Behavioral Spillovers from Promoting Healthier Consumer Choices

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Abstract

This paper investigates the consequences of a randomized information-based intervention involving about 10,000 online grocery shoppers. The four-month "Swap and Be Healthy" experiment exposed consumers to the nutritional advantages of healthier product alternatives when they added less healthy versions of certain food items to their shopping baskets, on average leading to a significant increase in the purchase of healthier alternatives. Using machine learning techniques to characterize consumers, we analyze the relationship between direct responsiveness to the nudge and broader changes in behavior. More responsive consumers exhibit modest but discernible shifts toward healthier purchasing behaviors that extend beyond the immediate scope of the intervention. Less-responsive consumers engage in more active shopping behaviors, including spending more time shopping and making cost-saving substitutions. These results highlight the capacity of information-based approaches not only to affect isolated consumer decisions but also to shape behavior across multiple domains.

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1 Introduction

Obesity has been one of the major public health challenges of the past several decades, affecting both adults and children and households in both developed and developing countries. The World Health Organization (WHO) officially recognized obesity as a global epidemic in 1997 as it began "replacing more traditional public health concerns, including undernutrition and infectious disease as one of the most significant contributors to ill health" (WHO, 2000), with over 1 billion adults now being overweight and at least 300 million clinically obese. The "fundamental causes" are sedentary lifestyles and unhealthy diets, with diet playing a particularly important role as specific nutrients—high intakes of saturated fat, sodium, added sugar, and low intakes of fiber, fruits, and vegetables—contribute to disease and mortality beyond their impact on body weight (WHO, 2000). Nearly 8 million deaths worldwide are attributable to dietary risk factors (Murray et al., 2020) and direct medical costs in the U.S. alone exceed $250 billion (Cawley et al., 2021).

The predominant public policy response to promote healthier consumer choices is information provision. Most importantly, nutrition education and food labels reach large audiences. The vast majority of Americans indicate that they have heard of the U.S. Food Guide Pyramid, even though few follow its recommendations (Guthrie, Mancino and Lin, 2015). About 80 percent of U.S. adults report using nutrition facts labels and 72 percent report using nutritional content claims (e.g., "low fat") when making purchase decisions (Choinière and Lando, 2008; Guthrie, Mancino and Lin, 2015). Puzzlingly, however, excessive intakes of saturated fat, sodium, and added sugar persist despite the significant consequences and the availability of information.

More recent food guidelines, motivated by behavioral insights, come with "clear and actionablesuggestions ", e.g. "make half your plate of fruits and vegetables," "drink water instead of sugary drinks," and "switch to low-fat or fat-free milk (1%)" (Sunstein, 2013*a*). The latest version of *Dietary Guidelines for Americans*, published by the U.S. Department of Agriculture (USDA) and Department of Health and Human Services (HHS), recommends to "start with small changes to make healthier choices you can enjoy." One of the developers of U.S. dietary guidelines emphasizes that "You can still choose foods that you enjoy, but you need to align them with healthy eating patterns: less sugar, sodium, and saturated fat... Making small changes in your diet over time... can pay off in the long run" (NIH, 2016). Similar recommendations appear in dietary guidelines outside the U.S. as well.[1] However, making dietary choices that moderate the consumption of saturated fat, sodium, and added sugar remains difficult as significant quantities are "hidden" in everyday foods, with numerous examples cited in scientific research (Ponzo et al., 2021), the media (ABC, 2012), and messaging from governmental agencies (CHP, 2017). Marketing insights suggest the need to go further than the existing guidelines-based approach by developing new technologies that provide consumers with personalized and personally relevant nutritional information during shopping trips (Lowe, de Souza-Monteiro and Fraser, 2013).

This article uses comprehensive data on roughly 10,000 online shoppers to study a novel intervention that provides consumers with information when they add less healthy versions of certain food items to their shopping carts. The intervention, which we refer to as "Swap and be Healthy" (SABH), provides brief, actionable and specific health information at the time of the decision. The intervention is *informative* (shoppers learn about an item's nutritional content), *shopper-specific* (information pertains to a product the buyer is actively considering), *actionable* (shoppers receive specific suggestions for healthier alternatives), *brief* (information is communicated clearly and concisely), and *timely* (shoppers receive information while making decisions).

In partnership with an established online platform for supermarket shopping across all major retailers in Israel, we conducted a randomized field experiment to evaluate the SABH intervention. Shoppers randomly assigned to the intervention group receive information on particular nutrients and alternative products when they add to their shopping basket one of 57 common food items that a registered dietitian identified as having healthier alternatives. Over 9,588 shoppers added at least one of these products to their baskets during the three months of the experiment. The information consists of a simple statement about the improved nutrient profile of the alternative(s): less sugar, less saturated fat, less sodium, more fiber, lower glycemic index, and more iodine.[2]

[1]For example, the National Health and Medical Research Council in Australia notes (emphasis added), "Many of the health problems in Australia today are linked to poor eating habits. Too many people eat too much saturated fat, added salt, added sugars, and alcohol. *Even reducing these by small amounts can make us healthier.* It can help us manage our weight better and reduce our risk of chronic diseases like heart disease, stroke, Type 2 diabetes, some cancers, and chronic kidney disease" (NHMRC, 2015).

[2]Iodine deficiency, while uncommon in the U.S. is a "major public health problem worldwide" that affects approximately 2 billion people, with about 50 million exhibiting clinical symptoms, and is particularly concerning for pregnant women and children (Biban and Lichiardopol, 2017). In Israel, a national iodine intake survey in 2017 revealed that 85 percent of pregnant women and 62 percent

Figure 1 uses our raw data to illustrate the significant change in shopping behavior observed among treated shoppers during the intervention. While the demand for healthier alternatives overlaps at around 22 percent for shoppers in both the treatment and control group in the pre-intervention period, treated shoppers become significantly more likely to purchase these alternatives during the intervention period. We use a difference-in-differences approach to measure how the intervention changes demand for the healthier alternatives. We find that the intervention caused a 19 percent increase in demand for healthier varieties, with a corresponding decrease for less healthy products.

We also estimate the direct effect of receiving a nudge in a given category on the probability of purchasing the healthier alternative in that category. We conduct this analysis using OLS, fixed effects, and an instrumental variable specification. Our first stage results highlight the importance of differentiating between assignment to treatment and receiving treatment, as treated shoppers during the intervention period only received the SABH nudge for roughly 10% of purchase categories. The reason for this is that shoppers only received the SABH nudge when they added a less healthy version of the product to their basket in periods and locations where the healthier alternative in that category was in stock. When correcting for this, we find that receiving information on healthier alternatives resulted in a 200 percent increase in demand for healthier products (a 9 percentage point increase at a baseline purchase rate of 4 percent).

We then use the recently developed causal forest method (Athey and Imbens, 2016; Wager and Athey, 2018) to examine how the intervention impacts various types of shoppers differently. This method identifies covariates that best predict heterogeneous treatment effects, denoted as Conditional Average Treatment Effect (CATE) estimates, which capture the expected effects of the intervention on specific subgroups defined by their covariates.

