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

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Abstract

How do consumers respond to uncertainty regarding price changes across multiple categories of items? Specifically, does noisy promotional information necessarily lead to savings? We address this question using data from a field experiment on a website for online grocery shopping. We compare purchasing decisions made by shoppers who received (coarse) promotional information on discounts, to shoppers who 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.

Keywords: Limited attention, Salience, Information processing, Supermarket shopping.

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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 changing. Thus, even if the consumer found and purchased the cheapest available product in a category in her last shopping trip, this may no longer be the case in the current shopping trip. Intuitively, promotions can help provide shoppers with information on these price changes, but because many promotions are relevant for only a subset of products in a category, this information may be noisy. For example, if many shoppers skim supermarket flyers of weekly promotions, without carefully reading the small print on the exact products included in the discount, they may mistakenly add products to the basket that are included in the category but are not discounted. Similarly, consumers often receive information on promotions from a provider with multiple services (e.g. a cellphone provider with plans for calls, texts, and data, or a cable TV and internet provider) where the promotion may only be relevant for a subset of the services.

How do consumers respond to uncertainty regarding price changes in the many categories of items they buy, and to the possibly noisy information they have about these changes? Specifically, does promotional information necessarily lead to higher savings? Addressing these questions can improve our understanding of how promotional information affects demand. The answer is important for both policy makers interested in helping consumers realize potential savings, and for retailers interested in using discounts to steer consumers to particular items.

To tackle these questions, we analyze data from a series of randomized controlled trials conducted over a three-month period on a website for online grocery shopping. 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 so that all shoppers faced the same exact prices. The only difference is that treatment shoppers were informed of some of 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 email 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, 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 shoppers respond to information - which is possibly noisy or coarse - about price changes in multiple categories. We study how this response depends on features of the information such as precision and framing, and on features of the shoppers such as previous product choices. To the best of our knowledge, we are the first to conduct a field experiment that examines how shoppers respond to signals 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 the signals on discounts, (ii) these shoppers respond to the signals on discounts by being 1.7 percentage points (s.e. 0.6) more likely to purchase a product in the discounted category that they had experience with prior to the experiment, which for most shoppers is the (currently) more expensive substitute item, (iii) more precise information on sales, and a personalized nudge seem to reduce the purchasing rate of the non-discounted substitute, and finally, (iv) our results suggest that coarse information on discounts increase consumer spending and seller revenue. More specifically, we find that coarse information on discounts doubled consumer demand for discounted products, but also increased demand by 44 percent for non-discounted products within that same category, which translates to pure profit 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*) costly search, (*ii*) obfuscation that makes price comparisons difficult, 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).

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. 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, Hitsch, and Rossi (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, our results suggest that consumers are less price sensitive in comparisons with higher search costs (that required scrolling down), relative to cases where substitutes appeared on the same line.

While Grubb's survey focuses on traditional offline shopping, some recent works have investigated whether online shopping reduces search frictions and increases the likelihood that consumers find the best prices. Using a large dataset on web browsing

and purchasing behavior, De los Santos, Hortacsu, and Wildenbeest (2012) reject the hypothesis that consumers search in accordance to classical search models. Helmers, Krishnan and Patnam (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. Clerides and Courty (2017) 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 suggests that some consumers are either not comparing all prices, or are not computing (or computing erroneously) the price per unit when making their purchasing decisions.

Our study adds to this literature by examining how consumers' shopping decisions are affected by the relative prices of substitute goods and how varying the precision and framing of information affect these choices. The experimental design sheds new light on the difficulty consumers face in allocating their attention and in making optimal choices even when the information is readily available on a single webpage. In contrast to previous research, the prices we observe were discounted exogenously for the purpose of the experiment and are not a product of market demand trends. Additionally, as supermarket shopping involves repeat purchases of goods over short time periods, we are able to examine how consumer's past choices impact their response to promotional material and price changes.

The experiment we conducted is naturally related to works that examine the effect of online promotions. Zhang et al. (2020) 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. Like us, they found that a significant proportion of treated shoppers did 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..

A somewhat similar effect was reported in Sahni, Zou and Chintagunta (2017). They observed that when a website selling tickets to sporting events offered dis-

counted 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. In our experiment, discounts offered on items 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). This may have resulted in more purchases of non-discounted items because these were the products shoppers were more likely to purchase in the past. Importantly, 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. This allowed us to document a surprising result that had not been reported in prior research: not only did the promotion increase the purchase rate of non-discounted products, these products *were in fact weakly more expensive substitutes for the on-sale products.*

Our findings suggest that shoppers may not have paid attention to all the prices of items relevant to their basket. In terms of documenting limited attention, the main empirical challenge is the difficulty in obtaining data on the information to which consumers paid attention. Abaluck and Adams (2018) propose an innovative approach to overcome this challenge. In a random utility framework, they identify sufficient conditions on preferences and on the products' attributes that enable identification of choice and consideration probabilities from differences in cross derivatives of the choice probabilities with respect to product attributes. The key insight is that under limited attention these cross derivatives exhibit an asymmetry, which can be exploited for the identification exercise. We take a different approach to overcoming the challenge of obtaining data on what consumers know: We conduct a field experiment that directly manipulates the information provided to shoppers.

Studies that also conducted field experiments in which shoppers appear to exhibit limited attention include Chetty, Looney and Kroft (2009) who show that posting prices that include taxes reduces demand. Blake, Moshary, Sweeney and Tadelis (2017) demonstrate that up-front display of the total cost of each available item, including all fees, (as opposed to displaying only the listed prices and adding the fees at check out) affects not only the likelihood of purchase but also the quality of the items purchased.

Finally, with regards to theoretical work, our paper is motivated by De Clippel, Eliaz and Rozen (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 (forthcoming) 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 (forthcoming) 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 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

[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.

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.

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 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. The website used this method of marking discounts because of the following: 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*. During the period with the lowest relative discounts (in percentages) on target items, the highest discount was 25 percent, while during the period with the highest relative discounts, the maximal discount was 75 percent. 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. 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

[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.

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).

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]

An important feature of the discounted items was the variation in their display: 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

[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.

next to each other is independent of their prices, or of the difference between their prices and there was no option on 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.

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). 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.[9] Treatment shoppers received additional information on 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.[10] But 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 percent-

[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] 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.

[10] As noted above, for roughly half of the experiment both the treatment and control emails 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 as well as including a control for rebate size in our analysis when including all weeks.

age 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.

Discussion. Borrowing the terminology of Ludwig, Kling, and Mullainathan (2011), our experimental design has both *policy* and *mechanism* dimensions. A policy dimension is meant to mimic a real-life intervention and to examine its implications in a controlled setting. In our context this includes the price changes in multiple categories (as is the case with real discounts, typically more than one product in a category was on sale) and giving aggregate/coarse promotional information (which serves as a noisy signal to the consumer), somewhat similar to weekly flyers in a supermarket, or weekly promotional emails to shoppers with member cards.

The mechanism dimension is meant to trigger some behavior, which is hypothesized to be relevant for the outcome. This trigger may be carried out by an artificial feature of the experiment, which does not necessarily have a real-life counterpart. Our use of asterisks to mark discounted items belongs to the mechanism dimension of our design. This is meant to mimic an environment where finding information on discounts requires costly search. The unique feature of our website is that prices were fixed until the experiment and so customers were used to the fact that there is no need to search for price changes. Our use of asterisks serves as a compromise between one extreme of having no markers of discounts on the site in which case, the control will never engage in costly price comparisons (since prior to our experiment prices were fixed), and the other extreme where sales were made salient, in which case, there would be no value to the treatment.

D The data

This paper analyzes purchasing decisions made by 355 shoppers over the thirteen weeks of the experiment in 28 product categories (see footnote 3). 177 shoppers were assigned to control, and 178 to treatment. For each of these 355 shoppers, we tracked their decision of whether to make a purchase in each category over the duration of the experiment (129,220 observations). 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 very strong predictor of current purchases with differential effects between those allocated to the control and treatment groups. 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 far more frequently than the target items by all shoppers.

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. 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 were neighbors (avocados, bananas, kiwis, lemons, raspberries, and

water).[11] 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 likely to purchase a discounted target item in these categories.

E Findings

We begin this section by examining how all shoppers respond to exogenous price changes, and then measure the impact of information on this response by differentiating between shoppers in the treatment and control groups. Surprisingly, our results suggest that the treatment group responded primarily by purchasing more of the items in the on-sale categories that they purchased in the past, which for most shoppers is the *higher-priced* (weakly lower-quality) substitute items.

One possible explanation for the differential response of the treatment group is that the emails they received increased the salience of specific categories. The question remains, whether a consumer purchased the higher priced (weakly lower-quality) substitute items because she *preferred* them to the onsale target products, or alternatively, because based on her past experience she *incorrectly* assumed that the substitute products were cheaper. In Section E.2, we examine this issue more closely by first focusing on categories where the target item is organic and thus, more likely to be perceived as higher quality. Second, we consider categories where the substitute product is visually separated from the target product, suggesting a higher search cost. We then focus on differential effects across categories where the salience gap between the treatment and control group varied. We do this by defining categories that appeared at the *top* of the email sent to the treatment group as those with the largest salience gap between treatment and control shoppers.[12] Lastly, we consider weeks where treatment shoppers received more information on the types of

[11] 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.

[12] In the first three weeks of the experiment, the top-listed category was vegetables, in weeks four and five it was eggs, in weeks six through nine it was yogurt, and in weeks ten through thirteen it was milk.

items that were on sale, as well as "nudges" that there exist cheaper alternatives to products they purchased on previous trips, thus altering the precision of information conveyed in the treatment email.

