How do Shoppers Respond to Noisy Signals on Price Changes? Evidence from a Field Experiment in Online Supermarket Shopping*

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December 14, 2021

Abstract

How does the content of promotional material impact demand? Specifically, does promotional information at the category level (e.g. "vegetables are on sale") lead to savings? We address this question using data from a field experiment on a website for online grocery shopping. We start out by measuring price elasticity in our unique environment of exogenous (researcher determined) price changes and find that shoppers are more price sensitive to products where price comparisons are more "costly" to calculate. We then compare purchasing decisions made by shoppers who received a coupon with promotional information on discounts, to shoppers who received the same coupon and had access to these same discounts but did not receive any information on them. We find that only shoppers who purchased in a discounted food category prior to the experiment exhibit a significant response to the information. These shoppers respond to the noisy promotional information by purchasing items in the discounted category that they had already purchased in the past regardless of whether or not that item is currently discounted. Thus, we observe an increase in demand for both the discounted items and their more expensive substitutes within the discounted category. We present evidence that the increase in demand for the non-discounted substitutes is more likely to be driven by mistakes than by rational choices. Our results suggest that coarse information on discounts increase both consumer spending and seller revenue.

*Financial support from the The Pinhas Sapir Center for Development at Tel-Aviv University and the Michigan Institute for Teaching and Research in Economics is gratefully acknowledged. We are in debt to Benny Wang for his tremendous help with this project.

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A Introduction

A consumer in the modern marketplace is often faced with the problem of repeatedly choosing the best bundle of goods or services in an environment where prices are constantly changing. This is particularly true for grocery shopping where consumers repeatedly purchase bundles containing many diverse products including food items, household goods and health and beauty products. Even if the consumer found and purchased the cheapest brand in a particular category during her previous shopping trip, this brand may no longer be the cheapest brand in the category during the current shopping trip.

How do shoppers then cope with frequent price changes across many relevant product categories? One possibility is that in each new shopping trip, they compare prices of all brands in each and every product category. Another possibility is that they learn about categories with discounts through promotional announcements. While this can potentially save them time and effort by alerting them to categories with price decreases, shoppers may still be facing additional uncertainty regarding price changes. First, promotional announcements typically do not inform shoppers that some items they bought in their previous shopping trip are no longer on sale, and consequently may now be more expensive than alternative substitutes. Second, promotional announcements often provide only coarse information on discounts - for instance, "Up to 30% off on select vitamins", or "40% off on vegan snacks" - in that they do not specify the exact items that are on sale or the precise discount on each item. Thus, shoppers who are faced with such promotional announcements need to exert effort and search for the specific items that are discounted in order to enjoy the savings that they offer.

The above discussion raises several natural questions regarding the impact of temporary discounts in multiple product categories, and information on these discounts, on shopper behavior. Do shoppers search each and every announced category for the discounted items? Once shoppers are drawn to a category, do they assume that if a product was the cheapest alternative in the past, it will remain so in subsequent shopping trips? How are these choices affected by the framing and coarseness of the promotional information? Finally, how do announcements on discounts across multiple categories affect shoppers' expenditures and sellers' revenues?

Addressing these questions empirically is challenging as it requires the analyst

to know exactly what promotional announcements shoppers were exposed to during their entire shopping trip, to observe variability in the precision and framing of the promotional announcements and to control for the exogeneity in the fluctuations of prices. Since this is difficult to accomplish with purely observational data, we partnered with a platform for online grocery shopping that conducted a series of randomized controlled trials over a three-month period.

In our field experiment, a subset of shoppers on the site were randomly assigned to either a treatment or a control group. Both groups received a weekly email offering an immediate rebate (given at checkout) for buying at least one unit from a certain category (e.g., bread), which changed each week. However, the email to the treatment group included *additional* information: It announced that some food items were on sale that week and listed the food categories with the biggest discounts in percentages. The website displayed only the final prices (i.e., after applying the discounts) without prominently announcing the discounts (hence, all shoppers faced the same final prices). The only difference is that treatment shoppers were given some information about the discounts, while control shoppers could learn about the discounts only by comparing prices on the website (prior to the experiment, prices were fixed and there were no sales offered on the website).

The discounted items were not chosen at random but were selected such that each had an obvious, (weakly) more expensive substitute of equal or lower perceived quality (e.g., organic fruits were priced the same or lower than their conventional counterparts), and each month there was a new set of discounted items. In addition to varying the set of discounted items during the course of the experiment, we also varied the precision and framing of the information provided to the treatment shoppers. In the first half of the experiment, the promotion listed only the four categories with the biggest percentage of discounts, while in the second half the treatment shoppers were also alerted to the fact that organic items are on sale. In addition, during the second half of the experiment, each treatment shopper, who previously bought a non-discounted item, received a personalized message notifying them that they might want to consider some cheaper alternatives that are on sale this month. Figure 1 displays the outline of the experiment.

Our objective is to understand how information on temporary discounts impacts shopper behavior. First, we estimate the aggregate price elasticity of shoppers on the site in response to price discounts. Second, we differentiate between treatment

and control shoppers to gain an estimate of the "information effect" as only treatment shoppers received information on discounts. To the best of our knowledge, we are the first to conduct a field experiment that examines how shoppers respond to (possibly coarse) information on multi-category price changes. Hence, we contribute to the literature by documenting the following novel findings: (i) only shoppers who purchased in the discounted category prior to the experiment exhibit a significant response to information on discounts, (ii) these shoppers respond by being 1.4 percentage points (s.e. 0.6) more likely to purchase a product in a discounted category than shoppers in the control group at an average purchase rate of 3.6 percent, (iii) shoppers who did not receive information on discounts (control shoppers) purchase less of the substitute product when the target product in that category is on sale, while shoppers who received information on discounts (treatment shoppers) increase consumption of the on-sale target product *without* substituting away from the substitute products in that category, (iiii) this effect remains for unbranded products (fruits & vegetables) where we would expect shoppers to exhibit less brand-loyalty, (iv) more precise information on sales, and a personalized nudge seem to reduce the purchasing rate of the non-discounted substitute, and (v) coarse information on discounts increase consumer spending and seller revenue. While demand for the discounted products in a category doubled among both treatment and control shoppers during the intervention, the demand for non-discounted products *within that same category* increased by 44 percent for treatment shoppers, which translated to increased profits for the retailer.

The remainder of the paper is organized as follows: Section B discusses related literature; Section C explains the design of the randomized control trials; Section D provides summary statistics on the sample; and Section E discusses the results. Section F discusses the responses to a post-experiment survey regarding consumer preferences. Section G concludes.

B Related literature

Our paper contributes to several strands of empirical and experimental literatures. These include studies that examine whether consumers search for the best price and papers that explore the implications of online promotions.

The question of whether consumers search for the lowest price has been the

subject of numerous studies in the literature. A recent survey by Grubb (2015) lists three main reasons for consumers' failure to buy at the lowest price: (i) obfuscation that makes price comparisons difficult, (ii) costly search, and (iii) inertia. In our context, the price of each item is just a number (in contrast to financial services that contain different contingencies and fees), and hence, the obfuscation channel is irrelevant.

Search costs in our environment may be proxied by the effort it takes to scroll down the screen in order to compare similar items (say, organic vs. non-organic produce). A standard model of a rational consumer who trades off search costs with the savings from lower prices would predict that announcements of discounts would lower search costs and increase purchases of the discounted items. For example, using data on purchases of a storable good (detergent) Seiler (2013) estimates a structural dynamic model that incorporates the search decision, jointly with the purchase decision. He finds that search costs are indeed quantitatively important as consumers do not search on approximately 70% of their trips. Based on his estimates, he shows that a promotional campaign that lowers search cost by 50% would lead to a more than threefold increase in the elasticity of demand for the promotional product, and would also lead to an overall increase in category traffic. Similarly, Honka, Hortacsu and Ana Vitorino (2017) estimate a structural model that explicitly incorporates three stages in the consumption decision: becoming aware of available options, searching for prices on some of these options, and choosing one of them. Using detailed survey data on shopping for banks, the authors show that advertising has a large indirect effect on consumer choices by making consumers aware of more options, which enables them to find better alternatives than they would otherwise. To estimate the returns from searching in a supermarket, Seiler and Pinna (2014) use "path-tracking" data recorded by shopping carts equipped with radio-frequency identification tags, to find that an additional minute spent searching lowers the price paid by \$2.10. With regards to how consumers search, De los Santos, Hortacsu, and Wildenbeest (2012) use a large dataset on web browsing and purchasing behavior and reject the hypothesis that consumers search in accordance to classical search models.

Our analysis is concerned mainly with the repeat purchases of perishable food items. Because we are looking at supermarket purchases in an online environment, we can differentiate between product categories with "low" and "high" search costs.

Consistent with the above studies, we find that search costs play an important role as shoppers exhibited higher price elasticity for neighboring products that do not require scrolling down the webpage to compare prices (low search costs), relative to cases where substitutes are located farther away (high search costs).

We observe inertia in our setting in the form of shoppers with a history of purchasing a specific item within a category, continuing to buy that item, even when they could have purchased a (weakly) higher quality alternative at a (weakly) lower price. Similar inertia is exhibited in Clerides and Courty (2017), who use scanner data from a supermarket chain to show that during periods in which the price of a discounted pack of detergent was lower than the corresponding price of a larger ("economy size") pack (of the same product), consumers still bought the larger, and more expensive pack. This could be partly explained by the fact that shoppers are used to seeing lower prices on economy size packages, and hence, do not check the price per unit when making their purchasing decisions. Our experiment (which focuses on product categories where the weakly more expensive/higher-quality product's price was exogenously reduced) provides an opportunity to examine whether this "product inertia" can be convincingly explained by consumer preferences. Dubé et al. (2010) rule out a search cost explanation for inertia in supermarket purchases of margarine and orange juice, attributing this observed behavior to brand loyalty. However, we find that the increase in purchases of the non-discounted items in response to the promotion are observed in unbranded categories where inertia due to brand loyalty seems less likely.