We use these estimates to characterize the shoppers who are most and least responsive to the intervention. Shoppers most responsive to the intervention tend to exhibit a distinct profile. First, a primary predictor of a consumer's responsiveness to the intervention is their propensity to purchase products that the intervention specifically targets. It is specifically these shoppers who encounter a higher intensity of

of school-age children have insufficient iodine levels, putting adults at risk of thyroid disease and putting fetuses, infants, and children at risk of impaired neurocognitive development (Ovadia et al., 2017; Lazarus, 2020).

treatment as the health nudge appears only when adding a relevant product. Second, their baskets tend to be less healthy, containing fewer fruits and more junk food, and they are more likely to be from households with children and more likely to purchase alcohol. Third, they usually allocate less time to evaluate each product, tend to shop on weekdays rather than weekends, make more frequent but smaller shopping trips, and show a reduced tendency to choose on-sale items or follow recommendations for more cost-effective alternatives.

A unique aspect of our data is that it allows us to examine the impact of the SABH intervention on behavior across other dimensions of the shopping trip. Our results suggest that the intervention impacts the type of products that are added to baskets, as well as the cost and size of baskets, and the probability of switching to an alternative supermarket. These findings suggest that while the intervention promoted healthier products, it also had externalities regarding the consumption of junk food, overall nutritional value, price-per-unit costs, and the likelihood of switching to a cheaper supermarket. Interestingly, when we consider the overall consequences of the SABH intervention, we find that the intervention had an effect on the demand for products *outside* of the intervention. Shoppers who were more likely to respond to the intervention by purchasing the healthier alternative were less likely to change supermarkets, buy less junk food, and purchase products with lower levels of sugar and cholesterol during the intervention period. In contrast, shoppers who were less responsive to the intervention were more likely to change supermarkets and purchase products with higher levels of cholesterol.

The remainder of the paper is organized as follows. The following section discusses the relevant literature. Section 3 describes the experimental design and the data and presents summary statistics on shopping behavior. Section 4 presents our estimates of the direct impacts of the intervention. Section 5 considers heterogeneous treatment effects and identifies shopper types who are most and least likely to be impacted by the intervention. Section 6 analyzes broader responses to the intervention and discusses possible mechanisms. Section 7 concludes.

2 Literature

Our paper builds on three broad areas of existing work, including policy-oriented, experimental, and theoretical research. The first area of related work focuses on food policy. Existing approaches for promoting healthier food consumption such as information provision (Balasubramanian and Cole, 2002), incentives (Loewenstein, Price and Volpp, 2016; Olsho et al., 2016; Griffith, von Hinke and Smith, 2018), and nudges (Wilson et al., 2016; Cadario and Chandon, 2020) face several challenges. Complexity poses a significant barrier for information-based approaches such as descriptive nutritional labeling (Guthrie, Mancino and Lin, 2015).[3] Simpler forms of information such as evaluative nutritional labeling may also be ineffectual due to tastes or behavioral factors such as habits, present focus, or inattention (Horgen and Brownell, 2002). More importantly, any attempt to promote healthier food consumption in one area may result in *behavioral spillovers* or compensatory changes in other areas. Such spillovers can undermine attempts to promote healthier food consumption via information, incentives, or nudges, and possibly even lead to the opposite conclusion about their efficacy. An important advantage of our data is that we observe the decision maker's entire purchase, beyond the set of products considered in the experiment.

Our analysis contributes to a broader literature on behavioral spillovers (Dolan and Galizzi, 2015; Galizzi and Whitmarsh, 2019). Several studies document spillover effects within the domain of food choice on a small scale.[4] Wilcox et al. (2009) documents that the presence of a healthy option can lead to greater indulgence. Wisdom, Downs and Loewenstein (2010) find that providing calorie information at a fast-food sandwich chain causes a reduction in sandwich calories but does not reduce total calories. Griffith, von Hinke and Smith (2018) show that government-provided vouchers for fruit, vegetables, and milk do not lead to offsetting changes in spending on unhealthy foods (i.e., added sugar and saturated fats) but slightly increase total calories. Relative to this set of papers, our work not only measures behavioral spillovers using a large-scale experiment with detailed data but also characterizes the consumers who exhibit such compensatory effects.

Our study also enriches the literature on the design of information interventions. We develop a novel information-provision intervention by combining insights about

[3] Perhaps not surprisingly then, the literature shows mixed results on information about calories (Downs et al., 2013; Cawley, Susskind and Willage, 2020).

[4] Another set of papers examines spillover effects across domains, such as food choice and exercise or effort (Polivy, Herman and McFarlane, 1994; Urbszat, Herman and Polivy, 2002; Chiou, Yang and Wan, 2011; De Witt Huberts, Evers and De Ridder, 2012; Dolan and Galizzi, 2014; Buyalskaya and Shum, 2020; Trachtman, 2022).

effective design from previous experiments. In the marketing literature, Lowe, de Souza-Monteiro and Fraser (2013) estimate using a discrete choice experiment that 88 percent of respondents are willing to pay for hypothetical new technologies that would provide customized information such as nutrition alerts during their shopping trips.[5] Our intervention provides information on products the shopper is actively considering, following research on the importance of providing personalized rather than generalized information (Kling et al., 2012; Hoxby and Turner, 2013; Herber, 2018; Arteaga et al., 2022) as well as research emphasizing the timeliness of information provision (Hulshof and De Jong, 2006; Nahum-Shani et al., 2018).[6] The information, unlike that of nutrition labels, is simple (Sunstein, 2013*b*; Bhargava and Manoli, 2015) and consists of "clear and actionable" (Sunstein, 2013*b*) suggestions for alternative products. To maximize the usefulness of the information, we do not provide information about products in categories where such information would be unlikely to change consumers' prior expectations, such as chocolates or cookies (Araya et al., 2022). The subsequent adoption of our intervention as a permanent feature of the online platform corroborates the practical value of this combination of design features.

Our work also advances the recent literature that uses field experiments in the context of online shopping to evaluate strategies for promoting healthier food choices. These papers tend to analyze the effects of different labeling schemes on product demand, finding mixed results (Sacks et al., 2011; Finkelstein et al., 2019; Finkelstein, Ang and Doble, 2020; Shin, van Dam and Finkelstein, 2020). The few papers that consider the impacts of suggested product alternatives or default options (Huang et al., 2006; Coffino, Udo and Hormes, 2020) do not capture possible spillover effects.[7] In comparison, our paper characterizes the mechanisms through which suggested product alternatives affect food-related decision-making more broadly.

Finally, we offer a new perspective in the extensive literature on health-related

[5] While this stated preference approach is widely used in marketing, see Drake, Thakral and Tô (2022); Drake et al. (2022) and the references therein for examples across a broad set of fields within economics as well as recent methodological developments.

[6] Other recent work emphasizes that providing information in advance of making decisions can lead to healthier food choices (Brownback, Imas and Kuhn, 2021) or generally more forward-looking behavior (Thakral and Tô, 2020; Imas, Kuhn and Mironova, forthcoming; Thakral and Tô, 2022); however, in these settings, information consists of upcoming choice sets, whereas in our setting, information consists of specific attributes of the choice alternatives.