We end the section with a discussion of how sales impacted the demand for products alongside supermarket revenue. We compare the observed results to two hypothetical alternatives: (i) an alternative of zero price elasticity, where shoppers would have continued to purchase the same products they purchased prior to the sale, and (ii) full price elasticity (assuming shoppers value the target product at least as much as the substitute product), where all shoppers purchasing in the onsale category during the sale period purchase the discounted target product.

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).

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

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

We find that demand increases in response to a sale (see Table 6). The average measured price elasticity is -1.586 (s.e. 0.264), 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 (6) 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 1.747 (s.e. 0.784) which suggests that price elasticity results not only from product characteristics, but also, the ease in which shoppers are able to compare prices across alternatives in different product categories.

Figure 6 provides an event study plot examining the change in the purchase rate of the target item within a category (which includes target and substitute items) over time relative to the month before an item went on sale (month $= -1$). In the 6 months leading up to a sale, shoppers consistently chose the target item in roughly 22 percent of purchases. During the month when the product was on sale shoppers were 12.9 percentage points (s.e. 3.1) more likely to choose the on-sale item versus its alternative than they had been prior to the sale. Thus, the sale resulted in shoppers choosing the on-sale item in roughly 35 percent of purchases. When we differentiate between categories where items appear in the same line of the website and categories where items are farther away, the response to the sale is 11.7 percentage points higher (s.e. 6.3) for neighboring categories (see Figure 7). The sale response within neighboring categories is 21.3 percentage points (s.e. 4.9) versus 10.6 percentage points (s.e. 3) in non-neighboring categories.[13]

Despite these significant responses to the sale, Figures 6 and 7 still illustrates that while some shoppers move from purchasing the substitute to the target item when it goes on sale, many (60 percent) pay the same price or more to remain with the substitute item. Why did a significant proportion of shoppers choose apparently dominated alternatives on their shopping trips (more expensive and of lower quality)? One plausible explanation may be that shoppers were not fully attentive to all available discounts. Our random assignment of shoppers to treatment and control provides an opportunity to look closely at how receiving promotional information impacted shopper behavior. Figure 8 provides a graphic illustration of the aggregated changes in shopper behavior within the intervention for four different outcomes: The probability of making a shopping trip in a given week, average spending per trip,

[13] All of these specifications controls for category and shopper fixed effects in order to focus on changes in shopper behavior as opposed to changes in the types of shoppers who purchase within the category.

the number of purchases made in relevant categories, and total spending on relevant categories. The largest observed difference between shoppers in the treatment and control group is that shoppers in the treatment group tend to purchase more in the categories impacted by the intervention.[14]

Regression analysis. Our main analysis focuses 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 an alternative item within the category (e.g., conventional tomatoes). Thus, we model the binary decision Y of shopper i regarding items in category c during week w ($Y \in \{buy_{icw}, target_{icw}, substitute_{icw}\}$) as a linear function of whether the shopper was in the treatment group ($treat_i$), whether the target item was on sale ($tsale_{cw}$) , and the interaction between these two variables ($treat_i \times tsale_{cw}$).[15]

$$Y_{icw} = \beta_0 + \beta_1 treat_i + \beta_2 tsale_{cw} + \beta_3 treat_i \times tsale_{cw} + \beta_4 hist_{ic} + \beta_5 rebate_{iw} + \eta_c + \rho_w + \varepsilon_{icw} \tag{2}$$

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. Thus, we would expect our estimate of β_3 to be significant and positive 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_3 to be zero when the outcome variable is buy_{icw}. Our intervention also provides an opportunity to examine whether the

[14] Figure 9 provides a baseline for comparison between the shopping behavior of the randomly assigned treatment and control groups in the 13 weeks leading up to the experiment. While both the treatment and control group similarly increase their probability of shopping during the intervention (presumably due to the weekly emails and promotions), we observe a larger increase in the purchase rate of relevant products for the treatment group.

[15] While our main analysis focuses on a linear probability model, Appendix Table A.1 illustrates that we find very similar results when running a logistic regression to more precisely account for the binary outcomes analyzed in this paper.

promotional information provided to the treatment group served to attract shoppers to *new* categories. Thus, in later specifications the measured treatment effect will also be a function of whether the shopper has a history of purchasing within the category in the pre-experiment period.

Our full sample consists of 355 shoppers (i) over the thirteen weeks of the experiment (w) in each of the 28 product categories (c).[16] 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_3) captures the differential response of the treatment group when controlling for week and category fixed effects, the size of the rebate offered to shopper if purchasing the rebate item ($rebate_{iw}$), and whether or not the shopper has a history of purchasing within this category/item in the pre-intervention period ($hist_{ic}$).[17]

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.[18] 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.

Columns (1) and (4) of Table 7 examine whether any item within category c was purchased by shopper i during week w ($Y_{icw} = buy_{icw}$), columns (2) and (5) focus on target item purchases (products whose price changed throughout the intervention period), and columns (3) and (6) focus on substitute products whose price remained constant throughout the intervention. In part A of Table 7 we run this analysis on the *full* sample. Columns (1)-(3) illustrate that there is no difference in shopping behavior (coefficient on $treat_i$) between shoppers who were randomly allocated to treatment (receiving a weekly promotional email with sale information and a rebate category) and control (receiving a weekly promotional email with only a rebate category) when looking across *all* product categories. In columns (4)-(6), we estimate

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

[17] We have also run our analysis including shopper fixed effects and find very similar results. Because receiving a promotional email may impact shopper behavior outside of the relevent categories/period of the email, we believe there is added value in focusing on comparisons between the treatment and control groups as opposed to differencing out within shopper behavior.

[18] 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.

the impact of a sale within the category on shopper behavior ($tsale_{cw}$) and include the interaction term ($treat_i \times tsale_{cw}$) to consider the differential response of treatment shoppers to a sale within a category. *Thus, when considering the full sample of shoppers we find little evidence that receiving the weekly promotional email had any impact on shopper behavior.*

Parts B and C of Table 7 suggest that the response to treatment was strongly conditional on past shopping behavior. Thus, when we restrict the sample to shoppers with no history of buying products within the discounted category (see part B), there is no difference in purchasing decisions between those who received promotional information and those that did not. However, part C, documents a significant treatment effect when restricting the sample to shoppers who purchased in this category in the pre-intervention period. The coefficient on $treat_i \times tsale_{cw}$ in part C of Table 7 is positive and significant in specifications (4), (5), and (6). Thus, treatment shoppers with a history in the on-sale category are 1.9 percent percentage points (s.e. 0.5) more likely to purchase in a category with a sale than shoppers in the control group with a history of purchase (see column (4)).

We find that among shoppers who had a history of purchasing the on-sale target item prior to the intervention, treatment shoppers are 1.5 percentage points (s.e. 0.8) more likely to take advantage of the sale than control shoppers (see column (5)). However, while shoppers in the control group with a history of purchase of the substitute product decrease their purchase rate of this product when the target item is on sale (see coefficient on $tsale_{cw}$ in column (6)), shoppers in the treatment group *increase* their purchase rate of the *non-discounted* substitute product when the target product is on sale. Thus, treatment shoppers with a history of purchasing the substitute product are 1.7 percentage points (s.e. 0.4) more likely than shoppers in the control group to purchase the substitute product during the sale on the target item. 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 same exact item she had bought before* (which is what part C shows).

Thus, our results suggest that noisy 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. We incorporate this idea into model 3 below, where we interact the treatment response to a sale $treat_i \times tsale_{cw}$ with $hist_{ic}$ to capture the differential response of treatment shoppers with a history of purchasing in any given category,

$$\begin{aligned} Y_{icw} &= \alpha_0 + \alpha_1 treat_i + \alpha_2 tsale_{cw} + \alpha_3 treat_i \times tsale_{cw} + \alpha_4 treat_i \times tsale_{cw} \times hist_{ic} \quad (3) \\ &\quad + \alpha_5 tsale_{cw} \times hist_{ic} + \alpha_6 treat_i \times hist_{ic} + \alpha_7 hist_{ic} + \alpha_8 rebate_{iw} + \eta_c + \rho_w + \varepsilon_{icw} \end{aligned}$$

The first three columns of Table 8 replicate our results from Table 7 using the *full* sample, demonstrating that the effect of treatment is concentrated among shoppers purchasing in an on-sale category in which they have a history of shopping previously (recall that parts B and C of Table 7 restricted the sample based on shopping history). The average purchase rate within product categories was 0.8 percent (s.d. 9) with a rate of 0.2 percent (s.d. 5) buying target and 0.6 percent (s.d. 7.5) buying the substitute. For shoppers who previously made a purchase in the category, the differential response of those in the treatment group is calculated as the sum of $\widehat{\alpha}_3$ and $\widehat{\alpha}_4$, the coefficients on $treat \times tsale$ and $treat \times tsale \times hist$. We find that shoppers in the treatment group with a history of shopping in category, increased their purchase rate within the category of the sale by 1.7 percentage points (s.e. 0.6) more than control shoppers (see column (1)). The effect of promotional material was primarily to increase purchase rates for products that shoppers had purchased in the past in a category where a sale was taking place. Thus, shoppers in the treatment group who had a history of purchasing target products in the on-sale category are 1.4 percentage points (s.e. 0.8) more likely than shoppers in the control group to take advantage of the sale on target products. However, treatment shoppers with a history of purchasing *substitute* products are 1.5 percentage points (s.e. 0.4) more likely than control shoppers to purchase a *substitute* item during this same period when the weakly higher quality target item was on sale. In the last two rows of estimates in Table 8 labeled A and B, we calculate the aggregate effect of a sale on shoppers who purchased in this category during the pre intervention period. Row A provides estimates from equation (3) of the change for treatment shoppers $(\widehat{\alpha}_2 + \widehat{\alpha}_3 + \widehat{\alpha}_4 + \widehat{\alpha}_5)$ and Row B provides estimates for control shoppers $(\widehat{\alpha}_2 + \widehat{\alpha}_5)$.