The general phenomenon of promotional announcements accompanied by price discounts has been widely researched in the marketing literature, where it was shown to cause increases in sales for the promoted brand (some classic references include Dodson et al. (1978), Blattberg et al. (1981) and Guadagni and Little (1983)). While this increase is typically explained by downward sloping demand, some studies also show that the mere salience of the promotion can lead to increased sales even when it is not accompanied by price discounts (e.g., Inman and Mcalister (1993)). Similarly, Helmers et al. (2019) use a unique data set from an online retailer to show that consumers are more likely to buy products that receive a saliency shock in the form of a recommendation "You may also like ..." that appear below items that consumers view.

More recent studies have demonstrated that promotional annoucements may have

a more subtle effect. For instance, using field experiments on online retail websites, Fong et al. (2016) and Fong (2017) showed that targeted promotions that are based on individual purchase histories can have negative spillover effects: they reduce search on the seller's website for other non-promoted items and consequently lowered sales of such items. Janakiraman et al. (2006) provided evidence from lab experiments that when consumers shop for a bundle of goods (as in a supermarket or pharmacy), encountering unexpected price changes in one product has an effect in the opposite direction on their purchases of other products: when the price increases (decreases), they reduce (increase) their purchases of other products.

Other forms of spillovers from online promotions were reported by Zhang et al. (2020) who conducted an experiment where treated shoppers were offered discounts on specific items placed in the shopping cart that were not subsequently purchased for a period of 24 hours. They found that shoppers responded to the promotion by (i) increasing the proportion of items that they add to their shopping cart, possibly in an attempt to draw more discounts, and (ii) decreasing the prices they pay for items. Both of our studies find that a significant proportion of treated shoppers do not respond to the promotion (i.e. purchase the promoted product). However, the interesting finding in our experiment is that shoppers with a history in the discounted categories increase their purchases of the *non-discounted* items relative to shoppers in the control group who did not receive information on the categories with on-sale products.

Some recent studies have shown that promoting a particular brand (either by advertising or by offering coupons) can increase the sales of other non-promoted brands. Anderson and Simester (2013) demonstrated that sending customers of some retailer advertisements of the retailer's competitor actually lead to an increase in the sales of the retailer (who did not engage in advertising). Sahni (2016) showed that advertising a particular restaurant on a restaurant-search website led to an increase in page visits and sales of competing restaurants that offer the same cuisine. A similar effect was reported in Sahni et al. (2017), which showed that when a website selling tickets to sporting events offered discounted tickets to some events, its revenues increased, but only a small proportion of this rise came from the sale of the discounted tickets. The authors interpret this finding as suggesting that promotional emails divert attention to the promoting firm (i.e., the website) and this may have increased the traffic to it. Gopalakrishnan and Park (2021) also conduct a field experiment on

an online retailing platform to study the effect of coupons on purchasing behavior. Relatedly, they find that coupons are effective in increasing revenue, primarily by attracting customers to the site who then purchase products unrelated to coupons. In all these studies shoppers were made aware of a discount on *one* particular product, but chose to purchases an alternative product. The interpretation is that promotional information diverts attention to a category, and then the shopper makes a choice based on her preferences.

In our experiment, coarse information on discounts in a particular food category may have diverted attention to that category (e.g., reminded shoppers that they need to buy items in that category). The reason this led to more purchases of non-discounted items may be partly due to the fact that these were the products shoppers were more likely to purchase in the past. However, in contrast to the previous studies, it is not clear that this increase in purchases can be attributed to a pure preference of the non-discounted items over the discounted ones for the following reasons. First, in our intervention we lowered the price of the weakly higher quality product in a category, while keeping the price of the substitute product constant. We find that the promotion increased the purchase rate of *weakly more expensive and lower quality substitutes* for the on-sale products. Second, we observe this effect in non-branded food categories (e.g., produce) where we would not have predicted a high level of brand loyalty. Additionally, we show that the spillover effect to the non-discounted items diminishes when the promotional annoucements become more precise (i.e., they specify the discounted items and not just the discounted category), and when shoppers are alerted to the fact that discounts have expired on items that they bought in their previous shopping trip. These findings suggest that the mechanism driving the increase in sales of the non-discounted substitutes may be more complex than the combination of saliency and brand loyalty documented in previous research.

Finally, with regards to theoretical work, our paper is motivated by De Clippel et al. (2014) who analyze how consumers allocate limited attention across many products with changing prices. In their model, the optimal consumer strategy is to focus on categories with the highest expected savings. Ke and Lin (2020) propose a model that, in equilibrium, generates the effect that a price decrease of one brand can increase the demand of another brand. This is relevant to our paper since we observe that a price cut of one product can increase the demand of an alternative product that is not on sale. The key ingredients in Ke and Lin's (2020) model that

generate this effect are (1) the fact that competing brands share common features, and (2) consumers are uncertain about the values of these features and try to learn about them.

C Experimental design

In this section we outline the different design components of our intervention. The intervention took place over three months and consisted of both exogenously determined price changes on specific products and weekly emails that were sent out to shoppers in both treatment and control groups. The following are the main components of the intervention.

The platform. We partnered with a website (whose name is not disclosed for confidentiality purposes) that offers a purchase and next-day delivery service from a large American supermarket in a university city. The website includes roughly 3,000 items that are sold in the supermarket store. These items are divided into several sections to help shoppers perform an intuitive search (e.g., produce, dairy, etc.). Shoppers need to add the items that they would like to purchase to their basket, and at checkout they pay for the products, plus a flat delivery fee of $2.99 for each order. During the period of the experiment there was no option to re-order previous baskets or to add items from previous orders. Additionally, all prices were fixed and there were no promotional sales. Shoppers are required to choose a delivery date and a two-hour delivery window. The cutoff time for next day delivery is midnight every day. These shoppers are mainly students (80 percent) with some professors (10 percent). Only 10 percent of shoppers are unaffiliated with the university.[1]

The website was interested in encouraging its registered customers to increase the frequency and volume of their purchases, and to learn how different promotional tactics affect shopping behavior. To achieve this goal, they planned to conduct a series of randomized controlled trials. They agreed to allow us to influence the design of these trials in a way that would also enable us to address our questions. Hence, the experimental design was somewhat constrained by the objectives of the website.

[1]This information was obtained from responses to an optional survey conducted at checkout during the first month of the experiment period. Eighty percent of the shoppers who made a purchase during the experiment period responded to the survey.

Temporary discounts. The experiment was conducted over a period of thirteen weeks during which the website offered temporary discounts so that the prices of some select items fluctuated, dropping during the sale and rising to pre-sale levels when the sale expired. Discounted items were marked on the website with two asterisks (**), and a footnote at the bottom of the screen explained that the marked item was on sale and specified the original higher price. We used this method of marking discounts for the following reasons. First, we did not want discounts to be too salient so there would be an advantage to receiving an email that provided information on which items were discounted; Second, we wanted to allow any shopper who accessed the website to find out about the temporary sale if she exerted some effort in noticing fine details.[2]

The experiment focused on items in twenty-eight product categories that were popular with shoppers in the pre-experiment period (see Table 1).[3] Each of these product categories (e.g. milk, tomatoes, water, etc.) included at least two items that could be considered close substitutes. Each month a different set of categories were discounted so that a discount on an item was valid for one month. The items whose prices were manipulated during the experiment are defined as *target items*, and their alternatives are defined as *substitute items*.

The levels of discounts were varied during the experiment, so that shoppers faced uncertainty regarding the benefit of extending effort to search for the lowest price. The average discount on an item was 20 percent, but could be as low as 5 percent or as high as 75 percent. The discounts were set so that the on-sale *target item* would be priced either the same or below the price of the *substitute item*.

The discounted target items fell into four general categories: (i) organic and conventional items, (ii) same items that are offered in different sizes (e.g., jumbo avocado and regular avocado) or bulk quantities (e.g., apples that are offered as single units or in 3-lb bags, or milk that is offered in 0.5 gal and 1 gal containers) (iii) brand names versus generic store brand (e.g., Aunt Millie's breads versus generic supermarket whole wheat bread), and (iv) two competing brands of the same exact product (e.g., Dasani vs. Ice Mountain mineral water in bottles of the same size).

[2] We operated under the constraint that all shoppers must face the same exact set of prices.

[3] The twenty-eight product categories are: bananas, kiwis, lemons, raspberries, apples, bulk apples, blueberries, pineapples, avocados, broccoli, cucumbers, kale, onions, green onions, peppers, lettuce, limes, tomatoes, bread, organic bread, eggs, brown eggs, organic eggs, milk, bulk milk, organic milk, yogurt, and water.

See Tables 2 and 3 for a full list of the relevant target and substitute items as well as the discounts given during the experiment period.

There are two motivating factors behind the choice of target items. First, we tried to select target items that had "almost perfect" substitutes and which had low levels of brand loyalty. Recent evidence suggests that consumers display relatively low brand loyalty to supermarket items as compared to clothing and appliances (Nielsen (2013)), and their choice of food brands is most affected by price considerations (Byron (2008)). Within the food and beverage category, consumers tend to exhibit more brand loyalty to breakfast cereals, carbonated drinks, and snacks (Chidmi and Lopez (2007), Nielsen (2013)). *None* of these were included as target items in the experiment, hence, we assume that price sensitivity is stronger than brand loyalty in deciding between a target item and its substitute.[4]

The second motivating factor is the public perception of organic items. Studies have indicated that consumers generally express positive attitudes toward organic foods, perceiving them as tastier and kinder to the environment (Roddy et al. (1996); Magnusson et al. (2001); Perkovic and Orquin (2017)). While there may be disagreement among researchers about whether this perception is backed by scientific evidence (see Baransky et al. (2014) for a meta-analysis that claims there are healthier aspects of organic food), what is important for this study is public perception.[5]

Two important features of the discounted items was the variation in their display and whether or not they were branded. Some close substitutes (where one was discounted and the other was not) appeared next to each other on the screen, while others appeared in different rows and required scrolling down to notice both items.[6] Whether a pair of substitutes are displayed next to each other is independent of their prices, or of the difference between their prices and there was no option on

[4]In a post-study questionnaire of the participants, 80 percent of 55 individuals who responded answered that they would switch brands for a discount of 20 percent. We found a similar response when surveying an additional 378 US respondents in the same age and education categories. See Section F for more detail.

