	-0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
	[1.14]	[1.08]	[1.28]	[1.26]	[0.39]	[0.44]
Fish	-0.028	-0.034	-0.026	-0.029	-0.016	-0.022
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.015)
	[2.01]	[2.55]	[1.91]	[2.24]	[1.15]	[1.47]
Breakfast/Lunch Meats	0.027	0.024	0.025	0.023	0.029	0.032
	(0.012)	(0.011)	(0.011)	(0.010)	(0.013)	(0.013)
	[2.30]	[2.16]	[2.25]	[2.15]	[2.30]	[2.49]

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
T statistics in brackets

Table 9: Thrifty Food Plan Calorie Shares

Average Treatment Effect for the Treated: 3 and 6 Months Post-Treatment

	Non-Parametric		Semi-Parametric		Parametric with 7 Pre-Periods	
Product Category	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Nuts, nut butters, and seeds	0.069	0.068	0.078	0.090	-0.014	-0.038
	(0.047)	(0.051)	(0.043)	(0.044)	(0.047)	(0.060)
	[1.46]	[1.34]	[1.79]	[2.03]	[0.30]	[0.63]
Eggs	-0.016	-0.027	-0.015	-0.025	-0.010	-0.022
	(0.018)	(0.021)	(0.017)	(0.019)	(0.012)	(0.014)
	[0.90]	[1.32]	[0.88]	[1.32]	[0.80]	[1.59]
Fats/condiments	-0.056	-0.045	-0.063	-0.053	-0.047	-0.024
	(0.035)	(0.041)	(0.035)	(0.038)	(0.034)	(0.044)
	[1.57]	[1.10]	[1.82]	[1.41]	[1.40]	[0.56]
Coffee and tea	-0.002	-0.001	-0.002	0.000	-0.004	-0.004
	(0.006)	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)
	[0.35]	[0.12]	[0.28]	[0.04]	[1.04]	[0.79]
Soft drinks	0.021	0.005	0.029	0.015	0.034	0.014
	(0.044)	(0.052)	(0.043)	(0.052)	(0.053)	(0.075)
	[0.48]	[0.10]	[0.67]	[0.28]	[0.63]	[0.18]
Sugars, sweets, and candies	-0.280	-0.241	-0.308	-0.288	-0.409	-0.396
	(0.119)	(0.158)	(0.117)	(0.152)	(0.103)	(0.144)
	[2.35]	[1.53]	[2.63]	[1.89]	[3.98]	[2.74]
Soups	-0.008	-0.013	-0.006	-0.010	-0.014	-0.021
	(0.014)	(0.020)	(0.014)	(0.019)	(0.018)	(0.023)
	[0.57]	[0.69]	[0.47]	[0.52]	[0.82]	[0.90]
Frozen/refrigerated entrees	0.182	0.182	0.168	0.158	0.163	0.179
	(0.057)	(0.061)	(0.050)	(0.051)	(0.059)	(0.065)
	[3.20]	[2.96]	[3.34]	[3.12]	[2.77]	[2.77]

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
T statistics in brackets

Table 10: Healthfulness Measures

Average Treatment Effect for the Treated: 3 and 6 Months Post-Treatment

	Non-Parametric		Semi-Parametric		Parametric with 7 Pre-Periods	
Product Category	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
TFP - Healthy Budget Share	0.214	0.295	0.202	0.278	0.052	0.041
	(0.077)	(0.079)	(0.077)	(0.078)	(0.108)	(0.121)
	[2.76]	[3.75]	[2.64]	[3.57]	[0.49]	[0.34]
TFP - Healthy Calorie Share	0.095	0.162	0.109	0.196	-0.049	-0.063
	(0.086)	(0.095)	(0.082)	(0.080)	(0.067)	(0.073)
	[1.10]	[1.70]	[1.34]	[2.43]	[0.73]	[0.87]
Nutrient Density Score	-0.001	-0.004	0.001	0.000	-0.035	-0.046
	(0.017)	(0.019)	(0.017)	(0.017)	(0.022)	(0.028)
	[0.06]	[0.23]	[0.08]	[0.02]	[1.60]	[1.63]
Calories per Ounce	-0.426	-0.451	-0.438	-0.459	-0.376	-0.406
	(0.126)	(0.136)	(0.112)	(0.113)	(0.096)	(0.107)
	[3.38]	[3.32]	[3.92]	[4.08]	[3.91]	[3.79]

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
T statistics in brackets

Table 11: Retailer Substitution Patterns - Total Grocery Expenditure

High Competition Areas						
	Non-Parametric		Semi-Parametric		Parametric	
Outcome	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Total Expenditure	12.63	12.09	11.55	10.89	14.56	15.41
	(3.15)	(3.25)	(2.96)	(2.81)	(3.51)	(3.87)
	[4.01]	[3.72]	[3.91]	[3.87]	[4.15]	[3.99]

Low Competition Areas						
	Non-Parametric		Semi-Parametric		Parametric	
Outcome	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Total Expenditure	8.90	8.08	9.37	8.29	1.05	-1.52
	(2.83)	(4.56)	(2.68)	(4.27)	(2.72)	(3.71)
	[3.15]	[1.77]	[3.49]	[1.94]	[0.39]	[0.41]