Our results from column (3) 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 at a lower price? Without a control group, one could be concerned that shoppers suspected that an item on sale was of lower quality (e.g., close to expiration date).[19] 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.[20] One possible explanation is that the email to the treatment group impacted two separate shopping decisions. The first is what product categories to purchase, and the second, is 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. We control for rebate size in all specifications, as there were weeks where the treatment group received a \$10 offer, while control shoppers received a \$2.99 offer. In order to make sure that our results are not driven by a selection issue where certain types respond to a \$2.99 versus \$10 rebate offer, in the second half of Table 8 we re-run our analysis including only weeks when the treatment and control group received the same rebate offer. Columns (4)-(6) of Table 8 illustrate that the observed differences in behavior between the treatment and control groups cannot be explained by differential incentives.

[19] 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.

[20] 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 have made purchases in the category in the past.

Suppose treatment shoppers chose the more expensive substitute item simply because they prefer it to the target item and are willing to pay a higher price for it. Then assuming organic items are perceived as higher quality, we expect the differential demand increase of the treatment group for the substitute products to be *weakest* when the target product is *organic* while the substitute item is *conventional*. Alternatively, suppose treatment shoppers *mistakenly* purchased the substitute product when the target was discounted because based on their prior experience, they wrongly asserted that the substitute was cheaper. Then this mistake should be more likely in categories where the substitute item is visually separated from the discounted target item. In the next subsection we exploit variations across food categories, as well as in the precision and framing of information in the email to treatment shoppers to argue that the higher purchasing rate of the expensive substitute item among these shoppers is more likely driven by mistakes than by rational choices.

E.2 The mechanism driving our results

Organic vs. conventional. Did shoppers simply prefer the substitute products to the target products and were therefore willing to pay the higher price? In some of our shopping categories (e.g. yogurt, bread, etc.) one may conjecture that shoppers prefer the flavor of the product that they regularly buy and thus, would continue purchasing the product regardless of the relative price change. In this case, one could argue that the promotional material served as a reminder to treatment shoppers to stock up on products so that these shoppers purchased the product they prefer despite its relatively higher price. However, this argument is harder to make when considering product categories with organic versus non-organic options. Table 9 illustrates that the effects from Table 8 remain even when constraining the sample to categories where the target product is organic.

Search costs. Were some shoppers not aware of discounts, especially those that required search? Recall that in Table 6 we reported a significant increase in price elasticities in product categories with the lowest search costs. Similarly, Figure 7 suggests that shoppers may have responded more strongly to sales in categories with lower search costs. In Table 10, we differentiate between categories with high search costs, where the target and substitute item appear on different lines of the website (column "Diff-Line"), and categories with low search costs, where the items appear

on the same line (column "Same-Line"). It is in these high-search cost categories that treatment shoppers with a history of purchasing in the category responded to sale information by increasing their purchase rate of the *regularly priced* substitute items by 1.9 percentage points (s.e. 0.6) relative to the control group (sum of coefficients on $Treat \times TargetSale$ & $Treat \times TargetSale \times Hist$ in column (3)). We also find a positive treatment effect for substitute items in the low-search cost categories (see column (6)), but it is roughly a fifth of the size and much more noisily measured (a 0.4 percentage point change (s.e. 1.1)). While we cannot reject the hypothesis that these results are the same, due to the large confidence interval surrounding the estimate in the low-search cost categories, focusing on high-search costs categories clearly increases the precision of our estimates.

Salience. Table 11 takes a closer look within these high-search categories in an attempt to uncover heterogeneity in the treatment response of shoppers who have a history of purchasing within these categories. Thus, we limit our sample to only include categories with high search costs (where the substitute and target products appear on different lines) and only include shoppers who have a made a purchase in these categories in the pre intervention period. Columns (1)-(3) consider the differential treatment effect in categories that appeared *first* in the treatment email. Since the categories that were listed first had the *lowest* discounts, we would expect that the response to sales in these categories would be the lowest. Hence, a higher purchasing rate for items in the top listed categories can only be attributed to the salience of appearing first. Thus, it is specifically in these product categories where the treatment group received the largest salience shock (assuming they are impacted more by information they see first) and the control group did not receive any information. 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) appeared *first* in the treatment email ($first$):

$$\begin{aligned} Y_{icw} &= \gamma_0 + \gamma_1 treat_i + \gamma_2 tsale_{cw} + \gamma_3 treat_i \times tsale_{cw} \\ &+ \gamma_4 treat_i \times tsale_{cw} \times first_{cw} + \gamma_5 tsale_{cw} \times first_{cw} + \gamma_6 treat_i \times first_{cw} \\ &+ \gamma_7 first_{cw} + \gamma_8 rebate_{iw} + \gamma_9 past\_purchases_{ic} + \eta_c + \rho_w + v_{icw} \end{aligned} \tag{4}$$

The coefficient γ_3 on the interaction term $treat \times tsale$ in equation (4) provides an estimate of the relative change in purchase rate between treatment and control shoppers for categories outside of the first-appearing product categories. Column (2) of Table 11 estimates γ_3, the effect of sale on the demand for target products and demonstrates that shoppers in the treatment group exhibited a similar response to those in the control group. Specifically, in these less salient categories, we measure a 0.1 percentage point (s.e. 0.4) difference between the purchase rate of the on-sale target item between treatment and control shoppers. This effect is stronger for first-appearing product categories where shoppers in the treatment group increase their purchase rate of the on-sale target items by an additional 1.2 percentage points (s.e. 0.5) relative to the control group (calculated as the sum of the coefficients $\widehat{\gamma}_3$ and $\widehat{\gamma}_4$).[21] The observed increase in substitute item purchases for the treatment group is fairly similar across these different salience categories (difference of 0.8 (s.e. 1.5)).

Details, precision and nudges. Columns (4)-(6) of Table 11 consider the impact of more detailed emails on the treatment group. During weeks 6-13, the email 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." Thus, 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 shopper received a more detailed email ($detailed$) :

$$\begin{aligned} Y_{icw} &= \pi_0 + \pi_1 treat_i + \pi_2 tsale_{cw} + \pi_3 treat_i \times tsale_{cw} + \pi_4 treat_i \times tsale_{cw} \times detailed_w \\ &\quad + \pi_5 tsale_{cw} \times detailed_w + \pi_6 treat_i \times detailed_w + \pi_7 detailed_w + \pi_8 rebate_{iw} + \\ &\quad \pi_9 past\_purchases_{ic} + \eta_c + \rho_w + v_{icw} \end{aligned} \tag{5}$$

Recall that treatment shoppers are significantly more likely than control shoppers to purchase the substitute product in categories where a weakly higher-quality target

[21] The effect of the sale on target item purchases made by the control group (see column (2) of row C) was smaller for the first-appearing product categories (and was even below regular purchase rates). For high search-cost categories, first-appearing product categories were always those with the smallest discounts which may explain the lower interest in these items.

item is on-sale. Column (6) of Table 11 illustrates that this holds true during non-detail weeks, as shoppers in the treatment group are 3.3 percentage points (s.e. 1.1) more likely than shoppers in the control group to purchase a substitute product during a target item sale (coefficient on $Treat \times TargetSale$). However, this effect shrinks to 0.6 (s.e. 0.5) during detailed email weeks.[22] During these more detailed weeks, shoppers in the treatment group had a similar response to target items as shoppers in the control group (see rows B and C in column (5)). 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.

An alternative explanation for this change in behavior over detailed weeks is that the treatment intensity weakened during this period if people were less likely to open their emails. Figure 10 documents the fraction of shoppers who opened their email during each week of the experiment.[23] Indeed, shoppers decreased their opening rate from 43 percent in the non-detailed weeks to 35 percent in the detailed weeks. In Table 12 we run our analysis while gradually dropping weeks with the lowest opening rates ranging from 30 to 35 percent from the detailed period to understand the extent to which differential opening rates may be impacting our results.[24] While dropping these weeks makes the mean opening-rate in the detailed weeks more similar to the 43 percent opening-rate in the non-detail weeks, we continue to find results of similar magnitude (though less precisely measured) for the differential effect of information precision on the demand of treatment shoppers for the substitute products. In these specifications, the magnitude of the demand increase for substitute products in categories with a target item sale ranges from 1.1 (s.e. 0.5) to 1.6 (s.e. 0.9) percentage points, relative to non-detail weeks where the treatment group increased their purchase rate of substitute products by 3.3 percentage points (s.e. 1.1).[25]

[22] This is calculated as the sum of the coefficients on $treat \times tsale$ and $treat \times tsale \times detailed$ from equation (5).

[23] We note that these percentages may not be fully accurate as the email-service was unable to track emails that were forwarded to other addresses and some virus-scanners may automatically activate the open-email flag.

[24] Specifically, we start by dropping the week with the lowest opening rate (week 13). In the next specification, we drop the two weeks with the lowest opening rates (weeks 10 and 13). Finally, we drop the five weeks with the lowest opening rates.

[25] The response in the detailed weeks is calculated as the sum of the coefficients on $treat \times tsale$ and $treat \times tsale \times detailed$ from equation (5).