[5]In our post-study questionnaire, 91 percent of 55 responders said they would buy an organic item if its price was weakly cheaper than a conventional version of the same item. This result also held in an additional survey follow-up with 378 participants. See Section F.

[6]The display of items on the screen was determined by the developer and remained constant throughout the experiment. The relative display of items–i.e., whether items are adjacent or not–remains true whether the shopper uses a computer or a mobile device.

the site to sort by price.[7] We will use the variation in location as a proxy for the cost involved in comparing the price of a target item with its substitutes. Seventy percent of the categories included in the experiment were unbranded (e.g. fruits and vegetables). Focusing on these categories allows us to examine an environment where brand loyalty should play less of a role.

Rebates. In weekly emails, shoppers were offered an immediate rebate applied at checkout if they spent at least $20 and also bought at least one unit of an item from a given group of eligible items which changed every week. During the first three weeks of the study, the rebate was equal to the flat delivery fee of $2.99 (it was presented to shoppers as free delivery), and in the last three weeks it was raised to $10.[8] Between the fourth and the tenth week, the rebate was $2.99 for the control group and $10 for the treatment group (the difference between these two groups is explained below). While it would have been ideal to keep the size of the rebate equal across the two groups, we were constrained by the website's wish to offer a higher incentive to shop to the treatment group.[9] Table 4 lists the rebate category offer for each week as well as the prices of the target item and substitute item in the category alongside the benefit of purchase for individuals in both the treatment and control groups.

Treatment and control. The 355 shoppers who made purchases in the second half of 2015 were randomly divided into two groups—178 in treatment and 177 in control.[10] Treatment shoppers received additional information on categories with discounted items in the weekly email. In order to separately measure the effect of the email contents from a general salience effect or compliance effect, both groups were sent weekly promotional emails with information on the rebate category.[11] But

[7] Buying a substitute item was on average 28 percent more expensive than the on-sale target item for non-neighboring items, and 25 percent more expensive than the on-sale target item for neighboring items.

[8] Starting with free delivery before moving to the high rebate was also intended to give credibility to the promotional offer.

[9] Online Appendix Table A4 lists the items included in the weekly rebates and their corresponding discounts. In online appendix Table A5, we also run our analysis focusing only on weeks where shoppers in the treatment and control groups were offered identical rebates in order to ensure that what drives the difference in results between these two groups is the difference in promotional information.

[10] While we have data on shoppers beginning in December 2014 (over a year before we ran the experiment) we only include shoppers who had made a purchase within the previous six months when defining the treatment and control groups. We expected these shoppers to be the most likely to make purchases during the period of the experiment.

[11] As noted above, for roughly half of the experiment both the treatment and control emails

during the entire period of the study, the email to the control group did not mention any price discounts.

In contrast, the email to the treatment group displayed the following: four product categories (e.g., milk, eggs, fruits, bread) that were on temporary sale that month; the biggest discount available in each of the categories expressed in percentage points; and a link to the relevant page of each category. The treatment group was also informed that discounted items were marked by "**".

During the second half of the study (from the sixth week on), shoppers in the treatment group began to receive a more detailed weekly email. For these weeks, the email alerted shoppers that many organic items were now on sale and even cheaper than non-organic items. Additionally, those who had purchased a substitute item in a category that was now on sale received a personalized email alerting them to this fact (e.g., "Don't forget to consider some alternatives to your last purchase of eggs that we have on sale this month"). Figures (2) and (3) depict examples of the email formats for both the treatment and control group.

D The data

From the customer base of the website, 355 shoppers were randomly allocated to treatment and control, such that 177 shoppers were assigned to control, and 178 to treatment. Over the thirteen weeks of the experiment, we tracked the purchasing decisions of these shoppers in 28 food categories (see footnote 3). In total, 130 shoppers made 1,046 category purchases over 338 shopping trips during the experiment period: 66 shoppers made 167 shopping trips in the control group, and 64 shoppers made 171 shopping trips in the treatment group.

Table 5 provides summary statistics in the pre-experiment period (December 2014 - January 2016) for both the full sample and a subset of 305 shoppers who had a history of purchasing in at least one of the 28 product categories (152 in control and 153 in treatment). This subset is important as it turns out that past purchases within the product category are a strong predictor of current purchases with differential effects between those allocated to the control and treatment groups.

provided the same rebate amount when buying an item in the rebate category. The observed differential effect of the sale on the treatment and control group is robust to running the analysis only on the same rebate weeks.

Not surprisingly, since individuals were randomly allocated to treatment and control, there are no significant differences in shopping trends between the treatment and control groups during the pre-experiment period. Generally, shoppers had shopped on the site five times prior to the experiment, with trips averaging roughly $70. Importantly, when conditioning on shoppers who made purchases of either the target or substitute items, the control and treatment groups continue to look very similar. In the pre-experiment period, the substitute items were generally purchased more frequently than the target items by all shoppers (prior to the experiment, they were cheaper than the target items).

Recall that when a shopper browses through items, some discounted target items are displayed right next to their substitutes (or in the same row), while others may require scrolling down. In light of this, we say that a target item and its substitute are "neighbors" if they appear on the same line on the website, and we refer to a category as a "neighboring" category if it includes a target and a substitute that are "neighbors". Figure 4 displays an illustrative screenshot from the website. The target item that is shown, organic bananas, was on sale for $0.24 per unit (regular price $0.49), while the two corresponding - and adjacent - substitutes are "banana ripe" and "banana mild green" whose prices remained constant at $0.39 per unit. Six out of the twenty-eight product categories included neighboring items (avocados, bananas, kiwis, lemons, raspberries, and water).[12] These neighboring categories made up roughly a quarter of purchases of target items and almost a third of substitute item purchases (as evident from Tables 2 and 3 there were no significant differences between the prices of neighboring and non-neighboring items). If comparing prices among neighboring items is simpler, we would expect shoppers to be more price sensitive in neighboring categories.

E Findings

We begin this section by examining the response of all shoppers to the (exogenous) price changes made in the experiment. We then measure the impact of information on this response by differentiating between shoppers in the treatment and control

[12]The twenty-two non-neighboring product categories are: apples, bulk apples, blueberries, pineapples, broccoli, cucumbers, kale, onions, green onions, peppers, lettuces, limes, tomatoes, bread, organic bread, eggs, brown eggs, organic eggs, milk, bulk milk, organic milk, yogurt. See a detailed explanation in Tables 2 and 3.

groups.

E.1 How do shoppers respond to sales?

Measuring how shoppers respond to price changes in a real world setting is usually complex due to the many factors that impact price changes and the concern that these factors may be correlated with demand. This experiment provides an opportunity to measure this response in an environment where prices were lowered for a specific group of (target) items while the prices of substitute products in that category remained constant. Figure 5 graphs the evolution of target item prices relative to the substitute item prices from the 6 months leading up to the intervention (period 0) through the last week of the intervention (week 13). It illustrates how the average price of a target item decreased by roughly 20 percent during its discount period while substitute products in the same category remained at an average price of about $2.50 (see Tables 2 and 3 for a list of all products included in each of the 3 discount periods).

The exogenous shift in prices created by the intervention provides an opportunity to measure price elasticities. We ran the following analysis on all products (p) included in the intervention using monthly (m) purchase rates (q):

$$\log(q)_{pm} = \lambda_0 + \lambda_1 \log(price)_{pm} + \gamma_p + \eta_m + \varepsilon_{pm} \tag{1}$$

The coefficient λ_1 on $\log(price)_{pm}$ estimates the price elasticity of shoppers when controlling for differences in demand across time and products using product (γ_p) and month (η_m) fixed effects. Since the changes in $\log(price)_{pm}$ were unrelated to any unobserved factors impacting monthly demand $\left(\varepsilon_{pm}\right)$, $\widehat{\lambda}_1$ provides an unbiased estimate of how consumer demand shifts in response to price changes.

We find that demand increases in response to a sale (see Table 6). The average measured price elasticity is -1.649 (s.e. 0.249), with shoppers exhibiting the highest price sensitivity to changes in fruit prices and the smallest sensitivity to changes in the price of perishable items (egg, milk, and yogurt). Specification (5) of Table 6 allows price elasticity to differ for products where their substitute appears on the same line of the website (those categories with the lowest search costs). The magnitude of the price elasticity increases in these low search cost categories by 1.655 (s.e. 0.776) which suggests that price elasticity depends not only on product characteristics, but

also on the ease in which shoppers are able to compare prices across alternatives in different product categories. Specification (6) allows price sensitivity to differ across branded and unbranded categories and demonstates the higher inertia in demand for products that are branded. We observe a decrease in price elasticity of 0.845 (s.e. 0.428) for branded products relative to unbranded products.

Familiarity with products in a category is another factor that could impact price elasticities if shoppers tend to focus on a particular group of product categories for purchase and do not pay much attention to prices or products outside of this group. We can look more closely at this issue by differentiating across shoppers based on whether they had made a purchase of any item in this product category in the period prior to the intervention. In specification (7) of Table 6, we find that shoppers with a purchase history in the product category exhibit higher price elasticities.