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
T statistics in brackets

Table 12: Retailer Substitution Patterns - Thrifty Food Plan Budget Shares

All Major Competitors Present						
	Non-Parametric		Semi-Parametric		Parametric	
Outcome	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Non-whole grains	-0.118	-0.168	-0.082	-0.126	-0.069	-0.096
	(0.080)	(0.083)	(0.080)	(0.081)	(0.090)	(0.099)
	[1.47]	[2.04]	[1.03]	[1.56]	[0.76]	[0.97]
Dark-green vegetables	0.039	0.052	0.037	0.047	0.063	0.085
	(0.020)	(0.020)	(0.018)	(0.017)	(0.023)	(0.025)
	[1.98]	[2.56]	[2.05]	[2.81]	[2.72]	[3.41]
Whole fruits	0.043	0.067	0.054	0.080	-0.010	-0.017
	(0.068)	(0.063)	(0.065)	(0.056)	(0.061)	(0.076)
	[0.64]	[1.06]	[0.84]	[1.42]	[0.17]	[0.22]
Breakfast/Lunch meats	0.159	0.168	0.161	0.172	0.163	0.201
	(0.044)	(0.045)	(0.042)	(0.041)	(0.034)	(0.038)
	[3.62]	[3.73]	[3.83]	[4.23]	[4.81]	[5.28]

Missing At Least One Major Competitor						
	Non-Parametric		Semi-Parametric		Parametric	
Outcome	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Non-whole grains	-0.131	-0.145	-0.126	-0.136	0.036	0.065
	(0.052)	(0.059)	(0.059)	(0.059)	(0.058)	(0.069)
	[2.51]	[2.46]	[2.14]	[2.29]	[0.61]	[0.94]
Dark-green vegetables	0.024	0.019	0.017	0.010	0.024	0.016
	(0.015)	(0.019)	(0.016)	(0.019)	(0.014)	(0.022)
	[1.55]	[1.00]	[1.10]	[0.55]	[1.71]	[0.73]
Whole fruits	0.238	0.215	0.223	0.198	0.163	0.124
	(0.074)	(0.070)	(0.069)	(0.065)	(0.102)	(0.117)
	[3.22]	[3.07]	[3.21]	[3.06]	[1.60]	[1.06]
Breakfast/Lunch meats	0.104	0.122	0.097	0.116	0.077	0.100
	(0.033)	(0.031)	(0.033)	(0.028)	(0.039)	(0.043)
	[3.14]	[3.98]	[2.97]	[4.14]	[1.97]	[2.30]

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
T statistics in brackets

Table 13: Retailer Substitution Patterns - Thrifty Food Plan Budget Shares

All Major Competitors Present						
	Non-Parametric		Semi-Parametric		Parametric	
Outcome	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Fats and condiments	-0.048	-0.052	-0.052	-0.059	-0.042	-0.047
	(0.025)	(0.029)	(0.020)	(0.022)	(0.018)	(0.021)
	[1.94]	[1.77]	[2.64]	[2.70]	[2.32]	[2.25]
Coffee and tea	-0.073	-0.060	-0.058	-0.041	-0.051	-0.042
	(0.034)	(0.029)	(0.033)	(0.027)	(0.043)	(0.041)
	[2.13]	[2.07]	[1.77]	[1.51]	[1.20]	[1.03]
Sugars/Sweets/Candies	-0.507	-0.646	-0.508	-0.646	-0.513	-0.680
	(0.125)	(0.124)	(0.128)	(0.128)	(0.100)	(0.097)
	[4.04]	[5.20]	[3.97]	[5.05]	[5.13]	[6.99]
Frozen/Refrigerated entrees	0.220	0.220	0.185	0.178	0.222	0.264
	(0.075)	(0.078)	(0.071)	(0.072)	(0.079)	(0.087)
	[2.95]	[2.81]	[2.60]	[2.48]	[2.80]	[3.05]

Missing At Least One Major Competitor						
	Non-Parametric		Semi-Parametric		Parametric	
Outcome	3 Months	6 Months	3 Months	6 Months	3 Months	6 Months
Fats and condiments	-0.022	-0.013	-0.028	-0.020	0.006	0.026
	(0.017)	(0.021)	(0.014)	(0.020)	(0.021)	(0.029)
	[1.29]	[0.61]	[1.95]	[1.02]	[0.31]	[0.91]
Coffee and tea	-0.072	-0.070	-0.076	-0.068	-0.047	-0.041
	(0.027)	(0.028)	(0.027)	(0.029)	(0.026)	(0.026)
	[2.65]	[2.51]	[2.77]	[2.29]	[1.81]	[1.53]
Sugars, sweets, and candies	-0.187	-0.110	-0.177	-0.094	-0.300	-0.220
	(0.080)	(0.085)	(0.090)	(0.097)	(0.095)	(0.126)
	[2.35]	[1.28]	[1.98]	[0.97]	[3.14]	[1.74]
Frozen/Refrigerated entrees	0.114	0.098	0.119	0.096	0.166	0.171
	(0.045)	(0.050)	(0.046)	(0.049)	(0.057)	(0.061)
	[2.51]	[1.95]	[2.58]	[1.96]	[2.94]	[2.80]

Robust standard errors in parentheses

Standard errors clustered at the store-availability level

T statistics in brackets