E.3 The effect of discounts on spending and revenue

Our results at the shopper level suggest that the supermarket may have benefitted from the noisy promotional information offered to consumers as it seemed to increase substitute purchases alongside the purchase of discounted target items. Table 13 summarizes the results from an event study analysis examining the aggregate change in consumer purchases and spending over time relative to the month before the target item went on sale within a category (month $= -1$). The sale increased demand by roughly 18 units (s.e. 7) at an average aggregate monthly purchase rate of 30 units per category. While this demand increase was roughly evenly split between target and substitute purchases, because target products were purchased less frequently leading up to the sale (an average purchase rate of 6 versus 20) the percent change is much larger for target versus substitute products (a 134 percent increase versus a 44 percent increase in demand). This increase in demand during the sale period resulted in an increase in total category spending of roughly \$25 (s.e. 13), with a \$9 (s.e. 5) increase in spending on the on-sale target products and a noisily measured \$16 (s.e. 10) increase in substitute product spending.

To put these numbers in context, Figures 11 & 12 graph the change in spending that occurred within the on-sale target products and in the full category during the sale month relative to other months. The two top graphs in each figure compare the observed response to the change in spending that would have occurred if shoppers had made the same purchasing decisions as in the previous month (prior to the sale) so that the change in spending is driven entirely by the price change without any demand effect. The bottom two graphs in each figure compare the observed response to the change in spending that would have occurred if all shoppers who purchased in the on-sale category during the sale period would have chosen the discounted target product. The top graphs in Figure 11 illustrate that total spending on the on-sale target products increased despite the fact that during the sale each product was cheaper. However, the bottom two graphs demonstrate that the observed increase in spending on the on-sale target product of \$9 was well below the potential increase of close to \$60 that would have occurred if all shoppers who purchased within the category had switched to the on-sale target product. The fact that some shoppers chose the substitute product during the target sale raised the supermarket's revenue as observed in the bottom two graphs of Figure 12. It is this comparison that suggests that it may be in the supermarket's best interest to provide noisy information to

consumers.

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. Much of the economic analysis is based on the premise that individuals are attuned to all price fluctuations and perfectly process signals of these price changes. In contrast, the results of our field experiment show that individuals can miss opportunities to save and tend to focus on price comparisons that are more salient. Moreover, a significant proportion of individuals forego opportunities to save that are brought to their attention. Indeed, a surprising conclusion that arises from our findings is that it is not straightforward to draw individuals' attention to price changes that can help them save, even when they are provided with personalized messages. Our analysis suggests that the advertising of sales can end up increasing purchase rates of all items in the category in which a sale is taking place. Specifically, information on items within category sales can increase purchase rates of both the on-sale item and other alternatives in that category. If promotional materials increase "mistakes" among consumers, firms could profit by increasing prices of "substitutes" while advertising "target" discounts. Our results suggest that shoppers may benefit from more precise and personalized information and may be willing to pay for a premium service that alerts them to new discounts and expiration of past discounts on items that they bought in the past.

