

The Effect of Online Shopping on Grocery Demand

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Abstract

This paper utilizes novel household panel data to analyze the effect of online grocery shopping on grocery demand. In order to obtain a causal estimate of the impact of online grocery shopping on purchasing decisions, 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. Local average treatment effects indicate that online shopping induces a 3.8, 5.9, 5.7 and 7.4 percent increase in the average budget shares for dairy, fruit, meats and vegetables, respectively. This reallocation of funds comes at the expense of drinks, oils and snacks/sweets with estimates indicating a 5.2, 4.1 and 13.6 percent decrease in the average budget shares, respectively. I further explore how shopping online influences grocery purchases by estimating a formal model of grocery demand. Comparisons of in-store and online price elasticities indicate that households are generally less price sensitive when shopping online. Specifically, I find that own-price (cross-price) elasticities are two (three) times larger in-store than they are online, on average. These insights into consumer purchasing behavior can be utilized to inform policies aimed at improving the nutritional quality of food purchases and can also inform optimal web design and online pricing strategies.

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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

Online grocery purchases amounted to \$20.5 billion dollars in sales and represented 4.3 percent of all groceries purchased in 2016 (Nielsen & FMI). In recent years, online grocery shopping has become more and more commonplace. Many brick and mortar retailers have begun to offer online grocery services and web based retailers, such as Amazon, have also entered the online grocery market. Due to increasing accessibility and consumer adoption of online grocery services, it is projected that within the next ten years 20 percent of all grocery purchases will be conducted online (Nielsen & FMI). Despite the large predicted growth rate, there has been relatively little research that examines how online purchasing environments influence consumer choice.

This paper evaluates how shopping for groceries online affects demand. In order to isolate the effect of an online shopping environment, I utilize grocery scanner data generated from the purchases of 34 thousand households, 25 thousand of whom have utilized an online 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 allows for a within household comparison of purchases across the two 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.¹

In a reduced form analysis, I employ panel difference-in-differences and two-stage least squares 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. I find that when ordering groceries online, households begin

¹This is true only for the online grocery service featured in this study. The retailer of this study also has an online shopping delivery service. The prices when shopping via the delivery service are different than the in-store prices.

to allocate a larger share of their grocery budget toward product categories that generally contain healthier items (dairy, fruit, meats and vegetables) at the expense of product categories that generally contain more indulgent products (drinks, oils and snacks/sweets). Specifically, I estimate local average treatment effects that indicate a 3.8, 5.9, 5.7 and 7.4 percent increase in the average budget shares for dairy, fruit, meat and vegetables. Additionally, this reallocation of funds comes at the expense of drinks, oils and snacks/sweets with estimates indicating a 5.2, 4.1 and 13.6 percent decrease in average budget shares, respectively. Motivated by these findings, I estimate a formal model of grocery demand and find that households are less price sensitive when shopping online. I find that own-price elasticities and cross-price elasticities are, on average, two and three times larger in-store than they are online, respectively.

The findings of this paper are consistent with behavioral theories that suggest consumers have difficulty exercising self-control due to time inconsistent preferences (Thaler 1981, Laibson 2004), 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.²

Policy makers can leverage the insights into consumer behavior that this paper provides to help consumers make decisions that are better aligned with their long term health goals. For example, one of the main findings of this paper is that in-store product place-

²The representation of products with pictures has also been theorized to improve the healthfulness of food purchases (Shiv and Fedorikhin 1999; Shiv and Fedorikhin 2002).

ment is an effective tool for influencing consumer purchases. Hence, policy makers interested in improving the healthiness of food purchases could potentially do so by implementing policies that optimally place healthier products throughout a store or in an online shopping environment.³ Additionally, differences in price elasticities across the two purchasing environments suggest that firms may be able to increase online revenues by implementing a more sophisticated pricing strategy in the online environment.

This paper contributes to a growing literature that analyzes how an online purchasing environment, in and of itself, may influence the healthiness 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).⁴ Milkman, Rogers, and Bazerman (2009) test whether increased delay in delivery improves the healthiness 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.⁵ In contrast, this paper utilizes a difference-in-differences and instrumental variables framework to estimate a causal effect of online grocery shopping on the healthiness of consumer purchases.

This paper also contributes to studies that have evaluated structural differences between online and in-store demand. Pozzi (2012) analyzes how online shopping lists and

³This type of policy could be implemented at little or no cost to the retailer.

⁴In 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 when consumers face pictures of products they are less likely to purchase indulgent items.

⁵For example, buying groceries in advance of an event at which you plan to have a specific meal prepared.

the convenience of being able to pre-select your grocery basket influences decisions over brand choice within breakfast cereals. He finds that brand exploration is systematically more prevalent in-store than online and quantifies how features of the ordering website (favorites lists and difficulty of quality verification) contribute to decreased brand exploration behavior.⁶ Chu et al. (2008) also study how purchasing patterns vary across in-store and online grocery shopping environments fulfilled by the same retailer. They find that households are more brand loyal, more size loyal and less price sensitive when they shop for groceries online.⁷ Pozzi (2012, 2013b) and Chu et al. (2008, 2010) provide valuable insight into how and why purchasing behavior is different online; however, they only shed light on decision making processes over very narrowly defined product spaces (cereal, drinks, laundry detergent, frozen pizza, etc.). In contrast, this paper estimates structural changes in demand over a more broadly defined product space that incorporates all grocery products; analysis at this level of aggregation effectively analyzes a different set of substitution patterns than those that have been previously studied.

The remainder of this paper is structured as follows: Section 2 discusses the online purchasing service and the different ways in which an online shopping environment might influence demand. Section 3 describes the data. Section 4 presents the reduced form estimation strategy and results. Section 5 discusses robustness checks for the reduced form estimation. Motivated by the reduced form findings, the paper then estimates a more formal model of grocery demand; Section 6 presents the Linear Approximate Almost Ideal Demand System (LA/AIDS) for grocery demand and discusses the estimated

⁶Pozzi (2013b) utilizes a reduced form approach to evaluate how online convenience influences purchases over products that are inconvenient to transport, namely, bulk products. He finds that when households use an online grocery service, they increase their monthly share of expenditure for bulk items in laundry detergent and soda by 30 and 80 percent, respectively. Pozzi attributes this finding to the decreased transportation cost of purchasing bulk products online; however, as Pozzi notes, these estimates could overstate the magnitude because there is evidence to suggest that households change their mix of retailers when shopping online. That is, households may not actually be buying more bulk items than before; they may just be buying more bulk items from the retailer featured in the study than they did before.

⁷The authors do not identify the mechanism that explains this finding but suggest that time constraints, online shopping list creation, the presence of non-price information for products (nutrition facts), lack of online competition and convenience could be contributing to this result. Furthermore, in a follow-up paper (Chu et al., 2010), the authors find that the magnitude of the effect of online shopping on brand loyalty, size loyalty and price sensitivity varies with household and product characteristics.

price elasticities. Lastly, Section 7 concludes.

2 In-Store and Online Purchasing Environments

The supermarket chain featured in this study offers grocery products as well as a large variety of general merchandise items. Over the past couple of years, this retailer has begun 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."⁸ 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.⁹

Over the course of two and a half years, thirty-three store locations introduced the online purchase service. The online 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 the online shopping service available to them over time.¹⁰ In March 2015, roughly 20% of households have access to the online shopping service. This proportion increases over time as more stores begin to

⁸The 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.

⁹Unfortunately, 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 used.

¹⁰I constructed the date it 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 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, Table A3 of the appendix presents estimation results that includes these households by changing the definition of online availability to be based off of 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.

offer the service and by March 2017, all of the households in my sample have access to the online shopping service.

The gradual roll-out of the online service lends itself nicely to a difference-in-differences 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 . In order to correctly employ this estimation strategy, 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.¹¹ Explicitly, I only use data prior to October 2016, the month in which the last group received access to the online shopping service.

The identifying assumption in this framework is that the service was made available to different households at different times for reasons that are independent of consumer demand. I believe this to be a valid assumption for two reasons: (1) the first location chosen to pilot this service was close to the corporate headquarters, where it was presumably easiest to manage; and (2) 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. I explore the validity of my identifying assumption further in Section 3.

One of the most predominant differences between the two purchasing environments is search. Sales filters and price sorting options featured in the online purchasing environment reduce the cost of price comparison, which may lead consumers to have heightened price sensitivities when shopping online (Bakos 1997; Brynjolfsson and Smith 2000; Clemons, Hann, and Hitt 2002; Ellison and Ellison 2005).¹² On the other hand, product recommendations and customer favorite's lists can also reduce shopping costs by elimi-

¹¹Borusyak & Jaravel (2016) show that event study estimates suffer from under identification and negative weighting when all units or groups are treated.

¹²Additionally, decreased search costs could also motivate consumers to seek out products that they have previously never purchased (Brown and Goolsbee 2002).

nating the need for search. The online favorites list allows the customer to instantly add the items they frequently purchase to their order on each shopping occasion. However, time savings come at the expense of price comparison; thus, features of website design could lead to decreased price sensitivity in the online shopping environment.

Online search functions and product recommendations change the way consumers "browse" when they are online relative 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.¹³ The time and effort that brick and mortar retailers put into product displays, store and web design suggests that search paths play an important role in nudging customers towards purchases.¹⁴ For example, the absence of a checkout lane when shopping online is likely to lead to decreased purchases of candy bars, mints and gum; additionally, if you are less likely to be hungry when shopping online we may expect to see less hunger driven impulse purchases. Search differences between the online and in-store purchasing environments could lead to less unplanned purchasing when shopping online.

Beyond differences in search, there are many other elements of the online purchasing experience that could influence consumer demand. For example, time delays between the point of purchase and actual receipt of the goods could also lead to differences in consumer demand 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.¹⁵ Additionally, the valuation of goods that are generally

¹³Customers can 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.

¹⁴Laibson (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 and hence different purchasing decisions being made.

¹⁵For more on multiple selves theory see the work of Schelling (1984), Bazerman et al. (1998) and Thaler and Shefrin (1981).

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. An inability to verify product quality is likely to lead to decreased brand exploration when shopping online. 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.¹⁶ 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 demand should differ from in-store demand. This paper explicitly tests two of these predictions. First, differences in search, timing and the representation of products suggest that households may be less likely to make unhealthy purchases when shopping online. Second, differences in search costs and convenience tools (online favorites lists and recently purchased items lists) suggest that price elasticities will differ across the two purchasing environments. However, reductions in search costs due to the ease of price comparison online suggest heightened price sensitivities when shopping online, while differences in convenience tools suggest decreased price sensitivities when shopping online. Hence, which element of the online purchasing environment influences price elasticities more remains an empirical question.

3 Data & Summary Statistics

I have access to household level purchasing data at the day, store, universal product code (UPC) level before and after the introduction of the online purchasing service. Within these data, I have the entire purchasing history (over grocery products) for roughly 130 thousand households from September 2014 through March 2017. This sample of house-

¹⁶Other research on this topic includes the following papers: Hoch and Loewenstein (1991); Loewenstein (1996); Mischel and Ebbesen (1970).

holds 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 had recently 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.¹⁷ 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 product name, category, nutritional content and product attribute claims made by the manufacturer (i.e. organic, gluten free, etc.). Most importantly, 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 eleven different product categories: Dairy, Drinks, Fruits, Grains, Meat, Oils, Other, Prepared, Snacks/Sweets, Sugars and Vegetables.¹⁸ I have also collapsed the purchasing data to the household-year-month level and defined an indicator for online service use if the service was used to buy any products in the monthly basket. 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 demand rather than understanding how online orders differ from in-store orders. 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

¹⁷First, 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 eligible households from my sample. Additional households were dropped based on the definition of online service availability; these restrictions were discussed in Section 2.

¹⁸These product categories were chosen and created based on a document authored by the United States Department of Agriculture (USDA) called, "What We Eat in America". The descriptions of the products assigned to each of these product categories can be found in Table A1 of the appendix.

the same household may be supplementing all of their healthy online purchases with unhealthy in-store purchases that could perfectly balance their overall demand (in-store and online) to where it was before the household began shopping online. Hence, in this hypothetical scenario, online service use has had no impact on demand; it has only impacted how the consumer chooses to purchase the various items in their basket.

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). The 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 tend to be younger, are more likely to be in a higher income group, are more likely to be married and are more likely to have children.¹⁹ Table 2 indicates that the households that eventually adopt the online purchasing service 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, relative to the households who never adopt the online purchasing service (in-store only households). Furthermore, online adoption households allocate a larger percentage of their grocery spending towards dairy (13.2% vs. 11.9%), fruit (7.5% vs. 7.3%), grains (7.6% vs. 7.2%) and other (1.8% vs. 1.7%); while in-store only households allocate a larger proportion of their budgets towards drinks (10.1% vs. 10.9%), meats (18.5% vs. 18.9%) and snacks/sweets (15.5% vs. 16.1%).²⁰ 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).²¹ The pre-existing differences between online adopters and in-store only households 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 pa-

¹⁹Most of my demographic variables are provided categorically. Table A2 in the appendix provides the specific categorical values for each demographic variable.

²⁰There are no statistically significant differences among the two household types in the budget shares for oils (4.4%), prepared (10.8%) and vegetables (9.1%).

²¹The in-store households (households that do not adopt the online purchasing service over the time frame of my data) are utilized in Section 5.2 as a robustness check.

per are representative of the effect of online shopping for the early adopters of the online purchasing service.

Tables 1 and 2 also compare the demographics and pre-online purchasing patterns of the online service adopters who received access to the service at earlier dates to those who received access to the service at later dates. In order to neatly compare the households that received access to the online shopping service first to those who received access later, I assign households to three waves based on the month and year that they received access. Households that received access to the online shopping service before or during January 2016 are assigned to wave one (53% of the online household sample), households that received access to the online service after January 2016 but before July 2016 are assigned to wave two (29% of the online household sample) and households who received access after or during July 2016 are assigned to wave three (18% of the online household sample). Table 1 illustrates that households in later availability dates tend to be smaller and older. Households in the last availability wave also have a higher proportion of households in lower income categories, are less likely to be married and are less likely to have children. Table 2 indicates that households in the first wave tend to spend roughly \$40 more per month, purchase roughly 15 more items and make one more trip to the store per month than households in the second or last wave. Wave 1 households also tend to allocate more of their grocery budget towards dairy, other and vegetables and less of their budget toward drinks, meat, prepared and snacks/sweets relative to households in other waves.

Table 3 presents the average price and nutrition content per ounce of food in each product category.²² It is interesting to note the positive correlation that exists between mean budget shares and the prices of the product categories. For example, the average price of meat and snacks/sweets is \$0.23/oz and \$0.21/oz, while the average price of grains and fruit is \$0.13/oz and \$0.09/oz, respectively.²³ Unsurprisingly, there are considerable differences in the mean amount of calories and nutrients contained in an ounce of

²²The price averages represent the average price paid by all households over all time periods, while the nutrition averages are conducted over all of the products assigned to that product category.

²³The category of other has the largest price (\$0.47/oz) because it contains spices, which are extremely expensive per ounce.

food across product categories. For example, snacks/sweets contains the highest amount of calories (120 kcal/oz), while meats contain the most protein (7.7 g/oz), grains the most carbs (18.5 g/oz), oils the most fat (7.7 g/oz) and sugars the most sugar (14.9 g/oz).

4 Reduced Form Estimation & Results

The pre-existing differences between the households assigned to different online service availability waves motivates the household fixed effects model I employ in the analysis that follows. I estimate the effect of online service use by utilizing availability of the service as an instrument for the decision to shop online. Specifically, my equation of interest is the following:

$$s_{ihm} = \alpha_i + \phi_i 1\{Online_{hm}\} + \gamma_{im} + \gamma_{ih} + \epsilon_{ihm} \quad (1)$$

where s_{ihm} is the budget share of product category i for household h in year-month m , $1\{Online_{hm}\}$ is an indicator that equals one if the online service was ever used by household h in year-month m , γ_{im} is a year-month fixed effect to control for differences across time and γ_{ih} is a household fixed effect to control for unobserved household preferences. Specifications without household and year-month fixed effects include treatment group indicators and post-online-availability time indicators in order to maintain the panel difference-in-differences framework that is featured in the two-stage least squares estimation strategy presented shortly. For specifications without household fixed effects, demographic characteristics of the households are included as covariates.²⁴

I estimate the local average treatment effect of online service availability by instrumenting online use, $1\{Online_{hm}\}$, with online availability, $1\{OnlineAvail_{hm}\}$. This produces panel difference-in-differences reduced form and first stage equations that estimate the average treatment effect of online availability on the expenditure shares for product

²⁴Since my demographic variables are provided categorically, I include the demographics by creating indicators for whether household h belongs to a given demographic category. Additionally, the demographic information I have access to does not vary over time within households.

category i and the probability of shopping online, respectively. Explicitly, the reduced form is:

$$s_{ihm} = v_i + \tau_i 1\{OnlineAvail_{hm}\} + \gamma_{im} + \gamma_{ih} + \omega_{ihm} \quad (2)$$

and the first stage is:

$$1\{Online_{hm}\} = \lambda_i + \theta_i 1\{OnlineAvail_{hm}\} + \gamma_{im} + \gamma_{ih} + v_{ihm} \quad (3)$$

Thus, the two-stage least squares estimate of ϕ_i , the average effect of online service use or the local average treatment effect of online availability, is the ratio of two difference-in-differences estimates; specifically, $\phi_{i,2SLS} = \tau_i / \theta_i$.

Table 4 presents the difference-in-differences estimates, $\hat{\tau}_i$. The estimates presented in column (1) do not include year-month or household fixed effects, column (2) presents estimates from regressions that include year-month fixed effects and column (3) presents the estimates that incorporate both year-month and household fixed effects. The results of these regressions indicate modest increases in the budget shares of dairy, fruit, meat and vegetables and modest decreases in the budget shares for drinks, oils and snacks/sweets. Specifically, the results of the full model indicate a 0.10, 0.08, 0.20 and a 0.13 percentage point increase in the budget shares for dairy, fruit, meat and vegetables (respectively) and a 0.10, 0.04 and a 0.41 percentage point decrease in the budget shares of drinks, oils and snacks/sweets (respectively). Each of these shifts represents less than a three percent change in the average pre-online service budget share, which is calculated over the six months prior to online service introduction at any store location. Table 5 presents the first-stage estimates, $\hat{\theta}_i$. These estimates indicate a strong and positive relationship between the availability of the online service and actual use of the online service.²⁵ The full model indicates that the introduction of the online service increases the probability of shopping online, in a given month, by 19.3 percentage points, on average.

Table 6 presents the ordinary least squares and two-stage least squares estimates of the effect of online shopping. The two-stage least squares estimates (columns 4, 5 and 6)

²⁵The first stage is a linear probability model.

are aligned with the findings of the reduced-form estimates. Furthermore, the two-stage least squares estimates are stable across three different specifications and indicate a 0.5, 0.4, 1.1 and 0.7 percentage point increase in the budget shares for dairy, fruit, meat and vegetables, (respectively), and a 0.5, 0.2 and 2.1 percentage point decrease in the budget shares for drinks, oil and snacks/sweets, respectively. Interpreted relative to the pre-online service average budget shares, these estimates indicate a 3.8, 5.9, 5.7 and 7.4 percentage increase in the average pre-online service budget shares for dairy, fruit, meat and vegetables, respectively. These estimates also indicate a 5.2, 4.1 and 13.6 percentage decrease in the average pre-online service budget shares for drinks, oil and snacks/sweets, respectively.

These results suggest that when households shop online they allocate a larger share of their budget towards healthier product categories at the expense of product categories that are traditionally thought to contain less healthy items. In order to better understand the implications that online shopping may have for consumer health, I evaluate changes in the average nutrient content per ounce of food purchased by the households in my sample. I follow the same estimation strategy presented above but with nutrients per ounce as the dependent variable.²⁶ The results of the ordinary least squares and two-stage least squares regressions are presented in Table 7, where $1\{Online_{hmt}\}$ is instrumented with $1\{OnlineAvail_{hmt}\}$. The results of the two-stage least squares models indicate that the average amount of calories, carbohydrates, fats and sugars per ounce of food purchased decreases in the months that households shop online. My estimates indicate an average decrease of 1.97 kcal/oz, 0.3 g/oz, 0.11 g/oz and 0.13 g/oz for the nutrient categories of calories, carbohydrates, fat and sugars, respectively. Furthermore, there are no significant changes in the average amount of protein, cholesterol and sodium content per ounce of food purchased. Interpreted relative to the pre-online service average, these results equate to a 4.2, 5.0, 5.8 and a 5.8 percent decrease in the average amount of calories,

²⁶Nutrition information is available for 90% of the items purchased by these households. Hence, these regressions test changes in the nutritional value of purchases made over the products for which I have nutrition information. The majority of the gaps in the nutrition information data occur for products that are not purchased in a package (i.e. fresh produce and meats).

carbohydrates, fats and sugars contained in an ounce of food purchased before the online service was available, respectively.

Before the online shopping service was available, households purchased 2,383 ounces of food per month, on average. Holding the amount of food purchased constant, an average decline of two calories per ounce equates to 4,766 fewer calories being purchased in the months in which a household shops online. Extrapolating this results to the individual-day level, the change in the amount of calories purchased represents a decline of 53 calories per person, per day.²⁷ If the declines in caloric purchases perfectly translated into declines in caloric intake, these changes would induce an average adult to lose one pound every ten weeks or roughly five pounds over the course of a year.

The magnitude and signs of the estimates presented above support the prediction that the online shopping environment reduces the incidence of impulsive and unhealthy purchases. Furthermore, estimated changes in the amount of calories purchased indicate that online shopping could contribute to slow but gradual improvements in consumer health through weight loss. However, more dramatic changes in consumer health could be made by improving the nutritional value of the purchases households *intend* to make.

4.1 Online Shopping & Retailer Substitution Patterns

If consumers change retailer substitution patterns differentially across product categories when shopping online, then consumer "crowd-in" could explain the changes we observe in grocery basket composition as well as the documented changes in the nutritional content of food purchased. 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. Then, further suppose that after transitioning to the online shopping service, these households stopped buying their produce from other retailers and began purchasing more produce with the retailer in this study because the online service made these purchases more convenient. In this hypothetical

²⁷This number is generated by dividing 4,766 by thirty days and three people (the size of the average online household).

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 an effect of shopping online on grocery demand.

Prior research by Pozzi (2013a) documents that online grocery services can lead consumers to divert their grocery business away from other retailers, toward the online shopping service provider. Pozzi also finds 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.

The households studied in this paper also exhibit increases in monthly grocery expenditure when they begin using the online shopping service. Following the estimation strategy outlined in equation (1), but with expenditures as the outcome variable, the two-stage least squares estimates presented in Table 8 indicate that households spend \$49 more per month (roughly a 10.9% increase over average pre-online service expenditures), on average, when shopping online.²⁸ Additionally, all product categories, with the exception of other and snacks/sweets, experience significant increases in overall expenditure.²⁹ The final column of Table 8 presents the percent change in average spending that the two-stage least squares estimates represent. The calculated percent changes in categorical expenditures illustrate that, in general, the estimated changes in budget shares are positive if the percent change for product category expenditure increased by more than 10.9% (the average percent change in total expenditure) and are negative if the percent change for product category expenditure increased by less than 10.9%. Assuming that shopping for groceries online does not increase a household's monthly grocery budget (across all retailers), the fact that there are relatively large estimated increases in expenditures for dairy (\$7.7), fruit (\$7.2), meat (\$11.8) and vegetables (\$8.0), while the estimated changes in expenditure for drinks (\$4.0) and snacks/sweets (\$0.76) are relatively small suggests that

²⁸Note that these figures are conditional on arrival to the store in a given month. Explicitly, observations of \$0 have not been imputed for year-month occasions in which a household does not buy any grocery products from the retailer of this study.

²⁹Specifically, the two-stage least squares estimates indicate a \$7.7, \$4.0, \$7.2, \$3.8, \$11.8, \$1.7, \$2.7, \$0.6 and \$8.0 average increase in monthly spending for the product categories of dairy, drinks, fruit, grains, meat, oil, prepared, sugars and vegetables, respectively.

households could be changing retailer substitution patterns differentially across product categories.

I explore whether consumer crowd-in can explain the entirety of the documented differences between online and in-store purchases in two ways. First, I assess whether or not there are heterogeneous effects of shopping online on grocery expenditures that can be attributed to the level of competition surrounding the store location. The goal of this exercise is to identify households that do not change retailer substitution patterns after shopping online; once those households have been identified, any changes in these households' budget shares after shopping online can be attributed to changes in grocery demand. Second, I further explore the extent to which consumer crowd-in can explain my findings by analyzing the effect of online shopping on purchasing decisions made within narrower product spaces. Consumer decisions over product choice in a more narrowly defined product space are less likely to be influenced by changes in the mix of retailers the consumer visits. For example, it is less likely that consumers shop for different types of bread at different types of retailers than it is for them to shop for different types of grocery products at different types of retailers. Under the assumption that households buy the same variety of bread at each retailer they shop with, if consumers allocate more of their bread purchases toward the retailer of this study when shopping online, we would not expect consumer "crowd-in" to change the composition of breads purchased, only total expenditures over bread. Hence, changes in purchasing decisions within these product spaces can be attributed to differences in the purchasing environments rather than changes in retailer substitution patterns.

4.1.1 Heterogeneous Effects of Online Availability on Retailer Substitution Patterns

I begin exploring the extent to which shopping online influences retailer substitution patterns by evaluating how the effect of online shopping on total grocery expenditures varies with the level of competition the store location faces. In order to do this, I split online households in two groups: those whose online service availability was determined by a store location that faces below average competition and those whose online service availability was determined by a store location that faces above average competition. The level

of competition faced by each store location was provided to me by the retailer; those in the low competition group have a competition index that is lower than the average store location and those in the high competition group have a competition index that is higher than the average store location.³⁰

Tables 9 and 10 present difference-in-differences estimates, utilizing the estimation strategy presented in equation (2), for the low competition and high competition online household population, respectively. Table 9 indicates that households who adopt the online purchasing service in store locations that face lower levels of outside competition do not increase their monthly expenditure with the retailer of this study after the online purchasing service becomes available; however, these households still exhibit changes in the composition of their grocery purchases. After the online service becomes available, low competition households exhibit significant increases in the budget shares of fruit and meat. Additionally, this reallocation of funds comes at the expense of the snacks/sweets product category. The point estimates indicate a 0.10, 0.22 and -0.24 percentage point change in the budget shares of fruit, meat and snacks/sweets, respectively. These findings illustrate that even when households do not exhibit changes in substitution patterns across retailers when shopping online, they still change the composition of their purchases when shopping online.

In contrast, households in competitive purchasing environments significantly increase monthly grocery expenditures after the online purchasing service becomes available. Specifically, Table 10 indicates that households in competitive environments increase monthly grocery expenditures by \$10.60 when the online purchasing service becomes available. These results suggest that the online purchasing service may be effective at poaching customer's grocery purchases from competitors. The point estimates of the effect of online availability on budget shares indicate a 0.04, 0.21 and 0.17 percentage point increase in the budget shares of grain, meat and vegetables respectively. This reallocation of funds also comes at the expense of snacks/sweets with point estimates indicating a 0.49 percentage

³⁰To provide some context on what the competition index is capturing, stores that have a lower than average competition index have (on average) two fewer major competitors and twelve fewer minor competitors compared to store locations that have a higher than average competition index.

point decrease, on average.

Comparing the results of difference-in-difference estimates for low competition households (Table 9) to the difference-in-difference estimates for all households (Table 4) provides a rough indication of how much of the documented changes in grocery basket composition could be due to differences in retailer substitution patterns after households begin shopping online. The point estimates for the product categories of fruit, grains, meat, oil and other are remarkably close for the two estimation procedures.³¹ In contrast, the estimates for the product categories of dairy, drinks, snacks/sweets, sugar and vegetables are not as closely aligned.³² The differences between these estimates suggest that, on average, roughly 40 percent of the estimated effect of online shopping on the budget shares of dairy, drinks, snacks/sweets, sugar and vegetables could be due to changes in retailer substitution patterns after households begin shopping online.