Our intervention introduced an additional degree of heterogeneity across shoppers. If shoppers do not respond to price changes because they are unaware of existing discounts, one might expect that treatment shoppers who received information on product categories with on-sale items may exhibit higher price elasticities. However, in column (8) of Table 6 , we find that treatment shoppers fail to exhibit a significant difference in price elasticities relative to control shoppers (a change of 0.115 (s.e. 0.079).

Table 7 examines the aggregate change in consumer purchases over time relative to the month before the target item went on sale within a category (month $= -1$) for both shoppers in the treatment and control groups. For treatment shoppers, the sale increased demand in the category where the sale took place by roughly 6 units (s.e. 2.5) at an average aggregate monthly purchase rate of 11 units per category (see column (1)). Interestingly, this demand increase was roughly evenly split between target and substitute purchases even though only the target products were discounted during this period (see columns (3) and (5)). Conversely, shoppers in the control group increased their demand for on-sale target products during the sale period by two units (s.e. 0.9) but did not exhibit any significant increase in demand for substitute products (sees column (4) and (6)).

In Table 8, we estimate the aggregate change in consumer spending for all consumers using a similar analysis strategy as in Table 7. Column (1) illustrates that the sale increased spending by \$23 (s.e. 14), a noisily measured 41 percent increase in category spending. The fact that some shoppers chose the substitute product dur-

ing the target sale (see column (1) "Observed") raised the supermarket's revenue relative to our estimates if consumers hadn't responded at all to sale (column (2)), or alternatively, only purchased the on-sale target item during the sale period (column (3)).[13] In the next section we look more carefully at the purchasing decisions made by shoppers in the treatment versus the control group and why more information seemed to have increased supermarket revenue and made shoppers worse off.

E.2 Estimating the "Information Effect"

To estimate the "information effect", we focus on how the treatment impacted three different weekly decisions of shoppers: buy_{icw}- the choice whether to make a purchase within one of the relevant categories in our intervention (e.g., tomatoes), $target_{icw}$ - the choice whether to purchase an item that had a temporary discount (when this item was organic produce, it could also be perceived as being of weakly higher quality than its conventional substitute), and $substitute_{icw}$ - the choice whether to purchase a non-discounted alternative to the target item within the category (e.g., conventional tomatoes). We estimate a model, where each of these decisions is a linear function of whether the target item was on sale ($tsale_{cw}$) , and the interaction between being a shopper in the treatment group and a sale on the target item ($treat_i \times tsale_{cw}$) when including fixed effects for shopper (γ_i), shopping week (ρ_w), category (η_c), and rebate size (r_{iw}).

$$Y_{icw} = \beta_0 + \beta_1 treat_i \times tsale_{cw} + \beta_2 tsale_{cw} + \gamma_i + \rho_w + \eta_c + r_{iw} + \varepsilon_{icw} \qquad (2)$$

Our full sample consists of 355 shoppers (i) over the thirteen weeks of the experiment (w) in each of the 28 product categories (c).[14] We measure the impact of the sale in a difference-in-differences framework. While (β_2) captures the response of shoppers in the control group to a sale on the target item, (β_1) captures the differential response of the treatment group when controlling for shopper, week, and category fixed effects, as well as the size of the rebate offered to shopper if pur-

[13] We estimate the "No Demand Response" by estimating consumer spending if they had continued to purchase exactly the same products during the sale as they had purchased in the previous month. We estimate the "Full Demand Response" by estimating consumer spending if all consumers who purchased in the category during the sale period purchased the on-sale target product.

[14] We focus our analysis on the weekly level because the rebate promotion and the email content changed on a weekly basis.

chasing the rebate item (r_{iw}). We include individuals in the sample who did not make a shopping trip during that week. For these shoppers, buy_{icw}, $target_{icw}$, and $substitute_{icw}$ are equal to zero for all product categories in that week.[15] We focus on intention-to-treat outcomes as opposed to limiting the sample to shoppers who made purchases or read the promotional email which could introduce selection concerns.

Suppose shoppers were not aware of all available discounts, and the only effect of promotional material on shoppers was to raise their awareness of prices. Then we might expect treatment shoppers to be more likely to purchase on sale target products and decrease their consumption of substitutes. This would imply a significant and positive estimate of β_1 when the outcome variable is $target_{icw}$ and negative when the outcome variable is $substitute_{icw}$. If the only effect of sales was to cause shoppers to replace a substitute item with a discounted target item, then we would expect the estimate of β_1 to be zero when the outcome variable is buy_{icw}.

The impact of purchasing history. Given the higher price elasticity of shoppers with a history of making purchases in the category observed in Table 6 , promotional material may have a differential impact across these shopper groups. On the one hand, the higher price elasticiy might suggest that the "information effect" will be strongest for those shoppers with a history in that category. Alternatively, the "information effect" may be most important for shoppers without a history, who otherwise would not bother to consider items in the category. Indeed, we show below that the effect of the intervention is concentrated among shoppers with a history of purchasing withing the category.

The first three columns of Table 9 examine shopper behavior only in categories where they made a purchase in the pre-experiment period and thus, have some familiarity with the category on the site. During the experiment period, the average purchase rate within these product categories was 3.6 percent with a rate of 1 percent buying target and 2.6 percent buying the substitute. For control shoppers, we don't observe a change in category level purchases but a shift from purchasing the substitute product to purchasing the target (on-sale) product (see columns (1) to (3) of row "Target Sale"). Treatment shoppers increase their purchase rate in categories with

[15] We include all shopper-weeks as excluding shoppers during weeks when they chose not to shop at the site could introduce selection concerns if different sales draw different types of consumers. However, our results remain very similar when excluding weeks when shoppers did not make a purchase on the site.

on-sale products by an additional 1.4 percentage points (s.e. 0.6) during the target item sale (see column (1) of row Treat x Target Sale). Interestingly, these treatment shoppers who had already made a purchase in this category in the pre-experiment period increased their purchase rate of the **substitute item** by an additional 1.2 percentage points (s.e. 0.4), relative to shoppers in the control group during this same period (see column (3) coefficient on interaction term).

Columns (4)-(6) of Table 9 apply this analysis to shoppers in categories where prior to the intervention they had never made a purchase. While we find a slight 0.1 (s.e. 0.1) percentage point increase in category level purchases for the control group, we find no significant differences between the response of the treatment and control groups. Thus, we find evidence of an "information effect" only in categories where shoppers have prior experience.

Explaining the increased demand for substitutes. It may seem that a rational shopper with a history of buying in a category would be more likely to buy in that category when she is told that items in that category are on sale. However, it seems less plausible that a fully rational shopper would respond to the sale (i.e., increase her purchase rate in that category) *not* by buying the discounted items, but by buying *the item she was likely to have bought before.* Thus, our results suggest that coarse promotional material may have an important interaction with past shopper behavior. Namely, promotional material may draw shoppers to a discounted category, but the product they choose may be strongly dependent on products that they purchased in the past.

Our results regarding the demand for substitute products are puzzling. Why do treatment shoppers who received information on category sales *increase* the probability of purchasing a substitute item when the target item was of equal or higher quality and also offered at a lower price? Without a control group, one might be concerned that shoppers suspected that an item on sale was of lower quality (e.g., close to expiration date).[16] However, this cannot explain the differential behavior between the randomly allocated treatment and control groups, as they both should have the same priors regarding the quality of on-sale items.[17] One possible explanation is

[16] We look into this explanation in our post-study questionnaire and find that only three out of twenty-seven respondents said they did not buy an item on sale because they thought it was of lower quality or close to its expiration date.

[17] Indeed we show in Table 5 that there are no significant differences in characteristics of shoppers between the treatment and control group for both the full sample and the sample of shoppers who

that the email to the treatment group impacted two separate shopping decisions: What product categories to purchase in, and whether to purchase the substitute or target item. In other words, receiving an email that notifies you that vegetables are on-sale may increase the probability of purchasing vegetables on the site. This increase could be driven by your interest in the sale and/or a salience reminder that you would like to buy vegetables. This salience reminder is unique to the treatment group and could lead to an increase in purchases of the substitute item. Shoppers who have a history of buying in a given category are more likely to be familiar with the substitute items, which were purchased three to four times more frequently than the target items in the pre experiment period.

Another alternative explanation for the differential information effect we just described is one of differential incentives. Recall that the size of the rebate ranged between \$2.99 and \$10 throughout the different weeks of the experiment. In order to make sure that our results are not driven by self selection where certain types respond to a \$2.99 versus \$10 rebate offer, in Table 10 we re-run our analysis including only weeks when the treatment and control group received the same rebate offer. While the precision of our estimates decreases significantly as a result of the much smaller sample, the magnitude of the estimates remain unchanged. Thus, it seems unlikely that the observed differences in behavior between the treatment and control groups are a result of differential incentives.

The question remains: Does providing aggregate level sale information helpful for shoppers? In other words, when these "better informed" consumers chose the "substitute product" that was not on sale, did they make this decision with full awareness that the alternative target product was cheaper? Table 11 takes a closer look at purchasing behavior in an attempt to uncover heterogeneity in the treatment response of shoppers who have a history of purchasing within these categories. Columns (1)-(3) consider the differential treatment effect in branded categories. If the demand for substitute products is driven by brand loyalty we might expect the effect to lessen when focusing our analysis on unbranded products. We therefore estimate the following equation that includes an interaction term between whether the target item was on sale ($tsale$), assignment to the treatment group ($treat$), and whether this category (c) is branded ($branded$):

have made purchases in the category in the past.

$$
\begin{aligned}
Y_{icw} &= \gamma_0 + \gamma_1 treat_i \times tsale_{cw} + \gamma_2 treat_i \times tsale_{cw} \times branded_c \\
&\quad + \gamma_3 tsale_{cw} + \gamma_4 tsale_{cw} \times branded_{cw} + \gamma_i + \rho_w + \eta_c + r_{iw} + \varepsilon_{icw} \qquad (3)
\end{aligned}
$$

The coefficient γ_1 on the interaction term $treat \times tsale$ in equation (3) provides an estimate of the relative change in purchase rate between treatment and control shoppers for unbranded categories. We estimate this coefficent in the first row of Table 11 and find that even in unbranded categories, receiving category level information on discounted products drives an increase in demand for the more commonly purchased substitute products. Specifically treatment shoppers are 1 percentage point (s.e. 0.5) more likely than control shoppers to purchase substitute products from a category where the target product is on sale (see column (3) of Table 11). The coefficient estimates on $treat \times tsale \times branded$ suggest that the response in product categories where the items are branded is not different from the response in product categories where they are not.