[7] In simulated online supermarket environments, treatments in which subjects are prompted with healthier product alternatives also find mixed effects (Forwood et al., 2015; Koutoukidis et al., 2019; Riches et al., 2019; Bunten et al., 2021; Jansen, van Kleef and Van Loo, 2021).

intertemporal decision-making. This literature primarily analyzes present-focused preferences (Ericson and Laibson, 2019), emphasizing that choices about immediate consumption tend to be inconsistent with longer-term goals such as health (Read and Van Leeuwen, 1998). For example, the survey article by Wilson et al. (2016) notes that field interventions for increasing healthier food choices take place almost exclusively in cafeterias, laboratories, and restaurants. The majority of food spending, however, occurs online or in supermarkets and therefore reflects decisions regarding future consumption. In fact, for populations with the highest obesity risks, food away from home shows no association with Body Mass Index (Drichoutis, Nayga and Lazaridis, 2012; Crespo-Bellido et al., 2021), further highlighting the importance of studying decisions on the food that is not immediately consumed. Our study thus offers a new perspective on health-related intertemporal decisions by examining future-oriented food choices in non-immediate consumption settings.

3 Swap and Be Healthy Intervention

In this section, we describe the platform where we conducted our field experiment, the nature of the experiment, and the data collected.

3.1 The environment

We conducted our field experiment on a leading online grocery shopping platform in Israel. This platform offers users a "smart" shopping experience, enabling them to easily compare the purchase cost of their shopping basket across different supermarkets and choose where they want to check out. Additionally, when a user adds a product to their basket, the platform automatically prompts them with cheaper alternatives if available. Given this context, our intervention focused on incorporating health considerations into this "smart" shopping experience.

Delving into the platform's core features, the first is to allow shoppers to compare their baskets across the four major supermarket chains. When a shopper assembles their basket, they can observe the cost of that basket in competing supermarkets. In instances where certain items, such as generic brands, are absent from another supermarket, the platform uses close substitutes. Shoppers are given the flexibility to transition between their supermarket of choice multiple times before settling on a final purchase.

In addition to facilitating price comparisons across supermarkets, the platform offers a "Swap and Save" feature designed to help shoppers save money within each supermarket. Whenever a shopper adds an item to their basket, the platform uses a proprietary algorithm to check for a cheaper close substitute or quantity discounts. If such options are available, a "Swap and Save" button appears on the screen. Clicking this button presents the shopper with choices to reduce the unit price of the added product, either by opting for more affordable brands or larger quantities. The shopper can then choose to replace their initial selection with one of the recommended alternatives or retain the original item and continue shopping.

To use the platform, shoppers must register for a free account and log in. Once logged in, users can choose to start their shopping trip in one of several supermarket chains.[8] After selecting a supermarket, the user can start adding items to their basket and utilizing the platform's features. Shoppers can add items to their basket from a direct search, a menu of product categories (e.g., dairy, fish, meat, produce), previous shopping trips, or promotional banners.

The platform logs all user activities. This includes the source of each item added to the basket, items that were added but then removed, the sequence in which items were added, swap and save prompts that were observed and those that were accepted, the time between each item that was added, the total duration of the shopping trip, supermarket switches, and the final basket sent to the retailer.

3.2 The experiment

In collaboration with a registered dietitian, we identified 65 food items in 15 categories of staple foods (e.g., milk, pretzels, pudding, and soup) that had healthier alternatives in terms of having less sugar, less saturated fat, less sodium, lower glycemic index, more fiber, and added iodine. The full list of these selected items, along with their healthier counterparts and the rationale for each healthier choice, appears in Table 1.

Two overarching goals influenced the selection of food items. First, we focus on nutritional components for which overconsumption or underconsumption is associated with an increase in disease risk. Excessive sodium intake can elevate blood pressure and elevate the risk of heart disease, while added sugars in food are linked to health

[8] Although the platform enables users to examine prices in any local supermarket, our analysis focuses on baskets created for online orders, which are sent directly to the retailer site upon completion.

issues such as weight gain, obesity, type 2 diabetes, and heart disease.[9] Saturated fats, commonly found in dairy products, can elevate the risk of heart diseases and strokes, leading the American Heart Association to advise limiting their intake.[10] Diets with a low glycemic index not only support the prevention of coronary heart disease in both diabetic and healthy subjects but also promote satiety and help manage food intake in those who are overweight or obese (Rizkalla, Bellisle and Slama, 2002). Iodine, primarily sourced from iodized salt in the diet, is crucial for growth and development, and its deficiency stands as the leading cause of preventable intellectual disability worldwide.[11]

Second, we selected healthier alternatives that closely resembled the unhealthy target items in both characteristics and price. For example, instead of suggesting brown rice as a healthier alternative to jasmine rice, we recommended a variety of white rice with a lower glycemic index (basmati rice). On average, the suggested healthier alternatives cost 2 NIS more than their counterparts, yet in about one-third of the categories, the healthier option was actually cheaper.

We randomly assigned 14,282 shoppers to either the treatment or control groups. Those in the treatment group encountered the SABH prompt every time they added one of the 57 designated less healthy varieties to their basket (in contrast with the "Swap and Save" feature which only appears if a shopper presses a button). As Figure 2 illustrates, the prompt showcases a list of healthier alternatives, detailing their prices and reasons for being healthier (e.g., reduced fat, no added sugars), allowing shoppers to effortlessly switch to a healthier choice with a simple click.

The intervention lasted for four months (May - August 2019). For each shopper in our sample, we collect data on any shopping basket created on the platform in the six months preceding the intervention and the three months after the intervention ended.

3.3 Data

Our analysis focuses on five databases collected by the online platform. These databases provide information on the basket choices of individual shoppers as well as

[9] See https://www.cdc.gov/heartdisease/sodium.htm and https://www.cdc.gov/nutrition/data-statistics/added-sugars.html.

[10] See https://www.heart.org/en/healthy-living/healthy-eating/eat-smart/fats/saturated-fats.

[11] See https://ods.od.nih.gov/factsheets/Iodine-HealthProfessional/.

the prices of alternative products within their chosen supermarket and among other online suppliers.

The "Products Added" database records the sequence in which each product was placed into the shopping basket. It specifies where the product was added from (e.g., free search, previous purchase, favorites), its price, any applicable discounts, the quantity purchased, whether a shopper considered or accepted cheaper product alternatives, and whether a shopper accepted a healthier alternative. The "Retailer" database contains the price of each basket across various online retailers, while the "Basket" database provides information on shopping time and the device used (app, computer, or mobile web). The "Swap" database offers details about the original item added to the shopping basket and its substitute, including the reason for the swap (health, price, or because the item is unavailable) and whether the swap was accepted. Finally, the "Prices" database is comprised of prices of all items at all stores during our study, facilitating the calculation of prices for unchosen alternative items.

Using these data, we construct a set of consumer characteristics based on their shopping behavior prior to the intervention.[12] We classified these characteristics into three domains: health preferences, lifestyle factors (Sacco et al., 2017), and price sensitivity.