4.1.2 Narrow Product Categories

I further explore the extent to which consumer crowd-in can explain the changes in online grocery basket composition by analyzing online product choice within narrower product spaces. The advantage of a more narrowly defined product space is that it is less likely that a consumer would buy different types of products, within these product spaces, at different retailers. For example, it is less likely that consumers shop for different types of yogurt at different types of retailers than it is for them to shop for different types of grocery products at different types of retailers. Under the assumption that households buy the same variety of yogurt at each retailer they shop with, if consumers allocate more of their yogurt purchases toward the retailer of this study when shopping online, we would not expect consumer "crowd-in" to change the composition of yogurts purchased, only total expenditures over yogurt.

This section evaluates whether there are significant differences in the types of bread,

³¹Note, I am comparing the estimates that utilize household and year-month fixed effects and am calculating the ratio of the low competition estimate to the all household estimate.

³²The estimates for dairy, drinks and vegetables are also no longer significant in the regressions that incorporate the low competition households only.

breakfast cereal, salty snacks and yogurt purchased when households shop online. Specifically, I analyze whether households begin to allocate a larger portion of their expenditures, within these product categories, towards healthier options. I begin by assigning individual products into different subcategories within the product group. For example, I assign individual bread UPCs to five different bread categories: white, wheat, other, seed and grain. Cereal UPCs are assigned to the categories of kids, organic kids, standard, frosted standard and healthy. Within salty snacks I create the product classifications of chips, healthy chips, popcorn, pretzels and tortilla chips. Lastly, I assign yogurt products to the categories of probiotic, light greek, greek, indulgent, kids, organic, light traditional and traditional.³³

Table 11 presents the average nutritional content (per ounce of food) for each product subcategory within breads, cereals, salty snacks and yogurt. In the product category of bread, wheat bread is generally considered a healthier choice. Table 11 illustrates that all breads contain roughly 70 calories per ounce; however, wheat, grain and seed breads tend to contain more protein per ounce (2.8 g vs. 2.3 g).³⁴ Within the product category of cereals, healthy (Grape Nuts, Kashi, Fiberone) and standard cereals (Cheerios, Chex, Cornflakes) tend to have better nutritional values than kids (Apple Jacks, Fruity Pebbles), organic kids (Annie's, Cascadian Farm) and frosted standard cereals (Frosted Flakes, Corn Pops). Healthy cereals contain less calories per ounce, more protein per ounce and less sugar per ounce. Standard cereals also exhibit lower levels of fat per ounce and sugars per ounce. Healthy chips (Sun Chips, Veggie chips etc.), pretzels and tortilla chips are healthier snack options relative to regular chips; healthy chips, pretzels and tortilla chips contain fewer calories per ounce, more protein and less fat than regular chips. Lastly, Table 11 illustrates that greek, light greek and light traditional yogurt have better nutritional values than other types of yogurt in terms of calorie, protein and sugar content. These yogurts have fewer calories per ounce, higher amounts of protein and contain less sugar

³³Table A4, in the appendix, briefly describes the subcategories of products that have been created within each product category.

³⁴Breads in the other category tend to have a higher sugar content per ounce, likely due to cinnamon raisin breads, etc.

than other yogurt varieties, on average.

In order to better understand how shopping online influences the composition of the different types of products purchased within these categories, I analyze the effect of online service availability on the budget shares for each product subcategory.³⁵ I analyze the budget share outcomes utilizing ordinary least squares and a fractional probit model, which accounts for the fractional nature of the share outcome and alleviates concerns associated with corner solutions. The underlying data in these regressions is generated from the year-month purchase occasions in which a household buys at least one item from the parent product category (i.e. households that purchase at least one bread for the bread share outcomes, one cereal for the cereal share outcomes, etc.). I estimate regressions of the following form:

$$s_{khm} = v_k + \tau_k 1\{OnlineAvail_{hm}\} + \gamma_{km} + \gamma_{kh} + \omega_{khm} \quad (4)$$

where s_{khm} is the share of product category sales (bread, cereal, etc.) allocated to product sub-category k for household h in year-month m , $1\{OnlineAvail_{hm}\}$ is an indicator that equals one if the online service is available to household h in year-month m , γ_{km} is a year-month fixed effect to control for differences across time and γ_{kh} is a household fixed effect to control for unobserved household preferences.³⁶

³⁵Tables A5, A6, A7 and A8 present the estimated effect of online service availability on sales ($\hat{\tau}_k$) for three ordinary least squares specifications, as well as the estimated average partial effects for two tobit specifications. The results of these regressions illustrate that online service availability has a positive and significant effect on the sales of wheat (\$0.09) and seed breads (\$0.01), frosted cereals (\$0.08), tortilla chips (\$0.06), traditional light (\$0.03), traditional (\$0.06), organic (\$0.02) and greek yogurts (\$0.12). Furthermore, there is no evidence for statistically significant changes in the sales volumes for white, other and grain breads; kids, standard and healthy cereals; pretzels, popcorn, healthy chips and chips; or kids and indulgent yogurts. A preliminary analysis of the data indicates that it is not uncommon for households to purchase more than one type of bread, cereal, salty snack and/or yogurt in a given month. Hence, I chose to model the decision of product choice in a continuous framework rather than a discrete choice environment. Specifically, 50% of bread purchases, 60% of cereal purchases, 70% of salty snack purchases and 62% of yogurt purchases in a year-month purchase occasion contain more than one type of bread, cereal, salty snack or yogurt product purchased.

³⁶Specifications without household and year-month fixed effects include treatment group indicators and post-availability time indicators in order to maintain the panel difference-in-differences framework. Additionally, specifications without household fixed effects include demographic characteristics of the households. Since my demographic variables are provided categorically, I include the demographics by creating indicators for whether household h belongs to a given demographic category.

Tables 12, 13, 14 and 15 present the estimates of τ_k from the ordinary least squares specifications, as well as estimates of the average partial effects for the fractional probit regressions. These tables indicate that after the online purchasing service becomes available, the only product categories that exhibit changes in the composition of products purchased are bread and salty snacks. The fractional probit estimates indicate that the budget share for wheat bread increases by 0.63 percentage points, while the budget share for other bread decreases by 0.37 percentage points. Additionally, the budget share for tortilla chips increases by 0.5 percentage points, while the budget share for pretzels decreases by 0.34 percentage points, on average. Lastly, the budget shares for product within the cereal and yogurt product categories remain unchanged.

These results suggest that shopping online does not induce households to become more health conscious within all product categories. I do not find any changes in the composition of cereals or yogurts purchased, a finding which is consistent with theories that predict decreased brand exploration in the online shopping environment due to an inability to verify product quality.³⁷ However, there are significant differences in the composition of bread and salty/snacks purchased when households shop online. These changes could be explained by differences in product search and (or) product placement across the two purchasing environments. For example, consider the purchasing patterns observed in bread. We observe that there are increases in wheat bread sales, as well as increases in the budget share for wheat bread. Furthermore, the increases in the budget share for wheat bread come at the expense of other bread. This result could be explained by in-store shopping behavior in which the consumer adds other breads (cinnamon raisin bread, etc.) to their cart because they see these breads and are reminded to buy them when shopping in the store. In the absence of these visual reminders when shopping online, the consumer may forgo purchases of other bread types. Differences in the location of products when shopping online could also lead to changes in purchasing patterns. For example, when in the store, the pretzels, popcorn and chips are all displayed on the

³⁷However, I do find that households spend significantly more on all types of yogurt when they shop online. This could be due to households bringing their yogurt demand from other retailers to the retailer of the study and (or) yogurt could be more attractive product when shopping online.

shelves of the same aisle. However, when shopping online, tortilla chips are nested within the chips category, while popcorn and pretzels are listed in their own product categories. Tortilla chips could become more popular when households shop online because, in the online purchasing environment, they are displayed relative to regular chips only.

5 Reduced Form Robustness Checks

This section tests the robustness of the panel difference-in-difference regressions performed earlier in the paper. First, I assess the validity of the parallel trends assumption by testing for pre-treatment differences in the budget shares for treated and control households. Then I run difference-in-differences regressions over the set of households in my sample who never shop online (i.e. in-store only households) to ensure that the effects captured in the main analysis are the result of online shopping and not other changes that could be occurring at the same time the online purchasing service was introduced. Lastly, I test whether the results of my main analysis can be explained by limited online product offerings. The results of these robustness checks indicate that the parallel trends assumption is valid for all product categories with the exception of dairy. Furthermore, I find no evidence that other changes are occurring in the purchasing environment at the same time the online service was introduced. Lastly, I do not find evidence that suggests limited online product offerings are responsible for the main results of this paper.

5.1 Event Study

I estimate event study specifications to determine whether or not there were shifts in budget share allocations before the online service was introduced and to evaluate the effect of online shopping over time. Specifically, I estimate regressions of the following form:

$$s_{ihm} = v_i + \sum_k \tau_{ik} 1\{TimeAvail_{hm} = k\} + \gamma_{im} + \gamma_{ih} + \omega_{ihm} \quad (5)$$

where s_{ihm} is the budget share of good, i , for household, h , in year-month, m , $1\{TimeAvail_{hm} = k\}$ is an indicator that equals one when the household is k time-periods from online ser-

vice introduction, γ_{im} and γ_{ih} are year-month and household fixed effects, respectively. I allow the reference time-period for $1\{TimeAvail_{hm} = k\}$ to be all time-periods that were more than five months prior to the online service introduction. Furthermore, k is discrete from $k = -5$ to $k = 5$ (5 months before online service introduction to 5 months following introduction, where time zero is the month of introduction) with one additional indicator for 6 months or more following introduction.

Figure 2 presents the estimates of τ_{ik} , with 95% confidence intervals, for each budget share outcome as well as for the outcome of online service use.³⁸ Eleven of the twelve graphs do not indicate a consistent pre-trend violation. However, the graph for dairy illustrates that the the point estimates of τ_{ik} were increasing in the months before online service introduction, indicating that caution should be exercised when drawing conclusions about the effect of online grocery shopping on dairy purchases.

The estimates for drinks, meat, snacks/sweets and vegetables illustrate post-treatment effects that remain fairly stable in the post-treatment time periods. However, the negative effects for drinks and snacks/sweets seem to fade six or more months after treatment. In contrast, the treatment effects on the budget shares for dairy, fruit and oil are fairly noisy, with each graph illustrating only one or two post-introduction coefficients that are significant. In summary, the graphs in Figure 2 illustrate striking discontinuities in the estimates of τ_{ik} at the period of online introduction ($t=0$) for the product categories of drinks, meat, snacks/sweets and vegetables.

5.2 Placebo Test

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 estimate difference-in-difference regressions over the subset of households that never adopt the online service. I expect these estimates to indicate that online service availability has no effect on the budget shares of households that never use the online service. Table 16 presents the difference-in-difference regressions for in-store only households. These

³⁸The estimates of these regressions are presented in Tables A17 and A18 of the appendix.

results are as one would expect; there is no strong 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. Although the difference-in-difference estimates for the prepared category are significant at the 10% significance level, regressions evaluating the effect of online service availability on in-store households' expenditures (Appendix Table A13), nutrition outcomes (Appendix Table A14) and ounce shares (Appendix Table A15) reveal no statistically significant changes over any of these outcomes. The results of these regressions suggest that there were no changes to other factors that influence demand at the time of online service introduction.

5.3 Online Product Offerings

When the online purchasing environment was launched the retailer only had select products available for online purchasing. At the time of launch, roughly 22 thousand unique items were available for purchase online. In contrast, by January 2016, roughly 78 thousand unique items were available for purchase online.³⁹ However, the retailer has indicated that most of the growth in product offerings came from general merchandise products rather than grocery products.

There are some challenges to understanding what products were available online. Primarily, I do not know what products were available online at any given point in time; I only have access to information regarding whether or not a product was purchased online and (or) in the store. Given that the online service was slowly introduced and that only a subset of households are able to shop online at any given point in time, there may be more products available online than are purchased online.

Figure 3 presents the percent of products that were purchased in-store and also purchased online. In March 2015, 27% of the products in the dairy category that were purchased in-store were also purchased online (the maximum of any product category); in

³⁹The retailer has provided me a list of roughly 108 thousand unique products within grocery that have been available for sale in their store at any point in time. Actual product offerings in the store are almost surely lower than this at any given point in time. As of March 2017 there were 89 thousand unique products available for purchase online.

contrast, only 9% of products in the other category that were purchased in-store were also purchased online (the minimum of any product category). However, by January 2016, these proportions significantly increased to the point where at least 53% of the products (in any given category) purchased in-store have also been purchased online. Figure 4 presents the percent of in-store sales that come from products that were also purchased online in each month. The column for January 2016 indicates that the minimum percentage of in-store sales represented by products that were also purchased online is 86%. Thus, 53% of the products represent 86% of the sales in a product category, snacks/sweets, that has been shown to be less popular online.⁴⁰ Given that the most popular in-store items are also being purchased online and that only half of my household sample has access to the online purchasing service by January 2016, I assume that online product offerings are representative of in-store product offerings from January 2016 on.

Under this assumption, I test whether limited product offerings are driving the results of the previous analysis by restricting the data to all dates after January 2016 and estimating equation (1). If limited product offerings are responsible for the main results of my paper, the time-restricted regressions should indicate that shopping online has no effect on any of the budget share outcomes. Table 17 presents the ordinary least squares and two-stage least squares estimates from the time restricted regressions. The results indicate that the effect of online shopping for dairy and fruit budget shares remains positive and significant and the effect for snacks and sweets remains negative and significant. In contrast, the estimated effects for drinks, meat, oils and vegetables retain the same signs as earlier regressions, but are no longer statistically significant.⁴¹ The magnitudes of the estimates over all time periods and the time restricted estimates are remarkably similar for the product categories of dairy, fruit and snacks/sweets with larger discrepancies occurring in the product categories of drinks, meat, oils and vegetables.

⁴⁰Additionally, only 56% of the households in my sample have access to the online shopping service by January 2016.

⁴¹The estimates obtained from running regressions over later time periods of the data indicate the following percent changes in average budget shares: dairy (5.2%), fruit (5.5%), meat (3.5%), vegetables (4.4%), drinks (-1.3%), oil (-1.2%), snacks/sweets (-13.5%). For comparison, the estimates over all time periods indicated the following percent changes in average budget shares: dairy (3.8%), fruit (5.9%), meat (5.7%), vegetables (7.4%), drinks (-5.2%), oil (-4.1%), snacks/sweets (-13.6%).

Identification is driven by the households whose status of online availability changes over time. Thus, estimates of the effect of online shopping that are derived from the restricted set of time periods are identified only by the Wave 2 and Wave 3 households defined in Section 3. There is no way to parse out the differences in these results that are due to heterogeneous treatment effects and those that are due to increased availability of online product offerings.⁴² However, because differences in online and offline budget shares continue to persist in time periods in which the online product offerings are representative of in-store offerings, this robustness check indicates that the results estimated over all time periods cannot be explained by limited online product offerings.

6 Modeling Grocery Demand

The reduced form findings of this paper indicate that purchasing environments have influence over consumer choice. My findings imply that, when shopping online, households may be less tempted to make unhealthy impulse purchases simply due to search and timing differences between the in-store and online purchasing environments. Shopping online also leads to monthly purchases that are of a higher nutritional quality compared to months in which all purchases were made in-store. In order to better understand how online demand differs from in-store demand, I present and estimate a formal model of grocery demand which allows me to test for differences in price elasticities across the two purchasing environments.

I estimate grocery demand by utilizing the LA/AIDS demand system, developed by Deaton and Muellbauer (1980); I also incorporate an extension from Atkin (2013) that models varying household tastes by allowing the vector of first price coefficients (τ_{ih} , in the expenditure system defined shortly) to vary by household.⁴³ The LA/AIDS demand

⁴²Figure A8, of the Appendix, illustrates that wave two and wave three households allocated more of their budget towards drinks and less of their budgets towards vegetables compared to wave one households. On the other hand, the drinks product category exhibited a lot of growth in product offerings between March 2015 and January 2016 but it is unclear if this growth came from additional products being offered online or more people purchasing these UPCs online.

⁴³Allowing the first price coefficients to vary by household is a reasonable way to model tastes for the following reason: if a household really values a particular item, price changes for that item are likely to

system is derived from an expenditure function, $e(p, u; \tau_h)$: the minimum expenditure necessary to achieve utility u , given a vector of prices p and varying household tastes, τ_h . The log expenditure function over I goods is defined as follows:

$$\ln(e(p, u; \tau_h)) = \alpha_0 + \sum_{i=1}^I \tau_{ih} \ln(p_i) + 1/2 \sum_{i=1}^I \sum_{i'=1}^I \gamma_{ii'} \ln(p_i) \ln(p_{i'}) + u \beta_0 \prod_{i=1}^I p_i^{\beta_i} \quad (6)$$

where i indexes good i and i' indexes good i' .⁴⁴ Note that by Shephard's Lemma: $\frac{\partial e(p, u; \tau_h)}{\partial p_i} = q_{ih}$. This equality implies:

$$\frac{\partial \ln(e(p, u; \tau_h))}{\partial \ln(p_i)} = \frac{p_i q_{ih}}{e(p, u; \tau)} = s_{ih} \quad (7)$$

where s_{ih} is the share of household h 's budget allocated to good i . Differentiating the right hand side of equation (6) with respect to $\ln(p_i)$ and setting it equal to s_{ih} produces the following:⁴⁵

$$s_{ih} = \tau_{ih} + \sum_{i'=1}^I \gamma_{ii'} \ln(p_{i'}) + \beta_i u \beta_0 \prod_{i=1}^I p_i^{\beta_i} \quad (8)$$

Recall that a utility maximizing consumer sets $e(p, u; \tau_h)$ equal to total expenditure, m ; thus, I re-write utility as a function of total expenditure and prices by rearranging equation (6). I use the functional form of utility to get budget shares as a function of tastes (τ_{ih}), prices (p), and total expenditure (m_h):

$$s_{ih} = \tau_{ih} + \sum_{i'} \gamma_{ii'} \ln(p_{i'}) + \beta_i \ln\left(\frac{m_h}{P}\right) \quad (9)$$

Where $\ln(P)$ is defined by the following equation:

$$\ln(P) = \alpha_0 + \sum_i \tau_{ih} \ln(p_i) + 1/2 \sum_i \sum_{i'} \gamma_{ii'} \ln(p_i) \ln(p_{i'}) \quad (10)$$

change their total expenditure differently than it would for a household who has little value for that item.

⁴⁴Goods i and i' are both within I and are sometimes equivalent and sometimes different than each other.

⁴⁵I use the fact that $\frac{\partial \ln(e(p, u; \tau_h))}{\partial \ln(p_i)} = \frac{\frac{\partial \ln(e(p, u; \tau_h))}{\partial p_i}}{\frac{\partial \ln(p_i)}{\partial p_i}}$ in order to get equation (8).

Following Deaton and Muellbauer (1980), I approximate $\ln(P)$ with a Stone Index, $\ln(P) = \sum_i \bar{s}_i \log(p_i)$, making the system linear.⁴⁶ I assume weak separability between grocery products and other expenditures which allows me to replace household expenditure with total expenditure over grocery products and calculate budget shares as the share of grocery expenditure allocated to product category i .

Note that household tastes, τ_{ih} , act as budget share shifters in this setting. I assume that tastes are a function of household demographics that influence household preferences (e.g. economic status, household size, age etc.) and seasonal fluctuations that influence preferences over food groups.⁴⁷ Hence, I define τ_{iht} as follows:

$$\tau_{iht} \stackrel{\text{def}}{=} \alpha_i + v_{ih}D_h + v_{it}Z_t \quad (11)$$

where D_h is a vector of demographic variables (household size, age, income, loyalty measures, marital status and number of children) and Z_t is a vector containing month dummies (to control for seasonality) and a linear time trend.

Adding a time subscript (year-month, t) and substituting τ_{iht} into equation (9) produces the following:

$$s_{iht} = \alpha_i + \sum_{i'=1}^{11} \gamma_{i'i} \ln(p_{i'ht}) + \beta_i \ln\left(\frac{m_{ht}}{P_{ht}}\right) + v_{ih}D_h + v_{it}Z_t + \epsilon_{iht} \quad (12)$$

I allow for structural differences to exist between the in-store and online demand functions by permitting the underlying parameters to vary in months that a household shops online. Explicitly, I include $1\{Online_{ht}\}$, an indicator that equals one when the household purchases at least one good online in year-month t , and I interact prices and expenditure with $1\{Online_{ht}\}$.⁴⁸ Modifying equation (12) to allow for structural differences between

⁴⁶In the definition of $\ln(P)$, \bar{s}_i is the average budget share of category i over all periods of the data. This is substituted in place of s_{iht} in order to avoid the endogeneity that arises when the dependent variable also appears as an independent variable.

⁴⁷Atkin (2013) provides evidence that tastes are a function of what type of food an individual was fed as a child.

⁴⁸These interactions nest two demand equations (in-store and online) within one estimating equation.

in-store and online demand produces the following:

$$s_{iht} = \alpha_i + \phi_i 1\{Online_{ht}\} + \sum_{i'=1}^{11} [\gamma_{iir} \ln(p_{i'ht}) + \gamma_{iio} \ln(p_{i'ht}) 1\{Online_{ht}\}] \\ + \beta_i \ln\left(\frac{m_{ht}}{P_{ht}}\right) + \beta_{io} \ln\left(\frac{m_{ht}}{P_{ht}}\right) 1\{Online_{ht}\} + v_{ih} D_h + v_{it} Z_t + \epsilon_{iht} \quad (13)$$

Theoretical properties of demand systems imply the following constraints on the parameters in equation (13):

Zero Homogeneity:

$$\sum_{i'=1}^{11} \gamma_{iir} = 0, \quad \sum_{i'=1}^{11} \gamma_{iio} = 0 \quad (14)$$

Slutsky Symmetry:

$$\gamma_{iir} = \gamma_{iri}, \quad \gamma_{iio} = \gamma_{iio} \quad (15)$$

Adding Up:

$$\sum_i \alpha_i = 1, \quad \sum_i \beta_i = 0, \quad \sum_i \phi_i = 0, \quad \sum_i \beta_{io} = 0 \quad (16)$$

I jointly estimate a system of ten demand equations, as presented in equation (13), subject to the constraints presented in equations (14) and (15). The parameters of the eleventh demand equation are derived from the estimation results of the ten equation system.⁴⁹ Specifically, I calculate $\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{\phi}_i$ and $\hat{\beta}_{io}$ of the eleventh demand equation by imposing the adding up restrictions presented in equation (16); additionally, the price coefficients of the eleventh equation are defined by the symmetry restrictions presented in equation (15).

Marshallian elasticities are computed from the estimated demand parameters as follows:

Own Price Elasticity

$$\eta_{ii} = \frac{\hat{\gamma}_{ii}^*}{\hat{s}_i^*} - \hat{\beta}_i^* - 1 \quad (17)$$

⁴⁹The iterated FGLS estimates, presented in this paper, are equivalent to MLE and are invariant to which equation is dropped.

Cross Price Elasticity

$$\eta_{iit'} = \frac{\hat{\gamma}_{iit'}}{\bar{s}_i^*} - \hat{\beta}_i^* \frac{\bar{s}_{i'}}{\bar{s}_i^*} \quad (18)$$

In-store price elasticities are obtained by setting $\hat{\gamma}_{ii}^* = \hat{\gamma}_{ii}$, $\bar{s}_i^* = \bar{s}_i$, $\hat{\beta}_i^* = \hat{\beta}_i$ and $\hat{\gamma}_{iit'}^* = \hat{\gamma}_{iit'}$, while the online elasticities are obtained by setting $\hat{\gamma}_{ii}^* = \hat{\gamma}_{ii} + \hat{\gamma}_{iio}$, $\bar{s}_i^* = \bar{s}_i + \hat{\phi}_i$, $\hat{\beta}_i^* = \hat{\beta}_i + \hat{\beta}_{io}$ and $\hat{\gamma}_{iit'}^* = \hat{\gamma}_{iit'} + \hat{\gamma}_{iio}$.⁵⁰

6.1 Demand Estimation

This section outlines how I address endogeneity and efficiency concerns when estimating the demand parameters. First, prices defined at the household level are likely endogenous to the demand system due to unobserved preference shocks and/or preferences over unobserved product quality. In order to alleviate these endogeneity concerns, I instrument prices with the mean wholesale costs of products available to the household. This isolates the variation in household prices that is due to factors that shift supply.⁵¹ I also instrument $1\{Online_{ht}\}$ with $1\{OnlineAvail_{ht}\}$ following the logic presented earlier in the paper.⁵² The second estimation concern is efficiency. Since I estimate ten demand equations for grocery products, it is likely that the errors for a given budget share equation, i , are correlated with the errors of another budget share equation, i' ; in other words, $cov(\epsilon_{iht}, \epsilon_{i'ht}) \neq 0$.⁵³ In order improve efficiency, and to address the endogeneity concerns

⁵⁰In the elasticity equations, \bar{s}_i is the average budget share for category i over all time periods of the data. Note that the standard errors of the elasticities are computed as in Chalfant (1987), treating the \bar{s}_i 's as constants.

⁵¹One of the challenges associated with defining instruments for household level prices is that the instrument must also vary at the household level. In order to ensure household level variation in the wholesale costs of products available, I utilize the fact that each household has a unique store footprint (i.e. the stores visited by the household) in a given year-month. Specifically, I define the price instruments as follows: first, I calculate the average cost of the products available at the category-store-year-month level, then, I average the category-store-year-month level wholesale costs over the stores the household visited in a given year-month. Explicitly, $c_{iht} = \sum_s \frac{\bar{c}_{ist}}{S_{ht}}$, where s indexes the store locations frequented by household h in year-month t , S_{ht} is the number of stores visited by household h in year-month t and \bar{c}_{ist} is the mean wholesale cost of the products sold in category i , at store s in year-month t . Additionally, since household prices appear in $\ln(P_{ht})$, I instrument $\ln(P_{ht})$ with $\ln(C_{ht}) = \sum_i \bar{s}_i \ln(c_{iht})$.

⁵²All interactions of $1\{Online_{ht}\}$ and $\ln(p_{iht})$ are instrumented with interactions of $1\{OnlineAvail_{ht}\}$ and $\ln(c_{iht})$.

⁵³The result that generalized least squares is equivalent to ordinary least squares when the set of dependent variables is the same in each equation is lost when restrictions are placed on parameters either within

outlined above, I utilize a three-stage least squares estimation strategy.⁵⁴ The three steps of the estimation procedure are as follows:

1. Perform the first stage for each endogenous variable and obtain the fitted values.
2. Perform second stage estimation (i.e. two-stage least squares), equation by equation, replacing endogenous variables with their fitted values. Obtain the estimated errors for each equation and estimate the covariance matrix for the errors.
3. Compute the feasible generalized least squares estimator utilizing the estimated covariance matrix from Step 2.

The results of the first-stage regressions are presented in Tables [A21](#), [A22](#), [A23](#), [A24](#) and [A25](#) of the appendix. Each of the proposed instruments is strong in the sense that it is highly correlated with its corresponding endogenous variable.⁵⁵ For prices, the cost instruments indicate a strong and positive relationship between wholesale costs and prices. The coefficients on the log cost instruments range from 0.3 to 1.0, indicating that a one percent increase in average store costs results in a 0.3 to 1 percent increase in household prices. The estimated demand parameters of the three-stage least squares procedure can be found in Tables [A26](#), [A27](#), [A28](#) and [A29](#) of the appendix.

6.2 Elasticities

The in-store and online price elasticity estimates and standard errors are reported in Tables [18](#) and [19](#), respectively.⁵⁶ The in-store own-price elasticities are overwhelmingly neg-

or across equations (Greene 2012). There are three cases in which there are no efficiency gains from generalized least squares relative to equation by equation ordinary least squares: (1) if the disturbance terms across equations are independent of each other, (2) the independent variables in each equation are identical and (3) if the regressors of one equation are a subset of the regressors in another equation (Greene 2012). My demand system satisfies the second of these conditions because each of the share equations contains the same independent variables.

⁵⁴Note that the generalized least squares procedure only accounts for the correlation of errors across equations. Hence, the standard errors are not robust to heteroskedasticity of the errors within each equation. If this is an area of concern, the standard errors could be corrected by employing a clustered bootstrap.

⁵⁵The t-statistics for the first-stages range from 4.6 to 60.1, in absolute value.