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Figure 1: The Experiment

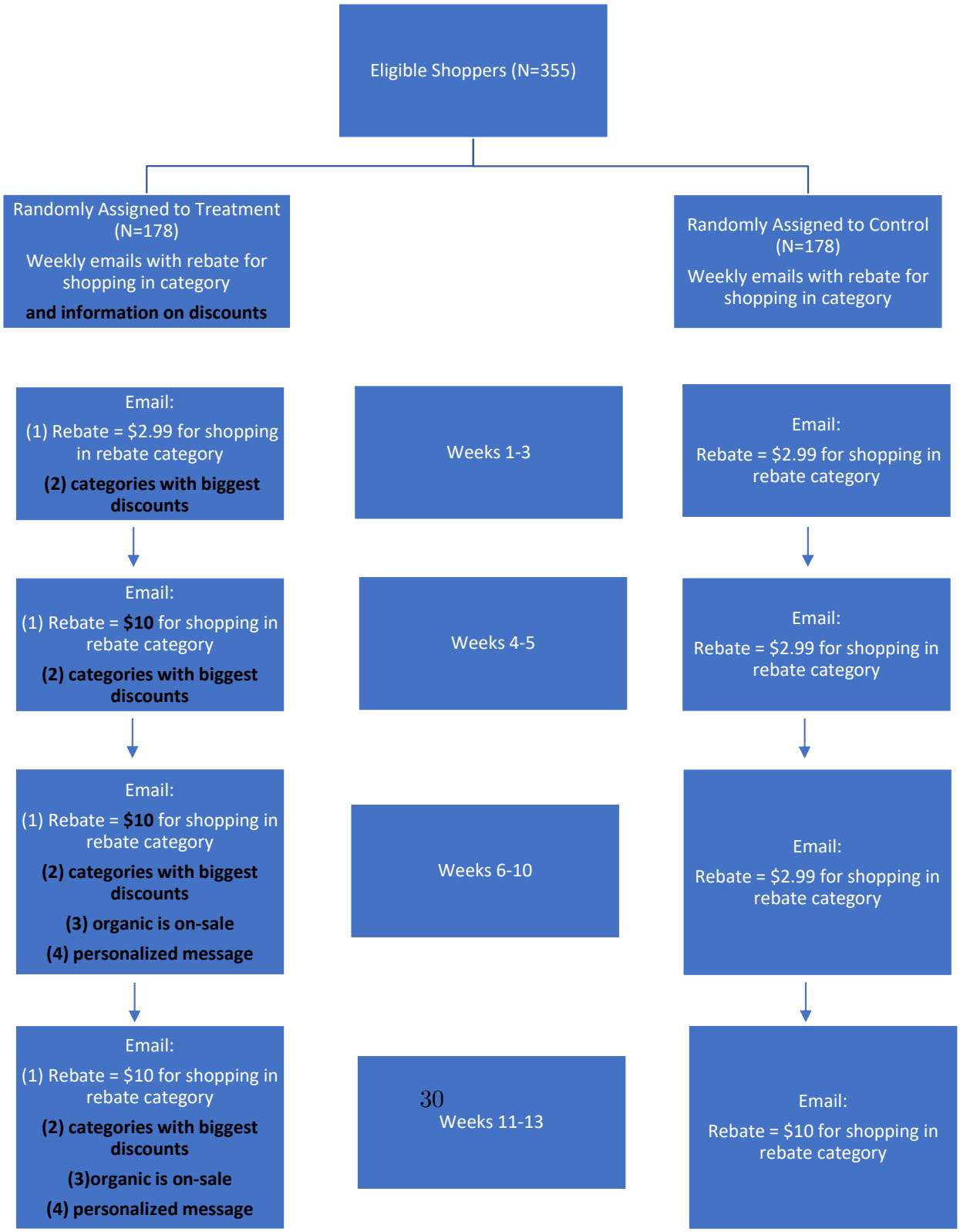


Figure 2: Examples of Email Format During Basic Weeks

<u>Control</u> (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 ---

<u>Treatment</u> (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

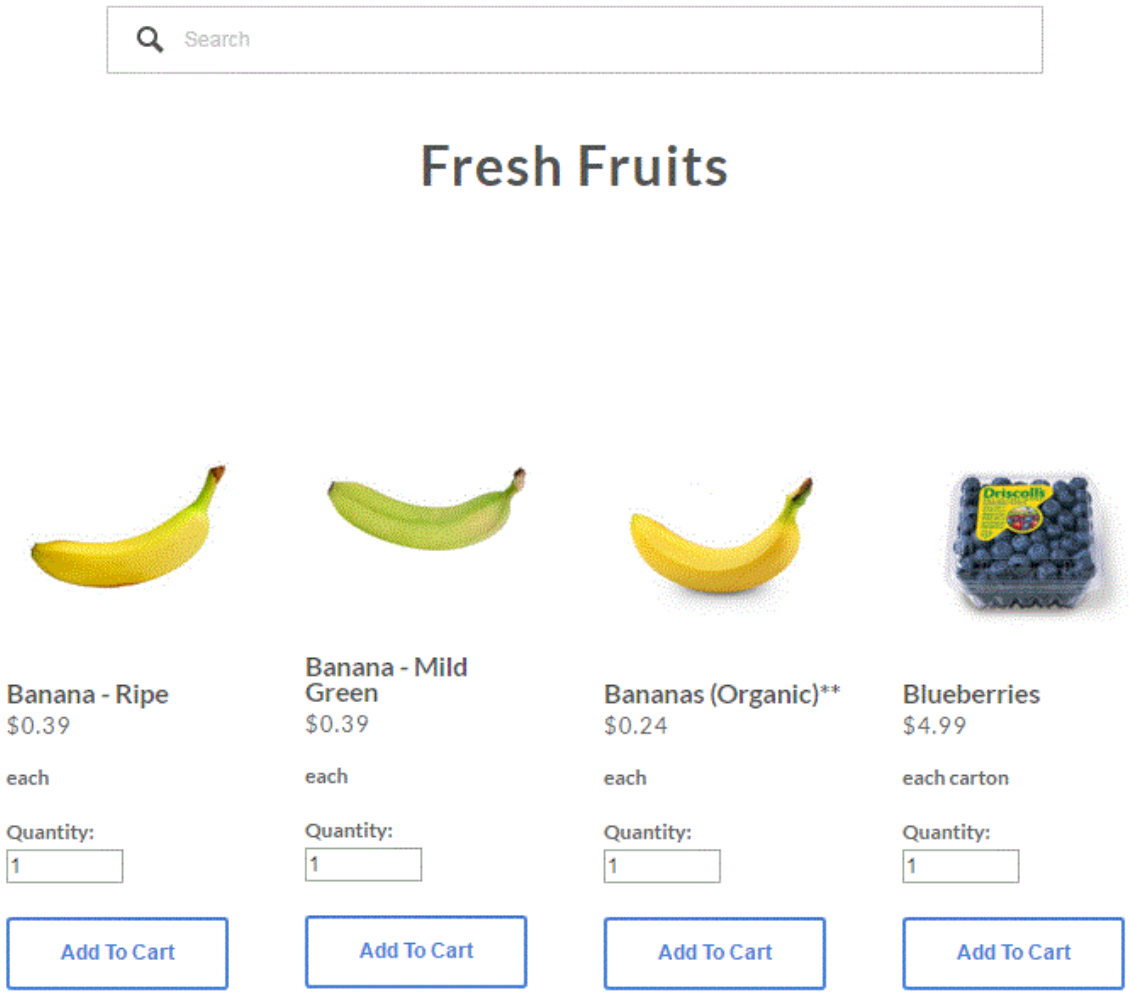
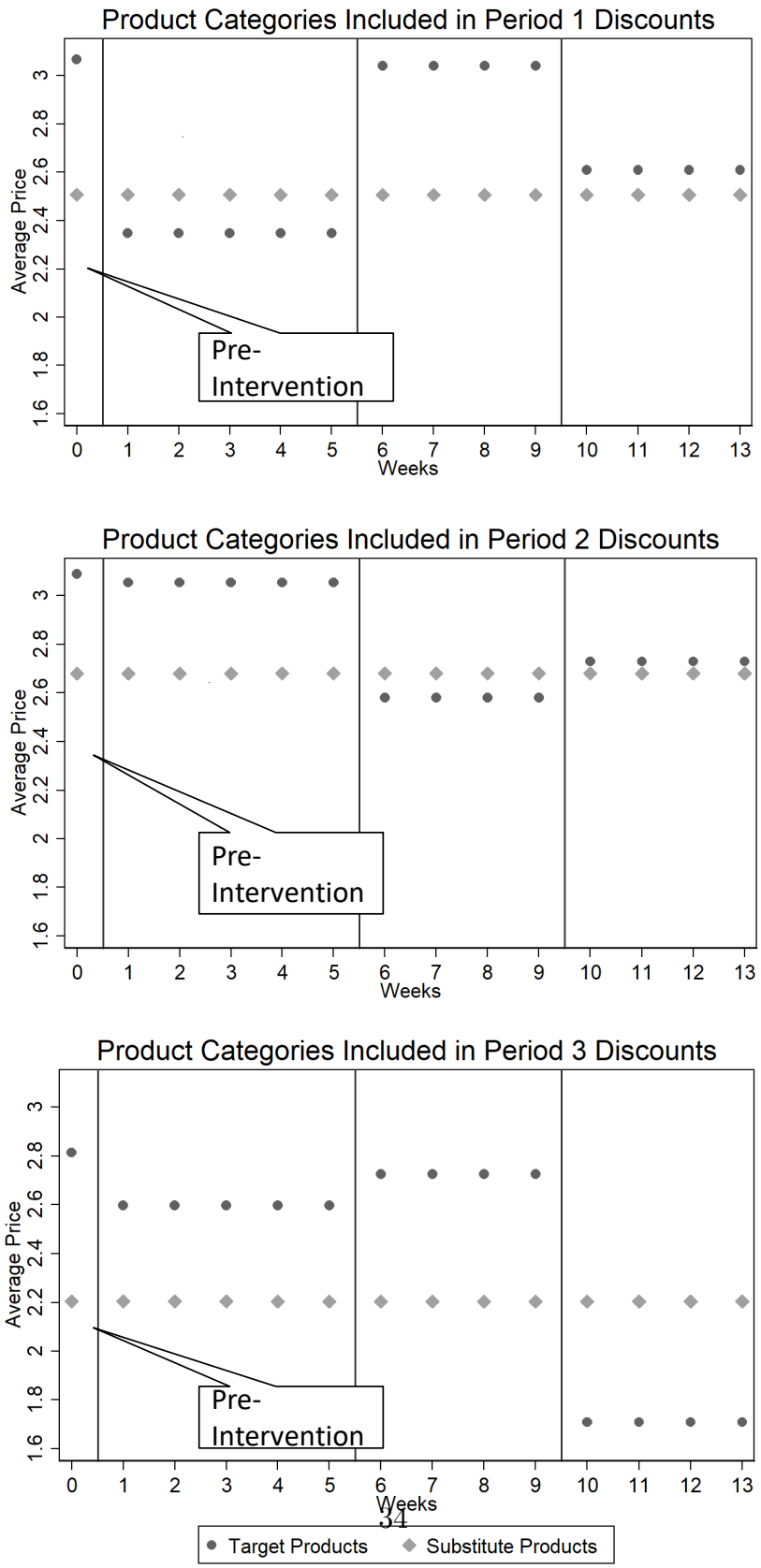


Figure 5: Price Variation in Target versus Substitute Items



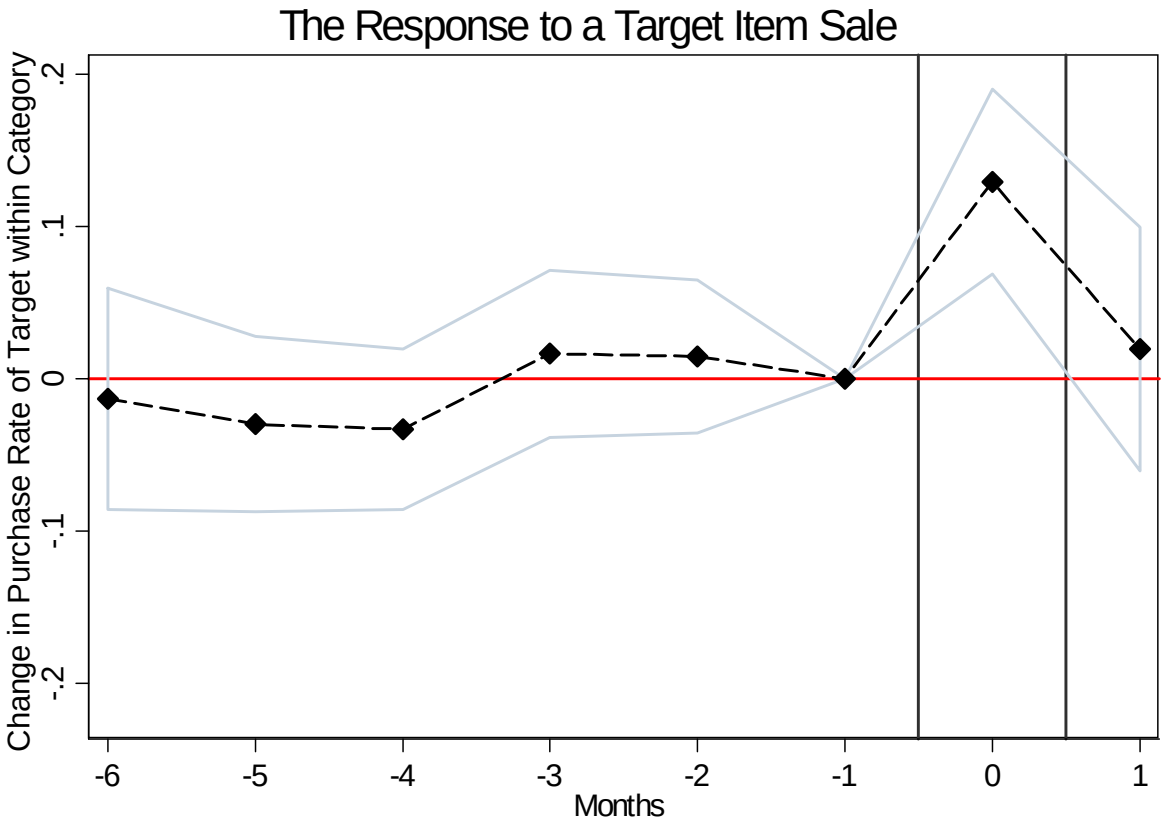


Figure 6: Results and 95 percent confidence interval from event study regression including category and shopper fixed effects.This analysis uses data on all purchases conducted in relevent categories from 6 months prior to the sale in that category up to 1 month after the sale ended. In the month leading up to the sale, target item purchases made up for 23 percent of purchases in category (s.d. 42).

Figure 7: Results and 95 percent confidence interval from event study regression including category and shopper fixed effects.This analysis uses data on all purchases conducted in relevent categories from 6 months prior to the sale in that category up to 1 month after the sale ended. In the month leading up to the sale, target item purchases made up for 24 percent of purchases in category (s.d. 43) in non-neighboring categories and 22 percent (s.d. 42) in neighboring categories.