General health awareness can potentially shape a shopper's response to the SABH intervention. On the one hand, health-focused shoppers might be most receptive to the information provided by the intervention. On the other hand, they may already know about the healthier alternatives and thus face little benefit from the prompts. To shed light on these factors, we construct measures of health-related characteristics by examining pre-intervention shopping patterns: the relative frequency of purchasing healthier alternative products, the order of buying produce versus junk food, the tendency to end a shopping trip with a junk food purchase, and the fraction of baskets containing junk food, alcohol, or cigarettes.

Lifestyle elements, such as having young children, religiosity, employment status, or available free time, may also influence responses to the intervention. For instance, families with young children, often balancing time constraints and health priorities, might find the prompts more beneficial. In addition, consumers who regularly buy from intervention-relevant product categories may exhibit stronger or weaker reactions depending on their shopping habits and tastes. Our analysis thus incorporates the

[12]We exclude shoppers who did not make any purchases in this timeframe.

following lifestyle variables: shopping during business hours and on each day of the week, purchasing products that have ultra-Orthodox (kosher) supervision, purchasing baby products, and the share of intervention-relevant products.

Consumers' financial considerations may also play a role in their response to health information. For instance, price-sensitive shoppers might exhibit a greater willingness to explore new products, especially when they align with cost savings. In many cases, the healthier alternative has a cost advantage, making it an attractive choice, but higher-priced alternatives may deter these consumers from responding to the intervention. We capture these factors by including the following pre-intervention characteristics: engagement with "Swap and Save" promotions, expenditures at the shopping basket and item levels, the tendency to purchase products at full price, and the tendency to select the supermarket that offers the lowest price for the shopping basket. The full list of features and their definition appears in Table 2.

To provide a benchmark for the typical shopping behaviors in our sample, we present summary statistics for the 8,463 shoppers observed during the pre-intervention period in Table 3. On average, shoppers make two shopping trips per month, spending approximately 580 NIS each time and filling their baskets within a 40-minute time frame. They take advantage of sales for approximately 5 percent of their purchases and opt for the platform's recommendations for more cost-effective alternatives 3 percent of the time. Roughly 60 percent of shopping baskets are purchased at the cheapest available supermarket. About 40 percent contain at least one baby product, while 20 percent contain at least one ultra-Orthodox product. A typical basket consists of 23 percent of its items as fruits and vegetables, with an additional 12-13 percent of items categorized as junk food.[13] About 90 percent of shopping baskets contain at least one junk-food item. Shoppers in the treatment and control groups exhibit similar average characteristics, as expected due to random assignment.

To examine the direct impact of the intervention on the probability of purchasing healthier alternatives, we construct a balanced panel dataset structured based on 15 shopper categories and three time periods (pre-intervention, during the intervention, and post-intervention). In this dataset, we track the behavior of each of the 8,381 consumers who shopped during the intervention period across the 15 categories

[13]Our definition of junk food includes items such as chocolate, candies, chewing gum, pastries, pizza, biscuits, cereal with added sugar, cookies, jams, sweet spreads, chips, pretzels, ice cream, drinks with added sugar, cakes, waffles, and halva, marzipan, and eastern desserts.

of products in the intervention. We focus on the fraction of times they purchase the healthier variety of each product in each period: before, during, and after the intervention.[14]

To investigate the nutritional implications, we gathered an extensive dataset containing detailed nutritional information at the product level. These data contain information on total calories, total fat, saturated fat, sodium, dietary fiber, sugar, protein, iron, carbohydrates, and cholesterol per serving for each product.[15] The primary source for obtaining this nutritional information is the platform that provided the product data. However, this source contains various gaps either because the product is no longer available for sale or because the relevant information is simply missing from the source. In these cases, we first attempt to collect the information manually by searching for the products online. If this approach does not yield the necessary information, we resort to broader categories (e.g., "canned peaches" instead of a specific brand) and scrape the nutritional data from Wolfram Alpha, which compiles this information from various external sources.

Table 4 provides a detailed nutritional breakdown per 100-gram serving of the typical product purchased by treatment and control shoppers before the intervention period. Each serving contains, on average, 92 calories, 3 grams of sugar, 240 milligrams of sodium, 2.4 grams of saturated fat, 1.15 grams of dietary fiber, 13 milligrams of cholesterol, 5 grams of protein, and 0.8 milligrams of iron.

As we cannot track additional purchases made outside of the platform, our study focuses on understanding the types of products shoppers choose to purchase rather than their overall nutritional intake. If the SABH intervention solely affects shoppers' decisions to switch to the suggested healthier alternatives, one might expect to observe no effect on the nutritional content of products chosen by treated shoppers outside the direct scope of the intervention. Alternatively, the intervention may impact shoppers' dietary choices beyond the specific products considered in the intervention.

[14] In cases where a shopper did not make any purchases within a specific product category during a particular period, the outcome takes a value of 0.

[15] The nutritional data for packaged items follow a standardized serving size of 100 grams, in accordance with Israeli packaging regulations.

4 Direct effect of the intervention

4.1 Effect of being assigned to receive SABH prompts

We begin our analysis by examining the impact of being assigned to receive the SABH prompts on the purchase of the healthier alternatives recommended to treatment shoppers. Specifically, we define $\text{FracHealthier}_{ict}$ as the fraction of times shopper i purchased a healthier alternative from category c out of all trips conducted during period t (and zero if the shopper did not purchase any healthier varieties in a given category). We model this outcome using the following difference-in-differences specification:

$$\text{FracHealthier}_{ict} = \alpha_1 \text{Treat}_i \times \text{During}_t + \alpha_2 \text{Treat}_i \times \text{After}_t + \theta_i + \rho_t + \delta_c + \varepsilon_{ict}, \quad (1)$$

Equation 1 allows us to measure the causal effect of the SABH intervention on the share of healthier purchases both during the intervention period (α_1) and after the intervention period (α_2). We include shopper fixed effects (θ_i), category fixed effects (δ_c) and time period fixed effects (ρ_t) to control for any pre-existing differences in demand between treatment and control shoppers as well as time trends in demand for healthier products. To capture changes in the demand of healthier products for treated shoppers relative to control shoppers across all 15 categories, we estimate Equation (1) using the balanced panel dataset described in Section 3.3, adjusting standard errors for clustering at the user level.

Across all shopper-category pairs, the baseline probability of purchasing one of the healthy varieties of the intervention products is 4.2 percent. During the intervention period, the probability of purchasing one of the healthy varieties across all shopper-category pairs increases to 5 percent (column 1 of Table 5). This corresponds to a 19 percent increase in the probability of purchasing a healthier product during the intervention period. The magnitudes of this estimate remains stable when we add fixed effects for categories (column 2) and shoppers (column 3). After the intervention period ends, about one-quarter of the effect on the share of healthier purchases persists.

To facilitate the interpretation of these magnitudes, we also estimate Equation (1) using a dataset of relevant purchases, in which each purchase of an experimental product corresponds to a separate observation, and the outcome variable is an indicator for purchasing the healthy rather than the unhealthy variety of the experimental product (see Appendix Table 2). At baseline, shoppers purchase less healthy varieties about four times as often as they purchase the healthier alternatives. Relative to this baseline rate, the share of healthy purchases among intervention products increases from 21 percent to 25 percent (columns 1 to 3), corresponding to a 19 percent increase as in the balanced panel analysis. Figure 3 illustrates the effect of the intervention by examining the probability of purchasing a healthier alternative for shoppers in the treatment and control groups, before and during the intervention period. Shoppers in the treatment group are about 5 percentage points more likely to select the healthier alternative during the intervention period. This holds regardless of whether the healthier alternative has a price advantage over the less healthy version. In fact, the effect of the intervention exceeds that of moving from a price disadvantage of 7 NIS (approximately 2 USD) to a price advantage of 7 NIS.