⁵⁶The elasticity matrices are not symmetric because I am computing Marshallian elasticities, which hold income (as opposed to utility for Hicksian demand) constant. Hence, the estimated cross-price elasticities reflect a symmetric price effect and an income effect, which is not necessarily symmetric.

ative and statistically significant; additionally, the negative and statistically significant in-store own-price elasticities range from -1.91 (drinks) to -0.66 (sugars).⁵⁷ In contrast, the online own-price elasticities are much less likely to be statistically significant. In fact, the only own-price elasticities that are significant for the online matrix are dairy (-0.66), drinks (-0.65), fruit (-0.81) and snacks/sweets (-1.53).⁵⁸

Figure 5 presents the ratio of the in-store price elasticity to the online price elasticity.⁵⁹ Specifically, each cell is colored black if $|\eta_{Instore}|$ is significantly different and larger in magnitude than $|\eta_{Online}|$, white if $\eta_{Instore}$ is not statistically different from η_{Online} and gray if $|\eta_{Instore}|$ is significantly different and smaller in magnitude than $|\eta_{Online}|$. Figure 5 illustrates that roughly one-third of the elasticities are significantly different for the months in which a household engages in online shopping. For the product categories of dairy, drinks, and fruits the own-price elasticities are larger (in absolute value) in-store than they are online. Many of the cross-price elasticities that are significantly different across the two shopping environments exhibit price substitution patterns across product categories are significantly different and larger in magnitude when the household is shopping in-store only. Of the own-price elasticities that are significantly different across the two purchasing environments, the in-store own-price elasticities are, on average, 2.0 times larger (in absolute value) than the online own-price elasticities.⁶⁰ Additionally, the

⁵⁷The two exceptions to this statement are the own-price elasticity for grains (0.29) and for prepared (0.62) both of which are statistically significant. Harding and Lovenheim (2017) also find positive and significant own-price elasticities for prepared foods and cereal utilizing similar data and a similar estimation strategy. In general, the estimated in-store elasticities are aligned with the current food demand literature.

⁵⁸Figures A13 and A14 present visual representations of the two elasticity matrices. In these figures, darker shades represent negative elasticities, lighter shades represent positive elasticities and white represents statistically insignificant elasticities. The own-price elasticities are presented in the left column and run along the diagonal of these matrices from the corner of the second to left hand column to the upper right hand corner. Notice that the in-store own-price elasticities are overwhelmingly significant and negative (with the exception of the product categories of prepared and grains), while the own-price elasticities in the online price elasticity matrix are a combination of white (statistically insignificant) and darker shades (negative). Additionally, comparing the cross-price elasticities of these two matrices, the in-store elasticity matrix illustrates many statistically significant cross-price substitution patterns, while the online price elasticity matrix illustrates that many of these substitution patterns become insignificantly different from zero in months when a household shops both in-store and online.

⁵⁹Table A30 presents the difference between the in-store and online price elasticities as well as the standard errors for that difference.

⁶⁰The in-store own-price elasticities are, on average, 0.15 times larger (in absolute value) than the online own-price elasticities when incorporating all own-price elasticities.

in-store cross price elasticities are, on average, 2.8 times larger (in absolute value) than the online cross-price elasticities.⁶¹

These findings illustrate that consumers are more price sensitive in-store than they are online. Consumers may be less sensitive to prices when shopping online due to convenience factors built into the online shopping experience and the search differences that exist across the two environments. For example, when shopping online a household may utilize features of the website that allow them to instantly generate their basket based off of their previous online order.⁶² An online shopper, who values convenience, may have a tendency to re-create their previous order without checking item prices and/or prices of substitutes. Furthermore, decreased price-sensitivity when shopping online occurs for product categories that contain goods that a household would likely add to an online favorites list. For example, products like milk, coffee, and bananas sound like reasonable candidates for an instant add to cart list.

The results of this paper are also consistent with the current e-commerce literature. Specifically, Pozzi (2012) finds that in-store own-price elasticities for cereal are roughly fifty percent higher than online own-price elasticities, while in-store cross price elasticities are nearly three times as large as online cross-price elasticities. Additionally, Chu et al. (2008) find evidence, across twelve different product categories, that households tend to be less sensitive to prices when shopping online.⁶³

⁶¹This average only includes the elasticities that are significantly different from each other and excludes two outliers. The excluded outliers are the two cross price elasticities between oil and fruit ($\eta_{oil,fruit}$ and $\eta_{fruit,oil}$). These elasticities are relatively large when households shop in-store only (0.40 and 0.77) and get quite close to zero in the months in which households shop online; hence, the ratio of the in-store to online price elasticity is quite large for these observations. The in-store cross-price elasticities are, on average, 3.6 times larger (in absolute value) than the online cross-price elasticities when incorporating all cross-price elasticities.

⁶²A household may also use the search engine to find a particular brand of an item and add that item to their cart without ever looking at the prices of competing brands. Alternatively, other features of the online website may make it easier for households to find sales; specifically, households can filter their search results to items that are currently on sale or sort their search results according to price.

⁶³Specifically, they find that in-store elasticities are higher (in absolute value) for the product categories of yogurt, milk, cooking oil, toilet paper, square bread, eggs, fabric softener, oranges, paper towels, potatoes and dish detergent.

7 Discussion & Conclusion

This paper utilizes novel household panel data to analyze the effect of online grocery shopping on grocery demand. In order to identify a causal effect of online grocery shopping, I utilize variation in the introduction of an online shopping service, at different store locations, as a source of exogenous variation in the household's decision to shop online. Estimates from panel difference-in-differences and instrumental variables estimation strategies indicate that households allocate a significantly larger share of their total grocery expenditures toward healthier product categories (dairy, fruit, meats, vegetables) at the expense of more indulgent product categories (drinks, oils, snacks/sweets) when shopping online. In addition, I find that the nutritional content of grocery purchases is improved in the months in which households shop online. Estimated declines in the average amount of calories purchased imply that the average adult would lose roughly five pounds over the course of a year simply from engaging in online grocery shopping.⁶⁴

Motivated by the reduced form findings, I then estimate a formal model of grocery demand and test for differences in price elasticities across the two purchasing environments. I find that households are generally less price sensitive when shopping online. Specifically, in-store own-price (cross-price) elasticities are, on average, two (three) times larger than the estimated online price elasticities. These findings indicate that households are less price sensitive and exhibit weaker substitution patterns when shopping online.

This paper illustrates that consumer demand is sensitive to differences in search and the varying levels of product placement that exist across purchasing environments. I find that when consumers shop online, they are less likely to purchase indulgent products and they are less sensitive to prices. Differences between in-store and online search are likely a large contributing factor to this result. Relative to the online purchasing environment, there are many elements of in-store design (checkout lanes, end of aisle displays, store layout) that dictate the consumer search path, influence the intensity of price-shopping and nudge consumers towards purchases. My findings suggest that product placement

⁶⁴This statement assumes that the declines in calories purchased perfectly translate to declines in caloric intake.

is effective in influencing purchases and initiatives that promote healthier choices (via product placement either in-store or online) could improve the quality of food purchases made. Furthermore, the structural findings of this paper suggest that the marginal cost of time dedicated to search is different between the online and in-store shopping environments. Hence, a more sophisticated online pricing strategy, that incorporates the fact that the value of convenience appears to be different across the two purchasing environments, would likely lead to increased online revenues.

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9 Figures

Figure 1: Online Shopping Service Availability

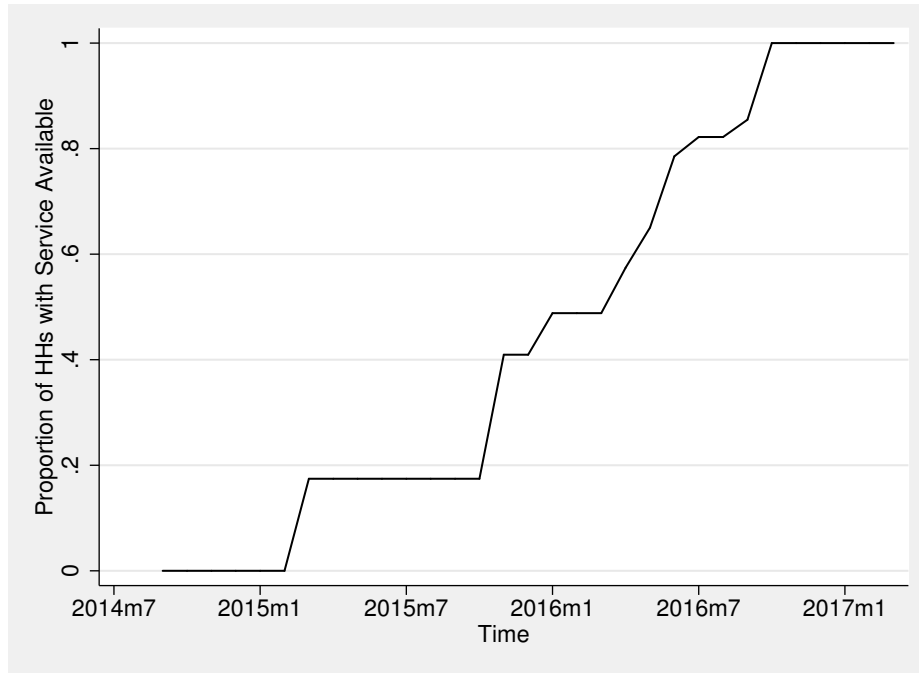


Figure 1 illustrates the proportion of households who have access to the online purchasing service over time.

Figure 2: Event Study Estimates for Online Use and Expenditure Shares

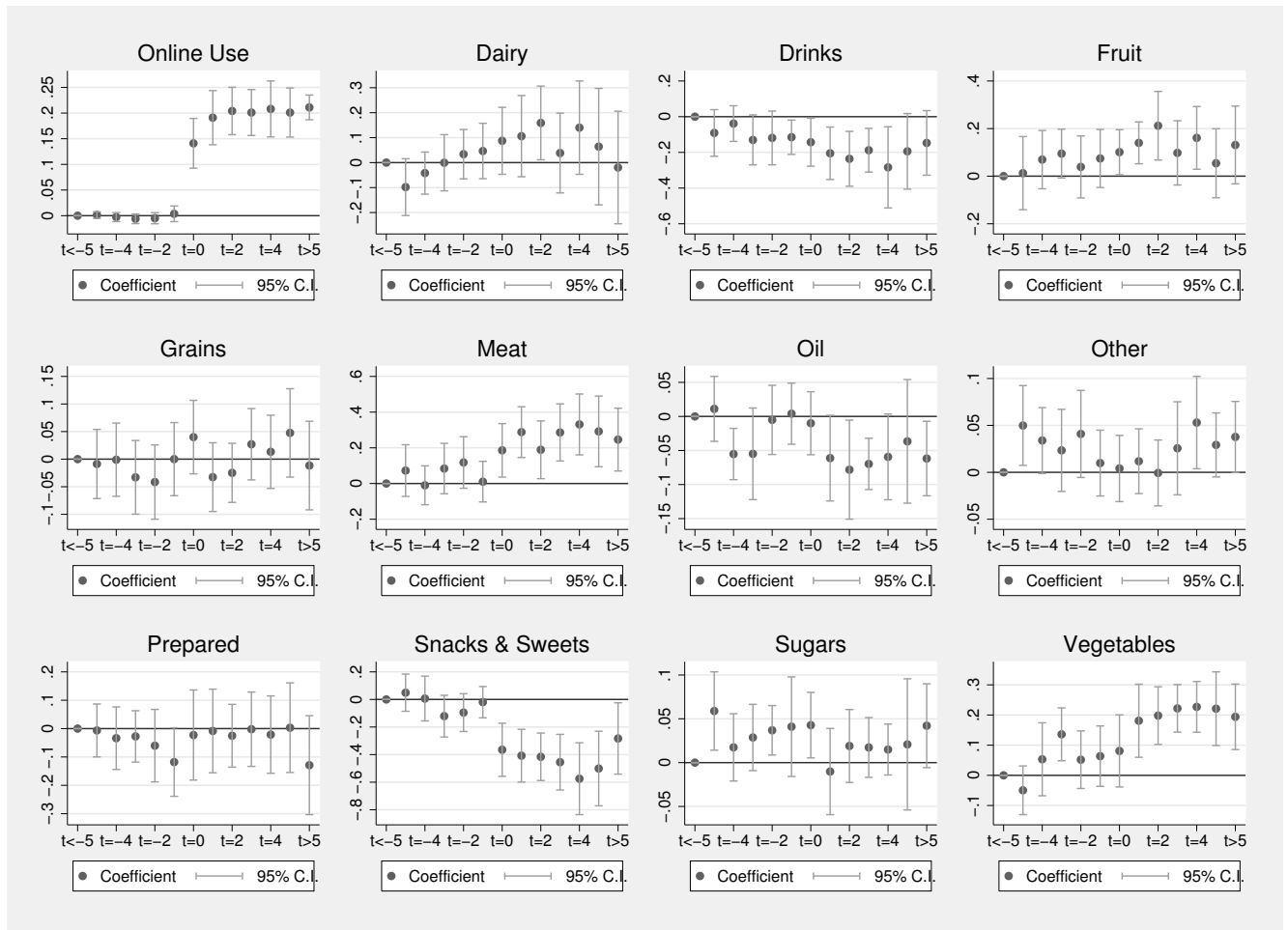


Figure 2 presents the event study estimates of the effect of online availability for online households.

Figure 3: Percent of Available Products Purchased Online

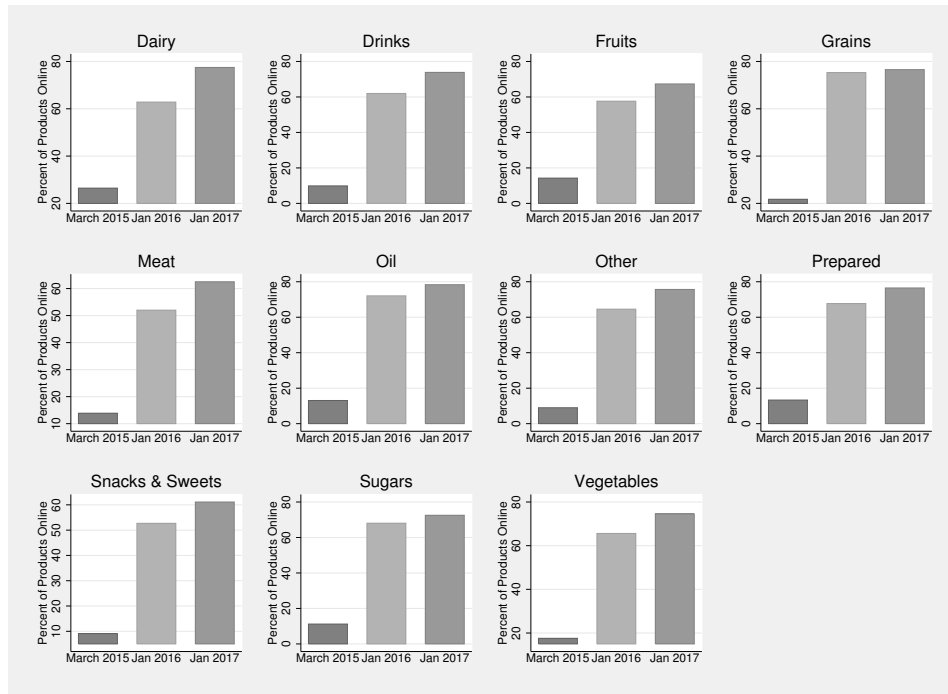


Figure 3 presents the percentage of upcs purchased both in-store and online in March 2015, January 2016 and January 2017.

Figure 4: Percent of In-Store Sales from Products Available Online

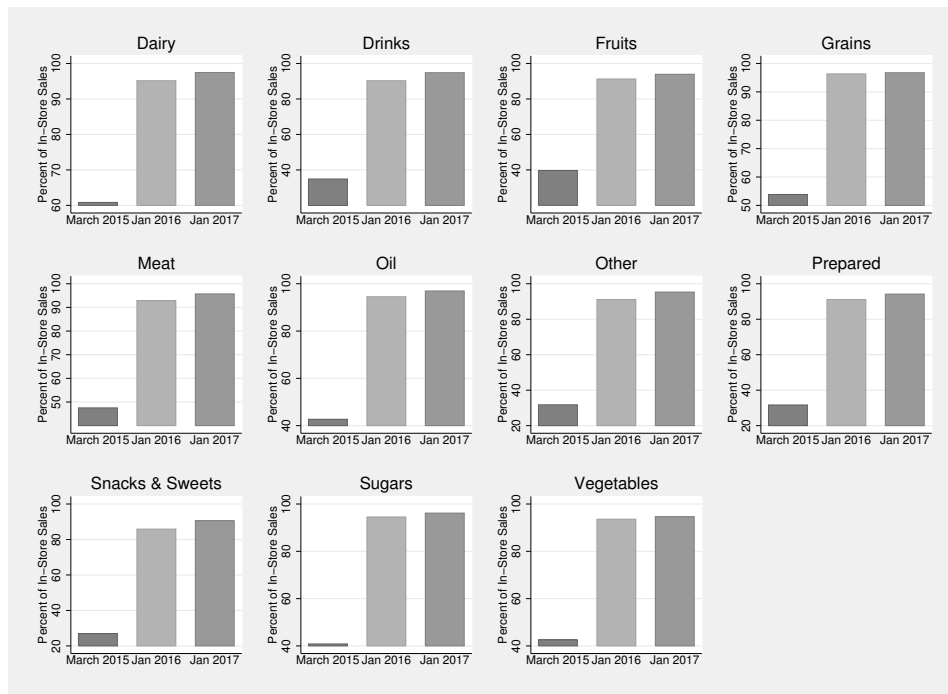


Figure 4 presents the percentage of in-store sales that are generated from upcs that have also been purchased online. This figure illustrates that by January 2016, the most popularly purchased in-store products are also available online.

Figure 5: Own and Cross Price Elasticity Ratio, $\frac{|\eta_{Instore}|}{|\eta_{Online}|}$

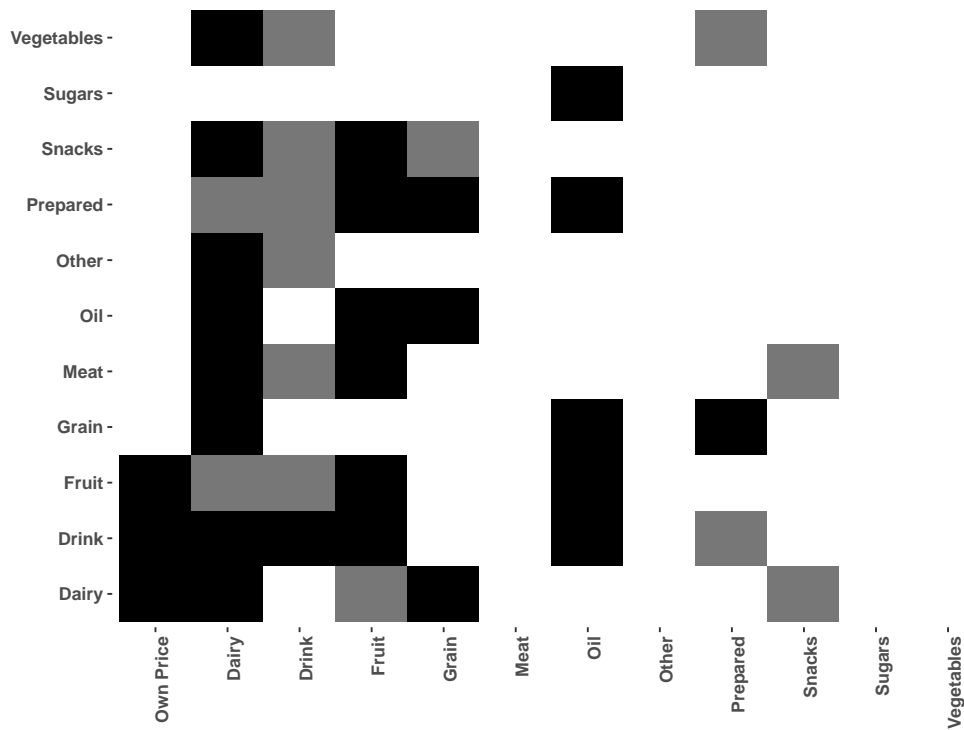


Figure 5 the ratio of the in-store and online own and cross price elasticities. Black indicates that the in-store elasticity is significantly different and greater, in absolute value, than the online elasticity. White means that the two elasticities are not significantly different from each other, at the 95% confidence level, and gray indicates that the in-store elasticity is significantly different and smaller, in absolute value, than the online elasticity.

10 Tables

Table 1: Household Demographics

Household Population	All HHs	In-Store Only HHs	Online Adoption HHs	Online Households		
				Wave 1	Wave 2	Wave 3
1{Married}	0.68	0.67	0.69	0.70	0.68	0.67
Household Size	All	In-Store	Online	Wave 1	Wave 2	Wave 3
1{1 Person}	0.10	0.12	0.10	0.09	0.10	0.10
1{2 People}	0.22	0.22	0.22	0.21	0.21	0.23
1{3 People}	0.24	0.22	0.25	0.25	0.25	0.24
1{4 People}	0.17	0.17	0.17	0.17	0.18	0.17
1{5+ People}	0.26	0.26	0.27	0.27	0.26	0.25
Household Income	All	In-Store	Online	Wave 1	Wave 2	Wave 3
1{0-29K}	0.11	0.14	0.10	0.09	0.10	0.10
1{30-50K}	0.16	0.17	0.16	0.16	0.15	0.17
1{51-79K}	0.30	0.28	0.31	0.31	0.31	0.32
1{80-99K}	0.15	0.15	0.15	0.16	0.15	0.14
1{100-149K}	0.12	0.12	0.12	0.12	0.13	0.13
1{150K+}	0.16	0.14	0.16	0.17	0.17	0.13
Number of Children	All	In-Store	Online	Wave 1	Wave 2	Wave 3
1{0 Children}	0.43	0.49	0.41	0.40	0.41	0.43
1{1 Child}	0.33	0.31	0.33	0.33	0.33	0.33
1{2 Children}	0.14	0.13	0.15	0.15	0.15	0.14
1{3 Children}	0.07	0.06	0.08	0.08	0.08	0.07
1{4+ Children}	0.03	0.02	0.04	0.04	0.04	0.03
Household Head Age	All	In-Store	Online	Wave 1	Wave 2	Wave 3
1{18-25}	0.02	0.02	0.02	0.03	0.02	0.02
1{26-35}	0.22	0.14	0.25	0.27	0.24	0.24
1{36-45}	0.28	0.20	0.32	0.31	0.32	0.32
1{46-55}	0.20	0.24	0.19	0.19	0.20	0.18
1{56-55}	0.16	0.21	0.14	0.14	0.14	0.15
1{66+}	0.11	0.18	0.08	0.07	0.08	0.09
Household Count	34,797	9,777	25,020	13,208	7,267	4,545

Table 2: Monthly Purchasing Patterns

Time Period	Before & After		Before		Before			
	Online Introduction	Online Introduction	In-Store	Online Introduction	Online Introduction	Wave 1	Wave 2	Wave 3
Household Population	All							
	HHs		Only HHs	Adoption HHs	Wave 1	Wave 2	Wave 3	
Monthly Shopping Habits	All	In-Store	Online	Wave 1	Wave 2	Wave 3		
Grocery Expenditure (\$)	437	331	448	467	420	434		
Items Purchased	176	135	178	187	166	172		
Visits to Store	7.7	6.8	7.5	8.0	6.9	7.1		
Share of Sales Online	0.0	0.0	0.0	0.0	0.0	0.0		
Share of Expenditure	All	In-Store	Online	Wave 1	Wave 2	Wave 3		
Dairy	12.5	11.9	13.2	13.4	13.1	12.9		
Drink	10.8	10.9	10.1	9.9	10.2	10.4		
Fruit	8.3	7.3	7.5	7.6	7.5	7.1		
Grains	7.5	7.2	7.6	7.6	7.6	7.6		
Meats	18.5	18.9	18.5	18.3	18.5	18.9		
Oils	4.4	4.4	4.4	4.4	4.3	4.4		
Other	1.6	1.7	1.8	1.8	1.8	1.8		
Prepared	10.1	10.9	10.8	10.7	10.8	10.9		
Snacks/Sweets	15.8	16.1	15.5	15.4	15.6	15.7		
Sugars	1.5	1.6	1.6	1.6	1.6	1.6		
Vegetables	9.1	9.2	9.1	9.3	9.0	8.6		
Observations	855,022	56,972	147,246	77,925	42,608	26,713		

Table 3: Average Price and Nutrient Content Per Ounce of Food

Product Category	Price (\$)	Calories (kcal)	Protein (g)	Carbs (g)	Total Fat (g)	Total Sugar (g)	Sodium (g)	Cholesterol (g)
Dairy	0.10	71	3.9	4.2	4.3	2.2	0.2	0.01
Drinks	0.07	22	0.2	4.5	0.2	3.9	0.0	0.00
Fruit	0.10	23	0.3	5.5	0.2	4.1	0.0	0.00
Grains	0.13	97	2.7	18.5	1.5	3.4	0.2	0.00
Meat	0.23	81	7.7	2.1	4.7	0.8	0.2	0.03
Oil	0.15	88	0.3	4.2	7.7	3.9	0.3	0.00
Other	0.46	73	1.4	11.5	2.5	5.4	1.9	0.00
Prepared	0.16	68	2.4	9.8	2.1	1.3	0.3	0.00
Snacks & Sweets	0.21	120	1.8	17.8	4.9	9.5	0.1	0.01
Sugars	0.11	98	1.4	18.1	3.6	14.9	0.0	0.00
Vegetables	0.09	22	0.7	4.1	0.4	1.5	0.3	0.00

Table 4: Difference in Difference / Reduced Form Estimates, (τ_i)
Online Households

Budget Shares	(1)	(2)	(3)	Avg. Budget Share (Pre-Online Service)
Dairy	0.104** (0.0386)	0.105** (0.0387)	0.0969** (0.0401)	13.21 (6.90)
Drinks	-0.103** (0.0380)	-0.104** (0.0382)	-0.100** (0.0384)	10.08 (8.31)
Fruit	0.0844** (0.0362)	0.0846** (0.0362)	0.0845** (0.0369)	7.48 (6.18)
Grain	0.0242 (0.0152)	0.0249 (0.0152)	0.0211 (0.0148)	7.6 (4.66)
Meat	0.204*** (0.0580)	0.205*** (0.0581)	0.204*** (0.0586)	18.46 (9.69)
Oil	-0.0350** (0.0143)	-0.0354** (0.0143)	-0.0352** (0.0150)	4.36 (3.56)
Other	-0.0121 (0.00771)	-0.0123 (0.00767)	-0.00970 (0.00802)	1.81 (2.72)
Prepared	0.0241 (0.0420)	0.0262 (0.0425)	0.0305 (0.0427)	10.78 (7.45)
Snacks/Sweets	-0.408*** (0.0665)	-0.413*** (0.0681)	-0.406*** (0.0677)	15.52 (9.84)
Sugar	-0.0141 (0.00957)	-0.0144 (0.00960)	-0.0151 (0.00976)	1.61 (2.32)
Vegetables	0.132*** (0.0310)	0.134*** (0.0308)	0.129*** (0.0324)	9.09 (6.20)
Time Availability f.e.	X			
Treatment Cohort f.e.	X	X		
Household Demographics	X	X		
Year-Month f.e.		X	X	
Household f.e.			X	
Observations	616,357	616,357	616,357	147,246

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Each cell represents an estimate of the effect of online availability on the budget shares.
These estimates were produced by running OLS equation by equation.
Equation by equation OLS is equivalent to SUR in this scenario.