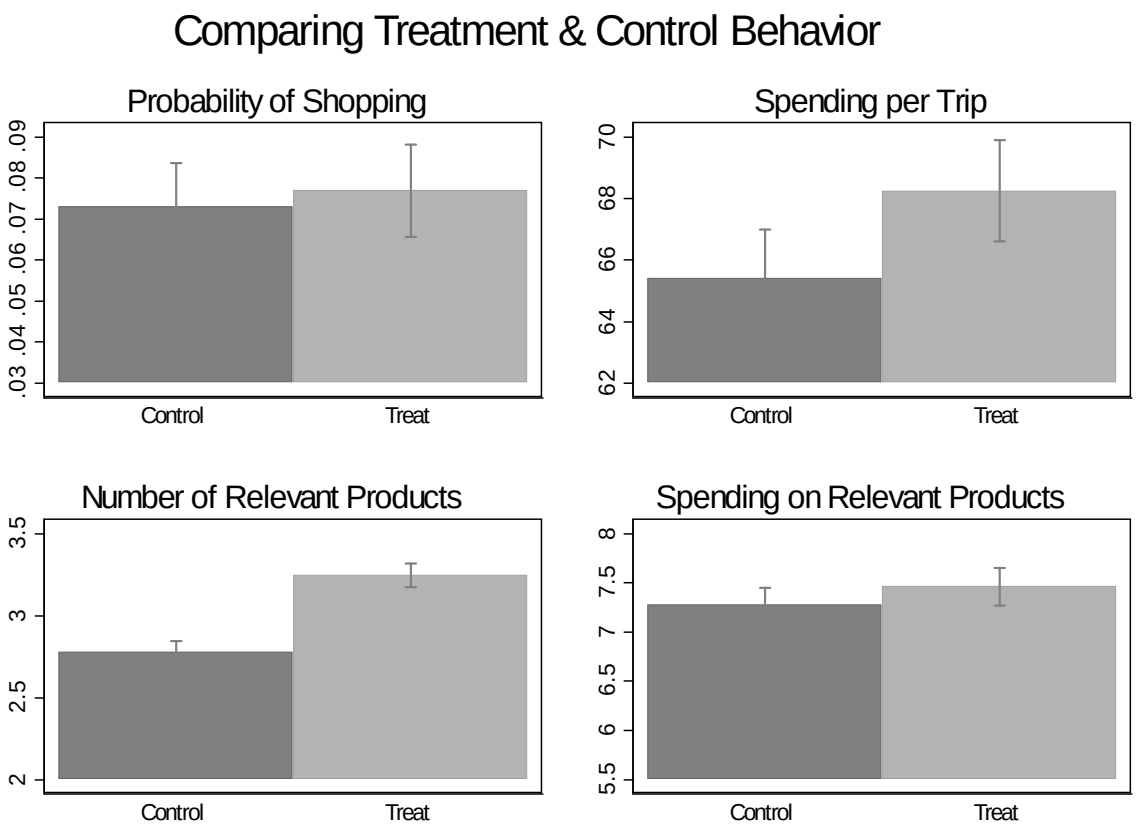


Figure 8: Mean and 95 percent confidence interval for comparing behavior of treatment and control group within the 13 weeks of the intervention. Number of relevant products and spending on relevant products is aggregated at the trip level.

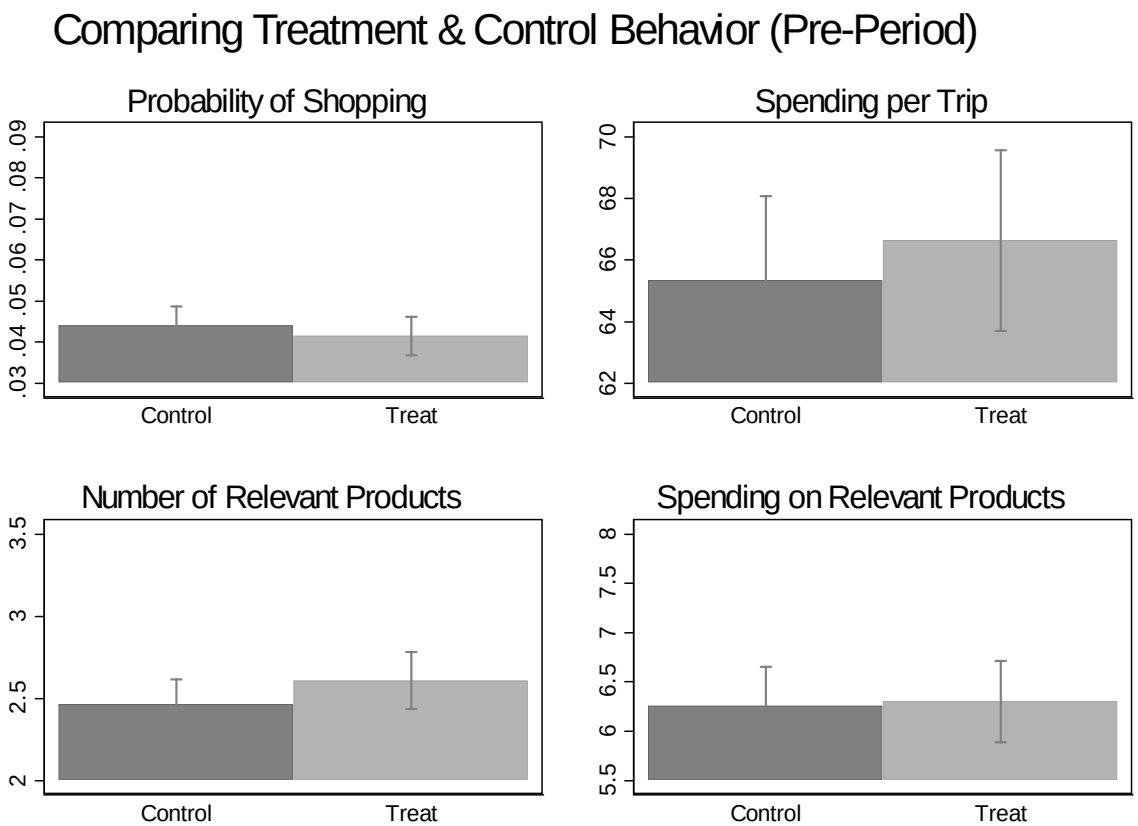


Figure 9: Mean and 95 percent confidence interval for comparing behavior of treatment and control group in the 13 weeks leading up to the intervention. Number of relevant products and spending on relevant products is aggregated at the trip level.

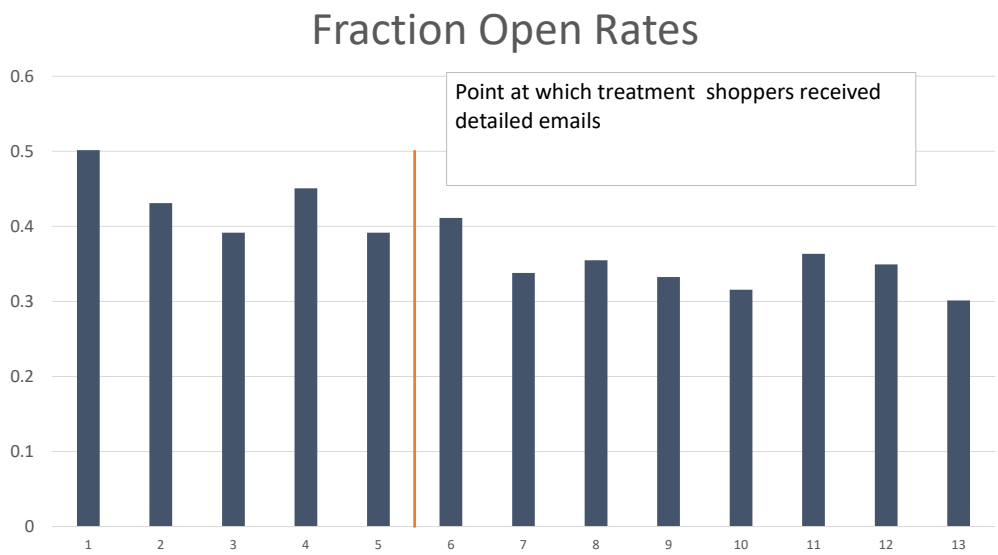


Figure 10: The fraction of shoppers who were flagged as opening their weekly email. We note that these percentages may not be fully accurate as the email-service was unable to track emails that were forwarded to other addresses and some virus-scanners may automatically activate the open-email flag.

Figure 11: The Change in Spending on Target Products in Response to a Sale

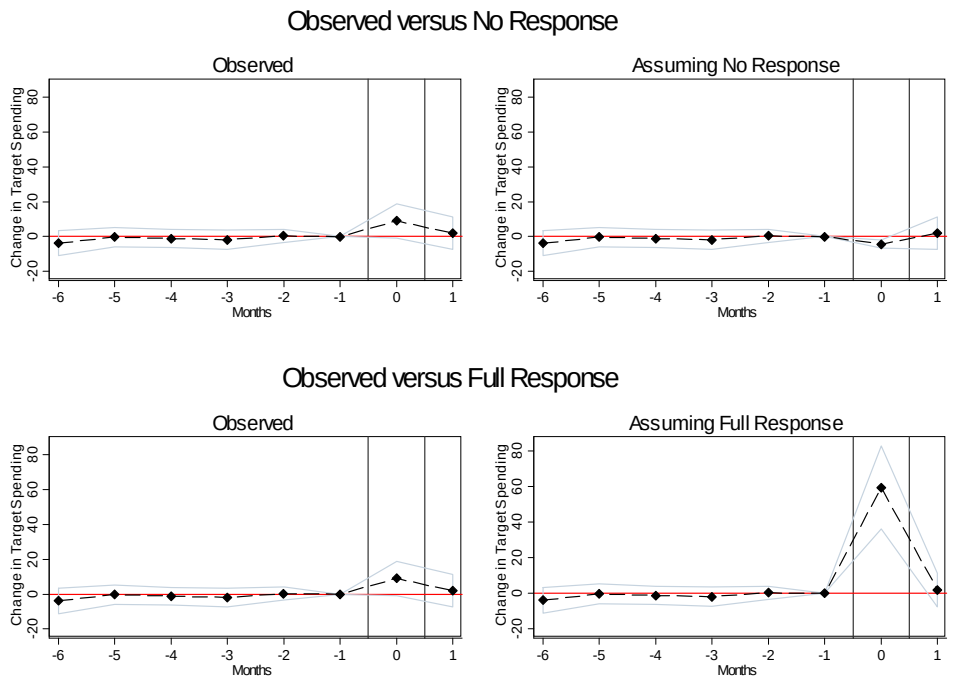


Figure 12: The Change in Category Spending in Response to a Sale on the Target Product