The estimates in Table 5 columns (1) to (3) understate the impact of the intervention because, in practice, not all shoppers assigned to the treatment group received SABH information. One part of the failure to receive SABH prompts is due to preferences. In particular, shoppers who did not purchase the less healthy product varieties relevant to the experiment naturally do not receive any SABH information. Another part of the failure to receive SABH prompts is due to constraints. For instance, a shopper would not receive SABH prompts after adding a relevant product to their basket if the healthier alternative was not available at the time they shopped, e.g., due to a stockout. In addition, the use of certain web browsers or advanced ad blockers potentially interfered with the delivery of the SABH intervention.

Thus, to analyze the effect of being assigned to receive SABH information on the group of shoppers for whom the intervention is relevant, we focus on the subsample of shoppers who (i) purchase at least one of the less healthy versions of the experimental products in the period before the intervention, and (ii) receive at least one SABH prompt during the intervention period if they are in the treatment group. Restriction (i) maintains a balance between the composition of the treatment and control groups. Restriction (ii), on the other hand, only removes shoppers from the treatment group. If treatment group shoppers who never received SABH prompts were disproportionately less likely to buy the healthier varieties, this would lead to an overestimation of the effect of the intervention. However, our data show the opposite: treatment group shoppers who never receive SABH prompts purchase healthy varieties in 37% of purchases involving experimental products, compared to only 21% for treatment group shoppers who receive at least one SABH prompt.

In the subsample of relevant shoppers, the estimated effect of being assigned to receive SABH information grows by 20% during the intervention period and by 60% after the intervention period (see columns 4 to 6 of Table 5). Imposing only restriction (i) does not materially change the effect sizes (see columns 1 to 3 of Appendix Table 1), suggesting that the increase in magnitudes arises primarily due to the removal of shoppers who failed to receive the SABH prompts. We also confirm that the results remain stable when we remove shoppers who begin their shopping trips with a pre-populated basket, i.e., from a pre-defined list or a previous shopping basket (see columns 4 to 6 of Appendix Table 1). Across all of these subsamples, the purchase rate of the healthier varieties remains significantly elevated after the intervention period ends.

4.2 Effect of receiving SABH prompts

The previous section focuses on how being assigned to receive SABH information affects the decision to buy the healthier alternative, both overall and among the group of shoppers for whom the intervention is relevant (i.e., who actually view a SABH prompt in at least one of the 15 product categories). Both of these constitute Intent-to-Treat (ITT) estimates of the impact of the intervention, albeit for different samples of shoppers. Since a shopper who receives an SABH prompt in a given product category will not necessarily receive prompts in other categories, this effect does not capture the direct consequences of receiving an SABH prompt. We now proceed to analyze these direct consequences by using assignment to the SABH treatment as an instrument for receiving SABH information.

We seek to uncover the relationship between receiving the prompt and decisions to purchase the healthier alternative:

$$\text{FracHealthier}_{ict} = \beta_1 \text{ReceivedSABH}_{ic} + \theta_i + \delta_c + \rho_t + \varepsilon_{ict}, \tag{2}$$

where ReceivedSABH_{ic} is an indicator for shopper i receiving at least one SABH prompt in category c. The OLS estimate of β_1 provides an unbiased estimate of the Average Treatment Effect of receiving SABH information as long as receiving the SABH prompt is unrelated to omitted factors that determine purchasing decisions of the healthier alternatives (ε_{ict}). However, as we have discussed previously, only treated shoppers who add the less healthy product varieties to their shopping basket receive the SABH prompt; thus, shoppers prone to making healthy choices will be less likely to receive the prompt. This would bias the OLS estimate of β_1 in the negative direction since receiving the prompt is correlated with lower tendencies toward healthy decision-making. In addition, treated shoppers with more advanced ad blockers may not have received the SABH prompt. To the extent that these more tech-savvy consumers are also more well-informed about health issues or prefer healthier products, receiving the SABH prompt would exhibit an even stronger negative correlation with factors that determine decisions to purchase the healthier alternative.

To overcome these endogeneity concerns, we leverage the random assignment to the treatment group. Assignment to the treatment group impacts the probability of receiving the SABH nudge but does not correlate with the factors discussed above or any other omitted determinants of healthier purchasing decisions. To estimate the effect of receiving SABH information on decision-making during the intervention period, we use the pre-intervention and during-intervention data to estimate Equation (2), with being in the treatment group during the treatment period ($\text{Treat}_i \times \text{During}_t$) as an instrument for receiving a SABH prompt in a given category (ReceivedSABH_{ic}). We follow the same approach using the pre-intervention and post-intervention data to estimate the extent to which the effect of the SABH information persists, with being in the treatment group after the intervention period ($\text{Treat}_i \times \text{After}_t$) as an instrument. This allows us to measure the impact of receiving an SABH prompt in category c during the intervention period on the probability of purchasing healthier product varieties after the intervention ends.

Shoppers assigned to the treatment group see SABH prompts on average in 9 percent of all product categories, as the first stage estimates in Table 6 show (without and with category and shopper fixed effects in columns 1 and 2).[16] Recall that shoppers do receive the SABH prompt if they directly purchase the healthier product variety within a given category, shop when the healthier alternative is out-of-stock, do not purchase in a given category at all during the intervention period, or use certain ad blockers. The fact that 91 percent of shopper categories did not receive SABH information suggests that the effect of receiving SABH information is an order of magnitude larger than the ITT estimates from Section 4.1.

We find that viewing the SABH prompt in a given category more than triples the fraction of healthier alternatives purchased in that category during the intervention

[16]The first-stage estimate is highly precise, mitigating weak instrument concerns.

period (see columns 3 and 4 of Table 6 Panel A). Specifically, we find a 9 percentage point increase relative to a baseline of around 4 percent. This aligns with the ITT estimates discussed previously, as a 0.8 percentage point (19 percent) effect of being assigned to receive the treatment on purchasing healthier alternatives largely driven by the 9 percent of cases in which shoppers view SABH prompts for a given category implies a 9 percentage point (210 percent) effect of actually receiving the treatment. For comparison, we also compute OLS estimates of β_1 from Equation (2). The OLS estimates are biased in the negative direction relative to the IV estimates (see columns 5 and 6 of Table 6), consistent with our previous discussion about how receiving the SABH prompt correlates negatively with healthy preferences.

We also find that over one-fourth of the effect persists beyond the intervention period. For product categories in which shoppers receive at least one SABH prompt during the experiment period, the purchase rate of healthier alternatives remains elevated by 2.2–2.5 percentage points in the three months after the end of the intervention period (see columns 3 and 4 of Table 6 Panel B). Thus, the intervention leads to a persistent 50–60 percent increase in the purchase rate of healthier alternatives compared to the baseline of 4.2 percent.