Table 5: Difference in Difference / First Stage Estimates, (θ_i)
Online Households

1{Online}	(1)	(2)	(3)
1{OnlineAvail}	0.193*** (0.0216)	0.193*** (0.0216)	0.193*** (0.0221)
Time Availability f.e.	X		
Treatment Cohort f.e.	X	X	
Household Demographics	X	X	
Year-Month f.e.		X	X
Household f.e.			X
Observations	616,357	616,357	616,357
R-squared	0.166	0.166	0.306
F-Statistic	79.80	79.56	76.32
Robust standard errors in parentheses			
Standard errors clustered at the store-availability level			
*** p<0.01, ** p<0.05, * p<0.1			

Table 6: Ordinary Least Squares & Two-Stage Least Squares Estimates, ϕ_i
Online Households

Budget Shares	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. Budget Share (Pre-Online Service)	Percent Change
Dairy	0.784*** (0.0381)	0.786*** (0.0381)	0.496*** (0.0544)	0.539*** (0.202)	0.543*** (0.202)	0.503** (0.208)	13.21 (6.90)	3.79
Drinks	-0.709*** (0.0559)	-0.713*** (0.0536)	-0.561*** (0.0422)	-0.535** (0.223)	-0.538** (0.225)	-0.520** (0.224)	10.08 (8.31)	-5.16
Fruit	0.317*** (0.0564)	0.336*** (0.0608)	0.114*** (0.0284)	0.437** (0.209)	0.438** (0.210)	0.439** (0.211)	7.48 (6.18)	5.88
Grain	0.239*** (0.0232)	0.242*** (0.0233)	0.162*** (0.0227)	0.125 (0.0775)	0.129* (0.0772)	0.110 (0.0758)	7.6 (4.66)	1.45
Meat	0.331*** (0.0883)	0.330*** (0.0929)	0.539*** (0.0714)	1.056*** (0.311)	1.060*** (0.310)	1.060*** (0.314)	18.46 (9.69)	5.74
Oil	-0.0466** (0.0212)	-0.0452** (0.0216)	-0.0112 (0.0202)	-0.181** (0.0767)	-0.183** (0.0772)	-0.183** (0.0807)	4.36 (3.56)	-4.13
Other	0.00392 (0.0152)	0.000906 (0.0146)	0.00842 (0.0113)	-0.0626 (0.0400)	-0.0637 (0.0400)	-0.0503 (0.0416)	1.81 (2.72)	-2.78
Prepared	-0.00622 (0.101)	-0.00580 (0.104)	0.0948 (0.0714)	0.125 (0.209)	0.136 (0.211)	0.158 (0.210)	10.78 (7.45)	1.47
Snacks/Sweets	-1.593*** (0.124)	-1.623*** (0.129)	-1.507*** (0.128)	-2.113*** (0.315)	-2.140*** (0.316)	-2.106*** (0.315)	15.52 (9.84)	-13.60
Sugar	0.0384*** (0.0105)	0.0380*** (0.0109)	0.0149* (0.00844)	-0.0732 (0.0499)	-0.0745 (0.0501)	-0.0783 (0.0506)	1.61 (2.32)	-4.86
Vegetables	0.643*** (0.0701)	0.656*** (0.0695)	0.652*** (0.0454)	0.684*** (0.166)	0.694*** (0.165)	0.668*** (0.173)	9.09 (6.20)	7.37
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
Household Demographics	X	X		X	X			
Year-Month f.e.		X	X	X	X	X		
Household f.e.			X			X		
Observations	616,357	616,357	616,357	616,357	616,357	616,357	147,246	

Robust standard errors in parentheses

Standard errors clustered at the store-availability level

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

Each cell represents an estimate from a separate regression; note that OLS (2SLS) is equivalent to SUR (3SLS) in this scenario. The percent change is calculated utilizing the estimates provided in Column 6 and average pre-online service budget shares.

Table 7: Ordinary Least Squares & Two-Stage Least Squares Estimates, ϕ_i
 Online Households - Nutrition Outcomes

	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Average (Pre-Online Service)	Percent Change
Nutrients per Ounce								
Calories	-1.548*** (0.138)	-1.600*** (0.133)	-1.374*** (0.133)	-2.087*** (0.350)	-2.122*** (0.351)	-1.974*** (0.345)	47.44 (13.81)	-4.16
Carbohydrates	-0.220*** (0.0246)	-0.225*** (0.0244)	-0.205*** (0.0213)	-0.307*** (0.0496)	-0.311*** (0.0504)	-0.296*** (0.0498)	5.99 (1.96)	-4.94
Cholesterol	0.000135** (5.88e-05)	0.000135** (5.76e-05)	2.06e-05 (5.58e-05)	-0.000484 (0.000374)	-0.000482 (0.000373)	-0.000464 (0.000387)	0.005 (0.01)	-9.28
Protein	0.00170 (0.00376)	0.000553 (0.00409)	0.00307 (0.00308)	0.0226 (0.0144)	0.0223 (0.0143)	0.0237* (0.0144)	1.74 (0.60)	1.36
Sodium	-0.00370 (0.00459)	-0.00345 (0.00471)	-0.00229 (0.00349)	-0.0167 (0.0172)	-0.0169 (0.0170)	-0.0173 (0.0177)	0.17 (0.67)	-10.18
Total Fat	-0.0812*** (0.00637)	-0.0843*** (0.00608)	-0.0695*** (0.00697)	-0.117*** (0.0195)	-0.119*** (0.0195)	-0.110*** (0.0189)	1.90 (0.82)	-5.79
Total Sugar	-0.114*** (0.0158)	-0.116*** (0.0165)	-0.114*** (0.0130)	-0.134*** (0.0384)	-0.136*** (0.0391)	-0.130*** (0.0391)	2.26 (1.06)	-5.75
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
Household Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	596,112	596,112	596,112	596,112	596,112	596,112	142,301	

Robust standard errors in parentheses

Standard errors clustered at the store-availability level

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

Each cell represents an estimate from a separate regression; note that OLS (2SLS) is equivalent to SUR (3SLS) in this scenario.
 The percent change is calculated utilizing the estimates provided in Column 6 and average pre-online service nutrition outcomes.

Table 8: Online Households - Expenditure

Ordinary Least Squares & Two-Stage Least Squares Estimates, ϕ_i

	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Average (Pre-Online Service)	Percent Change
Total Expenditure	56.17*** (1.950)	55.94*** (2.050)	48.64*** (2.580)	51.93*** (17.84)	52.11*** (17.70)	48.87*** (17.63)	447.52 (328.11)	10.92
Dairy	10.03*** (0.317)	10.01*** (0.317)	7.631*** (0.319)	8.059*** (2.605)	8.095*** (2.593)	7.662*** (2.586)	58.58 (47.25)	13.08
Drinks	4.079*** (0.413)	4.036*** (0.440)	4.089*** (0.504)	4.346*** (1.606)	4.352*** (1.606)	3.957** (1.612)	43.61 (41.12)	9.07
Fruit	6.807*** (0.533)	6.881*** (0.547)	4.957*** (0.257)	7.469** (3.319)	7.495** (3.300)	7.238** (3.298)	33.04 (32.35)	21.91
Grain	4.994*** (0.130)	4.990*** (0.127)	4.109*** (0.144)	4.048*** (1.313)	4.080*** (1.299)	3.836*** (1.288)	33.86 (28.49)	11.33
Meat	10.07*** (0.588)	10.02*** (0.636)	9.808*** (0.646)	12.40*** (4.423)	12.44*** (4.386)	11.82*** (4.387)	86.73 (77.43)	13.63
Oil	2.103*** (0.103)	2.098*** (0.101)	1.946*** (0.0813)	1.800*** (0.621)	1.798*** (0.609)	1.683*** (0.599)	19.67 (18.40)	8.56
Other	0.926*** (0.121)	0.908*** (0.117)	0.780*** (0.0677)	0.668 (0.414)	0.664 (0.423)	0.645 (0.443)	8.15 (10.72)	7.91
Prepared	4.847*** (0.587)	4.829*** (0.621)	4.692*** (0.521)	2.947** (1.497)	3.016** (1.522)	2.733* (1.550)	48.77 (45.27)	5.60
Snacks/Sweets	3.799*** (0.381)	3.626*** (0.386)	3.250*** (0.379)	1.386 (2.535)	1.287 (2.517)	0.764 (2.536)	67.4 (58.88)	1.13
Sugar	1.082*** (0.0721)	1.076*** (0.0729)	0.818*** (0.0454)	0.633*** (0.225)	0.629*** (0.226)	0.577** (0.234)	7.21 (8.93)	8.00
Vegetables	7.428*** (0.429)	7.465*** (0.428)	6.562*** (0.336)	8.180*** (1.886)	8.246*** (1.870)	7.963*** (1.877)	40.52 (36.55)	19.65
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
Household Demographics	X	X		X	X			
Year-Month f.e.	X	X	X		X	X		
Household f.e.			X			X		
Observations	616,357	616,357	616,357	616,357	616,357	616,357	147,246	

Robust standard errors in parentheses

Standard errors clustered at the store-availability level

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

Each cell represents an estimate from a separate regression; note that OLS (2SLS) is equivalent to SUR (3SLS) in this scenario. The percent change is calculated utilizing the estimates provided in Column 6 and average pre-online service expenditures.

Table 9: Difference in Difference / Reduced Form Estimates, (τ_i)
 Online Households, Low Competition Stores

	(1)	(2)	(3)	Pre-Online Average	Percent Change
Monthly Exp. (\$)	4.120 (2.733)	4.015 (2.704)	3.321 (2.599)	480.39 (339.57)	0.69
Budget Shares	(1)	(2)	(3)	Pre-Online Average	Percent Change
Dairy	0.0185 (0.0757)	0.0190 (0.0759)	0.0116 (0.0789)	13.39 (6.55)	0.09
Drinks	-0.0324 (0.0604)	-0.0339 (0.0601)	-0.0326 (0.0591)	9.89 (7.72)	-0.33
Fruit	0.0925** (0.0361)	0.0933** (0.0360)	0.101** (0.0360)	7.5 (5.84)	1.35
Grain	0.0185 (0.0232)	0.0187 (0.0232)	0.0179 (0.0244)	7.66 (4.41)	0.23
Meat	0.224** (0.0802)	0.222** (0.0796)	0.216** (0.0801)	18.42 (9.14)	1.17
Oil	-0.0283 (0.0276)	-0.0288 (0.0278)	-0.0296 (0.0283)	4.4 (3.26)	-0.67
Other	-0.0115 (0.0118)	-0.0119 (0.0119)	-0.00969 (0.0126)	1.83 (2.56)	-0.53
Prepared	-0.0857 (0.0497)	-0.0844 (0.0494)	-0.0824 (0.0498)	10.67 (7.03)	-0.77
Snacks/Sweets	-0.246*** (0.0707)	-0.246*** (0.0700)	-0.240*** (0.0696)	15.49 (9.23)	-1.55
Sugar	-0.00741 (0.00895)	-0.00755 (0.00889)	-0.00718 (0.00946)	1.61 (2.16)	-0.45
Vegetables	0.0599 (0.0539)	0.0613 (0.0538)	0.0567 (0.0554)	9.13 (5.85)	0.62
Time Availability f.e.	X				
Treatment Cohort f.e.	X	X			
Household Demographics	X	X			
Year-Month f.e.		X	X		
Household f.e.			X		
Observations	298,722	298,722	298,722	71,436	
Robust standard errors in parentheses Standard errors clustered at the store-availability level *** p<0.01, ** p<0.05, * p<0.1					
Each cell represents an estimate of the effect of online availability. These estimates were produced equation by equation. Percent change is derived utilizing the estimates in column (3) and the pre-online service average.					

Table 10: Difference in Difference / Reduced Form Estimates, (τ_i)
 Online Households, High Competition Stores

	(1)	(2)	(3)	Pre-Online Average	Percent Change
Monthly Exp. (\$)	11.31*** (3.346)	11.51*** (3.403)	10.59*** (3.385)	420.24 (314.68)	2.52
Budget Shares	(1)	(2)	(3)	Pre-Online Average	Percent Change
Dairy	0.0970* (0.0525)	0.0982* (0.0529)	0.0856 (0.0538)	13.09 (7.16)	0.65
Drinks	-0.0826 (0.0513)	-0.0823 (0.0513)	-0.0805 (0.0542)	10.21 (8.78)	-0.79
Fruit	0.0613 (0.0554)	0.0610 (0.0556)	0.0620 (0.0568)	7.48 (6.48)	0.83
Grain	0.0489* (0.0253)	0.0504* (0.0253)	0.0434* (0.0253)	7.53 (4.85)	0.58
Meat	0.205** (0.0882)	0.208** (0.0888)	0.205** (0.0887)	18.53 (10.13)	1.11
Oil	-0.0318 (0.0221)	-0.0320 (0.0222)	-0.0306 (0.0231)	4.32 (3.75)	-0.71
Other	-0.0132 (0.0141)	-0.0129 (0.0140)	-0.00983 (0.0145)	1.79 (2.81)	-0.55
Prepared	0.0485 (0.0631)	0.0520 (0.0641)	0.0572 (0.0647)	10.87 (7.76)	0.53
Snacks/Sweets	-0.495*** (0.0964)	-0.506*** (0.0994)	-0.488*** (0.0978)	15.49 (10.31)	-3.15
Sugar	-0.0145 (0.0146)	-0.0147 (0.0146)	-0.0175 (0.0149)	1.62 (2.45)	-1.08
Vegetables	0.175*** (0.0513)	0.177*** (0.0505)	0.172*** (0.0544)	9.07 (6.45)	1.90
Time Availability f.e.	X				
Treatment Cohort f.e.	X	X			
Household Demographics	X	X			
Year-Month f.e.		X	X		
Household f.e.			X		
Observations	359,571	359,571	359,571	85,823	
Robust standard errors in parentheses Standard errors clustered at the store-availability level *** p<0.01, ** p<0.05, * p<0.1					
Each cell represents an estimate of the effect of online availability. These estimates were produced equation by equation. Percent change is derived utilizing the estimates in column (3) and the pre-online service average.					

Table 11: Average Nutrient Content Per Ounce of Food
Narrow Product Categories

Bread Type	Healthier Choices	Calories (kcal)	Protein (g)	Carbs (g)	Total Fat (g)	Total Sugar (g)	Sodium (g)
Whole Grain	X	68	2.8	12.7	1.2	1.8	0.1
Other		74	2.4	14.0	1.0	2.3	0.1
Seed / Nut	X	67	2.8	12.2	1.2	1.5	0.1
Wheat	X	67	2.9	12.8	0.8	1.8	0.1
White		69	2.3	13.6	1.0	1.7	0.1

Cereal Type	Healthier Choices	Calories (kcal)	Protein (g)	Carbs (g)	Total Fat (g)	Total Sugar (g)	Sodium (g)
Kids		112	1.4	23.8	1.4	10.1	0.1
Organic Kids		108	2.1	22.9	1.5	6.9	0.1
Standard	X	106	2.4	23.2	0.8	2.7	0.2
Frosted Standard		108	2.3	22.9	1.3	7.3	0.1
Healthy Cereal	X	101	3.5	20.4	1.9	4.7	0.1

Snack Type	Healthier Choices	Calories (kcal)	Protein (g)	Carbs (g)	Total Fat (g)	Total Sugar (g)	Sodium (g)
Chips		150	1.8	15.9	8.9	1.0	0.2
Healthy Chips	X	132	2.0	18.1	5.7	1.7	0.2
Popcorn		148	2.4	15.9	8.7	3.1	0.2
Pretzels	X	124	2.3	20.6	3.7	2.0	0.3
Tortilla Chips	X	139	2.0	18.0	6.8	0.3	0.1

Yogurt Type	Healthier Choices	Calories (kcal)	Protein (g)	Carbs (g)	Total Fat (g)	Total Sugar (g)	Sodium (g)
Greek	X	27	2.3	3.4	0.4	2.7	0.0
Light Greek	X	20	2.3	2.5	0.1	1.7	0.0
Indulgent		36	1.3	4.6	1.4	3.7	0.0
Kids		32	1.4	5.3	0.6	4.3	0.0
Organic		27	1.5	3.2	0.9	2.7	0.0
Probiotic		22	1.6	3.6	0.2	3.0	0.0
Traditional		26	1.1	4.4	0.5	3.6	0.0
Light Traditional	X	14	0.9	2.6	0.0	1.7	0.0

Table 12: Ordinary Least Squares & Fractional Probit APE Estimates, τ_k
Bread Shares for Online Households

Shares	OLS (1)	OLS (2)	OLS (3)	F. Probit - APE (4)	F. Probit - APE (5)	Average (Pre-Online Service)	Percent Change
White	-0.167 (0.209)	-0.165 (0.210)	-0.182 (0.210)	-0.173 (0.212)	-0.167 (0.214)	23.56 (35.86)	-0.71
Wheat	0.615** (0.250)	0.611** (0.250)	0.652** (0.229)	0.631** (0.255)	0.627** (0.256)	35.63 (40.39)	1.76
Seed	0.0487 (0.122)	0.0427 (0.121)	0.0894 (0.116)	0.0362 (0.114)	0.0292 (0.113)	5.47 (18.35)	0.53
Other	-0.360* (0.192)	-0.360* (0.204)	-0.413** (0.187)	-0.367* (0.190)	-0.367* (0.202)	20.88 (32.79)	-1.76
Grain	-0.136 (0.179)	-0.128 (0.177)	-0.146 (0.163)	-0.167 (0.194)	-0.159 (0.192)	14.46 (28.63)	-1.10
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	478,724	478,724	478,724	478,724	478,724	112,039	

Robust standard errors in parentheses

Standard errors clustered at the specified level

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

Each cell represents an estimate of the effect of online availability on the budget share.

These estimates were produced equation by equation.

The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table 13: Ordinary Least Squares & Fractional Probit APE Estimates, τ_k
Cereal Shares for Online Households

Shares	OLS (1)	OLS (2)	OLS (3)	F. Probit - APE (4)	F. Probit - APE (5)	Average (Pre-Online Service)	Percent Change
Kids	-0.065 (0.191)	-0.0905 (0.187)	-0.144 (0.173)	-0.079 (0.195)	-0.103 (0.191)	37.28 (36.95)	-0.28
Org. Kids	-0.065 (0.191)	0.0533 (0.0432)	0.0271 (0.0404)	0.0362 (0.0392)	0.0394 (0.0382)	1.05 (8.13)	3.75
Standard	-0.065 (0.191)	-0.123 (0.219)	-0.0207 (0.194)	-0.141 (0.214)	-0.152 (0.209)	15.50 (27.58)	-0.98
Frosted Std.	-0.065 (0.191)	0.256 (0.191)	0.211 (0.196)	0.235 (0.196)	0.255 (0.191)	42.60 (36.74)	0.60
Super Healthy	-0.065 (0.191)	-0.0952 (0.0735)	-0.0736 (0.0697)	-0.119* (0.0632)	-0.107 (0.0653)	3.58 (14.64)	-2.99
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	435,202	435,202	435,202	435,202	435,202	100,846	

Robust standard errors in parentheses

Standard errors clustered at the specified level

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

Each cell represents an estimate of the effect of online availability on the budget share.

These estimates were produced equation by equation.

The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table 14: Ordinary Least Squares & Fractional Probit APE Estimates, τ_k
Salty Snack Shares for Online Households

Shares	OLS (1)	OLS (2)	OLS (3)	F. Probit - APE (4)	F. Probit - APE (5)	Average (Pre-Online Service)	Percent Change
Tortilla Chips	0.508* (0.269)	0.499* (0.268)	0.568** (0.237)	0.511** (0.236)	0.504** (0.235)	21.70 (28.54)	2.32
Pretzels	-0.388** (0.106)	-0.374*** (0.103)	-0.353*** (0.110)	-0.352*** (0.102)	-0.338*** (0.0996)	14.52 (24.62)	-2.33
Popcorn	-0.0758 (0.0902)	-0.0741 (0.0908)	-0.0743 (0.0907)	-0.0496 (0.0857)	-0.0467 (0.0860)	5.51 (16.00)	-0.85
Veggie Chips	-0.0335 (0.172)	-0.00863 (0.171)	0.000258 (0.164)	-0.0262 (0.159)	-0.00462 (0.157)	7.70 (19.32)	-0.06
Chips	-0.0108 (0.181)	-0.0431 (0.172)	-0.141 (0.158)	-0.00854 (0.183)	-0.0417 (0.173)	50.57 (35.25)	-0.08
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	512,645	512,645	512,645	512,645	512,645	118,761	

Robust standard errors in parentheses

Standard errors clustered at the specified level

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

Each cell represents an estimate of the effect of online availability on the budget share.

These estimates were produced equation by equation.

The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table 15: Ordinary Least Squares & Fractional Probit APE Estimates, τ_k
Yogurt Shares for Online Households

Shares	OLS (1)	OLS (2)	OLS (3)	F. Probit - APE (4)	F. Probit - APE (5)	Average (Pre-Online Service)	Percent Change
Traditional Light	-0.099 (0.139)	-0.0798 (0.136)	-0.0121 (0.138)	-0.08 (0.143)	-0.0605 (0.138)	12.41 (25.99)	-0.49
Traditional	0.0283 (0.134)	0.0428 (0.137)	0.221 (0.136)	0.00269 (0.126)	0.0162 (0.129)	14.99 (28.06)	0.11
Probiotics	0.0725 (0.0552)	0.076 (0.0561)	0.0718 (0.0639)	0.0749 (0.0551)	0.0785 (0.0559)	3.41 (14.84)	2.30
Organic	0.123 (0.0845)	0.124 (0.0840)	0.138 (0.0976)	0.0951 (0.0925)	0.0972 (0.0914)	5.20 (18.06)	1.87
Kids	-0.0171 (0.241)	-0.0292 (0.241)	-0.0496 (0.224)	-0.0198 (0.241)	-0.0322 (0.241)	17.42 (29.86)	-0.18
Indulgent	-0.0313 (0.0890)	-0.0326 (0.0886)	-0.0728 (0.0833)	-0.0266 (0.0836)	-0.0278 (0.0832)	4.09 (15.29)	-0.68
Greek Light	0.0506 (0.194)	0.0587 (0.195)	0.0382 (0.206)	0.0612 (0.185)	0.0679 (0.187)	12.34 (26.39)	0.55
Greek	-0.127 (0.203)	-0.16 (0.197)	-0.334 (0.224)	-0.139 (0.205)	-0.172 (0.200)	30.14 (37.12)	-0.57
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	454,041	454,041	454,041	454,041	454,041	102,503	

Robust standard errors in parentheses

Standard errors clustered at the specified level

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

Each cell represents an estimate of the effect of online availability on the budget share.

These estimates were produced equation by equation.

The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table 16: Difference in Difference / Reduced Form Estimates, (τ_i)
In-Store Households

Budget Shares	(1)	(2)	(3)	Avg. Budget Share (Pre-Online Service)
Dairy	0.0876 (0.0676)	0.0888 (0.0676)	0.0855 (0.0699)	11.95 (8.01)
Drinks	-0.0451 (0.0858)	-0.0454 (0.0858)	-0.0299 (0.0845)	10.9 (10.26)
Fruit	-0.0106 (0.0462)	-0.0114 (0.0463)	-0.0293 (0.0453)	7.26 (7.55)
Grain	-0.0291 (0.0432)	-0.0276 (0.0428)	-0.0203 (0.0445)	7.2 (5.61)
Meat	-0.00571 (0.0890)	-0.00406 (0.0887)	0.0142 (0.0902)	18.88 (12.09)
Oil	0.0259 (0.0267)	0.0258 (0.0267)	0.0228 (0.0268)	4.36 (4.49)
Other	0.0105 (0.0286)	0.0101 (0.0287)	0.00930 (0.0287)	1.73 (3.04)
Prepared	-0.116* (0.0644)	-0.112* (0.0648)	-0.111* (0.0639)	10.87 (9.19)
Snacks/Sweets	0.0295 (0.0681)	0.0221 (0.0666)	0.0128 (0.0688)	16.11 (11.86)
Sugar	0.00935 (0.0237)	0.00896 (0.0238)	0.00731 (0.0238)	1.56 (2.87)
Veg	0.0413 (0.0547)	0.0432 (0.0544)	0.0364 (0.0532)	9.19 (7.77)
Time Availability f.e.	X			
Treatment Cohort f.e.	X	X		
Household Demographics	X	X		
Year-Month f.e.		X	X	
Household f.e.			X	
Observations	238,665	238,665	238,665	56,973

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the budget share.
These estimates were produced equation by equation.

Table 17: Ordinary Least Squares & Two-Stage Least Squares Estimates, ϕ_i
 Online Households - After January 2016

	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. Budget Share (Pre-Online Service)	Percent Change
Dairy	0.768*** (0.0553)	0.773*** (0.0546)	0.539*** (0.0577)	0.726*** (0.152)	0.732*** (0.154)	0.678*** (0.149)	13.21 (6.90)	5.15
Drinks	-0.729*** (0.0596)	-0.729*** (0.0592)	-0.564*** (0.0575)	-0.137 (0.242)	-0.135 (0.242)	-0.126 (0.245)	10.08 (8.31)	-1.25
Fruit	0.297*** (0.0607)	0.294*** (0.0608)	0.118*** (0.0370)	0.424** (0.183)	0.423** (0.183)	0.412** (0.190)	7.48 (6.18)	5.48
Grain	0.214*** (0.0276)	0.216*** (0.0277)	0.148*** (0.0310)	0.0686 (0.147)	0.0779 (0.147)	0.0286 (0.139)	7.6 (4.66)	0.38
Meat	0.402*** (0.0805)	0.404*** (0.0821)	0.583*** (0.0676)	0.656 (0.444)	0.676 (0.445)	0.640 (0.455)	18.46 (9.69)	3.47
Oil	-0.0545** (0.0223)	-0.0554** (0.0222)	-0.0228 (0.0272)	-0.0430 (0.100)	-0.0441 (0.100)	-0.0536 (0.107)	4.36 (3.56)	-1.23
Other	-0.00758 (0.0196)	-0.00691 (0.0196)	0.000401 (0.0143)	-0.0877 (0.0819)	-0.0860 (0.0814)	-0.0932 (0.0847)	1.81 (2.72)	-5.15
Prepared	0.103 (0.0736)	0.110 (0.0749)	0.138** (0.0561)	0.314 (0.288)	0.333 (0.286)	0.347 (0.269)	10.78 (7.45)	3.22
Snacks/Sweets	-1.679*** (0.0953)	-1.691*** (0.100)	-1.623*** (0.106)	-2.210*** (0.399)	-2.281*** (0.398)	-2.099*** (0.381)	15.52 (9.84)	-13.53
Sugar	0.0341*** (0.00971)	0.0343*** (0.00978)	0.0102 (0.00969)	-0.138*** (0.0460)	-0.140*** (0.0459)	-0.136*** (0.0451)	1.61 (2.32)	-8.70
Vegetables	0.652*** (0.0749)	0.652*** (0.0751)	0.674*** (0.0502)	0.428* (0.260)	0.445* (0.258)	0.403 (0.263)	9.09 (6.20)	4.43
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
Household Demographics	X	X		X	X			
Year-Month f.e.		X	X	X	X	X		
Household f.e.			X			X		
Observations	222,261	222,261	222,261	222,261	222,261	222,261	147,246	

Robust standard errors in parentheses

Standard errors clustered at the store-availability level

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

Each cell represents an estimate of the effect of online service use on the budget share.

These estimates were produced equation by equation.

The percent change is derived utilizing the 2SLS estimates in column (6) and the pre-online service average.