The effect of information precision and nudges. Recall that during weeks 6-13 of the intervention, the email to the treatment group included a line alerting shoppers to the fact that many organic items are on sale, and in some cases, even cheaper than the non-organic alternative. Additionally, if a treatment shopper purchased a substitute item in her previous trip, these personalized emails included the line "you may want to consider some alternatives to your last purchase in category — that are now on sale." These later weeks with more detailed emails provide an opportunity to examine the differential response of treatment shoppers to a sale when they have more precise information on the *products* (in addition to the categories) that are on sale. To do this, we examine shoppers decisions when including an interaction term between whether the target item was on sale ($tsale$), assignment to the treatment group ($treat$), and whether this was a week where treatment shoppers received a more detailed email ($detailed$) :

$$
\begin{aligned}
Y_{icw} &= \pi_0 + \pi_1 treat_i \times tsale_{cw} + \pi_2 treat_i \times tsale_{cw} \times detailed_w \\
&\quad + \pi_3 tsale_{cw} + \pi_4 tsale_{cw} \times detailed_w + \gamma_i + \rho_w + \eta_c + r_{iw} + \varepsilon_{icw} \qquad (4)
\end{aligned}
$$

Our estimate of π_1 in columns (4) to (6) of Table 11 illustrate that treatment shoppers are significantly more likely than control shoppers to purchase the substitute product in categories where a weakly higher-quality target item is on-sale during non-detail weeks. Specifically, shoppers in the treatment group are 2.5 percentage points (s.e. 0.9) more likely than shoppers in the control group to purchase a substitute product during a target item sale (see column (6)). However, these large differences between treatment and control shoppers disappear during detailed email weeks (see coefficient on $treat \times tsale \times detailed$ in columns (4) to (6) of table 11 that are roughly the same size as those estimated for the coefficent on $treat \times tsale$ but of opposite sign). During these weeks with more detailed emails, shoppers in the treatment group had a similar response to target items as shoppers in the control group. Thus, the effect of more detailed information was primarily a reduction in purchasing "mistakes" of the substitute item for treatment shoppers. This suggests that "mistakes" were avoided by simply not purchasing in the category, as opposed to purchasing the on-sale item.

F Discussion

Our main finding is that providing shoppers with information on categories with on-sale items increases the purchase rate within the category for the regularly priced substitutes. This behavior may be viewed as anomalous if the following is true:

1. Shoppers prefer organic items if they are not more expensive than their non-organic counterparts.

2. Shoppers would switch brands if a competing brand is reduced to, or below, the price of the regular brand they usually purchase.

To verify these assertions, we conducted two follow- up surveys. The first was sent only to the participants of our study and had a response rate of only 24 percent (55 shoppers). 91 percent of the responders answered that they would choose an organic item if it was weakly cheaper than its non-organic alternative. 80 percent of the responders reported that they would switch brands for a discount of 20 percent.

Because of the low response rate of our first follow-up survey, we conducted an additional survey using the Qualtrics platform on 378 American participants ranging

from 18 to 30 years old, with at least some college education. Over 70 percent of respondents reported that they would choose organic if it was the same price as the non-organic alternative for prices ranging between \$1.00-\$3.50. This climbs to close to 90 percent when organic is cheaper than the non-organic alternative. Lastly, 68 percent of respondents replied that they would switch brands if the alternative brand was discounted to the same price as the item they usually purchased. This climbs to 80 percent when the discounted alternative becomes cheaper than the item they usually purchase.

These survey results lend support to our interpretation of the data as reflecting shopping behavior under limited attention. The behavior of our participants stands in stark contrast to the vast majority of the survey responses. While our finding that promotional materials on sales increases consumption of regularly priced alternatives is not dependent on assumptions (1) and (2), these assumptions have important implications regarding consumer welfare.

G Concluding remarks

Comparing prices across a large variety of products is a non-trivial task, especially when prices are constantly changing. Despite this, mainstream economic models of consumer behavior are based on the premise that consumers are attuned to all price fluctuations and perfectly process signals of these price changes. In contrast, our findings reveal that not only do consumers miss opportunities to save, but that bringing their attention to broad sale categories does not necessarily decrease spending.

Furthermore, our experiment yields some novel results that contribute to the growing literature on consumers' response to signals of price changes. First, we show that announcements of broad category level discounts primarily affect shoppers with a history of shopping in the discounted category. Second, while discounting a product generally leads to an increase in demand for that product and a decrease in demand for its lower quality substitute, receiving information on these discounts at the broad category level results in an increase in demand for the discounted product and its more expensive substitute. While previous studies have shown that advertising an item may increase the demand for alternative items in that category, we show increased sales for unbranded items that are close substitutes and are weakly dominated (e.g., increased purchases of a conventional fruit when its organic version

is priced lower). This spillover effect is diminished when the announcements include more information on the types of items that are discounted and when shoppers receive a personalized "nudge" that alerts them to the fact that previous items they bought are no longer on sale. This suggests that the source of the increased demand for the more expensive substitutes is a combination of inertia (continuing to buy what the shopper is used to) and a cost of acquiring more information (looking for which specific items are discounted in the broad category).

The above findings hint at implications for retailers that are deciding which products to discount and how to announce these discounts to shoppers. If retailers are interested in boosting overall sales, they may benefit from announcing discounts only at the category level ("select fruits are on sale"), and targeting these announcements to shoppers with a history of buying in that category. If, on the other hand, a retailer is interested in increasing the sales of a promoted brand, then more precise information at the item level may be preferred.

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Figure 1: The Experiment

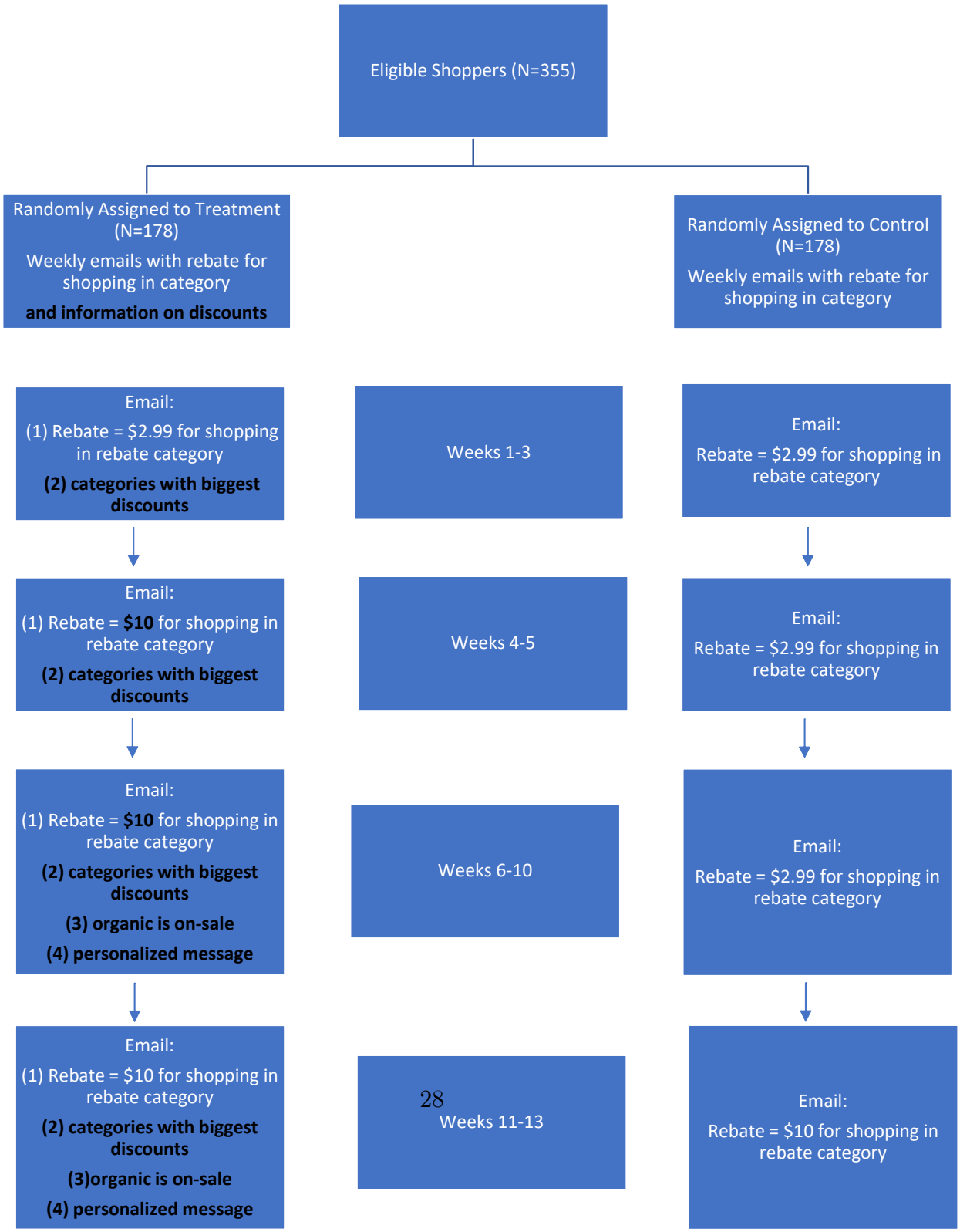

Figure 2: Examples of Email Format During Basic Weeks

Control (email title: Free Shipping on ---- if you Buy a Banana!!!)