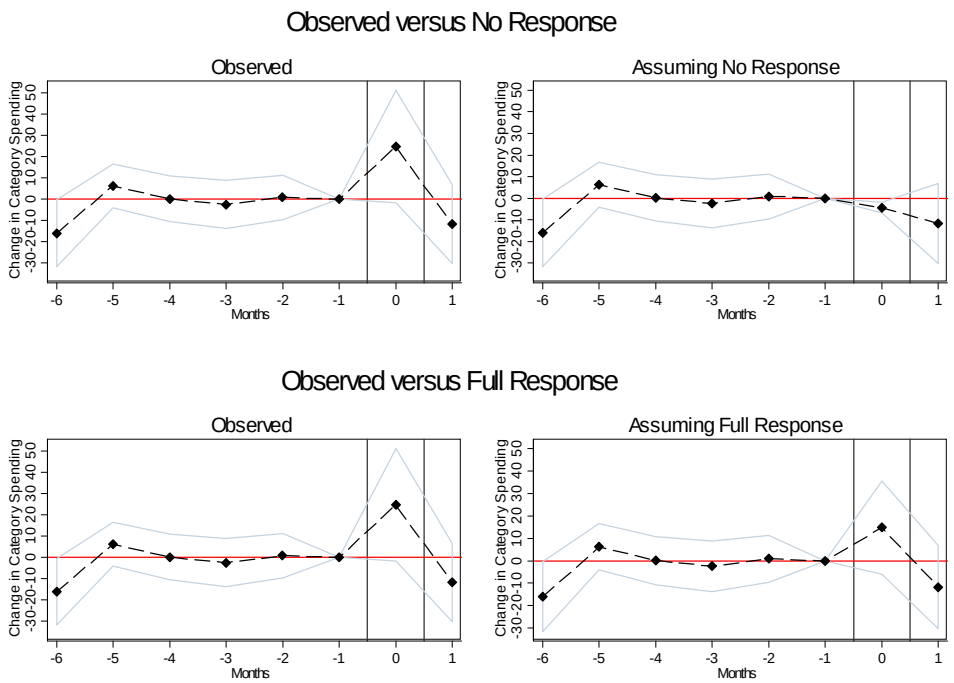


Table 1: Purchasing Frequency of Target and Substitute Items Prior to Experiment

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 Product Categories	Bread	Vegetables	Fruit	Perishable	All Product Categories
	(1)	(2)	(3)	(4)	(5)	(6)
Log Price	-1.586***	-1.424*	-1.619***	-3.276***	-1.010***	-1.418***
	(0.264)	(0.741)	(0.438)	(0.830)	(0.285)	(0.290)
Log Price x Same Line						-1.747**
						(0.784)
Item Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Items	1,079	126	243	222	416	1,079

Standard errors are presented in parenthesis and clustered at the item level.
An observation is defined by month and item (120 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.
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 7: The Differential Response of Treatment Shoppers

	Category	Target	Substitute	Category	Target	Substitute
	(1)	(2)	(3)	(4)	(5)	(6)
A. All Shoppers:						
Treat	-0.001	-0.0001	-0.001	-0.002	-0.001	-0.002
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Treat X Target Sale				0.0005	0.001*	-0.001
				(0.001)	(0.001)	(0.001)
Target Sale (TS)				0.002*	0.001	0.001*
				(0.001)	(0.001)	(0.001)
N	129220	129220	129220	129220	129220	129220
Mean of Dependent	0.008	0.002	0.006	0.008	0.002	0.006
Variable:	[0.09]	[0.048]	[0.075]	[0.09]	[0.048]	[0.075]
B. Never purchased this product/category on the site in the past:						
Treat	-0.001	-0.0002	-0.001	-0.0004	-0.0001	-0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Treat X Target Sale				-0.001	-0.0001	-0.001
				(0.001)	(0.001)	(0.001)
Target Sale (TS)				0.001*	0.001**	0.0003
				(0.001)	(0.001)	(0.0004)
N	109005	123812	112515	109005	123812	112515
Mean of Dependent	0.003	0.001	0.002	0.003	0.001	0.002
Variable:	[0.053]	[0.037]	[0.043]	[0.053]	[0.037]	[0.043]
C. Purchased this product/category on the site in the past:						
Treat	-0.003	-0.002	-0.002	-0.013	-0.010	-0.010
	(0.010)	(0.011)	(0.009)	(0.010)	(0.010)	(0.009)
Treat X Target Sale				0.019***	0.015*	0.017***
				(0.005)	(0.008)	(0.004)
Target Sale (TS)				-0.005	-0.002	-0.007***
				(0.003)	(0.006)	(0.003)
N	20215	5408	16705	20215	5408	16705
Mean of Dependent	0.036	0.024	0.031	0.036	0.024	0.031
Variable:	[0.188]	[0.153]	[0.174]	[0.188]	[0.153]	[0.174]

Standard errors are presented in parenthesis and clustered at the shopper and category level. Standard deviations appear in brackets. An observations is defined by a shopper, week, and item category. All specifications control for category and week fixed effects as well as an indicator for a high rebate week (a rebate of $10 versus $2.99).

Table 8: The Effect of Promotional Material on Shopping Behavior

	All Weeks			Identical Rebate Weeks		
	Category	**Target**	**Substitute**	**Category**	**Target**	**Substitute**
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Target Sale X Hist	0.018***	0.014	0.016***	0.024**	0.027**	0.018**
	(0.005)	(0.009)	(0.004)	(0.01)	(0.013)	(0.008)
Treat X Target Sale	-0.001	-0.0001	-0.0005	-0.002	-0.00037	-0.0008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Target Sale X History	-0.005	-0.004	-0.007*	-0.009	-0.011	-0.009
	(0.005)	(0.007)	(0.004)	(0.008)	(0.01)	(0.007)
Target Sale (TS)	0.001	0.001**	0.0001	0.002	0.001	0.0006
	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.0009)
Treat X Hist	-0.002	-0.007	-0.001	-0.016	-0.019**	-0.011
	(0.009)	(0.008)	(0.008)	(0.01)	(0.009)	(0.009)
Treat	-0.002*	-0.0003	-0.002**	-0.0002	0.000001	-0.0004
	(0.001)	(0.0004)	(0.001)	(0.001)	(0.0002)	(0.0005)
History of Purchase	0.03***	0.023***	0.028***	0.03***	0.023***	0.028***
(0/1)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
Item Category FE's	X	X	X	X	X	X
Week FE's	X	X	X	X	X	X
N ItemsxWeeks	129,220	129,220	129,220	59,640	59,640	59,640
Mean of Dependent	0.008	0.002	0.006	0.008	0.003	0.005
Variable:	[0.09]	[0.048]	[0.075]	[0.09]	[0.05]	[0.074]
A. Change in Purchase Rate of Treatment Group with History During Sale Period:						
TS + TSxHistory	0.014***	0.012***	0.008***	0.015***	0.017***	0.008
+ TreatxTS + TreatxTSxHist	(0.004)	(0.004)	(0.003)	(0.006)	(0.004)	(0.005)
B. Change in Purchase Rate of Control Group with History During Sale Period:						
TS + TSxHistory	-0.004	-0.002	-0.007*	-0.008	-0.01	-0.009
	(0.005)	(0.007)	(0.004)	(0.008)	(0.01)	(0.007)

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. History of Purchase is equal to 1 if the shopper purchased a relevant item (from this category in column (1) or of this type in columns (2) & (3)) in the pre experiment period. All specifications control for whether or not this is a high rebate week (a rebate of $10 versus $2.99).

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

Table 9: The Effect of Promotional Material on Shopping Behavior (Categories where Target Product is Organic)

	Categories w/ Organic		
	Category	**Target**	**Substitute**
	(1)	(2)	(3)
Treat X Target Sale X Hist	0.017**	0.004	0.016***
	(0.008)	(0.009)	(0.006)
Treat X Target Sale	-0.0005	0.0002	-0.0004
	(0.001)	(0.001)	(0.001)
Target Sale X History	-0.0006	0.006	-0.004
	(0.005)	(0.007)	(0.004)
Target Sale (TS)	0.001	0.001*	-0.0001
	(0.001)	(0.001)	(0.0005)
Treat X Hist	0.003	0.007	0.001
	(0.01)	(0.008)	(0.011)
Treat	-0.002**	-0.001	-0.002*
	(0.001)	(0.001)	(0.001)
History of Purchase	0.024***	0.011***	0.024***
in Category (0/1)	(0.006)	(0.004)	(0.006)
Item Category FE's	X	X	X
Week FE's	X	X	X
N ItemsxWeeks	92,300	92,300	92,300
Mean of Dependent	0.008	0.002	0.006
Variable:	[0.09]	[0.05]	[0.074]
A. Change in Purchase Rate of Treatment Group with History During Sale Period:			
TS + TSxHistory	0.017***	0.011**	0.012***
+ TreatxTS + TreatxTSxHist	(0.004)	(0.005)	(0.003)
B. Change in Purchase Rate of Control Group with History During Sale Period:			
TS + TSxHistory	0.001	0.007	-0.004
	(0.005)	(0.007)	(0.004)

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. History of Purchase is equal to 1 if the shopper purchased a relevant item (from this category in column (1) or of this type in columns (2) & (3)) in the pre experiment period. All specifications control for whether or not this is a high rebate week (a rebate of $10 versus $2.99).