Table 18: In-Store Elasticity Matrix

	Own Price Elasticity	Dairy	Drink	Fruit	Grain	Meat	Oil	Other	Prepared	Snacks	Sugars	Vegetables
Dairy	-1.08 (0.03)	-1.08 (0.03)	0.39 (0.02)	0.01 (0.04)	-0.23 (0.04)	0.10 (0.03)	0.43 (0.05)	0.40 (0.08)	-0.17 (0.04)	-0.55 (0.03)	0.05 (0.09)	0.47 (0.03)
Drink	-1.91 (0.03)	0.28 (0.02)	-1.91 (0.03)	0.75 (0.03)	0.18 (0.03)	-0.19 (0.02)	-0.29 (0.04)	0.57 (0.06)	-0.02 (0.03)	-0.05 (0.02)	0.41 (0.07)	0.29 (0.02)
Fruit	-1.16 (0.06)	0.01 (0.02)	0.63 (0.02)	-1.16 (0.06)	-0.29 (0.06)	-0.20 (0.03)	0.77 (0.07)	-0.12 (0.11)	-0.52 (0.05)	0.25 (0.03)	0.50 (0.14)	-0.23 (0.04)
Grain	0.29 (0.14)	-0.14 (0.02)	0.15 (0.02)	-0.28 (0.05)	0.29 (0.14)	0.05 (0.04)	0.62 (0.13)	0.03 (0.18)	-0.74 (0.06)	-0.07 (0.04)	-0.52 (0.26)	-0.18 (0.05)
Meat	-1.23 (0.07)	0.16 (0.04)	-0.24 (0.03)	-0.43 (0.08)	0.17 (0.10)	-1.23 (0.07)	-0.52 (0.13)	-0.05 (0.20)	0.58 (0.07)	0.69 (0.06)	-1.00 (0.23)	-0.66 (0.08)
Oil	-0.27 (0.14)	0.14 (0.02)	-0.11 (0.02)	0.40 (0.04)	0.36 (0.08)	-0.13 (0.03)	-0.27 (0.14)	-0.15 (0.14)	-0.38 (0.04)	-0.24 (0.03)	-0.75 (0.20)	0.15 (0.04)
Other	-0.90 (0.10)	0.05 (0.01)	0.09 (0.01)	-0.02 (0.02)	0.01 (0.04)	-0.01 (0.02)	-0.05 (0.05)	-0.90 (0.10)	-0.03 (0.02)	-0.01 (0.02)	-0.36 (0.10)	-0.03 (0.02)
Prepared	0.62 (0.09)	-0.14 (0.03)	0.01 (0.03)	-0.66 (0.06)	-0.99 (0.08)	0.30 (0.04)	-0.86 (0.10)	-0.20 (0.15)	0.62 (0.09)	-0.03 (0.04)	-0.17 (0.17)	-0.27 (0.05)
Snacks	-0.89 (0.06)	-0.71 (0.03)	-0.06 (0.03)	0.42 (0.06)	-0.17 (0.08)	0.53 (0.05)	-0.87 (0.11)	-0.14 (0.16)	-0.07 (0.07)	-0.89 (0.06)	1.20 (0.19)	0.05 (0.06)
Sugar	-0.66 (0.18)	0.00 (0.01)	0.06 (0.01)	0.09 (0.03)	-0.11 (0.05)	-0.09 (0.02)	-0.26 (0.07)	-0.36 (0.10)	-0.03 (0.03)	0.12 (0.02)	-0.66 (0.18)	0.05 (0.02)
Vegetables	-0.76 (0.06)	0.34 (0.02)	0.29 (0.02)	-0.26 (0.05)	-0.20 (0.06)	-0.33 (0.04)	0.32 (0.08)	-0.18 (0.12)	-0.23 (0.05)	-0.02 (0.05)	0.30 (0.15)	-0.76 (0.06)

Standard errors reported in parentheses

Standard errors clustered at the store-availability level

Table 19: Online Elasticity Matrix

	Own Price Elasticity	Dairy	Drink	Fruit	Grain	Meat	Oil	Other	Prepared	Snacks	Sugars	Vegetables
Dairy	-0.66 (0.03)	-0.66 (0.03)	0.21 (0.10)	0.53 (0.09)	-0.01 (0.08)	1.27 (0.91)	0.50 (0.20)	0.32 (0.42)	-2.02 (1.04)	1.06 (0.43)	-3.99 (63.11)	1.53 (0.97)
Drink	-0.65 (0.22)	-0.04 (0.02)	-0.65 (0.22)	0.23 (0.08)	0.03 (0.06)	0.41 (0.49)	0.25 (0.19)	1.13 (1.48)	-0.91 (0.37)	0.38 (0.25)	2.65 (43.09)	1.78 (1.35)
Fruit	-0.81 (0.10)	0.25 (0.03)	-0.64 (0.30)	-0.81 (0.10)	-0.66 (0.21)	0.53 (0.46)	0.02 (0.21)	-1.07 (1.43)	-0.25 (0.31)	-0.14 (0.24)	29.99 (458.13)	-1.59 (1.23)
Grain	0.17 (0.28)	-0.03 (0.03)	-0.09 (0.13)	-0.51 (0.15)	0.17 (0.28)	0.27 (0.41)	-0.40 (0.45)	-0.27 (0.85)	0.42 (0.26)	-0.65 (0.46)	-28.67 (443.17)	-1.69 (1.31)
Meat	1.72 (2.43)	-0.10 (0.04)	0.40 (0.24)	-0.09 (0.12)	-0.05 (0.17)	1.72 (2.43)	-0.10 (0.30)	1.62 (1.99)	1.44 (0.78)	-0.88 (0.49)	-14.25 (218.00)	0.87 (0.83)
Oil	-0.62 (0.46)	0.07 (0.02)	-0.23 (0.12)	0.00 (0.07)	-0.18 (0.14)	0.19 (0.38)	-0.62 (0.46)	-1.26 (1.34)	-0.07 (0.18)	0.15 (0.23)	8.74 (137.77)	-0.18 (0.31)
Other	-0.55 (0.76)	0.01 (0.01)	-0.21 (0.07)	-0.07 (0.03)	-0.02 (0.06)	-0.34 (0.24)	-0.24 (0.10)	-0.55 (0.76)	0.00 (0.09)	-0.02 (0.08)	-11.49 (173.14)	-0.02 (0.13)
Prepared	0.48 (0.81)	-0.38 (0.04)	0.99 (0.39)	-0.12 (0.09)	0.22 (0.14)	-1.86 (1.51)	-0.11 (0.22)	-0.01 (0.54)	0.48 (0.81)	0.32 (0.29)	-0.42 (10.64)	0.97 (0.78)
Snacks	-1.53 (0.48)	-0.29 (0.04)	0.59 (0.29)	0.06 (0.13)	0.47 (0.28)	-1.86 (1.50)	-0.28 (0.38)	0.20 (0.87)	-0.52 (0.38)	-1.53 (0.48)	-11.80 (178.03)	0.01 (0.57)
Sugars	23.90 (378.55)	-0.01 (0.01)	-0.04 (0.06)	0.18 (0.05)	-0.23 (0.12)	0.30 (0.31)	0.16 (0.15)	-1.05 (1.43)	0.00 (0.11)	0.13 (0.13)	23.90 (378.55)	0.03 (0.18)
Vegetables	-2.93 (1.62)	0.20 (0.03)	-1.31 (0.52)	-0.41 (0.13)	-0.59 (0.24)	-0.71 (0.84)	-0.12 (0.26)	-0.05 (0.56)	0.68 (0.34)	0.09 (0.25)	1.11 (16.32)	-2.93 (1.62)

Standard errors reported in parentheses

Standard errors clustered at the store-availability level

11 Figure Appendix

Figure A1: Budget Allocation & Prices

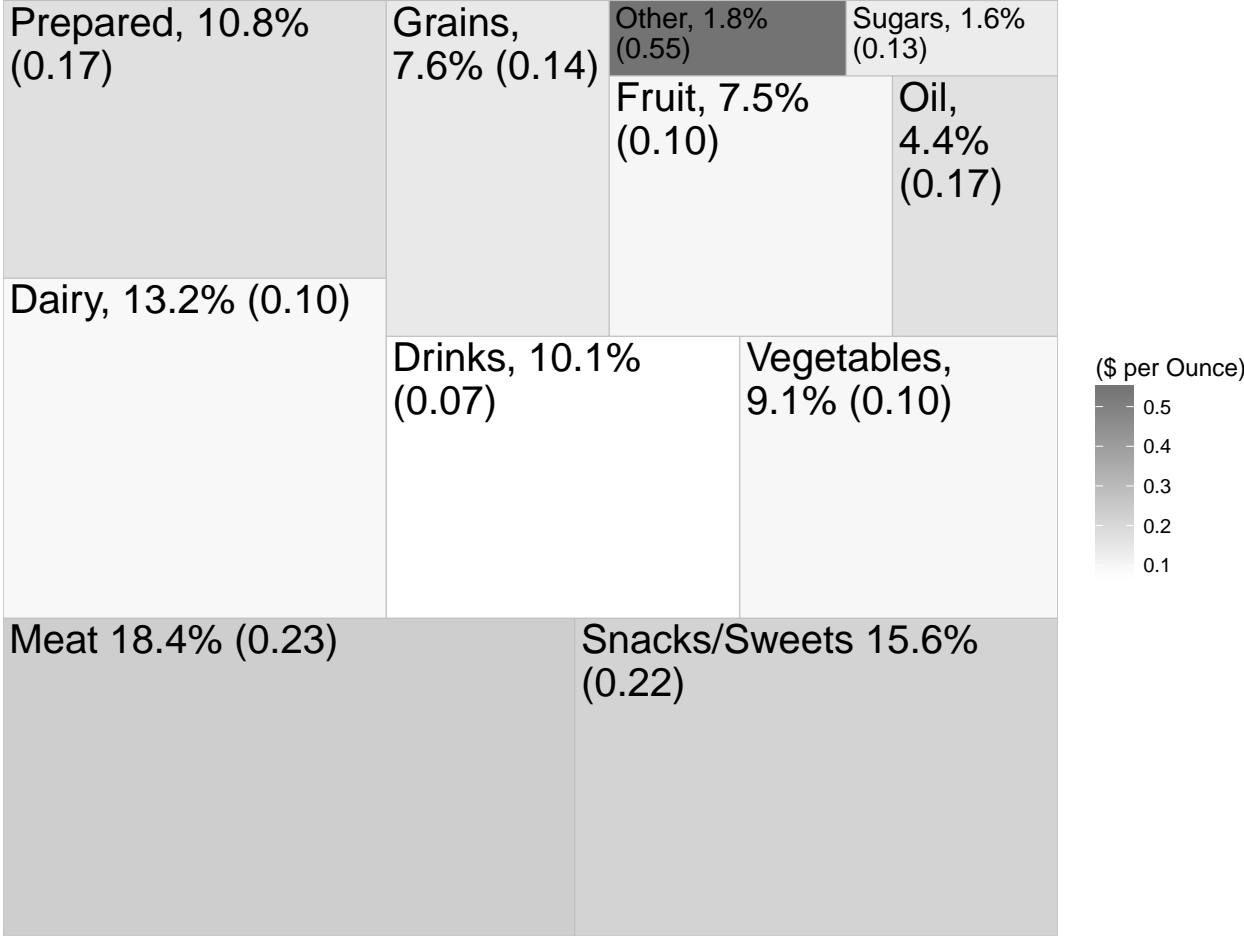


Figure A1 presents the average budget allocation, of the online households, in the six months before the online service was ever available to any household (i.e. before March 2015). The size of each box corresponds to the average budget share amount and the shade of the each box corresponds to how expensive the product category is in terms of price per ounce. Darker shade indicate more expensive product categories and lighter shades represent less expensive product categories.

Figure A2: Event Study Estimates for Online Use and Expenditure Shares
In-Store Households Only

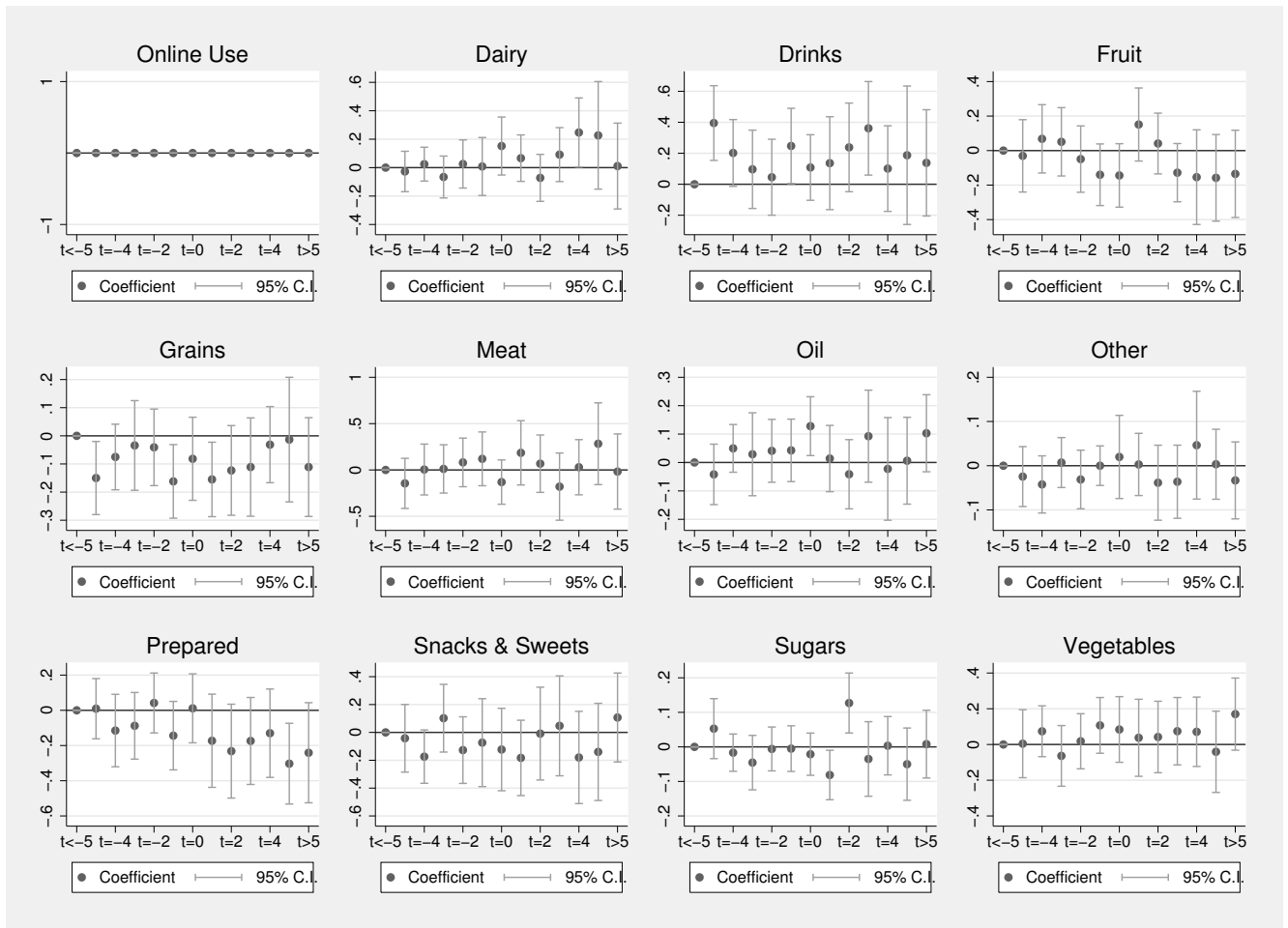


Figure A3: Mean Demographics of In-Store & Online Households

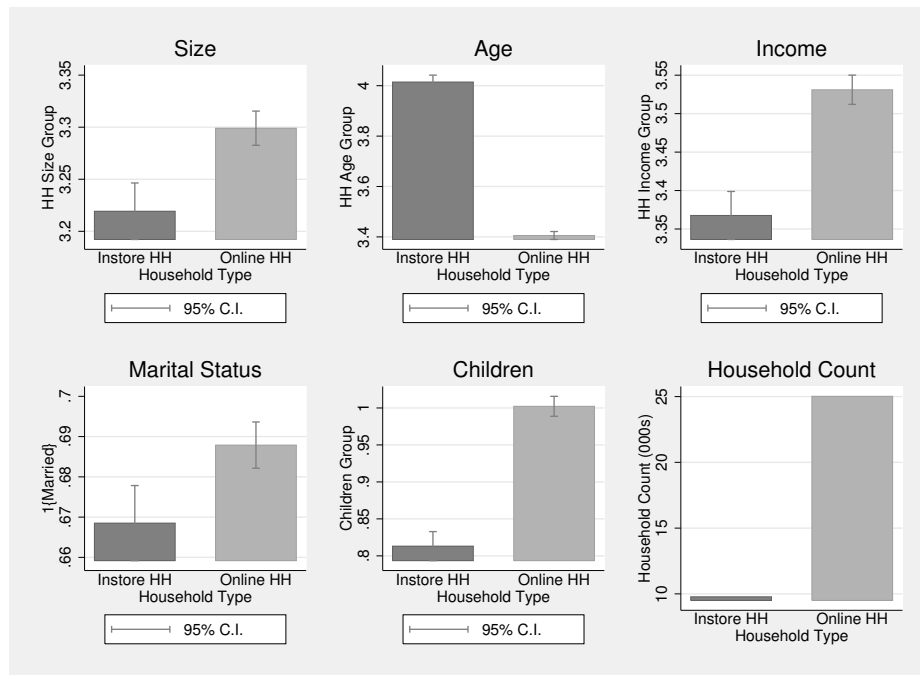


Figure A3 illustrates the demographic differences between households who have adopted the online shopping service over the time frame of my data (online households) and the households who have not adopted the online shopping service over the time frame of my data (in-store households). Specifically, this figure illustrates that early adopters of the online shopping service are, on average, larger households (3.3 vs. 3.2 people), have heads of household that are younger (36-45 vs. 46-55), have higher incomes (\$80-\$99k vs \$51-\$79k per year), are more likely to be married (69% vs. 67%) and are more likely to have a child (1 vs. 0.8). Note that my demographic variables are categorical and the specific categorical definitions can be found in Table A2 of the appendix.

Figure A4: Mean Shopping Behavior of In-Store & Online Households Pre-Online Service

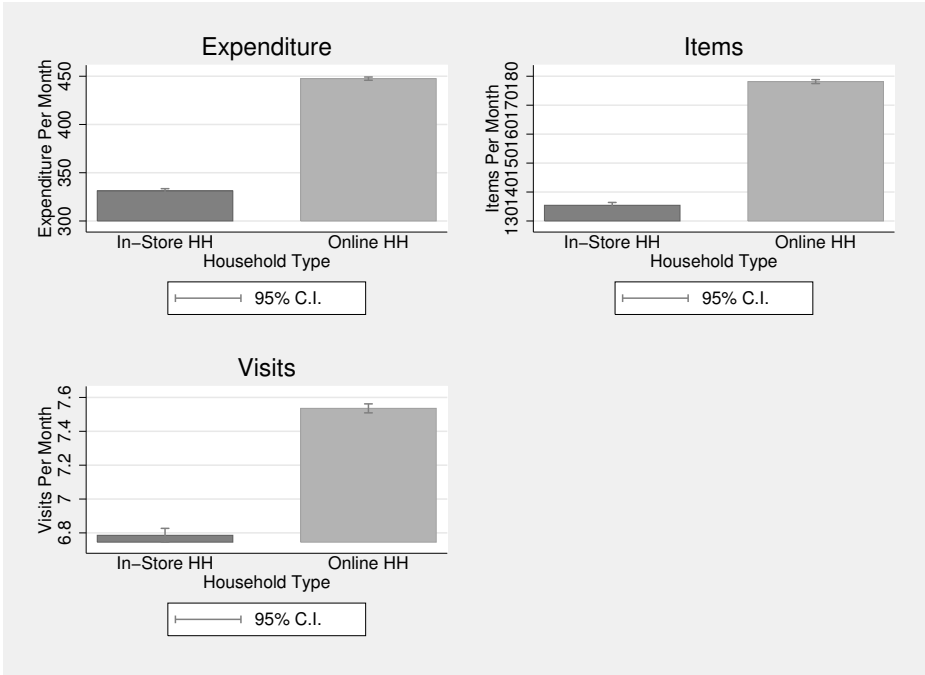


Figure A4 illustrates the differences in purchasing patterns that exist between online households and in-store households before the online service was ever introduced.

Figure A5: Mean Budget Shares of In-Store & Online Households Pre-Online Service

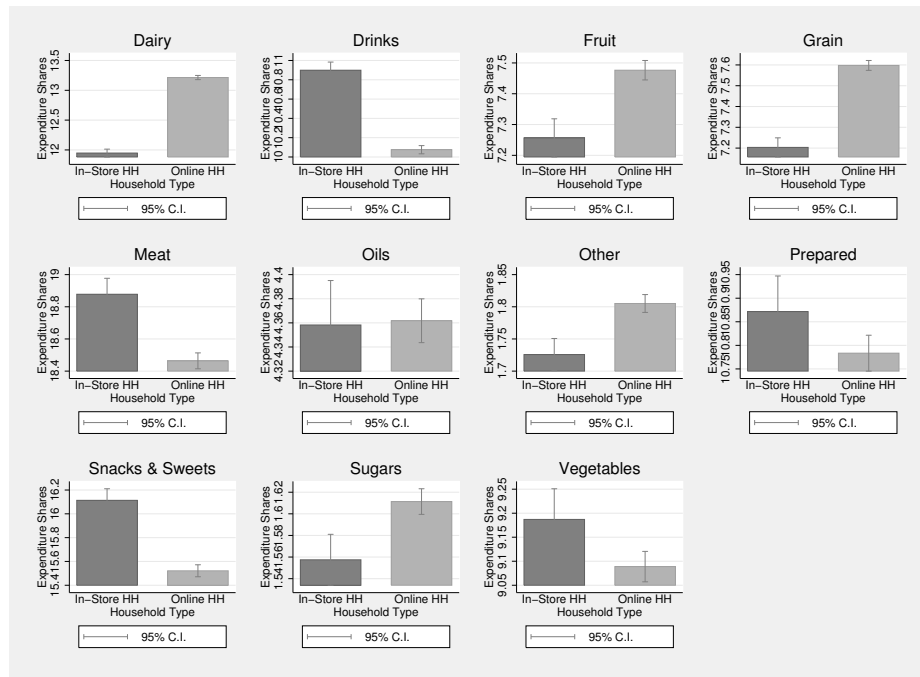


Figure A5 illustrates the differences in budget shares that exist between online households and in-store households before the online service was ever introduced.

Figure A6: Mean Demographics of Availability Waves

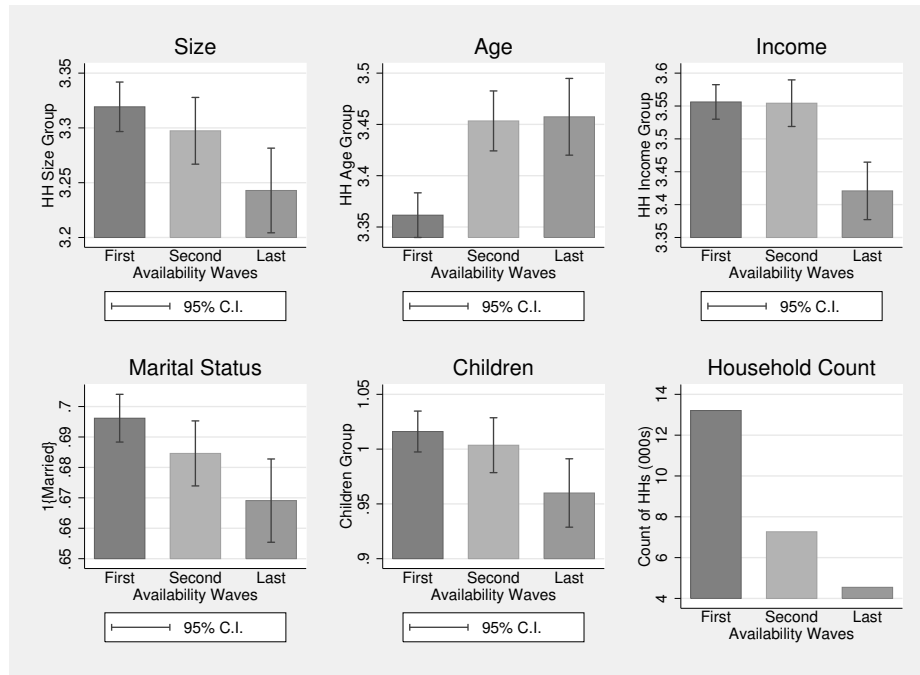


Figure A6 presents a demographic comparison of the households who received access to the online purchasing early to the households who received access to the online purchasing service later.⁶⁵ Figure A6 illustrates the following demographic information: on average, the household is composed of three individuals, the household head is between the ages of 36-45, annual household income is between \$80K to \$99K, roughly 70% of these households are married and they are likely to have at least one child. In contrast, households in later availability dates tend to be smaller and older. Additionally, households in the last availability wave have a higher proportion of households in lower income categories, are less likely to be married and are less likely to have children.

⁶⁵Households that received access to the online shopping service before or during January 2016 are assigned to wave one (53% of the online household sample), households that received access to the online service after January 2016 but before July 2016 are assigned to wave two (29% of the online household sample) and households who received access after or during July 2016 are assigned to wave three (18% of the online household sample).

Figure A7: Mean Shopping Behavior of Availability Waves

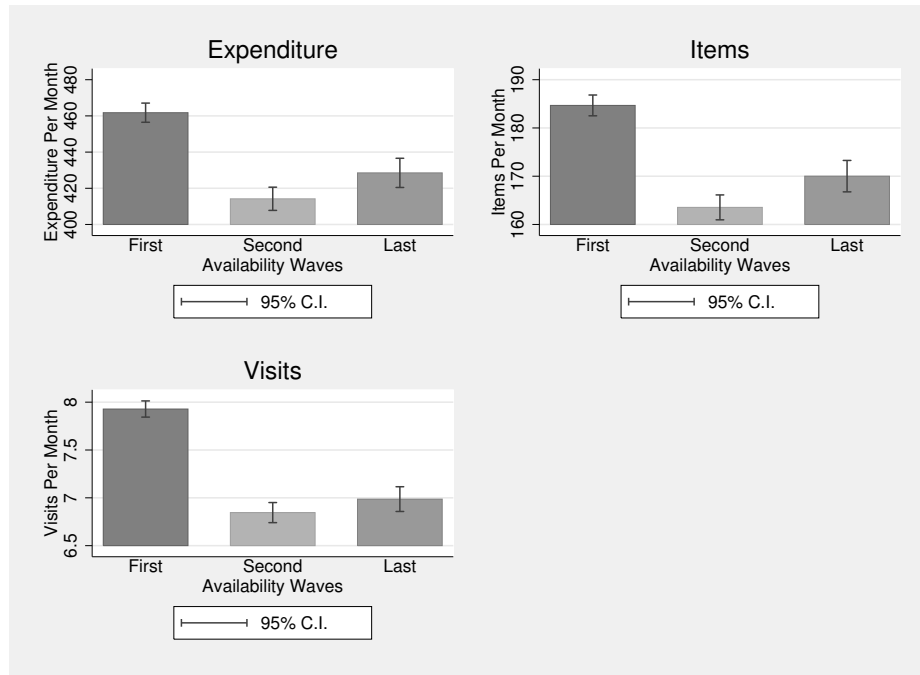


Figure A7 present averages over household shopping patterns restricted to the six months before the online service was ever available to any household (i.e. before March 2015) for the different availability waves.⁶⁶

⁶⁶Households that received access to the online shopping service before or during January 2016 are assigned to wave one (53% of the online household sample), households that received access to the online service after January 2016 but before July 2016 are assigned to wave two (29% of the online household sample) and households who received access after or during July 2016 are assigned to wave three (18% of the online household sample).