Greetings from ----, your local grocery delivery service!

Got a banana? Get a one-time refund on shipping for a purchase of over $20 if you buy one banana or more![1](Click here)

[1] Offer valid on all bananas. Use this email address when placing your purchase and a refund of $2.99 will be applied within 24 hours of purchase. Valid until ---

Treatment (email title: Free Shipping on ---- if you Buy a Banana!!!)

Greetings from ----, your local grocery delivery service!

Got a banana? Get a one-time refund on shipping for a purchase of over $20 if you buy one banana or more![1] (Click here)

… and if that's not enough, make sure you check our discounts for the month of February (discounted items are marked by **).

Our biggest discounts are in the following categories:

1. Vegetables – up to 45% off select items (Click here)

2. Milk – up to 40% off select items (Click here)

3. Fruits – up to 30% off select items (Click here)

4. Eggs – up to 20% off select items (Click here)

[1] Offer valid on all bananas. Use this email address when placing your purchase and a refund of $2.99 will be applied within 24 hours of purchase. Valid until ---

Figure 3: Examples of Email Format During Detailed Weeks

Control: (email title: Click for $10 off your ---- purchase!!)

Greetings from ----, your local grocery delivery service!

Got apples? Get a $10 refund by simply purchasing at least one apple and inserting the coupon code dcash at checkout! [1] (Click here)

[1] Offer valid on all apples. Use this email address and the dcash coupon code when placing your purchase and you will receive a $10.00 one-time refund on your purchase of $20 or more. The refund will be applied within 24 hours. Valid until ---.

Treatment: (email title: Click for $10 off your ---- purchase!!)

Greetings from ----, your local grocery delivery service!

We are devoted to helping our customers get the "best bang for the buck".

So don't miss out on our April discounts! Our April sale prices are so low that organic sale items are often even cheaper than the non-organic alternative! (discounted items are marked by **)

Don't forget to consider some alternatives to your last purchase of eggs that we have on sale this month.

To use your $10 refund - simply click on one of the links below to the site, purchase at least one apple and insert the coupon code found below.

Our biggest discounts are on the following products:

1. Milk – up to 33% off select items (Click here)

2. Eggs – up to 49% off select items (Click here)

3. Fruit – up to 51% off select items (Click here).

4. Vegetables – up to 75% off select items (Click here)

Make sure to purchase one or more apples and enter coupon-code dcash at checkout![1]

[1] Offer valid on all apples. Use this email address and the dcash coupon code when placing your purchase and you will receive a $10.00 one-time refund on your purchase of $20 or more. The refund will be applied within 24 hours. Valid until ---.