5 Categorizing consumers by responsiveness to the intervention

5.1 Methodology for categorizing consumers

We use the causal forest methodology to identify the treatment effect of the intervention on each specific subgroup of shoppers. To estimate the CATE, we define a list of features (see Table 2) that are likely to impact the decision to purchase healthier products. These features generally categorise shoppers based on their healthiness, thriftiness, and general demographics.[17] We can then estimate the conditional average treatment effect ($\tau(z)$) as:

$$\tau(z) = \mathbb{E}[y_{ic}(1) - y_{ic}(0) \mid Z_i = z] \tag{3}$$

[17] Note that each feature is defined in the pre-period to satisfy the stable unit treatment value assumption (Rubin, 1978). As we have a randomized controlled trial, we can assume unconfoundedness (see Athey and Imbens, 2016, p. 4).

Where $y_{ic}(1)$ is the probability of selecting a healthier alternative product in category c for individuals with characteristics z in the treated group (treatment=1) and $y_{ic}(0)$ is this outcome for similar individuals in the control group. Note that estimating Equation 3 without conditioning on $Z_i = z$ is the population average treatment effect which we measure in our standard DID model.

We run the causal forest model on the same balanced panel of shoppers used in the difference-in-differences analysis so that each shopper has one observation per category during the intervention period (even if this shopper has made multiple purchases during this period). In cases where the shopper has not bought any products in a category, the outcome is, therefore, naturally missing. In these cases, we set the outcome to 0. This gives 15 observations per shopper in each period.

5.2 Defining most- and least-responsive shopper types

To identify which shoppers were most and least impacted by the SABH intervention, we estimate the conditional average treatment effect (CATE) for each shopper in our database following the approach outlined in the previous section. Once we have calculated the CATE estimate for each shopper, we label more-responsive shoppers (those most impacted by the intervention) as those with predicted CATEs in the top 25 percent and less-responsive shoppers (those least impacted by the intervention) as those with predicted CATEs in the bottom 25 percent. Table 7 reports the differences in the observed characteristics of more-responsive and less-responsive consumers. The features are ordered within their feature category (general, price-related, health-related, and lifestyle) by their absolute value so that the first one shows the largest absolute difference between the less-responsive and more-responsive groups.

It is not surprising that shoppers who shopped more frequently on the site and had larger supermarket baskets during the pre-period (and were therefore more likely to shop during the intervention period and receive the SABH nudge) tended to be more impacted by the intervention. A similar difference in size but with an opposite sign can be seen for purchasing on-sale items and swapping supermarkets, suggesting that those most impacted by the intervention may be less price sensitive. While the most impacted shoppers were more likely to have had experience with purchasing the healthier alternative, we find that generally these shoppers had less healthy tendencies such as being more likely to have added junk food to their basket. make sure this is up to date with new causal forest variables: fraction of products removed, not just junk

We can apply this categorization of more-responsive and less-responsive shoppers to the difference-in-differences analysis in Section 4.1. In particular, we can re-estimate Equation (1) for more-responsive and less-responsive shoppers separately. When running the analysis on the more responsive shoppers (top panel of Table 8), we observe a 47–60 percent increase in the probability of purchasing a healthier alternative during the intervention period and a nearly 10 percent increase after the intervention period. In contrast, less-responsive shoppers, if anything, decrease consumption of healthier alternatives (bottom panel of Table 8)).

Similarly, we can replicate the IV analysis from Section 4.2 separately for the more-responsive and less-responsive shoppers. For the more responsive group, viewing the SABH prompt in a given category increases the fraction of healthier alternatives purchased in that category during the intervention period by a factor of 8–9 and after the intervention period by a factor of 1.5–3 (see columns 3 and 4 of the top panel of Table 6). The less-responsive group, by contrast, exhibits a decrease in healthier purchases.

6 Spillover effects of the intervention

6.1 Methodology for estimating spillovers

While our intervention focuses on encouraging consumers to make healthier choices for certain goods, there are several reasons why decision-making beyond the direct scope of the experiment may change. For example, the SABH nudge might raise shoppers' awareness of nutrition more broadly, potentially leading them to choose healthier products among those not directly covered by the intervention. Alternatively, if shoppers have a target for healthy consumption and choose to balance their selection of healthier alternatives with less healthy indulgences, the average product added to their basket during the intervention period may not exhibit an overall improvement in nutritional quality and may even be less healthy than their previous selections.

To analyze how the intervention may affect shopping decisions more generally, we use LASSO (Least Absolute Shrinkage and Selection Operator) regression (Tibshirani, 1996). This is a powerful method for variable selection and model regularization, which are particularly useful when working with data sets containing a large number of predictors.

We consider a wide range of factors that could potentially be influenced by the intervention, such as expenditure patterns, nutrient composition, and shopping behaviors. We begin by confirming that none of the variables predict treatment status in the pre-experiment period. This provides further evidence of balance between the treatment and control groups, consistent with successful random assignment.

We then assess the ability of these variables to predict treatment status using measures during the experiment period. The underlying logic behind this approach is that variables that emerge as significant predictors of treatment status after the intervention start to reveal behavioral changes attributable to the treatment—i.e., spillover effects of the intervention. The capability of LASSO to accommodate a large number of predictors while reducing model overfitting makes it well-suited for this analysis, allowing us to identify which aspects of consumer behavior are affected by the intervention.

6.2 Effects beyond the scope of the intervention

Having established the role of LASSO regression in our analysis, we proceed to introduce the specific aspects of the shopping experience that we consider when analyzing spillover effects. The basic features include metrics such as the total value of the shopping basket, time spent shopping, and proxies for price sensitivity such as whether a shopper bought items on sale, switched supermarkets, or bought at the cheapest supermarket. In addition to these basic features, we also consider three other sets of variables. One set consists of the fraction of spending falling into specific categories such as junk food, produce, products tailored to the ultra-Orthodox community, and products for children. The second set consists of expenditures in each product category. The final set of variables focuses on the nutritional content of the products purchased, such as sugar, sodium, and cholesterol levels.

To systematically examine the effects of the intervention and ensure our conclusions are robust, we define a number of specifications. The most comprehensive specification consists of all four sets of variables. We consider three alternative specifications that each maintain the basic features but drop one of the additional sets of variables.

We apply LASSO regression separately for the two types of shoppers, those most responsive to the intervention and those least responsive to the intervention. To obtain reliable conclusions, we ran the LASSO regression 1,000 times (with different seeds) for each specification and each group of shoppers. We then average the results of these runs to obtain our final estimates. This provides us with a comprehensive assessment of the factors influenced by the intervention while safeguarding against findings that may arise due to random chance. We present results from the most comprehensive specification, with the full list of variables, in Table 10.

The overarching pattern that emerges from these analyses is that the intervention appears to influence distinct behavioral shifts in the two groups of shoppers. Specifically, the intervention encourages the most responsive group to make healthier purchasing decisions outside the direct scope of the intervention but has the opposite effect for the least responsive group. In addition, the intervention prompts the least responsive group to engage in more active search behavior.