Figure A8: Mean Expenditure Shares of Availability Waves

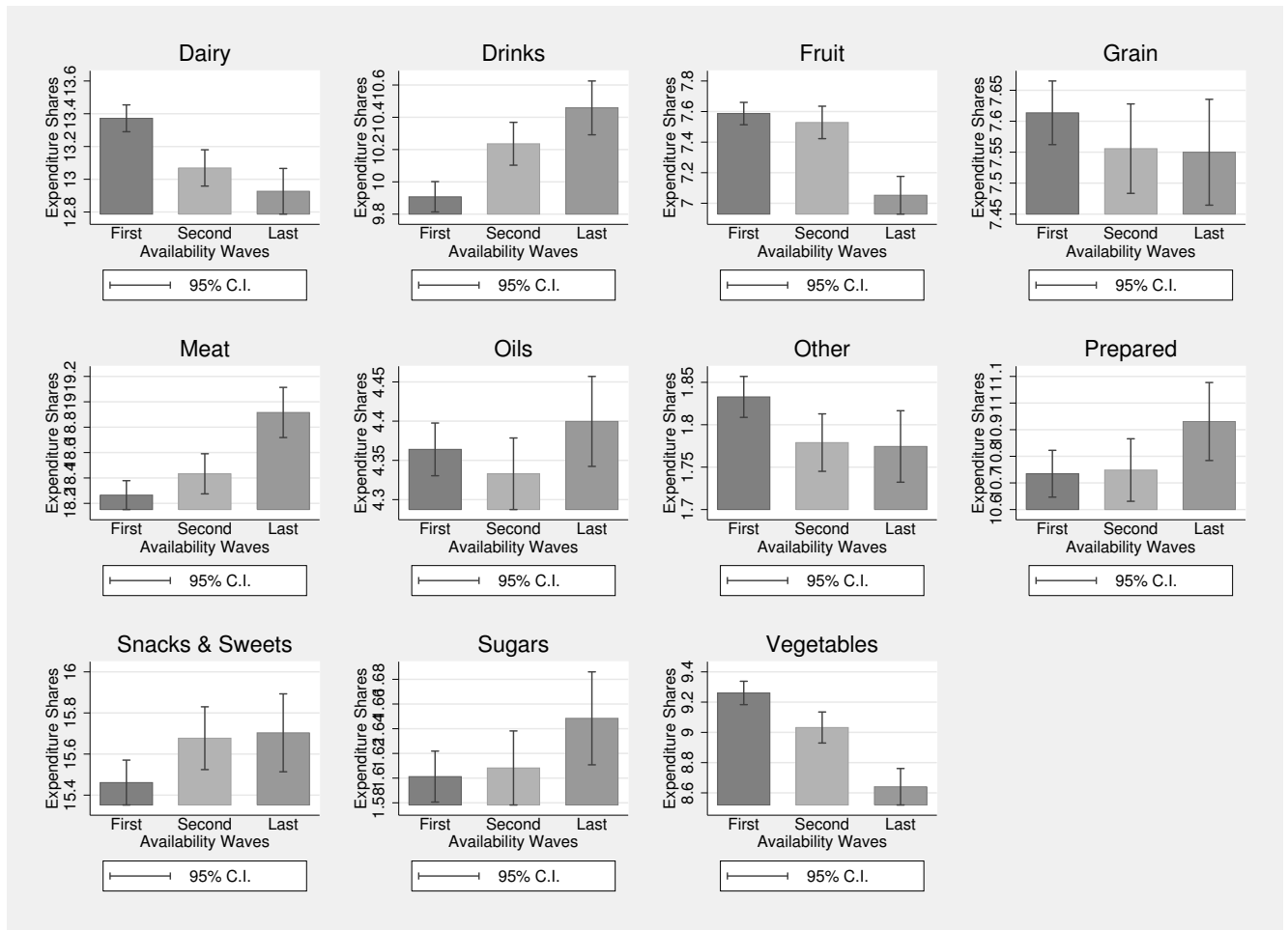


Figure A8 present averages over household shopping patterns restricted to the six months before the online service was ever available to any household (i.e. before March 2015) for the different availability waves.⁶⁷

⁶⁷Households that received access to the online shopping service before or during January 2016 are assigned to wave one (53% of the online household sample), households that received access to the online service after January 2016 but before July 2016 are assigned to wave two (29% of the online household sample) and households who received access after or during July 2016 are assigned to wave three (18% of the online household sample).

Figure A9: Bread Nutrition Comparison

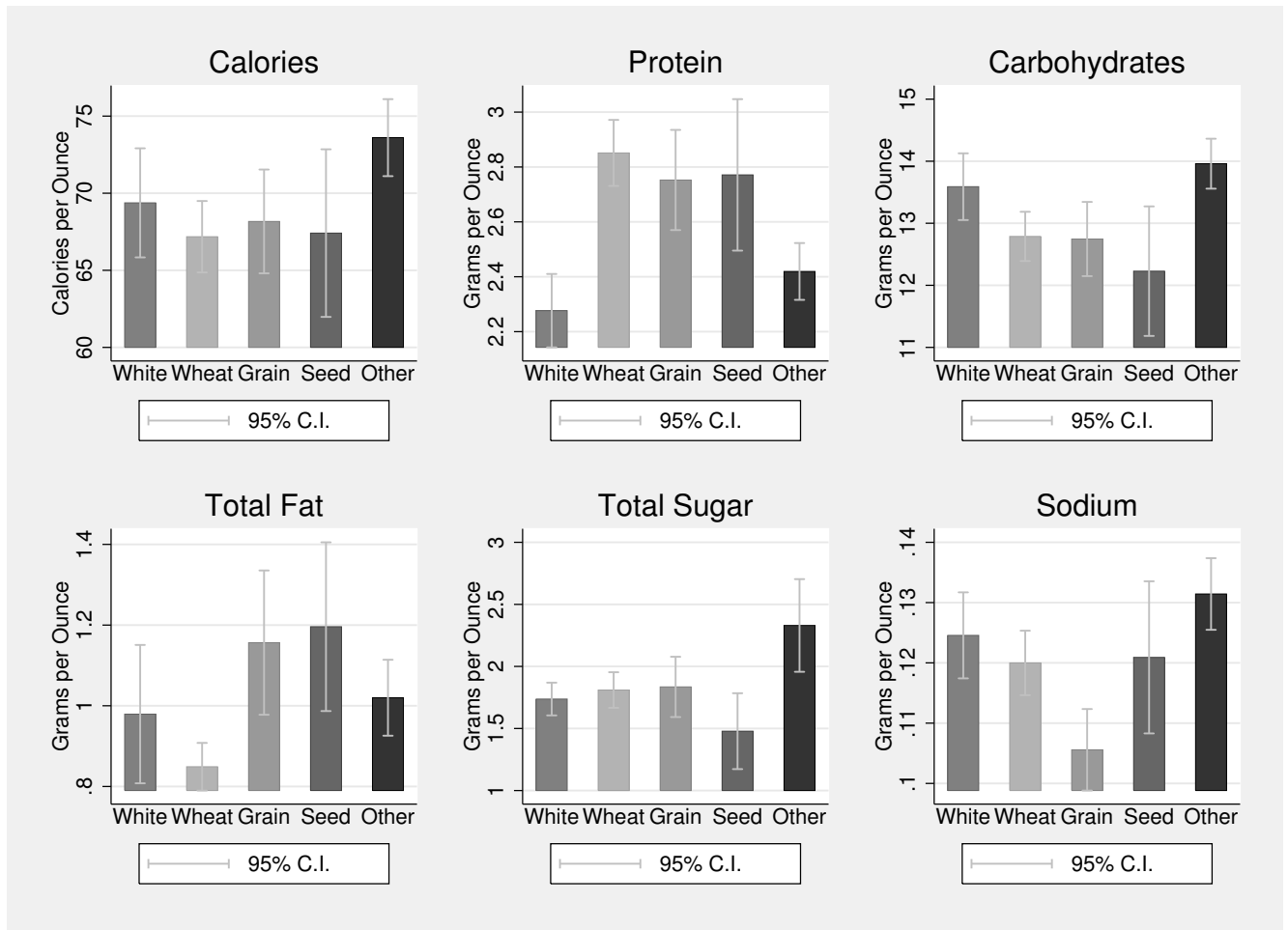


Figure A9 presents the average nutritional content (per ounce) of each type of bread.

Figure A10: Cereal Nutrition Comparison

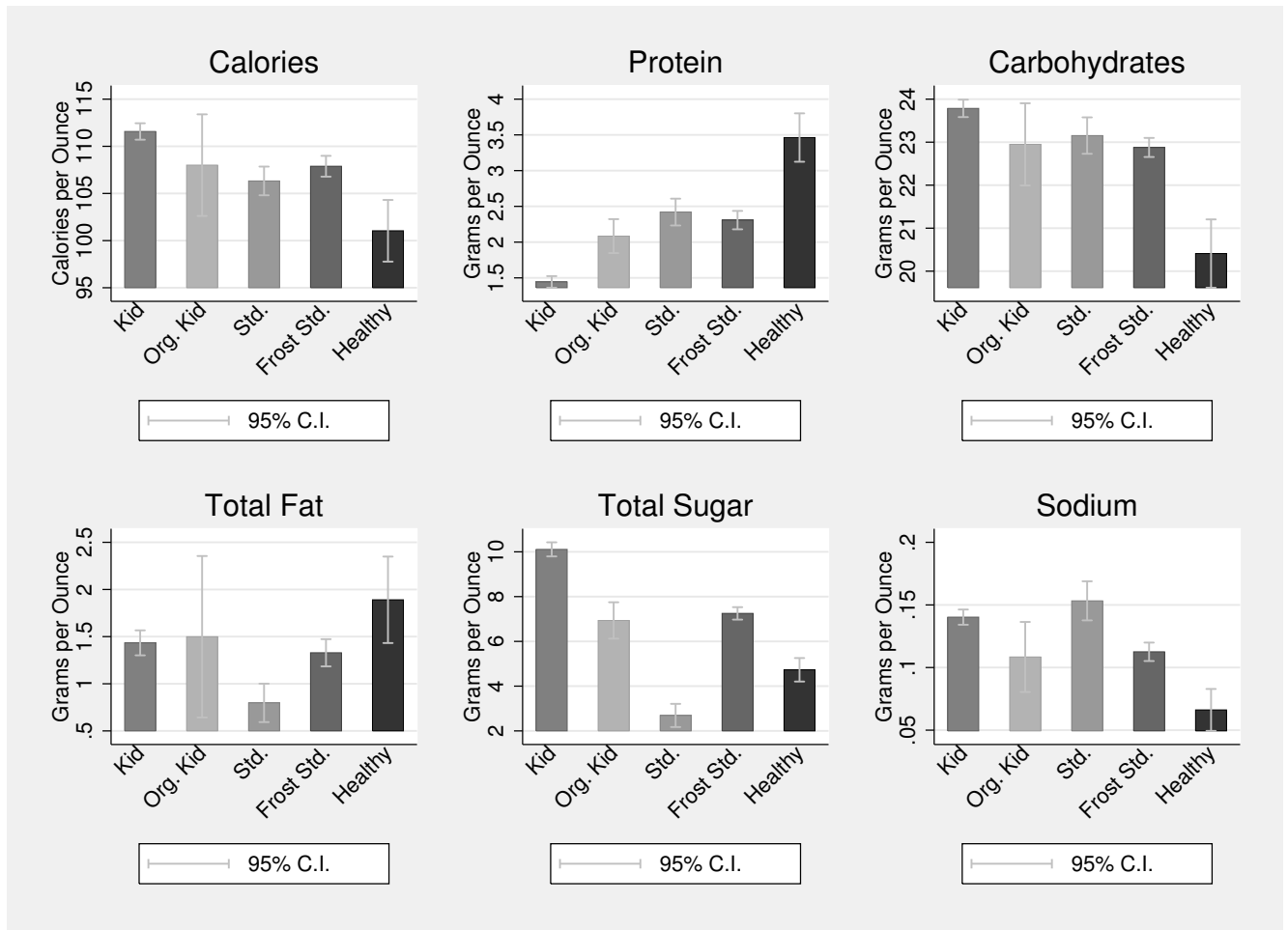


Figure A10 presents the average nutritional content (per ounce) of each type of cereal.

Figure A11: Salty Snack Nutrition Comparison

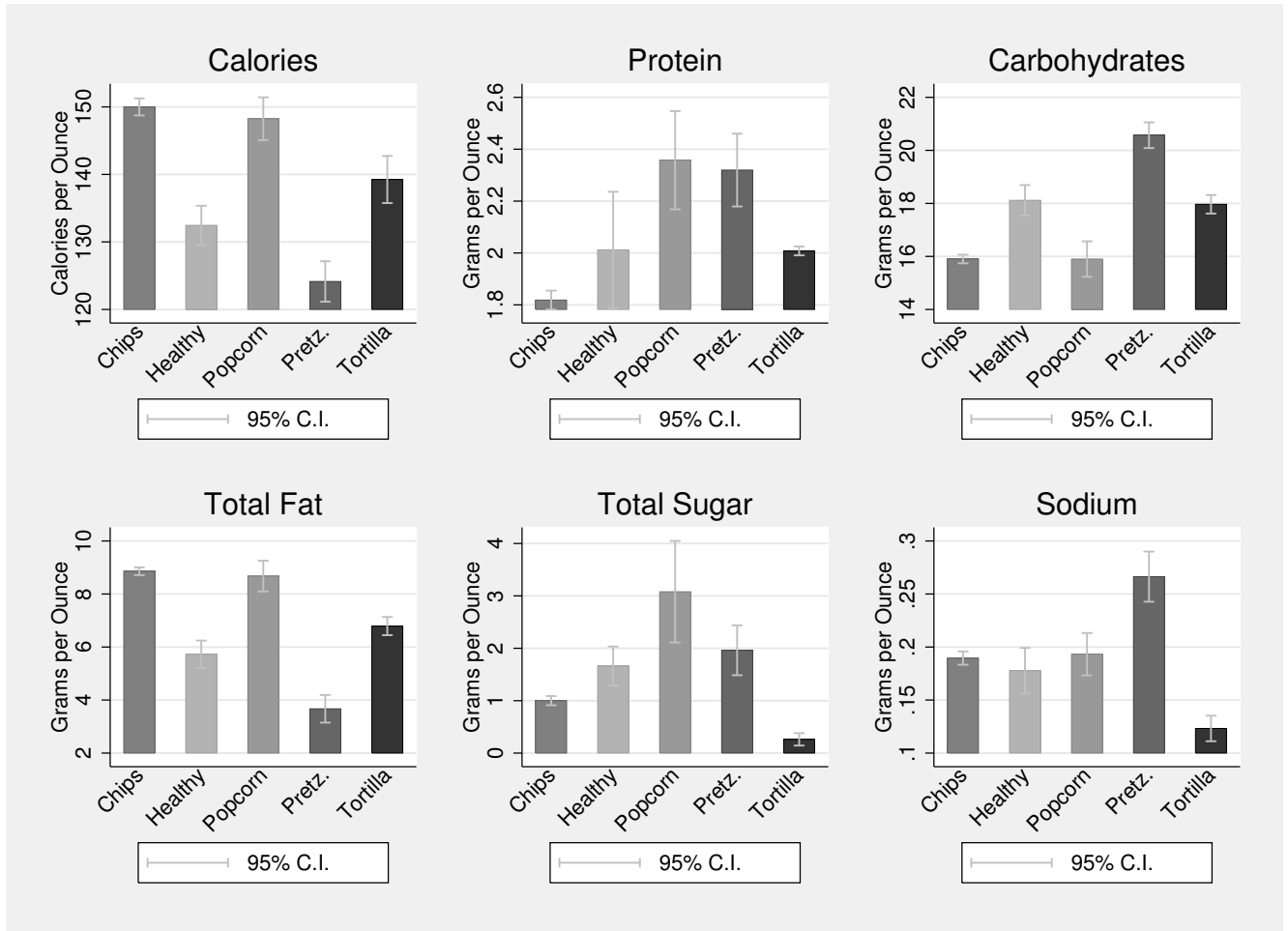


Figure A11 presents the average nutritional content (per ounce) of each type of salty snack.

Figure A12: Yogurt Nutrition Comparison

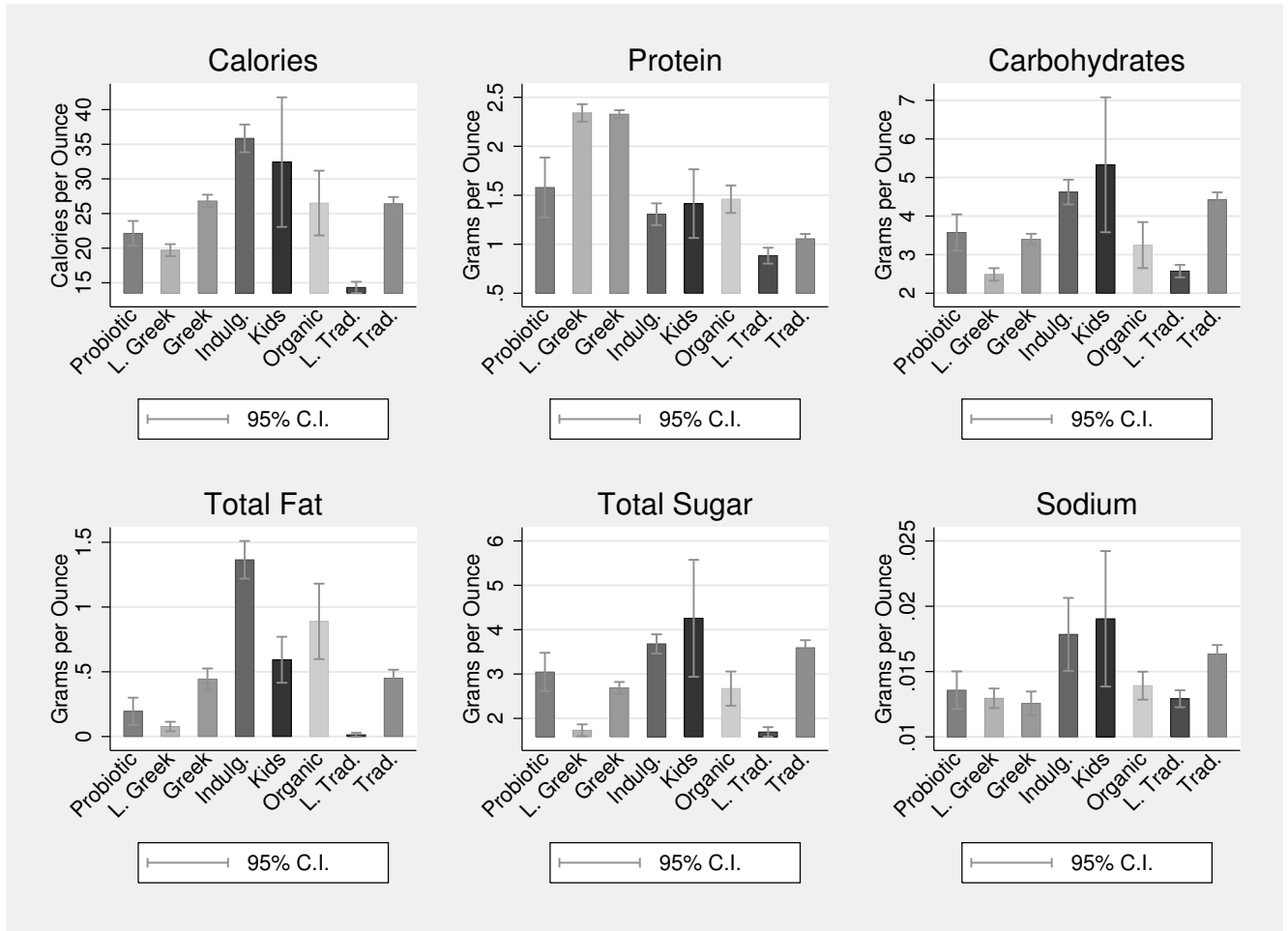


Figure A12 presents the average nutritional content (per ounce) of each type of yogurt.

Figure A13: In-store Own and Cross Price Elasticities

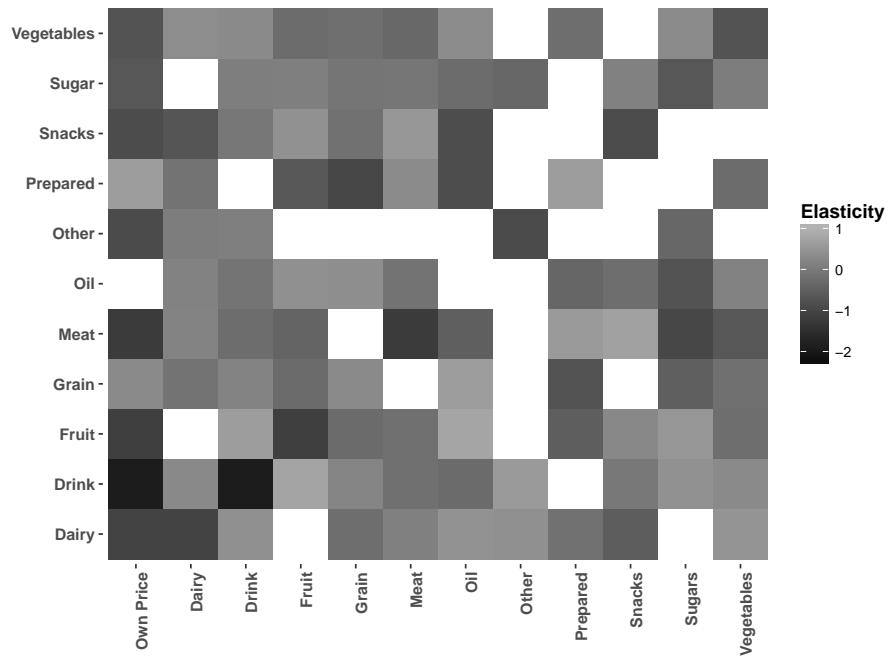


Figure A13 presents in-store own and cross price elasticities that are significant at the 95% confidence level. Darker shades represent negative elasticities (complements), while lighter shades represent positive elasticities (substitutes). White means that the elasticity is not statistically significant.

Figure A14: Online Own and Cross Price Elasticities

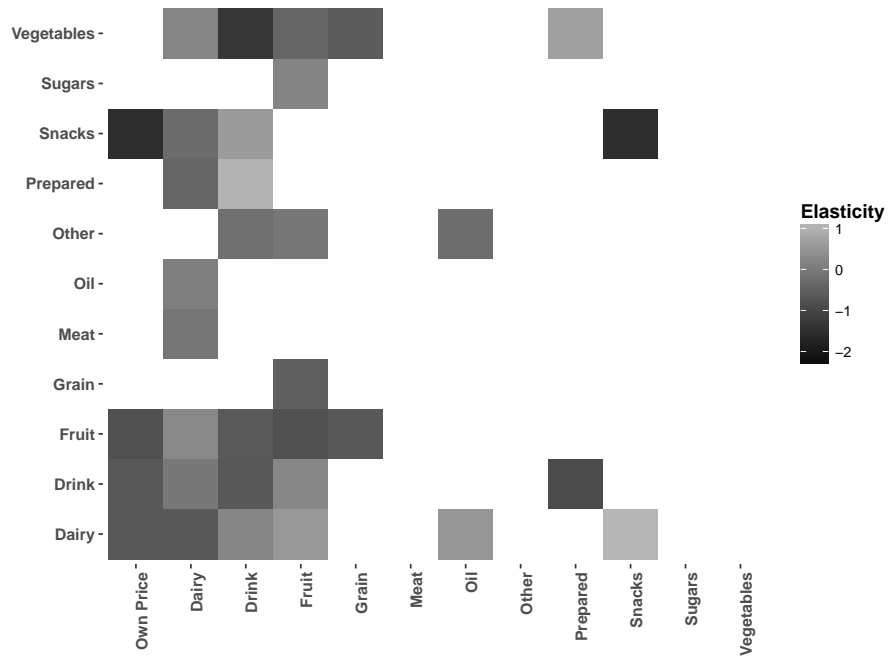


Figure A14 presents online own and cross price elasticities that are significant at the 95% confidence level. Darker shades represent negative elasticities (complements), while lighter shades represent positive elasticities (substitutes). White means that the elasticity is not statistically significant.

12 Table Appendix

Table A1: Product Category Key

Product Category	Description
Dairy	Milk & Milk Substitutes, Cheese, Yogurt, Cream Cheese
Drinks	Non-Alcoholic Beverages, Water, Soda, Juice
Fruit	Fresh, Dried and Frozen Fruits
Grains	Rice, Pasta, Bread, Cereal, Oatmeal
Meat	Beef, Poultry, Seafood, Eggs, Beans, Legumes
Oils	Butter, Mayonnaise, Salad Dressings, Vegetable Oils
Other	Flour, Gravy, Seasonings, Baking Items
Prepared	Rice Mixed Dishes, Pizza, Macaroni, Soups
Snacks and Sweets	Chips, Crackers, Granola Bars, Cakes, Candy, Ice Cream
Sugar	Sugar, Honey, Jams, Syrups
Vegetables	Fresh & Frozen Vegetables

Table A2: Demographic Variables Description

Household Size		Number of Children	
Variable	Category	Variable	Category
1	1 Person	0	0 Children
2	2 People	1	1 Child
3	3 People	2	2 Children
4	4 People	3	3 Children
5	5+ People	4	4+ Children

Household Income		Household Age	
Variable	Category	Variable	Category
1	0–29k	1	18-25
2	30–50k	2	26-35
3	51–79k	3	36-45
4	80–99k	4	46-55
5	100–149k	5	56-65
6	150k+	6	66+

Marital Status	
Variable	Category
0	Single
1	Married

Table A3: Ordinary Least Squares & Two-Stage Least Squares Estimates, ϕ_i
 Online Availability Definition Based on Entire Store Footprint, Online Households Only

Budget Shares	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. Ounce Share (Pre-Online Service)	Percent Change
Dairy	0.767*** (0.0504)	0.769*** (0.0506)	0.496*** (0.0755)	0.811*** (0.215)	0.817*** (0.217)	0.782*** (0.218)	13.25 (6.96)	5.90
Drinks	-0.758*** (0.0645)	-0.762*** (0.0610)	-0.594*** (0.0353)	-0.915*** (0.293)	-0.922*** (0.298)	-0.909*** (0.297)	10.09 (8.43)	-9.01
Fruit	0.335*** (0.0548)	0.354*** (0.0566)	0.125*** (0.0215)	0.623*** (0.239)	0.626*** (0.240)	0.644*** (0.241)	7.45 (6.21)	8.64
Grain	0.272*** (0.0212)	0.274*** (0.0213)	0.179*** (0.0223)	0.222** (0.0944)	0.226** (0.0934)	0.211** (0.101)	7.62 (4.73)	2.77
Meat	0.288*** (0.0692)	0.287*** (0.0728)	0.531*** (0.0673)	1.036*** (0.301)	1.038*** (0.302)	1.049*** (0.305)	18.43 (9.75)	5.69
Oil	-0.0473* (0.0265)	-0.0462* (0.0270)	-0.00967 (0.0193)	-0.192* (0.100)	-0.195* (0.100)	-0.200** (0.100)	4.36 (3.59)	-4.59
Other	0.00428 (0.0149)	0.00116 (0.0140)	0.00646 (0.0100)	-0.0937* (0.0529)	-0.0952* (0.0529)	-0.0840 (0.0545)	1.8 (2.74)	-4.67
Prepared	0.0314 (0.103)	0.0315 (0.108)	0.118* (0.0692)	0.186 (0.238)	0.199 (0.240)	0.221 (0.239)	10.8 (7.51)	2.05
Snacks/Sweets	-1.584*** (0.0891)	-1.613*** (0.0958)	-1.527*** (0.139)	-2.430*** (0.275)	-2.462*** (0.274)	-2.429*** (0.278)	15.53 (9.97)	-15.64
Sugar	0.0407*** (0.00613)	0.0403*** (0.00643)	0.0124 (0.00745)	-0.0975* (0.0500)	-0.0988** (0.0501)	-0.103** (0.0503)	1.62 (2.36)	-6.36
Vegetables	0.653*** (0.0474)	0.665*** (0.0473)	0.663*** (0.0241)	0.853*** (0.189)	0.867*** (0.189)	0.819*** (0.194)	9.05 (6.23)	9.05
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
Household Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	690,152	690,152	690,152	690,152	690,152	690,152	164,750	

Robust standard errors in parentheses

Standard errors clustered at the store-availability level

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

Table A4: Product Subcategories

Bread	Brands/Description
White	White breads, Wonder, etc.
Wheat	Whole wheat breads
Grain	Whole grain breads, Oat breads
Seed	Seeded/nut breads
Other	Cinnamon bread, raisin bread, sourdough
Cereal	Brands/Description
Kids	Fruity Pebbles, Apple Jacks, Cocoa Puffs
Organic Kids	Annies, Cascadian Farm
Standard	Cheerios, Chex, Cornflakes, Rice Crispies
Frosted Standard	Frosted Flakes, Cornpops, Frosted Mini Wheats
Super Healthy	Kashi, Fiberone, Grapenuts
Salty Snacks	Brands/Description
Tortilla Chips	Mission, On the Border, Tostitos
Pretzels	Rold Gold, Snyder
Popcorn	Cape Cod, Skinny Pop, Smart Food
Healthy Chips	Sun Chips, Sensible Portions, Quaker
Chips	Doritos, Cheetos, Lays, Pringles
Yogurt	Brands/Description
Greek	Chobani, Dannon, Yoplait
Greek Light	Chobani, Dannon, Yoplait
Indulgent	YoCrunch, Noosa, Yoplait
Kids	Yoplait, Stoneyfield, Dannon
Organic	Stoneyfield, Wallaby, Silk
Probiotic	Dannon
Traditional	Yoplait, Dannon
Traditional Light	Yoplait, Dannon

Table A5: Ordinary Least Squares & Tobit APE Estimates, τ_k
Bread Sales for Online Households

Sales	OLS (1)	OLS (2)	OLS (3)	Tobit- APE (4)	Tobit- APE (5)	Average (Pre-Online Service)	Percent Change
White	0.0151 (0.0159)	0.0154 (0.0160)	0.0112 (0.0162)	0.0178 (0.0164)	0.0180 (0.0165)	1.26 (2.67)	1.43
Wheat	0.100***	0.100***	0.0972***	0.0894***	0.0895***	1.92 (3.31)	4.66
Seed	(0.0175)	(0.0175)	(0.0178)	(0.0162)	(0.0162)	0.37 (1.49)	3.35
	0.0195**	0.0194**	0.0183*	0.0127**	0.0124**		
Other	(0.00895)	(0.00886)	(0.00907)	(0.00538)	(0.00533)	1.41 (3.08)	0.05
	0.00552	0.00553	0.00327	0.000964	0.000707		
Grain	(0.0135)	(0.0135)	(0.0135)	(0.0141)	(0.0141)	0.96 (2.48)	1.17
	0.0138	0.0141	0.0116	0.0111	0.0112		
	(0.0109)	(0.0108)	(0.0112)	(0.00850)	(0.00855)		
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	616,899	616,899	616,899	616,900	616,899	147,372	

Robust standard errors in parentheses

Standard errors clustered at the specified level

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

Each cell represents an estimate of the effect of online availability on the sales volume.