Figure 4: Example of Target versus Substitute Item During Sale Period

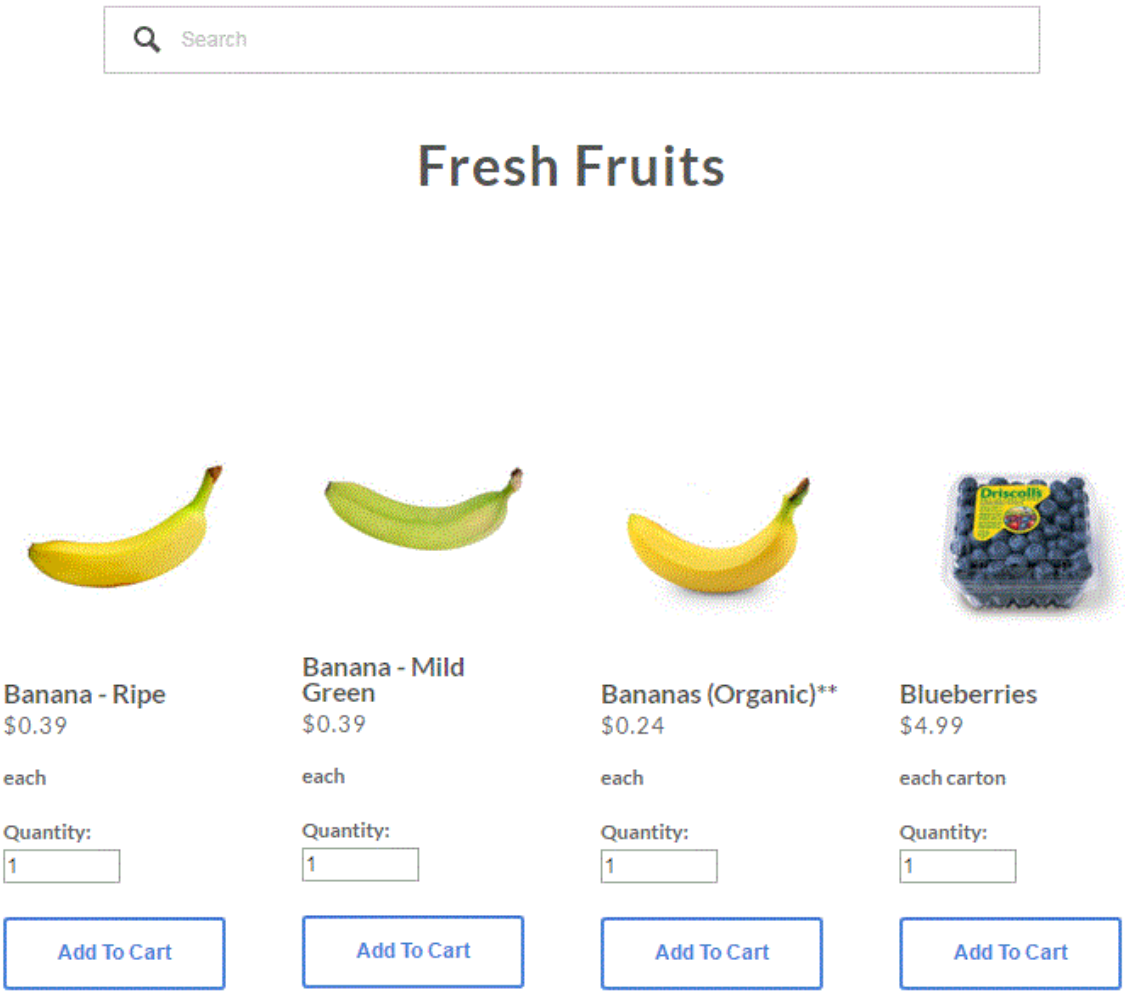

Figure 5: Price Variation in Target versus Substitute Items

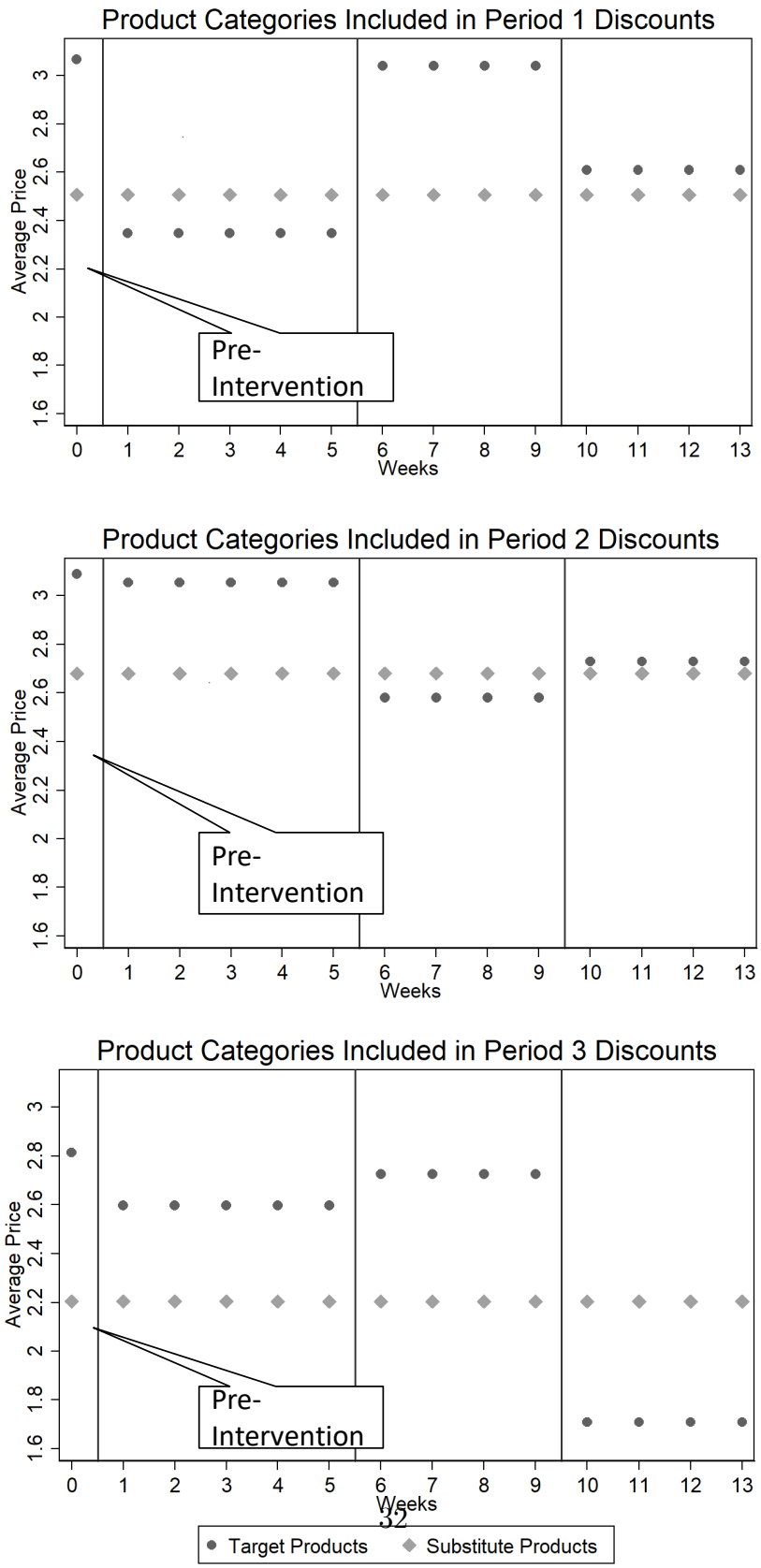

Table 1: Purchasing Frequency of Target and Substitute Items Prior to Experiment

Product Name	Quantity Purchased
Bananas	***357***
Bananas (Organic)	72
Onions	***191***
Onions (Organic)	42
Kroger: Bread	***139***
Aunt Millie's Bread	56
Kroger: Eggs - 12ct	***134***
Egg-Lands Best: Cage Free Large Brown Eggs - 12ct	14
Kroger: Grade A Large Brown Eggs - 12ct	19
Simple Truth: Natural Cage Free Large Brown Eggs - 12ct	78
Kroger: Milk (1gal)	***114***
Kroger: Milk (0.5gal)	96
Horizon: Organic Milk (0.5gal)	22
Simple Truth Organic: Milk (0.5gal)	43
Apple (Lg)	***103***
Apple (Organic)	69
Apple Bag - 3 lb bag	65
Bell Pepper	***99***
Bell Pepper (Organic)	15
Blueberries	***94***
Blueberry (Organic)	11
Avocado	***76***
Jumbo Avocado	28
Cucumber	***75***
Cucumber (Organic)	15
Ice Mountain: Water - 24pk	***74***
Kroger: Purified Drinking Water - 24pk	11
Dasani: Water - 24pk	20
Aquafina - 24pk	11
Chobani: Greek Yogurt	***71***
Fage: Greek Yogurt	55
Raspberries	***62***
Raspberries (Organic)	10
Roma Tomato	***41***
Roma Tomato (Organic)	4
Romaine Lettuce	***33***
Romaine Lettuce (Organic)	3

The most popular substitute item within each category appears first and in bold. Broccoli, Kiwi, Kale, Pineapples, Lemons, Limes, Green Onions, Organic Bread, and Organic Eggs were excluded from this table for lack of space.

Table 2: Target and Substitute Produce Items

Weeks	Target Item	Price	Sale Price	Substitute Item	Price
1-5	Organic Banana **(N)**	0.49	0.39	Regular Banana	0.39
1-5	Organic Blueberries	5.49	4.99	Regular Blueberries	4.99
1-5	Organic Kiwi **(N)**	0.99	0.79	Regular Kiwi	0.79
1-5	Organic Apple (Fuji)	1.49	1.25	Regular Apple (Fuji)	1.25
1-5	Organic Apple (Gala)	1.49	1.25	Regular Apple (Gala)	1.25
1-5	Organic Apple (Granny Smith)	1.49	1.25	Regular Apple (Granny Smith)	1.25
1-5	Organic Lime	1.29	0.89	Regular Lime	0.89
1-5	Organic Broccoli	3.49	3.25	Regular Broccoli	3.25
1-5	Organic Romaine Lettuce	3.29	2.59	Regular Romaine lettuce	2.59
1-5	Organic Cucumber	1.89	0.99	Regular Cucumber	0.99
1-5	Jumbo Ripe Avocado **(N)**	2.25	1.49	Jumbo Unripe Avocado	2.25
6-9	Organic Tomato	0.79	0.59	Regular Tomato	0.59
6-9	Organic Red Bell Pepper	2.79	2.59	Regular Red Bell Pepper	2.59
6-9	Organic Onion	2.59	1.99	Regular Sweet Onion	1.99
6-9	Organic Kale	2.19	1.99	Regular Kale	1.99
6-9	Organic Green Onion	0.99	0.95	Regular Green Onion	0.95
6-9	Apples 3 lb bag (~4 ct.)	5.39	4.49	Regular Apple	1.25
6-9	Organic Lemon **(N)**	1.49	1.29	Regular Lemon	1.29
6-9	Organic Pineapple	6.49	5.49	Regular Pineapple	5.49
10-13	Organic Banana **(N)**	0.49	0.24	Regular Banana	0.39
10-13	Organic Blueberries	5.49	4.00	Regular Blueberries	4.99
10-13	Organic Apple	1.49	1.00	Regular Apple	1.25
10-13	Organic Apple (Fuji)	1.49	1.00	Regular Apple	1.25
10-13	Organic Raspberries **(N)**	5.49	3.89	Regular Raspberries	3.99
10-13	Organic lemon **(N)**	1.49	0.99	Regular Lemon	1.29
10-13	Organic Broccoli	3.49	2.00	Regular Broccoli	3.25
10-13	Organic Cucumber	1.89	0.75	Regular Cucumber	0.99
10-13	Roma Tomato Organic	0.79	0.20	Regular Tomato	0.59
10-13	Red Bell Pepper Organic	2.79	1.99	Regular Red Bell Pepper	2.59
10-13	Sweet Onion Organic	2.59	1.00	Regular Sweet Onion	1.99
10-13	Organic Green Onion	0.99	0.50	Regular Green Onion	0.95

(N) – refers to neighboring categories where the target and substitute appear on the same line of the website.

Table 3: Target and Substitute Dairy, Egg, and Durable Items

Dairy

Weeks	Target Item	Price	Sale Price	Substitute Item	Price
1-5	Kroger: Milk (0.5gal)	2.99	1.75	Kroger: Milk (1gal)	3.99
1-5	Horizon Organic: 0% fat free Milk (0.5gal))	5.45	4.49	Simple Truth Organic: Fat Free Milk	4.49
1-5	Fage: 0% and 2% fat Yogurt (plain and cherry)	1.89	1.50	Chobani: Yogurt, Fage: Yogurt (Other)	1.89
6-9	Fage: 0% and 2% fat Yogurt (plain and cherry)	1.89	1.50	Chobani: Yogurt, Fage: Yogurt (Other)	1.89
10-13	Simple Truth Organic: Milk (0.5gal)	4.49	2.99	Horizon Organic: Milk	5.45

Eggs

Weeks	Target Item	Price	Sale Price	Substitute Item	Price
1-5	Kroger: Grade A large Brown Eggs-12ct	3.69	2.89	Kroger Grade A Large Eggs-12ct	2.99
1-5	Egg-Land's Best: Cage Free Large Brown Eggs-12ct	5.49	4.35	Simple Truth: Natural Cage Free Grain Fed Large Brown Eggs-12ct	4.45
10-13	Kroger: Grade A Large Brown Eggs-12ct	3.69	1.89	Kroger Grade A Large Eggs-12ct	2.99
10-13	Simple Truth: Natural Cage Free Grain Fed Large Brown Eggs-12ct	4.45	2.50	Kroger Grade A Large Eggs-12ct	2.99

Durables

Weeks	Target Item	Price	Sale Price	Substitute Item	Price
6-9	Kroger: Multigrain Bread	2.59	1.99	Kroger: 100% Whole Wheat Bread	2.59
6-9	Kroger: Wheat Bread	2.45	1.99	Kroger: Buttermilk Bread	2.19
6-9	Dasani: Water **(N)**	6.99	5.49	Ice mountain: Water	5.99
				Aquafina: Water	6.99
				Kroger: Water	5.49
				Niagara: Water	5.99
12-13	Aunt Millie's Bread: 100% Whole Wheat	3.65	2.19	Aunt Millies: 12 Whole Grain, Honey Oat, Honey Wheat, Multi Grain	3.65
				Kroger Whole Wheat	2.59
12-13	Aunt Millie's Bread: Butter Top White	3.65	2.19	Kroger: Buttermilk Bread, Wheat Bread	2.45
12-13	Aunt Millie's Bread: Whole Grain White	3.65	2.19	Aunt Millies: Italian	3.65
				Kroger: White, Italian	2.19

(N) – refers to neighboring categories where the target and substitute appear on the same line of the website.

Table 4: Offered Rebate Categories By Week

Week	Rebate Category	Rebate Item Price Target (in $'s)	Rebate Item Price Substitute (in $'s)	Rebate Item Refund Control Group	Rebate Item Refund Treat Group
1	Bananas	0.39	0.39	2.99	2.99
2	Blueberries	4.99	5.49	2.99	2.99
3	Apples	1.25	1.25	2.99	2.99
4	Broccoli	3.25	3.25	2.99	10
5	Bananas, Blueberries, Apples, or Broccoli	See Prices Above	See Prices Above	2.99	10
6	Tomatoes	0.59	0.59	2.99	10
7	Red bell pepers	2.59	2.59	2.99	10
8	Bread	1.99	2.59	2.99	10
9	Yogurt	1.5	1.89	2.99	10
10	Bananas	0.24	0.39	2.99	10
11	Apples	1	1.25	10	10
12	Bread	2.19	2.59	10	10
13	Eggs	2.5	2.99	10	10