The strongest and most consistent effects we observe are more frequent supermarket switching and an increase in saturated fat purchased among the group that is least responsive to the intervention. The increase in supermarket switching aligns well with other patterns for this group such as a decrease in prices and increased time taken between adding items to their shopping baskets. These factors suggest that the intervention prompts the least responsive group to explore more options, compare prices, and generally be more deliberate in their shopping decisions. Moreover, the increase in saturated fat aligns with other indications of less healthy decision-making, such as an increase in junk food and a decrease in fruits and vegetables.

The group most responsive to the intervention, by contrast, exhibits a consistent tendency toward making healthier choices. Across all specifications, we find that this group purchases fewer junk food items, reduces saturated fat consumption, and tends to purchase products with more fiber and less cholesterol. In addition, their purchases tend to have higher prices. While we also see some evidence of increases in sodium, the overall patterns suggest that the intervention has a secondary effect of further encouraging healthier purchasing decisions among the most responsive group.

In addition to the consistent patterns highlighted above, we also observe some effects on other shopping-related behaviors. For example, Table 10 shows an increase in “Swap and Save” offers opened (but not “Swap and Save” offers accepted) for the most responsive group. These effects, however, do not detract from the overall patterns highlighted above.

6.3 Mechanisms

We conclude by discussing potential mechanisms for why the group least responsive to the intervention shows a pattern of increased search behavior during shopping.

One possible explanation is the role of information. The intervention itself serves as a source of new information, making shoppers aware of healthier or potentially more cost-effective alternatives. Even if they do not ultimately choose the healthier option, this knowledge could prompt them to spend more time exploring their choices, thereby leading to the increased time spent shopping that we've observed.

Another possible mechanism is guilt or internal conflict. In particular, the intervention may trigger a sense of guilt for not selecting the healthier alternative, leading shoppers to take more time to deliberate on their options. This emotional state might also drive them to compensate by making choices they perceive as "better" in some other way that doesn't necessarily align with healthiness, such as being more cost-effective.

Skepticism could also play a role. If shoppers perceive the intervention as merely a marketing tactic, they might scrutinize their choices more closely to avoid feeling manipulated. This increased level of scrutiny could result in them spending more time shopping while not necessarily making healthier choices.

A final factor we consider is cognitive load. On the one hand, decision fatigue might prompt quicker, less thoughtful choices, a pattern inconsistent with our results. On the other hand, an increased cognitive load might make shoppers more susceptible to other decision-making heuristics, such as opting for cheaper items or experiencing indecisiveness, which could contribute to the longer shopping durations we observe.

7 Conclusion

The worldwide obesity crisis demands impactful interventions. Over the past few decades, many have adopted strategies such as mandated nutritional labeling. Despite these efforts, much of the literature indicates that these labels might not significantly influence consumer choices (Balasubramanian and Cole, 2002; Van Herpen and Van Trijp, 2011). A recurring observation is that the sheer complexity of nutritional information is challenging for consumers (Downs, Loewenstein and Wisdom, 2009). As a result, various countries including Chile, Israel, the UK, Canada, and Ecuador have introduced simplified labeling techniques. However, these approaches, too, have mixed results (see the meta-analysis by Cecchini and Warin, 2016).

Amidst this backdrop, the SABH intervention emerges as a promising direction. The approach of making healthier choices as simple as clicking a button capitalizes on the digital habits of modern consumers. The roughly 20 percent overall increase in healthier product purchasing rates during the intervention period provides an encouraging result. Furthermore, the richness of the data from the online shopping platform further reveals insights into consumer behavior. Machine learning analysis of the SABH intervention points to specific consumer types responding most favorably, notably those who shop more frequently, purchase more products, and buy junk food.

In addition, we observe behavioral shifts in shoppers that suggest consequences beyond the direct scope of the intervention. Some shoppers—those who are least likely to respond to the intervention by selecting healthier alternatives—spent more time shopping and comparing products across supermarkets, which may occur due to shoppers' cognitive responses to the information provided by the intervention.

The SABH intervention stands out in the broader landscape of research on healthier food choices by integrating elements from nudges that are informational (e.g., providing calorie data) and attentional (e.g., amplifying the visibility of healthier options). While differences in the specific consumption goods across studies preclude a more detailed comparison of effect sizes, our design provides a unique combination of features that likely contribute to its effectiveness. The effect sizes we observe fall within the range of previous experiments, though we note that many informational interventions result in insignificant effects (see Wilson et al. 2016 for a survey). Building on the personalized nature of the SABH intervention, future research can develop a more comprehensive understanding of the design features that would be most impactful. One direction would be to consider the impacts of information focused on different nutrients such as fat, sugar, or sodium, which could be tailored based on shoppers' responsiveness to previous informational nudges. The timing of information also deserves careful consideration: for instance, nudges implemented during the checkout phase may limit spillover consequences but may reduce effectiveness compared to the real-time SABH intervention. Finally, examining the interaction with pricing strategies or interventions would provide further insights into promoting healthfulness.