These estimates were produced equation by equation.

The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A6: Ordinary Least Squares & Tobit APE Estimates, τ_k
Cereal Sales for Online Households

Sales	OLS (1)	OLS (2)	OLS (3)	Tobit- APE (4)	Tobit- APE (5)	Average (Pre-Online Service)	Percent Change
Kids	0.0372 (0.0350)	0.0375 (0.0349)	0.0300 (0.0355)	0.0338 (0.0290)	0.0339 (0.0290)	3.49 (6.10)	0.97
Org. Kids	0.0132*** (0.00469)	0.0133*** (0.00472)	0.0129** (0.00473)	0.00575 (0.00351)	0.00559 (0.00347)	0.10 (0.97)	5.59
Standard	0.0314 (0.0226)	0.0313 (0.0228)	0.0296 (0.0232)	0.0147 (0.0168)	0.0139 (0.0170)	1.36 (3.27)	1.02
Frosted Std.	0.110*** (0.0306)	0.111*** (0.0305)	0.106*** (0.0307)	0.0822*** (0.0281)	0.0831*** (0.0282)	4.02 (6.51)	2.07
Super Healthy	0.00292 (0.0115)	0.00314 (0.0115)	0.00299 (0.0119)	-0.00580 (0.00715)	-0.00580 (0.00711)	0.34 (1.80)	-1.71
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	616,899	616,899	616,899	616,899	616,899	147,372	

Robust standard errors in parentheses

Standard errors clustered at the specified level

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

Each cell represents an estimate of the effect of online availability on the sales volume.

These estimates were produced equation by equation.

The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A7: Ordinary Least Squares & Tobit APE Estimates, τ_k
Salty Snack Sales for Online Households

Sales	OLS (1)	OLS (2)	OLS (3)	Tobit- APE (4)	Tobit- APE (5)	Average (Pre-Online Service)	Percent Change
Tortilla Chips	0.0683** (0.0250)	0.0676** (0.0255)	0.0666** (0.0265)	0.0627** (0.0254)	0.0616** (0.0262)	2.42 (3.89)	2.55
Pretzels	-0.0123 (0.0169)	-0.0125 (0.0169)	-0.0140 (0.0172)	-0.0232 (0.0170)	-0.0239 (0.0169)	1.55 (3.05)	-1.54
Popcorn	0.00396 (0.0158)	0.00393 (0.0158)	0.00257 (0.0159)	-0.00844 (0.0130)	-0.00822 (0.0131)	0.71 (2.43)	-1.16
Veggie Chips	0.0253 (0.0324)	0.0259 (0.0321)	0.0260 (0.0328)	0.00154 (0.0209)	0.00181 (0.0207)	0.92 (2.70)	0.20
Chips	0.0569 (0.0637)	0.0551 (0.0631)	0.0432 (0.0653)	0.0543 (0.0627)	0.0520 (0.0623)	6.54 (8.64)	0.80
Time Availability f.e.	X						
Treatment Cohort f.e.	X	X					
Household Demographics	X	X					
Year-Month f.e.		X	X				
Household f.e.			X				
Observations	616,899	616,899	616,899	616,899	616,899	147,372	

Robust standard errors in parentheses

Standard errors clustered at the specified level

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

Each cell represents an estimate of the effect of online availability on the sales volume.

These estimates were produced equation by equation.

The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A8: Ordinary Least Squares & Tobit APE Estimates, τ_k
Yogurt Sales for Online Households

Sales	OLS (1)	OLS (2)	OLS (3)	Tobit- APE (4)	Tobit- APE (5)	Average (Pre-Online Service)	Percent Change
Traditional Light	0.0197 (0.0125)	0.0205 (0.0126)	0.0187 (0.0128)	0.0252** (0.0127)	0.0253** (0.0127)	1.11 (3.11)	2.28
Traditional	0.0746***	0.0755***	0.0742***	0.0602***	0.0606***	1.32 (3.35)	4.59
Probiotics	0.0164 (0.0210)**	0.0165 (0.0212)**	0.0165 (0.0204)**	0.0122 (0.0117)*	0.0123 (0.0117)*	0.40 (2.25)	2.93
Organic	0.00915 (0.0505***)	0.00917 (0.0506***)	0.00930 (0.0496***)	0.00668 (0.0200**)	0.00667 (0.0195**)	0.58 (2.84)	3.36
Kids	0.0158 (0.0401)	0.0159 (0.0408)	0.0168 (0.0367)	0.00973 (0.0371)	0.00979 (0.0373)	1.87 (4.62)	1.99
Indulgent	0.0341 (0.0125)	0.0341 (0.0127)	0.0346 (0.0116)	0.0319 (0.00928)	0.0319 (0.00948)	0.46 (2.38)	2.06
Greek Light	0.0210 (0.0788***)	0.0209 (0.0800***)	0.0212 (0.0757***)	0.0105 (0.0534**)	0.0105 (0.0530*)	1.49 (4.68)	3.56
Greek	0.0262 (0.202***)	0.0263 (0.203***)	0.0270 (0.199***)	0.0269 (0.116***)	0.0273 (0.116***)	3.65 (7.64)	3.18
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.	X	X	X		X		
Household f.e.			X				
Observations	616,899	616,899	616,899	616,899	616,899	147,372	

Robust standard errors in parentheses

Standard errors clustered at the specified level

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

Each cell represents an estimate of the effect of online availability on the sales volume.

These estimates were produced equation by equation.

The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A9: Tobit Estimates, τ_k
Bread Sales for Online Households

Sales	(1)	(2)
White	0.0609 (0.0560)	0.0615 (0.0564)
Wheat	0.216*** (0.0390)	0.216*** (0.0390)
Seed	0.145** (0.0611)	0.142** (0.0607)
Other	0.00346 (0.0505)	0.00254 (0.0506)
Grain	0.0551 (0.0421)	0.0557 (0.0424)
Time Availability f.e.	X	
Treatment Cohort f.e.	X	X
Household Demographics	X	X
Year-Month f.e.		X
Household f.e.		
Observations	616,899	616,899

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A10: Tobit Estimates, τ_k
Cereal Sales for Online Households

Sales	(1)	(2)
Kids	0.0781 (0.0670)	0.0781 (0.0668)
Org. Kids	0.372 (0.227)	0.365 (0.226)
Standard	0.0617 (0.0704)	0.0585 (0.0714)
Frosted Std.	0.169*** (0.0578)	0.171*** (0.0580)
Super Healthy	-0.111 (0.137)	-0.111 (0.137)
Time Availability f.e.	X	
Treatment Cohort f.e.	X	X
Household Demographics	X	X
Year-Month f.e.		X
Household f.e.		
Observations	616,899	616,899

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A11: Tobit Estimates, τ_k
Salty Snack Sales for Online Households

Sales	(1)	(2)
Tortilla Chips	0.138** (0.0559)	0.136** (0.0575)
Pretzels	-0.0681 (0.0497)	-0.0700 (0.0496)
Popcorn	-0.0536 (0.0826)	-0.0523 (0.0832)
Veggie Chips	0.00796 (0.108)	0.00939 (0.107)
Chips	0.0821 (0.0948)	0.0785 (0.0940)
Time Availability f.e.	X	
Treatment Cohort f.e.	X	X
Household Demographics	X	X
Year-Month f.e.		X
Household f.e.		
Observations	616,899	616,899

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A12: Tobit Estimates, τ_k
Yogurt Sales for Online Households

Sales	(1)	(2)
Traditional Light	0.139** (0.0697)	0.140** (0.0697)
Traditional	0.254*** (0.0517)	0.256*** (0.0522)
Probiotics	0.235* (0.134)	0.236* (0.134)
Organic	0.243** (0.118)	0.237** (0.119)
Kids	0.150 (0.129)	0.151 (0.129)
Indulgent	0.121 (0.137)	0.124 (0.137)
Greek Light	0.283** (0.143)	0.282* (0.146)
Greek	0.314*** (0.0952)	0.312*** (0.0955)
Time Availability f.e.	X	
Treatment Cohort f.e.	X	X
Household Demographics	X	X
Year-Month f.e.		X
Household f.e.		
Observations	616,899	616,899

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A13: In-Store Households - Expenditure

Difference in Difference / Reduced Form Estimates, (τ_i)

Expenditure	(1)	(2)	(3)
1{OnlineAvail}	1.099 (2.035)	1.153 (2.030)	0.537 (1.977)
Time Availability f.e.	X		
Treatment Cohort f.e.	X	X	
Household Demographics	X	X	
Year-Month f.e.		X	X
Household f.e.			X
Observations	238,665	238,665	238,665
R-squared	0.501	0.506	0.809

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A14: In-Store Households - Nutrient Outcomes

Difference in Difference / Reduced Form Estimates, (τ_i)

Nutrients per Ounce	(1)	(2)	(3)
Calories	0.00383 (0.118)	-0.00427 (0.118)	0.00624 (0.121)
Carbohydrates	-0.0108 (0.0161)	-0.0117 (0.0161)	-0.0108 (0.0172)
Cholesterol	-0.000187 (0.000134)	-0.000187 (0.000135)	-0.000203 (0.000138)
Protein	0.00554 (0.00476)	0.00550 (0.00474)	0.00572 (0.00487)
Sodium	0.00236 (0.00605)	0.00238 (0.00602)	0.00247 (0.00596)
Total Fat	0.00188 (0.00775)	0.00136 (0.00772)	0.00200 (0.00787)
Total Sugar	-0.00252 (0.00822)	-0.00326 (0.00828)	-0.00320 (0.00883)
Time Availability f.e.	X		
Treatment Cohort f.e.	X	X	
Household Demographics	X	X	
Year-Month f.e.		X	X
Household f.e.			X
Observations	226,532	226,532	226,532

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A15: In-Store Households - Ounce Shares

Difference in Difference / Reduced Form Estimates, (τ_i)

Ounce Shares	(1)	(2)	(3)
Dairy	0.0406 (0.114)	0.0424 (0.113)	0.0323 (0.115)
Drinks	0.0894 (0.186)	0.0869 (0.185)	0.0962 (0.181)
Fruit	-0.0482 (0.0713)	-0.0475 (0.0711)	-0.0665 (0.0679)
Grain	-0.0128 (0.0431)	-0.0121 (0.0428)	-0.00194 (0.0441)
Meat	-0.0333 (0.0556)	-0.0323 (0.0554)	-0.0207 (0.0571)
Oil	0.0218 (0.0233)	0.0213 (0.0233)	0.0216 (0.0245)
Other	0.0117 (0.0210)	0.0113 (0.0210)	0.00995 (0.0212)
Prepared	-0.0448 (0.0463)	-0.0413 (0.0463)	-0.0366 (0.0466)
Snacks/Sweets	0.0119 (0.0594)	0.00792 (0.0597)	0.00261 (0.0573)
Sugar	0.00341 (0.0288)	0.00248 (0.0289)	0.00225 (0.0292)
Veg	-0.0397 (0.0722)	-0.0392 (0.0720)	-0.0392 (0.0714)
Time Availability f.e.	X		
Treatment Cohort f.e.	X	X	
Household Demographics	X	X	
Year-Month f.e.		X	X
Household f.e.			X
Observations	238,563	238,563	238,563

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A16: Ordinary Least Squares & Two-Stage Least Squares Estimates, ϕ_i
 Online Households - Ounce Shares

Ounce Shares	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. Ounce Share (Pre-Online Service)	Percent Change
Dairy	1.420*** (0.0686)	1.430*** (0.0688)	0.933*** (0.0890)	1.450*** (0.220)	1.460*** (0.221)	1.412*** (0.232)	17.97 (10.57)	7.85
Drinks	-0.799*** (0.116)	-0.822*** (0.121)	-0.298*** (0.0995)	0.0246 (0.360)	0.00715 (0.364)	-0.0362 (0.371)	24.63 (16.99)	-0.15
Fruit	0.0619 (0.0652)	0.0851 (0.0687)	-0.134*** (0.0339)	-0.127 (0.190)	-0.120 (0.191)	-0.114 (0.197)	9.02 (7.39)	-1.26
Grain	0.233*** (0.0221)	0.234*** (0.0215)	0.160*** (0.0153)	0.194 (0.122)	0.195 (0.121)	0.190 (0.126)	6.3 (4.27)	3.02
Meat	0.107*** (0.0321)	0.110*** (0.0340)	0.209*** (0.0268)	0.313** (0.141)	0.315** (0.141)	0.336** (0.142)	9.46 (6.70)	3.59
Oil	-0.0949*** (0.0168)	-0.0922*** (0.0176)	-0.0613** (0.0227)	-0.146* (0.0763)	-0.149* (0.0770)	-0.144* (0.0784)	3.36 (3.33)	4.17
Other	0.0233 (0.0147)	0.0207 (0.0147)	0.0184* (0.00978)	-0.0457 (0.0376)	-0.0472 (0.0376)	-0.0358 (0.0384)	1.02 (2.22)	-3.51
Prepared	-0.0424 (0.0485)	-0.0444 (0.0524)	0.0215 (0.0318)	0.0142 (0.150)	0.0267 (0.152)	0.0501 (0.153)	7.99 (6.03)	0.63
Snacks/Sweets	-1.018*** (0.0926)	-1.036*** (0.0949)	-1.003*** (0.0973)	-1.215*** (0.220)	-1.231*** (0.224)	-1.179*** (0.221)	8.83 (7.59)	-13.36
Sugar	0.0251* (0.0133)	0.0221 (0.0136)	0.0219** (0.00978)	-0.0452 (0.0428)	-0.0490 (0.0433)	-0.0528 (0.0455)	1.57 (2.52)	-3.36
Vegetables	0.0850 (0.0549)	0.0927* (0.0546)	0.132*** (0.0365)	-0.416** (0.209)	-0.409** (0.209)	-0.425* (0.218)	9.84 (7.30)	-4.37
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
Household Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	616,163	616,163	616,163	616,163	616,163	616,163	147,172	

Robust standard errors in parentheses

Standard errors clustered at the store-availability level

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

Table A17: Event Study Estimates, τ_{ik}
Online Households

	1{Online}	Dairy	Drink	Fruit	Grain	Meat
t=-5	0.00125 (0.00329)	-0.0982 (0.0580)	-0.0911 (0.0667)	0.0128 (0.0784)	-0.00870 (0.0320)	0.0726 (0.0738)
t=-4	-0.00273 (0.00446)	-0.0420 (0.0430)	-0.0385 (0.0509)	0.0695 (0.0625)	-0.00102 (0.0339)	-0.00999 (0.0556)
t=-3	-0.00609 (0.00479)	-0.000427 (0.0574)	-0.130* (0.0715)	0.0949* (0.0523)	-0.0330 (0.0341)	0.0838 (0.0720)
t=-2	-0.00495 (0.00553)	0.0339 (0.0504)	-0.119 (0.0768)	0.0389 (0.0664)	-0.0415 (0.0344)	0.118 (0.0737)
t=-1	0.00364 (0.00776)	0.0465 (0.0566)	-0.115** (0.0490)	0.0744 (0.0623)	4.54e-06 (0.0338)	0.0104 (0.0580)
t=0	0.141*** (0.0247)	0.0873 (0.0685)	-0.143** (0.0686)	0.101** (0.0483)	0.0400 (0.0340)	0.186** (0.0764)
t=1	0.191*** (0.0269)	0.106 (0.0830)	-0.205*** (0.0750)	0.140*** (0.0449)	-0.0326 (0.0318)	0.288*** (0.0725)
t=2	0.204*** (0.0236)	0.159** (0.0753)	-0.236*** (0.0784)	0.212*** (0.0735)	-0.0249 (0.0273)	0.189** (0.0825)
t=3	0.201*** (0.0228)	0.0383 (0.0815)	-0.188*** (0.0626)	0.0979 (0.0689)	0.0270 (0.0330)	0.286*** (0.0816)
t=4	0.208*** (0.0278)	0.140 (0.0954)	-0.284** (0.116)	0.161** (0.0672)	0.0133 (0.0339)	0.331*** (0.0870)
t=5	0.201*** (0.0244)	0.0641 (0.119)	-0.194* (0.108)	0.0542 (0.0739)	0.0476 (0.0409)	0.292*** (0.101)
t>5	0.211*** (0.0123)	-0.0196 (0.115)	-0.147 (0.0923)	0.131 (0.0834)	-0.0116 (0.0410)	0.246*** (0.0897)
Year-Month f.e.	X	X	X	X	X	X
Household f.e.	X	X	X	X	X	X
Observations	616,357	616,357	616,357	616,357	616,357	616,357
R-Squared	0.306	0.364	0.332	0.399	0.312	0.368

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

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

Table A18: Event Study Estimates, τ_{ik}
Online Households

	Oil	Other	Prepared	Snack/Sweet	Sugar	Vegetables
t=-5	0.0111 (0.0243)	0.0499** (0.0217)	-0.00653 (0.0476)	0.0489 (0.0689)	0.0589** (0.0228)	-0.0497 (0.0412)
t=-4	-0.0552*** (0.0192)	0.0339* (0.0179)	-0.0339 (0.0563)	0.00647 (0.0829)	0.0174 (0.0196)	0.0532 (0.0617)
t=-3	-0.0549 (0.0343)	0.0234 (0.0223)	-0.0276 (0.0462)	-0.121 (0.0772)	0.0287 (0.0193)	0.136*** (0.0447)
t=-2	-0.00510 (0.0259)	0.0409* (0.0237)	-0.0602 (0.0652)	-0.0952 (0.0699)	0.0369** (0.0144)	0.0518 (0.0487)
t=-1	0.00404 (0.0229)	0.00982 (0.0179)	-0.118* (0.0616)	-0.0197 (0.0579)	0.0410 (0.0290)	0.0636 (0.0511)
t=0	-0.0100 (0.0236)	0.00407 (0.0180)	-0.0227 (0.0810)	-0.365*** (0.0983)	0.0428** (0.0191)	0.0808 (0.0610)
t=1	-0.0612* (0.0321)	0.0118 (0.0176)	-0.00837 (0.0752)	-0.408*** (0.0976)	-0.0102 (0.0251)	0.181*** (0.0618)
t=2	-0.0782** (0.0371)	-0.000670 (0.0179)	-0.0252 (0.0565)	-0.416*** (0.0878)	0.0190 (0.0212)	0.198*** (0.0488)
t=3	-0.0697*** (0.0192)	0.0256 (0.0253)	-0.00214 (0.0669)	-0.455*** (0.103)	0.0173 (0.0174)	0.222*** (0.0402)
t=4	-0.0594* (0.0321)	0.0530** (0.0251)	-0.0212 (0.0696)	-0.575*** (0.133)	0.0149 (0.0148)	0.227*** (0.0429)
t=5	-0.0366 (0.0463)	0.0292 (0.0174)	0.00314 (0.0806)	-0.501*** (0.138)	0.0208 (0.0382)	0.221*** (0.0623)
t>5	-0.0618** (0.0279)	0.0377* (0.0193)	-0.129 (0.0890)	-0.283** (0.132)	0.0421* (0.0244)	0.194*** (0.0554)
Year-Month f.e.	X	X	X	X	X	X
Household f.e.	X	X	X	X	X	X
Observations	616,357	616,357	616,357	616,357	616,357	616,357
R-Squared	0.183	0.172	0.353	0.319	0.166	0.414

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A19: Event Study Estimates, τ_{ik}
In-Store Households

	Dairy	Drink	Fruit	Grain	Meat
t=-5	-0.0272 (0.0725)	0.395*** (0.123)	-0.0306 (0.107)	-0.150** (0.0663)	-0.145 (0.138)
t=-4	0.0244 (0.0608)	0.202* (0.110)	0.0682 (0.101)	-0.0752 (0.0595)	0.00469 (0.140)
t=-3	-0.0659 (0.0752)	0.0965 (0.129)	0.0508 (0.101)	-0.0342 (0.0813)	0.0113 (0.133)
t=-2	0.0257 (0.0863)	0.0452 (0.125)	-0.0493 (0.0981)	-0.0409 (0.0694)	0.0815 (0.134)
t=-1	0.00804 (0.104)	0.247* (0.124)	-0.140 (0.0911)	-0.162** (0.0667)	0.120 (0.148)
t=0	0.152 (0.104)	0.108 (0.108)	-0.144 (0.0938)	-0.0816 (0.0753)	-0.131 (0.122)
t=1	0.0666 (0.0834)	0.136 (0.153)	0.151 (0.108)	-0.155** (0.0675)	0.185 (0.177)
t=2	-0.0720 (0.0843)	0.238 (0.146)	0.0410 (0.0898)	-0.123 (0.0813)	0.0676 (0.158)
t=3	0.0915 (0.0968)	0.361** (0.154)	-0.128 (0.0861)	-0.111 (0.0892)	-0.180 (0.185)
t=4	0.247* (0.124)	0.101 (0.141)	-0.154 (0.140)	-0.0314 (0.0690)	0.0294 (0.152)
t=5	0.227 (0.193)	0.187 (0.228)	-0.158 (0.128)	-0.0134 (0.113)	0.283 (0.225)
t>5	0.0111 (0.154)	0.138 (0.175)	-0.135 (0.129)	-0.111 (0.0896)	-0.0173 (0.207)
Year-Month f.e.	X	X	X	X	X
Household f.e.	X	X	X	X	X
Observations	238,665	238,665	238,665	238,665	238,665
R-Squared	0.343	0.329	0.405	0.272	0.371
Robust standard errors in parentheses					
Standard errors clustered at the store-availability level					
*** p<0.01, ** p<0.05, * p<0.1					

Table A20: Event Study Estimates, τ_{ik}
In-Store Households

	Oil	Other	Prepared	Snack/Sweet	Sugar	Vegetables
t=-5	-0.0419 (0.0543)	-0.0246 (0.0346)	0.00916 (0.0873)	-0.0421 (0.124)	0.0528 (0.0443)	0.00442 (0.0971)
t=-4	0.0497 (0.0429)	-0.0424 (0.0330)	-0.115 (0.105)	-0.174* (0.0977)	-0.0167 (0.0275)	0.0740 (0.0726)
t=-3	0.0290 (0.0745)	0.00712 (0.0288)	-0.0880 (0.0965)	0.102 (0.124)	-0.0455 (0.0402)	-0.0639 (0.0866)
t=-2	0.0411 (0.0565)	-0.0312 (0.0338)	0.0416 (0.0868)	-0.127 (0.122)	-0.00604 (0.0324)	0.0181 (0.0787)
t=-1	0.0427 (0.0561)	1.12e-05 (0.0228)	-0.144 (0.0992)	-0.0735 (0.161)	-0.00508 (0.0337)	0.107 (0.0796)
t=0	0.128** (0.0529)	0.0198 (0.0480)	0.0113 (0.100)	-0.123 (0.151)	-0.0212 (0.0312)	0.0840 (0.0938)
t=1	0.0139 (0.0595)	0.00288 (0.0359)	-0.173 (0.135)	-0.183 (0.138)	-0.0814** (0.0365)	0.0375 (0.110)
t=2	-0.0414 (0.0622)	-0.0385 (0.0433)	-0.232* (0.136)	-0.00862 (0.170)	0.127*** (0.0443)	0.0420 (0.102)
t=3	0.0926 (0.0827)	-0.0363 (0.0422)	-0.174 (0.126)	0.0472 (0.183)	-0.0350 (0.0551)	0.0743 (0.0962)
t=4	-0.0226 (0.0922)	0.0464 (0.0622)	-0.130 (0.128)	-0.180 (0.169)	0.00337 (0.0431)	0.0711 (0.0990)
t=5	0.00623 (0.0780)	0.00329 (0.0404)	-0.303** (0.117)	-0.140 (0.178)	-0.0501 (0.0534)	-0.0408 (0.116)
t>5	0.103 (0.0692)	-0.0333 (0.0444)	-0.241 (0.145)	0.107 (0.163)	0.00797 (0.0500)	0.170 (0.103)
Year-Month f.e.	X	X	X	X	X	X
Household f.e.	X	X	X	X	X	X
Observations	238,665	238,665	238,665	238,665	238,665	238,665
R-Squared	0.174	0.156	0.357	0.319	0.169	0.400

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A21: First Stage Estimates

Endogenous Variable	$\ln(p_{Dairy})$	$\ln(p_{Drink})$	$\ln(p_{Fruit})$	$\ln(p_{Grain})$	$\ln(p_{Meat})$	$\ln(p_{POil})$
$1\{OnlineAvail\}$	-0.57	0.06	-0.14	-0.12	0.19	0.25
$\ln(c_{Dairy})$	1.01	0.25	0.17	0.10	0.04	0.15
$\ln(c_{Drink})$	0.14	1.00	0.12	0.10	0.05	0.11
$\ln(c_{Fruit})$	-0.08	0.02	0.54	0.03	0.04	-0.01
$\ln(c_{Grain})$	-0.34	0.27	-0.35	0.40	-0.07	0.09
$\ln(c_{Meat})$	0.20	0.16	0.21	0.15	0.76	0.31
$\ln(c_{Oil})$	0.06	0.14	-0.04	-0.01	0.06	0.41
$\ln(c_{Other})$	-0.04	-0.15	-0.03	-0.02	0.01	-0.04
$\ln(c_{Prep})$	0.19	0.33	0.08	0.01	-0.12	-0.07
$\ln(c_{Snacks})$	-0.33	-0.43	-0.29	-0.04	-0.13	-0.09
$\ln(c_{Sugar})$	-0.02	0.05	-0.03	0.02	0.02	0.04
$\ln(c_{Veg})$	-0.07	-0.16	0.10	0.00	0.04	0.00
$\ln(c_{Dairy})x1\{OnlineAvail\}$	0.20	0.14	0.04	0.09	0.07	0.06
$\ln(c_{Drink})x1\{OnlineAvail\}$	-0.07	0.06	-0.12	0.01	0.06	0.05
$\ln(c_{Fruit})x1\{OnlineAvail\}$	-0.09	-0.12	-0.04	-0.06	-0.05	-0.01
$\ln(c_{Grain})x1\{OnlineAvail\}$	-0.33	-0.25	0.13	-0.20	-0.14	-0.26
$\ln(c_{Meat})x1\{OnlineAvail\}$	0.49	0.21	0.01	0.14	0.13	0.14
$\ln(c_{Oil})x1\{OnlineAvail\}$	-0.03	0.02	0.15	0.07	0.14	0.15
$\ln(c_{Other})x1\{OnlineAvail\}$	0.03	-0.02	0.01	-0.01	0.01	0.03
$\ln(c_{Prep})x1\{OnlineAvail\}$	-0.18	0.06	0.30	0.02	0.10	0.16
$\ln(c_{Snacks})x1\{OnlineAvail\}$	-0.23	-0.22	-0.26	-0.24	-0.15	-0.22
$\ln(c_{Sugar})x1\{OnlineAvail\}$	-0.09	-0.04	-0.01	0.00	-0.02	-0.01
$\ln(c_{Veg})x1\{OnlineAvail\}$	0.10	0.14	-0.13	0.09	-0.07	0.00
$\ln(\frac{M}{C})$	-0.11	-0.24	-0.09	-0.03	-0.05	-0.08
$\ln(\frac{M}{C})x1\{OnlineAvail\}$	0.01	0.01	0.02	0.00	0.00	0.00
Constant	X	X	X	X	X	X
Household Demographics	X	X	X	X	X	X
Month f.e.	X	X	X	X	X	X
Linear Time Trend	X	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157	616,157
R ²	0.06	0.10	0.05	0.04	0.05	0.06