Table 5: Sample Characteristics in Pre Experiment Period

	Full Sample			Target or Substitute History		
	Control[a]	Treat[a]	Diff[b]	Control[a]	Treat[a]	Diff[b]
Number of Shopping Trips	4.373	4.264	-0.097	4.829	4.732	-0.097
	(5.814)	(5.678)	(0.693)	(6.122)	(5.988)	(0.693)
Number of Items Purchased	12.544	13.039	0.856	13.529	14.385	0.856
	(7.157)	(8.553)	(0.883)	(7.017)	(8.337)	(0.883)
Number of Target Items Purchased:	2.198	2.758	0.65	2.559	3.209	0.65
(28 Categories)	(4.856)	(6.372)	(0.689)	(5.153)	(6.769)	(0.689)
Neighboring Categories:	0.599	0.702	0.103	0.697	0.817	0.120
(6 Categories)	(1.683)	(2.397)	(0.220)	(1.798)	(2.569)	(0.254)
Non-Neighboring Categories:	1.599	2.056	0.457	1.862	2.392	0.530
(22 Categories)	(3.900)	(4.989)	(0.475)	(4.151)	(5.308)	(0.546)
Number of Substitute Items Purchased:	8.565	8.360	-0.205	9.974	9.725	-0.248
(28 Categories)	(11.585)	(12.901)	(1.302)	(11.929)	(13.433)	(1.455)
Neighboring Categories:	2.904	2.427	-0.477	3.382	2.824	-0.558
(6 Categories)	(6.555)	(5.125)	(0.624)	(6.961)	(5.428)	(0.714)
Non-Neighboring Categories:	5.661	5.933	0.272	6.592	6.902	0.310
(22 Categories)	(7.341)	(8.624)	(0.850)	(7.525)	(8.937)	(0.946)
Number of Categories Purchased	4.260	4.500	0.240	4.961	5.235	0.275
	(3.587)	(3.690)	(0.386)	(3.390)	(3.462)	(0.392)
Total $ Amount Spent on Purchase	66.186	65.198	-0.988	70.957	70.166	-0.791
	(38.556)	(40.119)	(4.177)	(38.403)	(39.833)	(4.481)
Number of Shoppers	177	178		152	153	

[a]Standard deviations are presented in parenthesis

[b]Standard errors are presented in parenthesis

Our analysis focuses on 28 product categories. Six of these are classified as Neighbor Categories - categories where the substitute and target items appear on the same line of the webpage (avocados, bananas, kiwis, lemons, raspberries, and water). The remaining 22 non-neighboring categories are the following: apples, bulk apples, blueberries, pineapples, broccoli, cucumbers, kale, onions, green onions, peppers, lettuces, limes, tomatoes, bread, organic bread, eggs, brown eggs, organic eggs, milk, bulk milk, organic milk, yogurt. Target or Substitute History is a sample that includes only shoppers who made at least one purchase of a target or substitute good during the pre-experiment period.

*Significant at 10%; **significant at 5%; ***significant at 1%

Table 6: Price Elasticities

	All	Vegetable	Fruit	Perishable	All	All	All	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Price	-1.649***	-1.619***	-3.096***	-1.224***	-1.496***	-1.924***	-1.119***	-1.121***
	(0.249)	(0.438)	(0.756)	(0.260)	(0.269)	(0.341)	(0.266)	(0.226)
Log Price x Same Line					-1.655**			
					(0.776)			
Log Price x Branding						0.845*		
						(0.428)		
Log Price x History							-0.347**	
							(0.155)	
Log Price x Treatment								-0.115
								(0.079)
Item Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Items	1,089	243	225	423	1,089	1,089	2,178	2,178

Standard errors are presented in parenthesis and clustered at the item level.
An observation is defined by month and item (121 items tracked from 6 months prior to intervention until the end of intervention (a total of 9 months)). Same Line refers to item categories where the substitute and target items appear on the same line of the website. Branding refers to products that are defined by brand (e.g. Horizon Organic Milk). History refers to shoppers who made a purchase in this category of products (e.g. milk) prior to the intervention.
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 7: The Effect of a Sale on Aggregate Demand across Treatment and Control Shoppers

	Total Category Purchases		Total Target Purchases		Total Substitute Purchases	
	Treatment	Control	Treatment	Control	Treatment	Control
	(1)	(2)	(3)	(4)	(5)	(6)
Pre Sale	2.321	1.571	0.571	-0.250	1.393	1.321
(Month -3)	(1.922)	(1.124)	(0.431)	(0.478)	(1.532)	(1.021)
Pre Sale	-0.357	1.500	0.214	0.036	-0.821	1.107
(Month -2)	(1.199)	(1.031)	(0.326)	(0.432)	(0.968)	(0.909)
Sale Month	6.036**	2.393	3.071***	1.893**	2.786*	0.393
(Month 0)	(2.491)	(1.740)	(1.096)	(0.868)	(1.604)	(0.996)
Item Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	196	196	196	196	196	196
Mean of Dependent	10.77	11.13	2.15	2.08	7.66	7.82
Variable (Pre Period)	[11.24]	[11.3]	[2.91]	[3.01]	[7.31]	[7.2]

Standard errors are presented in parenthesis and clustered at the category level.
An observation is defined by category and month (28 items tracked from 6 months prior to sale until month of sale). The analysis includes additional controls for Months -6 through -4.
The month prior to the sale event is excluded from the analysis, so that these estimates show the change relative to the excluded month.
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 8: The Effect of a Sale on Consumer Spending

	Observed	No Demand Response	Full Demand Response
	(1)	(2)	(3)
Pre Sale	-2.933	-2.933	-2.933
(Month -3)	(5.958)	(5.958)	(5.958)
Pre Sale	-1.490	-1.490	-1.490
(Month -2)	(4.920)	(4.920)	(4.920)
Sale Month	23.265	-4.239***	13.730
(Month 0)	(14.023)	(1.284)	(10.972)
Item Fixed Effects	Yes	Yes	Yes
N	196	196	196
Mean of Dependent	55.63	55.63	55.63
Variable (Pre Period)	[49.96]	[49.96]	[49.96]

Standard errors are presented in parenthesis and clustered at the category level.
An observation is defined by category and month (28 items tracked from 6 months prior to sale until month of sale). The analysis includes additional controls for Months -6 through -4.
The month prior to the sale event is excluded from the analysis, so that these estimates show the change relative to the excluded month.
No Demand Response - estimates the change in spending if consumers had continued to purchase the same products in the sale period as they had purchased in the previous month.
Full Demand Response - estimates the change in spending if all consumers who made a purchase in categories with an on-sale target item had chosen the target item.
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 9: Measuring the Effect of Promotional Information on Customer Purchase Decisions

	Shoppers with History			Shoppers without History		
	Category	**Target**	**Substitute**	**Category**	**Target**	**Substitute**
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Target Sale	0.014**	0.0029	0.012***	-0.001	-0.0001	-0.001
	(0.006)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Target Sale (TS)	-0.002	0.004	-0.0065**	0.001**	0.001**	0.0004
	(0.004)	(0.0032)	(0.003)	(0.001)	(0.0004)	(0.0003)
High Rebate Week FE	X	X	X	X	X	X
User FE's	X	X	X	X	X	X
Item Category FE's	X	X	X	X	X	X
Week FE's	X	X	X	X	X	X
N	20,215	20,215	20,215	109,005	109,005	109,005
Mean of Dependent	0.036	0.01	0.026	0.003	0.001	0.002
Variable:	[0.185]	[0.098]	[0.16]	[0.052]	[0.031]	[0.042]

Standard errors are presented in parenthesis and clustered at the shopper level. Standard deviations appear in brackets. An observations is defined by a shopper, week, and item category. High rebate week is equal to 1 if this is a high rebate week (a rebate of $10 versus $2.99).
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 10: Measuring the Effect of Promotional Information on Customer Purchase Decisions (Identical Rebate)

	Shoppers with History			Shoppers without History		
	Category	**Target**	**Substitute**	**Category**	**Target**	**Substitute**
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Target Sale	0.013	0.0034	0.011*	-0.001	-0.0003	-0.001
	(0.008)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
Target Sale (TS)	0.0004	0.004	-0.0038	0.001	0.001	0.0007
	(0.006)	(0.004)	(0.0043)	(0.001)	(0.0005)	(0.0006)
User FE's	X	X	X	X	X	X
Item Category FE's	X	X	X	X	X	X
Week FE's	X	X	X	X	X	X
N	9,330	9,330	9,330	50,310	50,310	50,310
Mean of Dependent	0.037	0.01	0.027	0.003	0.001	0.001
Variable:	[0.188]	[0.1]	[0.162]	[0.051]	[0.034]	[0.038]

Standard errors are presented in parenthesis and clustered at the shopper level. Standard deviations appear in brackets. An observations is defined by a shopper, week, and item category.
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 11: The Role of Branding and Information in Determining the Effect of Promotional Information on Shopping Behavior

	Special =Branded Category			***Special*** =Detailed Period		
	Category	**Target**	**Substitute**	**Category**	**Target**	**Substitute**
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Target Sale (TS)	0.012*	0.003	0.0102**	0.032***	0.009*	0.025***
	(0.007)	(0.005)	(0.005)	(0.01)	(0.005)	(0.009)
Treat X TS X ***Special*** (S)	-0.0003	-0.005	0.003	-0.032***	-0.011	-0.022*
	(0.011)	(0.007)	(0.009)	(0.011)	(0.008)	(0.012)
Target Sale (TS)	-0.0004	0.005	-0.006	-0.006	-0.002	-0.004
	(0.005)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)
Special (S) X (TS)	-0.003	-0.001	-0.0007	0.008	0.01	-0.0031
	(0.008)	(0.005)	(0.0075)	(0.009)	(0.006)	(0.0093)
High Rebate Week FE	X	X	X	X	X	X
User FE's	X	X	X	X	X	X
Item Category FE's	X	X	X	X	X	X
Week FE's	X	X	X	X	X	X
N	20,215	20,215	20,215	20,215	20,215	20,215

Standard errors are presented in parenthesis and clustered at the shopper and category levels. Standard deviations appear in brackets. An observations is defined by a shopper, week, and item category. Branded (columns (1)-(3)) refers to the product categories where items are branded by different companies as opposed to fruits and vegetables. Detailed (columns (4)-(6)) refers to weeks where the treatment email provided personalized nudges towards onsale items and specifically mentioned that some organic items are on sale.

*Significant at 10%; **significant at 5%; ***significant at 1%