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

Table 10: The Role of Search Cost in Determining the Effect of Promotional Material on Shopping Behavior

	Diff-Line Categories			Same-Line Categories		
	Category	**Target**	**Substitute**	**Category**	**Target**	**Substitute**
	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Target Sale X Hist	0.02***	0.014	0.019***	0.012	0.015	0.004
	(0.006)	(0.009)	(0.006)	(0.013)	(0.02)	(0.01)
Treat X Target Sale	-0.001	-0.00021	-0.0006	-0.0006	0.0004	-0.0001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Target Sale X History	-0.007	-0.003	-0.009*	-0.0026	-0.007	-0.004
	(0.005)	(0.005)	(0.005)	(0.016)	(0.02)	(0.014)
Target Sale (TS)	0.001	0.001*	-0.00001	0.003	0.003	0.0009
	(0.001)	(0.001)	(0.0006)	(0.003)	(0.002)	(0.0022)
Treat X Hist	-0.004	-0.003	-0.004	0.004	-0.019	0.01
	(0.007)	(0.008)	(0.008)	(0.022)	(0.021)	(0.018)
Treat	-0.002*	-0.0005	-0.002*	-0.002	0.0003	-0.002
	(0.001)	(0.0004)	(0.001)	(0.002)	(0.001)	(0.001)
History of Purchase	0.03***	0.023***	0.028***	0.024***	0.011***	0.024***
in Category (0/1)	(0.007)	(0.006)	(0.006)	(0.006)	(0.004)	(0.006)
Item Category FE's	X	X	X	X	X	X
Week FE's	X	X	X	X	X	X
N ItemsxWeeks	101,530	101,530	101,530	27,690	27,690	27,690
Mean of Dependent	0.007	0.002	0.005	0.013	0.004	0.009
Variable:	[0.082]	[0.043]	[0.069]	[0.114]	[0.063]	[0.094]
A. Change in Purchase Rate of Treatment Group with History During Sale Period:						
TS + TSxHistory	0.013***	0.013**	0.009**	0.012**	0.011***	0.001
+ TreatxTS + TreatxTSxHist	(0.004)	(0.006)	(0.004)	(0.005)	(0.004)	(0.006)
B. Change in Purchase Rate of Control Group with History During Sale Period:						
TS + TSxHistory	-0.006	-0.002	-0.009*	0.001	-0.005	-0.003
	(0.005)	(0.005)	(0.005)	(0.014)	(0.019)	(0.013)

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. History of Purchase is equal to 1 if the shopper purchased a relevant item (from this category in column (1) or of this type in columns (2) & (3)) in the pre experiment period. All specifications control for whether or not this is a high rebate week (a rebate of $10 versus $2.99).

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

Table 11: The Role of Salience and Information in High Search Cost Categories

	Special =Category in First Line			***Special*** =Detailed Period		
	Category	**Target**	**Substitute**	**Category**	**Target**	**Substitute**
	(1)	(2)	(3)	(4)	(5)	(6)
Target Sale (TS)	-0.006	0.005	-0.011**	-0.008	0.002	-0.009
	(0.005)	(0.003)	(0.005)	(0.008)	(0.004)	(0.008)
Treat X Target Sale (TS)	0.019***	0.001	0.018***	0.035***	0.002	0.033***
	(0.007)	(0.004)	(0.007)	(0.01)	(0.006)	(0.011)
Treat X TS X ***Special*** (S)	0.003	0.011*	-0.008	-0.028**	-0.001	-0.026**
	(0.019)	(0.007)	(0.015)	(0.014)	(0.007)	(0.013)
Special (S) X (TS)	-0.005	-0.015**	0.0102	0.003	0.002	0.0014
	(0.017)	(0.006)	(0.0134)	(0.011)	(0.006)	(0.0114)
N ItemsxWeeks	15,093	15,093	15,093	15,093	15,093	15,093
Mean of Dependent	0.03	0.007	0.022	0.03	0.007	0.022
Variable:	[0.173]	[0.086]	[0.148]	[0.173]	[0.086]	[0.148]
Change in Purchase Rate of Treatment Group During Sale Period:						
A. TS+ Treat x TS	0.013***	0.006**	0.007*	0.027***	0.004	0.023***
	(0.004)	(0.002)	(0.004)	(0.006)	(0.004)	(0.007)
B. Special : TS+ Treat x TS +	0.011	0.002	0.009*	0.003	0.005	-0.001
S x TS + Treat x TS X S	(0.007)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Change in Purchase Rate of Control Group During Sale Period:						
C. Special :	-0.011	-0.01**	-0.0008	-0.004	0.004	-0.008
TS+ Special x TS	(0.014)	(0.005)	(0.01)	(0.006)	(0.004)	(0.006)

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.All specifications focus on the 22 highsearch cost (DiffLine) categories and include product category, and week fixed effects. First Line (columns (1)-(3)) refers to the product category that appeared first in the email to
the treatment group. Detail (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. Additional controls include: an indicator variable for treatment, an indicator variable for whether or not this was a firstline category (columns (1)-(3)) or detailed email week (columns (4)-(6)), as well as this variable interacted with treatment, an indicator
for a high rebate week (a rebate of $10 versus $2.99) and a control for the number of times this shopper purchased in this category during the pre-experiment period.
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 12: A Closer Look at the Role of Information in the Purchase of Substitute Products in High Search Cost Categories

	Special =Detailed Period					
	Substitute	**Substitute**	**Substitute**	**Substitute**	**Substitute**	**Substitute**
	(1)	(2)	(3)	(4)	(5)	(6)
Target Sale (TS)	-0.009	-0.009	-0.011	-0.008	-0.009	-0.01
	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)
Treat X Target Sale (TS)	0.033***	0.033***	0.033***	0.033***	0.033***	0.033***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Treat X TS X ***Detail***	-0.026**	-0.021*	-0.018	-0.017	-0.016	-0.017
	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)
Detail X (TS)	0.001	-0.002	-0.001	-0.005	-0.001	0.002
	(0.011)	(0.011)	(0.01)	(0.01)	(0.009)	(0.012)
N ItemsxWeeks	15,093	13,932	12,771	11,610	10,449	9,288
Mean of Dependent	0.022	0.023	0.022	0.023	0.023	0.025
Variable:	[0.148]	[0.148]	[0.147]	[0.15]	[0.151]	[0.155]
Detailed Weeks Dropped	0	1	2	3	4	5
Mean Open Rate (Detailed)	0.346	0.352	0.358	0.363	0.370	0.377

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.All specifications focus on the 22 highsearch cost (DiffLine) categories and product category and week fixed effects. Detail refers to weeks where the treatment email provided personalized nudges towards onsale items and specifically mentioned that some organic items are on sale. The average open-rate of weekly emails in the pre-detailed period was 43%. Colums (2)-(6) consecutively drop weeks from the detailed period with low open rates. Additional controls include: an indicator for treatment, and indicator variable for whether or not this was a detailed email week, as well as this variable interacted with treatment, an indicator for a high rebate week (a rebate of $10 versus $2.99) and a control for the number of times this shopper purchased in this category during the pre-experiment period.
*Significant at 10%; **significant at 5%; ***significant at 1%

Table 13: The Effect of a Sale on Aggregate Demand & Supermarket Profit

	Total Category Purchases (1)	Total Target Purchases (2)	Total Substitute Purchases (3)	Total Category Spending (4)	Total Target Spending (5)	Total Substitute Spending (6)
Pre Sale (Month -5)	2.222	-0.148	2.926**	6.252	-0.216	6.468
	(3.135)	(0.973)	(1.394)	(5.232)	(2.829)	(3.829)
Pre Sale (Month -4)	1.481	0.185	0.556	0.118	-1.157	1.276
	(2.188)	(0.745)	(1.615)	(5.451)	(2.596)	(5.898)
Pre Sale (Month -3)	-1.148	-0.593	-0.074	-2.432	-1.803	-0.629
	(3.457)	(0.890)	(2.212)	(5.714)	(2.729)	(4.710)
Pre Sale (Month -2)	-0.866	0.094	-0.405	0.857	0.364	0.493
	(2.494)	(0.622)	(1.560)	(5.298)	(1.935)	(4.169)
Sale Month (Month 0)	17.630**	8.630***	8.778*	24.736*	9.055*	15.681
	(7.036)	(2.464)	(4.602)	(13.415)	(5.009)	(10.213)
Post Sale Month (Month 1)	-1.300	1.101	-7.027**	-11.728	1.919	-13.647
	(5.681)	(1.629)	(2.983)	(9.357)	(4.737)	(8.218)
N	199	199	199	199	199	199
Mean of Dependent Variable	29.623	6.357	19.889	60.687	15.268	45.419
	[30.413]	[8.721]	[18.284]	[56.426]	[19.505]	[44.296]

Standard errors are presented in parenthesis and clustered at the category level.
An observation is defined by category and month.
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%

A Appendix

Table A.1: The Differential Response of Treatment Shoppers: Logistic Model

	Linear Probability Model			Logistic Regression		
	Category	**Target**	**Substitute**	**Category**	**Target**	**Substitute**
	(1)	(2)	(3)	(4)	(5)	(6)
Target Sale (TS)	-0.005	-0.002	-0.007**	-0.102	-0.063	-0.257**
	(0.004)	(0.007)	(0.003)	(0.114)	(0.300)	(0.127)
Treat X Target Sale (TS)	0.019***	0.015*	0.017***	0.490***	0.677*	0.534***
	(0.006)	(0.009)	(0.005)	(0.149)	(0.372)	(0.164)
Calculated Marginal Effect:				0.016***	0.016	0.016***
Difference in dy/dTS by Treat				(0.006)	(0.010)	(0.005)
Item Category FE's	X	X	X	X	X	X
Week FE's	X	X	X	X	X	X
N Item CategoriesxWeeks	20,215	5,408	16,705	20,215	5,408	16,705
Mean of Dependent	0.036	0.024	0.031	0.036	0.024	0.031
Variable:	[0.188]	[0.153]	[0.174]	[0.188]	[0.153]	[0.174]

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. Each analysis is run only on shoppers who either purchased within the category (columns (1) & (4)) or purchased the target or substitute products (columns (2),(3),(5),(6)) in that category in the pre experiment period. All specifications include an indicator for whether this was a high rebate week (a rebate of $10 versus $2.99).
*Significant at 10%; **significant at 5%; ***significant at 1%