Standard errors available from the author upon request

Table A22: First Stage Estimates

Endogenous Variable	$\ln(p_{Other})$	$\ln(p_{Prep})$	$\ln(p_{Snacks})$	$\ln(p_{Sugar})$	$\ln(p_{Veg})$
$1\{OnlineAvail\}$	0.06	0.17	0.13	0.36	0.15
$\ln(c_{Dairy})$	-0.11	0.05	0.12	-0.04	0.25
$\ln(c_{Drink})$	0.15	0.03	0.05	0.11	0.10
$\ln(c_{Fruit})$	0.01	0.03	0.06	0.00	-0.01
$\ln(c_{Grain})$	-0.31	-0.09	-0.19	0.15	-0.21
$\ln(c_{Meat})$	0.56	0.30	0.10	0.42	0.29
$\ln(c_{Oil})$	-0.06	0.08	0.01	0.08	-0.10
$\ln(c_{Other})$	0.30	-0.02	0.00	0.00	-0.03
$\ln(c_{Prep})$	0.16	0.67	0.02	-0.14	0.02
$\ln(c_{Snacks})$	0.33	-0.10	0.64	-0.09	-0.23
$\ln(c_{Sugar})$	0.09	0.04	-0.01	0.36	-0.02
$\ln(c_{Veg})$	-0.07	-0.04	-0.06	-0.05	0.55
$\ln(c_{Dairy}) \times 1\{OnlineAvail\}$	-0.04	0.11	0.13	0.05	-0.02
$\ln(c_{Drink}) \times 1\{OnlineAvail\}$	-0.22	0.15	0.03	-0.13	-0.03
$\ln(c_{Fruit}) \times 1\{OnlineAvail\}$	-0.10	0.00	-0.05	-0.13	-0.08
$\ln(c_{Grain}) \times 1\{OnlineAvail\}$	0.46	-0.42	-0.27	-0.34	-0.07
$\ln(c_{Meat}) \times 1\{OnlineAvail\}$	-0.25	0.18	0.12	0.07	0.14
$\ln(c_{Oil}) \times 1\{OnlineAvail\}$	0.11	0.00	0.08	0.29	0.10
$\ln(c_{Other}) \times 1\{OnlineAvail\}$	0.01	0.01	0.00	-0.05	0.00
$\ln(c_{Prep}) \times 1\{OnlineAvail\}$	0.43	0.06	0.05	0.54	0.15
$\ln(c_{Snacks}) \times 1\{OnlineAvail\}$	-0.33	-0.05	-0.10	-0.44	-0.23
$\ln(c_{Sugar}) \times 1\{OnlineAvail\}$	0.13	0.00	0.00	0.14	-0.05
$\ln(c_{Veg}) \times 1\{OnlineAvail\}$	-0.12	-0.05	0.03	0.07	0.15
$\ln(\frac{M}{C})$	-0.34	-0.07	-0.04	-0.21	-0.09
$\ln(\frac{M}{C}) \times 1\{OnlineAvail\}$	-0.01	0.00	0.00	-0.03	0.00
Constant	X	X	X	X	X
Household Demographics	X	X	X	X	X
Month f.e.	X	X	X	X	X
Linear Time Trend	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157
R ²	0.13	0.06	0.04	0.12	0.07

Standard errors available from the author upon request

Table A23: First Stage Estimates

Endogenous Variable	$1\{\text{Online}\}$	$\ln(\frac{M}{P})$	$\ln(\frac{M}{P}) \times 1\{\text{Online}\}$
$1\{\text{OnlineAvail}\}$	3.39	0.11	25.69
$\ln(c_{Dairy})$	0.01	-0.14	0.13
$\ln(c_{Drink})$	0.07	0.01	0.58
$\ln(c_{Fruit})$	-0.08	0.09	-0.66
$\ln(c_{Grain})$	-0.18	0.26	-1.42
$\ln(c_{Meat})$	0.05	-0.10	0.42
$\ln(c_{Oil})$	-0.03	0.01	-0.26
$\ln(c_{Other})$	-0.02	0.02	-0.18
$\ln(c_{Prep})$	0.06	-0.20	0.48
$\ln(c_{Snacks})$	-0.18	0.09	-1.50
$\ln(c_{Sugar})$	0.05	0.03	0.40
$\ln(c_{Veg})$	0.14	0.09	1.15
$\ln(c_{Dairy}) \times 1\{\text{OnlineAvail}\}$	-0.53	-0.05	-4.22
$\ln(c_{Drink}) \times 1\{\text{OnlineAvail}\}$	0.03	-0.04	0.21
$\ln(c_{Fruit}) \times 1\{\text{OnlineAvail}\}$	0.52	0.02	4.21
$\ln(c_{Grain}) \times 1\{\text{OnlineAvail}\}$	0.26	0.27	2.25
$\ln(c_{Meat}) \times 1\{\text{OnlineAvail}\}$	-1.25	-0.13	-9.96
$\ln(c_{Oil}) \times 1\{\text{OnlineAvail}\}$	0.48	-0.04	3.79
$\ln(c_{Other}) \times 1\{\text{OnlineAvail}\}$	-0.09	0.02	-0.61
$\ln(c_{Prep}) \times 1\{\text{OnlineAvail}\}$	1.11	-0.06	8.61
$\ln(c_{Snacks}) \times 1\{\text{OnlineAvail}\}$	0.73	0.14	5.78
$\ln(c_{Sugar}) \times 1\{\text{OnlineAvail}\}$	0.17	-0.01	1.29
$\ln(c_{Veg}) \times 1\{\text{OnlineAvail}\}$	0.17	-0.06	1.31
$\ln(\frac{M}{C})$	0.01	1.00	0.07
$\ln(\frac{M}{C}) \times 1\{\text{OnlineAvail}\}$	0.05	-0.01	0.56
Constant	X	X	X
Household Demographics	X	X	X
Month f.e.	X	X	X
Linear Time Trend	X	X	X
Observations	616,157	616,157	616,157
R ²	0.19	0.93	0.19
Standard errors available from the author upon request			

Table A24: First Stage Estimates

Endogenous Variable	$\ln(p_{Dairy})x1\{O\}$	$\ln(p_{Drink})x1\{O\}$	$\ln(p_{Fruit})x1\{O\}$	$\ln(p_{Grain})x1\{O\}$	$\ln(p_{Meat})x1\{O\}$	$\ln(p_{Oil})x1\{O\}$
1{OnlineAvail}	-7.49	-8.25	-7.10	-6.19	-4.52	-5.44
$\ln(c_{Dairy})$	-0.02	-0.03	-0.02	-0.01	-0.01	-0.01
$\ln(c_{Drink})$	-0.17	-0.20	-0.17	-0.14	-0.10	-0.12
$\ln(c_{Fruit})$	0.20	0.26	0.17	0.15	0.11	0.15
$\ln(c_{Grain})$	0.43	0.53	0.39	0.35	0.27	0.31
$\ln(c_{Meat})$	-0.11	-0.14	-0.10	-0.09	-0.08	-0.08
$\ln(c_{Oil})$	0.08	0.08	0.07	0.06	0.04	0.05
$\ln(c_{Other})$	0.05	0.06	0.04	0.04	0.03	0.04
$\ln(c_{Prep})$	-0.15	-0.14	-0.14	-0.11	-0.09	-0.11
$\ln(c_{Snacks})$	0.43	0.50	0.41	0.34	0.26	0.33
$\ln(c_{Sugar})$	-0.14	-0.16	-0.13	-0.11	-0.09	-0.11
$\ln(c_{Veg})$	-0.35	-0.43	-0.31	-0.27	-0.20	-0.25
$\ln(c_{Dairy})x1\{OnlineAvail\}$	1.57	1.67	1.19	1.09	0.81	1.03
$\ln(c_{Drink})x1\{OnlineAvail\}$	-0.05	0.28	-0.03	-0.04	-0.06	-0.04
$\ln(c_{Fruit})x1\{OnlineAvail\}$	-1.27	-1.50	-1.07	-1.02	-0.79	-0.97
$\ln(c_{Grain})x1\{OnlineAvail\}$	-0.76	-1.01	-0.54	-0.42	-0.41	-0.53
$\ln(c_{Meat})x1\{OnlineAvail\}$	3.14	3.70	2.87	2.46	2.02	2.30
$\ln(c_{Oil})x1\{OnlineAvail\}$	-1.09	-1.34	-1.08	-0.91	-0.62	-0.67
$\ln(c_{Other})x1\{OnlineAvail\}$	0.23	0.23	0.18	0.17	0.14	0.15
$\ln(c_{Prep})x1\{OnlineAvail\}$	-2.74	-3.22	-2.45	-2.18	-1.61	-1.99
$\ln(c_{Snacks})x1\{OnlineAvail\}$	-1.79	-2.17	-1.70	-1.46	-1.13	-1.35
$\ln(c_{Sugar})x1\{OnlineAvail\}$	-0.42	-0.46	-0.39	-0.32	-0.24	-0.27
$\ln(c_{Veg})x1\{OnlineAvail\}$	-0.45	-0.47	-0.39	-0.32	-0.25	-0.30
$\ln(\frac{M}{C})$	-0.02	-0.03	-0.02	-0.02	-0.01	-0.02
$\ln(\frac{M}{C})x1\{OnlineAvail\}$	-0.14	-0.19	-0.12	-0.11	-0.08	-0.11
Constant	X	X	X	X	X	X
Household Demographics	X	X	X	X	X	X
Month f.e.	X	X	X	X	X	X
Linear Time Trend	X	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157	616,157
R ²	0.18	0.18	0.19	0.19	0.18	0.18

Standard errors available from the author upon request

Table A25: First Stage Estimates

Endogenous Variable	$\ln(p_{Other})x1\{O\}$	$\ln(p_{Prep})x1\{O\}$	$\ln(p_{Snacks})x1\{O\}$	$\ln(p_{Sugar})x1\{O\}$	$\ln(p_{Veg})x1\{O\}$
1{OnlineAvail}	-1.69	-5.42	-4.89	-5.06	-7.12
$\ln(C_{Dairy})$	-0.02	-0.02	-0.01	-0.02	-0.01
$\ln(C_{Drink})$	-0.05	-0.12	-0.11	-0.12	-0.17
$\ln(C_{Fruit})$	0.03	0.12	0.13	0.14	0.18
$\ln(C_{Grain})$	0.07	0.31	0.28	0.28	0.43
$\ln(C_{Meat})$	0.03	-0.07	-0.07	-0.08	-0.11
$\ln(C_{POil})$	0.05	0.05	0.05	0.05	0.07
$\ln(C_{Other})$	0.01	0.03	0.03	0.04	0.05
$\ln(C_{Prep})$	-0.08	-0.12	-0.09	-0.10	-0.14
$\ln(C_{Snacks})$	0.19	0.32	0.28	0.32	0.40
$\ln(C_{Sugar})$	-0.08	-0.10	-0.09	-0.11	-0.14
$\ln(C_{Veg})$	-0.05	-0.24	-0.23	-0.22	-0.32
$\ln(C_{Dairy})x1\{OnlineAvail\}$	0.30	0.96	0.89	0.95	1.27
$\ln(C_{Drink})x1\{OnlineAvail\}$	-0.16	-0.04	-0.02	-0.10	-0.02
$\ln(C_{Fruit})x1\{OnlineAvail\}$	-0.37	-0.92	-0.82	-0.95	-1.23
$\ln(C_{Grain})x1\{OnlineAvail\}$	-0.12	-0.54	-0.51	-0.43	-0.69
$\ln(C_{Meat})x1\{OnlineAvail\}$	0.62	2.23	2.00	2.09	2.96
$\ln(C_{Oil})x1\{OnlineAvail\}$	-0.45	-0.79	-0.71	-0.81	-1.10
$\ln(C_{Other})x1\{OnlineAvail\}$	0.10	0.16	0.14	0.12	0.21
$\ln(C_{Prep})x1\{OnlineAvail\}$	-0.36	-1.68	-1.75	-1.80	-2.54
$\ln(C_{Snacks})x1\{OnlineAvail\}$	-0.46	-1.35	-1.05	-1.21	-1.71
$\ln(C_{Sugar})x1\{OnlineAvail\}$	0.13	-0.29	-0.25	-0.09	-0.39
$\ln(C_{Veg})x1\{OnlineAvail\}$	-0.17	-0.32	-0.27	-0.30	-0.24
$\ln(\frac{M}{C})$	0.00	-0.02	-0.01	-0.01	-0.02
$\ln(\frac{M}{C})x1\{OnlineAvail\}$	-0.09	-0.10	-0.09	-0.13	-0.13
Constant	X	X	X	X	X
Household Demographics	X	X	X	X	X
Month f.e.	X	X	X	X	X
Linear Time Trend	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157
R ²	0.05	0.18	0.18	0.16	0.19

Standard errors available from the author upon request

Table A26: Demand Estimates
Online Households

Budget Shares	(1)	(2)	(3)	(4)	(5)
	Dairy	Drinks	Fruit	Grains	Oil
$\ln(p_{dairy})$	-0.00878** (0.00396)	0.0368*** (0.00227)	0.00242 (0.00309)	-0.0176*** (0.00308)	0.0188*** (0.00236)
$\ln(p_{drink})$	0.0368*** (0.00227)	-0.0992*** (0.00283)	0.0632*** (0.00237)	0.0137*** (0.00227)	-0.0127*** (0.00174)
$\ln(p_{fruit})$	0.00242 (0.00309)	0.0632*** (0.00237)	-0.0121** (0.00521)	-0.0224*** (0.00432)	0.0338*** (0.00323)
$\ln(p_{grain})$	-0.0176*** (0.00308)	0.0137*** (0.00227)	-0.0224*** (0.00432)	0.0978*** (0.0108)	0.0274*** (0.00589)
$\ln(p_{meat})$	0.0231*** (0.00470)	-0.0311*** (0.00339)	-0.0335*** (0.00626)	0.0128* (0.00728)	-0.0230*** (0.00564)
$\ln(p_{oil})$	0.0188*** (0.00236)	-0.0127*** (0.00174)	0.0338*** (0.00323)	0.0274*** (0.00589)	0.0321*** (0.00624)
$\ln(p_{other})$	0.00649*** (0.00129)	0.00915*** (0.000901)	-0.00177 (0.00179)	0.000621 (0.00291)	-0.00228 (0.00222)
$\ln(p_{prep})$	-0.0173*** (0.00387)	-0.00231 (0.00277)	-0.0533*** (0.00489)	-0.0753*** (0.00573)	-0.0381*** (0.00426)
$\ln(p_{snack})$	-0.0893*** (0.00434)	-0.0112*** (0.00307)	0.0363*** (0.00493)	-0.0132** (0.00631)	-0.0385*** (0.00469)
$\ln(p_{sugar})$	0.000759 (0.00147)	0.00630*** (0.00104)	0.00777*** (0.00211)	-0.00805** (0.00396)	-0.0116*** (0.00311)
$\ln(p_{veg})$	0.0446*** (0.00312)	0.0274*** (0.00217)	-0.0204*** (0.00379)	-0.0157*** (0.00472)	0.0141*** (0.00354)
$\ln(\frac{m}{p})$	0.0108*** (0.000609)	-0.0322*** (0.000584)	0.00994*** (0.000780)	-0.00270** (0.00111)	-0.00134* (0.000795)
Constant	0.149*** (0.0207)	0.215*** (0.0218)	0.0638*** (0.0246)	0.156*** (0.0250)	0.0927*** (0.0182)
Linear Time Trend	X	X	X	X	X
Month f.e.	X	X	X	X	X
Household Demographics	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157
R-squared	-0.690	-0.641	-0.873	-0.699	-0.778

Standard errors in parentheses

Standard errors clustered at the store-availability level

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

Table A27: Demand Estimates
Online Households

	(1)	(2)	(3)	(4)	(5)
Budget Shares	Dairy	Drinks	Fruit	Grains	Oil
$1\{\text{Online}\}$	0.455*** (0.0392)	-0.199*** (0.0327)	0.183*** (0.0462)	0.117** (0.0490)	0.0442 (0.0388)
$\ln(p_{dairy})x1\{O\}$	0.198*** (0.0226)	-0.0557*** (0.0117)	0.138*** (0.0183)	-0.00168 (0.0167)	0.0230* (0.0131)
$\ln(p_{drink})x1\{O\}$	-0.0557*** (0.0117)	0.0664*** (0.0132)	-0.00266 (0.0127)	-0.00481 (0.0120)	0.0350*** (0.00925)
$\ln(p_{fruit})x1\{O\}$	0.138*** (0.0183)	-0.00266 (0.0127)	0.0612** (0.0305)	-0.113*** (0.0260)	-0.0332* (0.0194)
$\ln(p_{grain})x1\{O\}$	-0.00168 (0.0167)	-0.00481 (0.0120)	-0.113*** (0.0260)	0.122** (0.0524)	-0.0638** (0.0318)
$\ln(p_{meat})x1\{O\}$	-0.0805*** (0.0266)	-0.00716 (0.0179)	0.0109 (0.0320)	-0.0199 (0.0332)	0.0143 (0.0265)
$\ln(p_{oil})x1\{O\}$	0.0230* (0.0131)	0.0350*** (0.00925)	-0.0332* (0.0194)	-0.0638** (0.0126)	0.000709 (0.0338)
$\ln(p_{other})x1\{O\}$	-0.000976 (0.00654)	0.0102** (0.00469)	-0.0166* (0.00859)	-0.00523 (0.0114***)	-0.0193* (0.0107)
$\ln(p_{prep})x1\{O\}$	-0.208*** (0.0207)	-0.0903*** (0.0142)	0.0207 (0.0267)	0.114*** (0.0258)	0.0282 (0.0196)
$\ln(p_{snack})x1\{O\}$	-0.0795*** (0.0275)	-0.0448** (0.0179)	-0.0189 (0.0343)	0.109** (0.0442)	0.0148 (0.0349)
$\ln(p_{sugar})x1\{O\}$	-0.00408 (0.00794)	-0.00259 (0.00594)	0.0409*** (0.0120)	-0.0362* (0.0188)	0.0258* (0.0154)
$\ln(p_{veg})x1\{O\}$	0.0713*** (0.0187)	0.0964*** (0.0139)	-0.0874*** (0.0239)	-0.100*** (0.0291)	-0.0254 (0.0227)
$\ln(\frac{p}{P})x1\{O\}$	-0.0288*** (0.00441)	0.0345*** (0.00412)	-0.0118** (0.00503)	-0.0269*** (0.00512)	-0.00255 (0.00418)
Linear Time Trend	X	X	X	X	X
Month f.e.	X	X	X	X	X
Household Demographics	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157
R-squared	-0.690	-0.641	-0.873	-0.699	-0.778

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A28: Demand Estimates
Online Households

Budget Shares	(6)	(7)	(8)	(9)	(10)
$\ln(p_{dairy})$	Other	Prepared	Snacks/Sweets	Sugars	Vegetables
	0.00649***	-0.0173***	-0.0893***	0.000759	0.0446***
	(0.00129)	(0.00387)	(0.00434)	(0.00147)	(0.00312)
$\ln(p_{drink})$	0.00915***	-0.00231	-0.0112***	0.00630***	0.0274***
	(0.000901)	(0.00277)	(0.00307)	(0.00104)	(0.00217)
$\ln(p_{fruit})$	-0.00177	-0.0533***	0.0363***	0.00777***	-0.0204***
	(0.00179)	(0.00489)	(0.00493)	(0.00211)	(0.00379)
$\ln(p_{grain})$	0.000621	-0.0753***	-0.0132**	-0.00805**	-0.0157***
	(0.00291)	(0.00573)	(0.00631)	(0.00396)	(0.00472)
$\ln(p_{meat})$	-0.000450	0.0586***	0.102***	-0.0154***	-0.0581***
	(0.00305)	(0.00747)	(0.00954)	(0.00358)	(0.00706)
$\ln(p_{oil})$	-0.00228	-0.0381***	-0.0385***	-0.0116***	0.0141***
	(0.00222)	(0.00426)	(0.00469)	(0.00311)	(0.00354)
$\ln(p_{other})$	0.00154	-0.00297	-0.00200	-0.00562***	-0.00271
	(0.00162)	(0.00233)	(0.00248)	(0.00153)	(0.00190)
$\ln(p_{prep})$	-0.00297	0.164***	-0.00772	-0.00258	-0.0232***
	(0.00233)	(0.00867)	(0.00656)	(0.00268)	(0.00478)
$\ln(p_{snack})$	-0.00200	-0.00772	0.0114	0.0185***	0.00608
	(0.00248)	(0.00656)	(0.00955)	(0.00294)	(0.00555)
$\ln(p_{sugar})$	-0.00562***	-0.00258	0.0185***	0.00518*	0.00466**
	(0.00153)	(0.00268)	(0.00294)	(0.00276)	(0.00228)
$\ln(p_{veg})$	-0.00271	-0.0232***	-0.00657	0.00466**	0.0231***
	(0.00190)	(0.00478)	(0.00775)	(0.00228)	(0.00575)
$\ln(\frac{M}{P})$	0.00150***	-0.00180*	-0.0323***	0.000122	0.0122***
	(0.000526)	(0.000973)	(0.00104)	(0.000537)	(0.000772)
Constant	-0.00676	-0.0762***	-0.0380	0.0565***	0.0883***
	(0.00979)	(0.0278)	(0.0309)	(0.0116)	(0.0224)
Linear Time Trend	X	X	X	X	X
Month f.e.	X	X	X	X	X
Household Demographics	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157
R-squared	-0.160	-0.872	-0.343	-0.564	-0.491

Standard errors in parentheses

Standard errors clustered at the store-availability level

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

Table A29: Demand Estimates
Online Households

	(6)	(7)	(8)	(9)	(10)
Budget Shares	Other	Prepared	Snacks/Sweets	Sugars	Vegetables
1{Online}	0.00128 (0.0196)	0.00274 (0.0491)	-0.308*** (0.0664)	-0.0139 (0.0241)	-0.0208 (0.0480)
$\ln(p_{dairy})x1\{O\}$	-0.000976 (0.00654)	-0.208*** (0.0207)	-0.0795*** (0.0275)	-0.00408 (0.00794)	0.0713*** (0.0187)
$\ln(p_{drink})x1\{O\}$	0.0102** (0.00469)	-0.0903*** (0.0142)	-0.0448** (0.0179)	-0.00259 (0.00594)	0.0964*** (0.0139)
$\ln(p_{fruit})x1\{O\}$	-0.0166* (0.00859)	0.0207 (0.0267)	-0.0189 (0.0343)	0.0409*** (0.0120)	-0.0874*** (0.0239)
$\ln(p_{grain})x1\{O\}$	-0.00523 (0.0126)	0.114*** (0.0258)	0.109** (0.0442)	-0.0362* (0.0188)	-0.100*** (0.0291)
$\ln(p_{meat})x1\{O\}$	0.0281** (0.0120)	0.0930*** (0.0358)	0.0316 (0.0506)	-0.00748 (0.0159)	0.118*** (0.0364)
$\ln(p_{oil})x1\{O\}$	-0.0193* (0.0107)	0.0282 (0.0196)	0.0148 (0.0349)	0.0258* (0.0154)	-0.0254 (0.0227)
$\ln(p_{other})x1\{O\}$	0.00608 (0.00596)	0.00272 (0.00973)	0.00547 (0.0144)	-0.0124 (0.00808)	0.00188 (0.0100)
$\ln(p_{prep})x1\{O\}$	0.00272 (0.00973)	-0.0128 (0.0382)	-0.0426 (0.0381)	0.00245 (0.0125)	0.0925*** (0.0270)
$\ln(p_{snack})x1\{O\}$	0.00547 (0.0144)	-0.0426 (0.0381)	0.0710 (0.0791)	-0.0379* (0.0199)	-0.00764 (0.0420)
$\ln(p_{sugar})x1\{O\}$	-0.0124 (0.00808)	0.00245 (0.0125)	-0.0379* (0.0199)	0.0341*** (0.0130)	-0.00255 (0.0139)
$\ln(p_{veg})x1\{O\}$	0.00188 (0.0100)	0.0925*** (0.0270)	-0.00764 (0.0420)	-0.00255 (0.0139)	-0.157*** (0.0399)
$\ln(\frac{m}{p})x1\{O\}$	-0.00154 (0.00212)	-0.0239*** (0.00563)	0.0186** (0.00748)	0.00498** (0.00248)	0.00261 (0.00510)
Linear Time Trend	X	X	X	X	X
Month f.e.	X	X	X	X	X
Household Demographics	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157
R-squared	-0.160	-0.872	-0.343	-0.564	-0.491

Standard errors in parentheses

Standard errors clustered at the store-availability level

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

Table A30: Difference in Elasticity Matrices, $\eta_{Instore} - \eta_{Online}$

	Own Price Elasticity	Dairy	Drink	Fruit	Grain	Meat	Oil	Other	Prepared	Snacks	Sugars	Vegetables
Dairy	-0.42 (0.05)	-0.42 (0.05)	0.18 (0.10)	-0.52 (0.10)	-0.22 (0.10)	-1.17 (0.91)	-0.07 (0.22)	0.07 (0.45)	1.85 (1.04)	-1.61 (0.43)	4.04 (63.11)	-1.05 (0.98)
Drink	-1.26 (0.21)	0.31 (0.03)	-1.26 (0.21)	0.52 (0.09)	0.15 (0.08)	-0.60 (0.48)	-0.53 (0.20)	-0.57 (1.49)	0.89 (0.37)	-0.43 (0.25)	-2.25 (43.10)	-1.50 (1.35)
Fruit	-0.34 (0.12)	-0.24 (0.04)	1.26 (0.30)	-0.34 (0.12)	0.37 (0.22)	-0.73 (0.46)	0.75 (0.22)	0.95 (1.43)	-0.28 (0.31)	0.39 (0.24)	-29.49 (458.14)	1.36 (1.23)
Grain	0.12 (0.31)	-0.12 (0.04)	0.24 (0.13)	0.23 (0.16)	0.12 (0.31)	-0.21 (0.42)	1.03 (0.51)	0.30 (0.90)	-1.16 (0.27)	0.58 (0.44)	28.15 (443.21)	1.51 (1.32)
Meat	-2.95 (2.42)	0.27 (0.06)	-0.64 (0.24)	-0.34 (0.14)	0.22 (0.20)	-2.95 (2.42)	-0.42 (0.32)	-1.66 (2.00)	-0.86 (0.79)	1.57 (0.50)	13.25 (217.96)	-1.54 (0.85)
Oil	0.35 (0.51)	0.07 (0.03)	0.13 (0.12)	0.40 (0.08)	0.54 (0.18)	-0.33 (0.38)	0.35 (0.51)	1.11 (1.34)	-0.30 (0.19)	-0.39 (0.22)	-9.49 (137.81)	0.33 (0.33)
Other	-0.35 (0.79)	0.04 (0.02)	0.30 (0.07)	0.05 (0.03)	0.03 (0.08)	0.33 (0.24)	0.19 (0.10)	-0.35 (0.79)	-0.03 (0.09)	0.01 (0.08)	11.13 (173.10)	-0.02 (0.13)
Prepared	0.14 (0.82)	0.24 (0.05)	-0.98 (0.38)	-0.53 (0.12)	-1.20 (0.17)	2.16 (1.51)	-0.75 (0.25)	-0.18 (0.58)	0.14 (0.82)	-0.35 (0.28)	0.25 (10.66)	-1.23 (0.79)
Snacks	0.64 (0.46)	-0.42 (0.07)	-0.65 (0.28)	0.36 (0.15)	-0.64 (0.32)	2.39 (1.49)	-0.59 (0.43)	-0.34 (0.91)	0.45 (0.40)	0.64 (0.46)	13.00 (178.05)	0.04 (0.59)
Sugars	-24.56 (378.50)	0.01 (0.02)	0.10 (0.06)	-0.09 (0.06)	0.12 (0.14)	-0.38 (0.31)	-0.42 (0.18)	0.70 (1.46)	-0.02 (0.12)	-0.01 (0.13)	-24.56 (378.50)	0.02 (0.19)
Vegetables	2.17 (1.64)	0.14 (0.04)	1.60 (0.52)	0.15 (0.15)	0.39 (0.27)	0.38 (0.83)	0.45 (0.30)	-0.13 (0.61)	-0.91 (0.34)	-0.11 (0.24)	-0.81 (16.31)	2.17 (1.64)

Standard errors reported in parentheses

Standard errors clustered at the store-availability level