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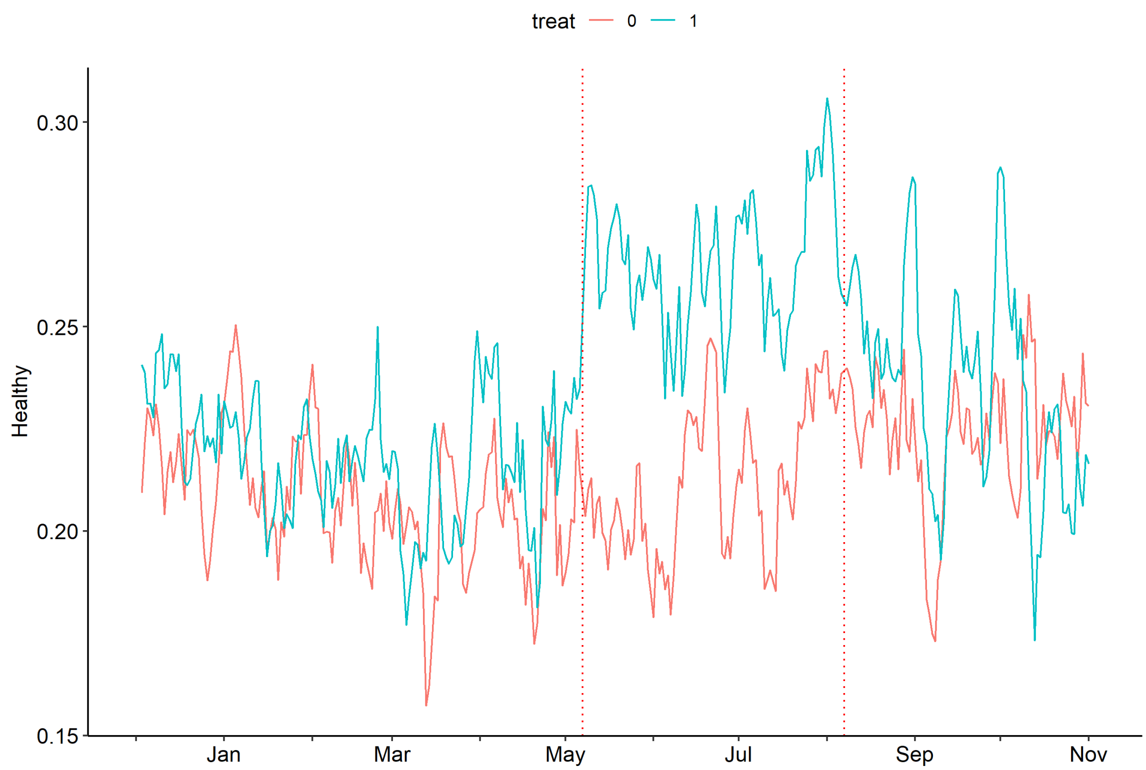
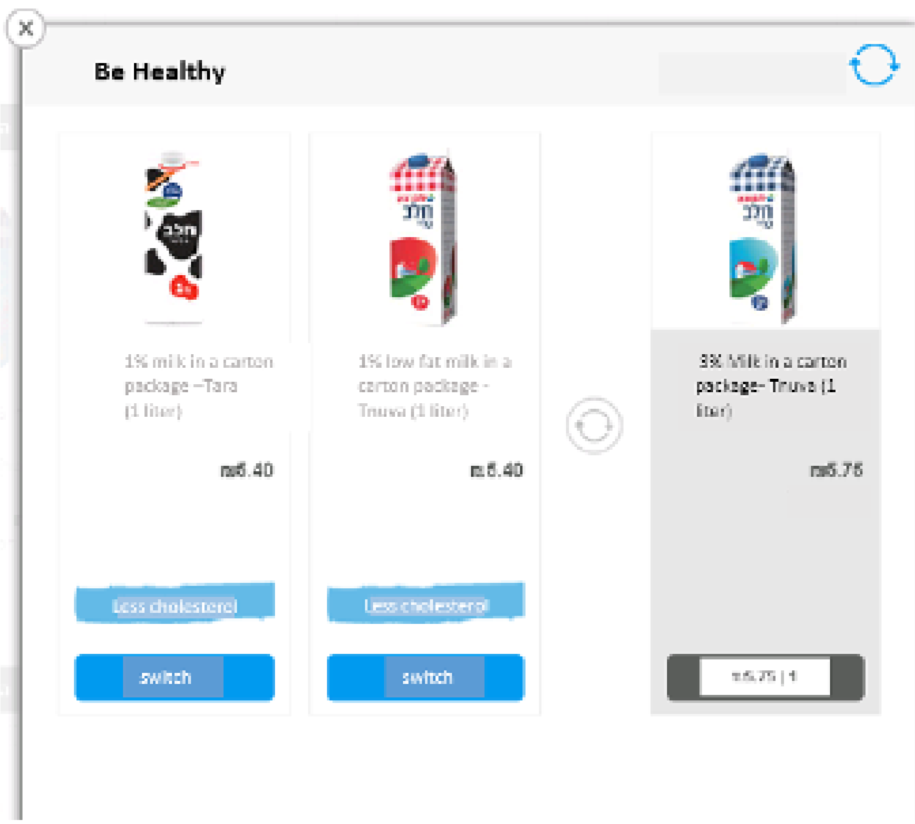
Figure 1: Effect of SABH: Event study



Note: This event study figure maps the five-day moving average of the fraction of healthy alternatives out of all relevant purchases for shoppers in the treatment and control groups.

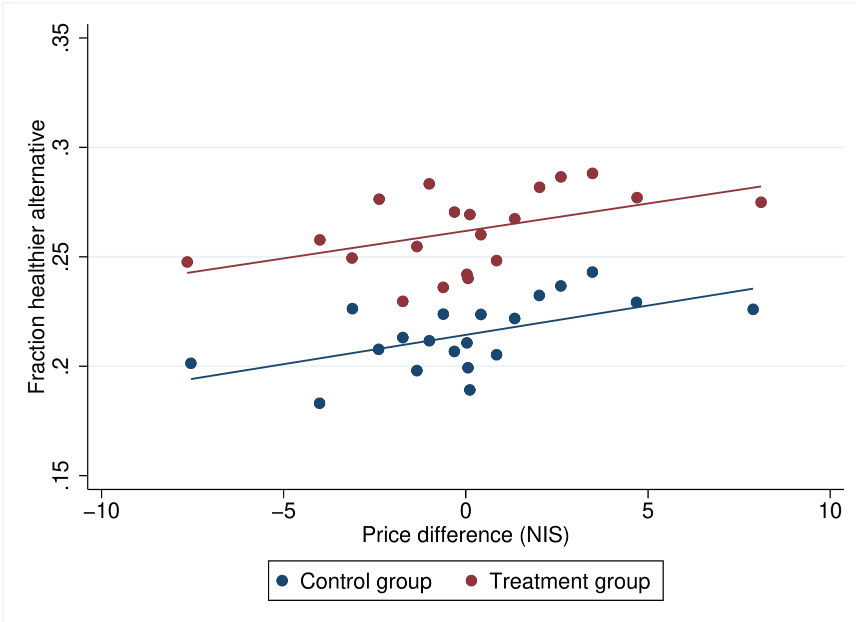
Figure 2: Screenshot of SABH



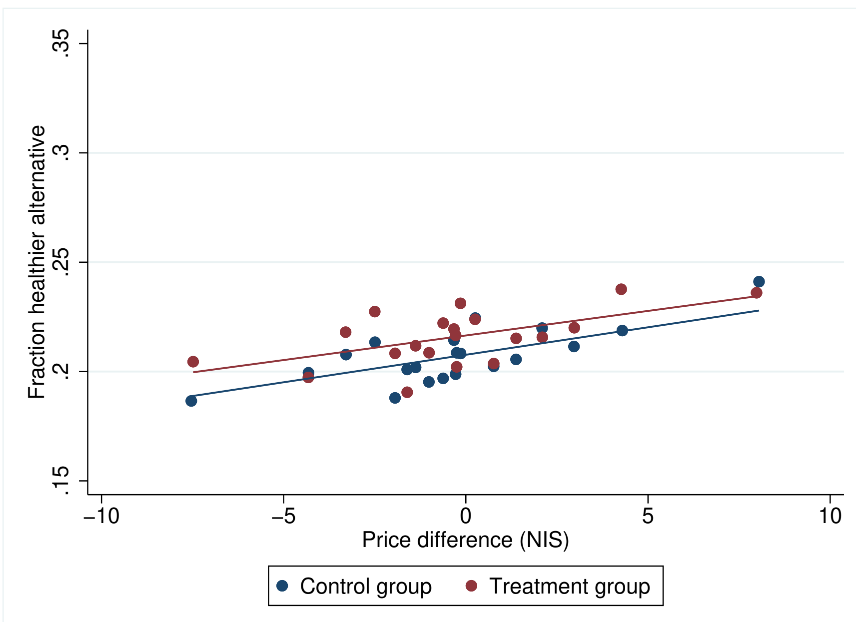
Note: This is a screenshot of the milk SABH nudge. This popup appeared on the screen for any treatment shopper who added a 3 percent milk carton to their basket during the intervention period.

Figure 3: Effect of treatment by price difference

(a) During intervention



(b) Before intervention



Note: Each panel shows a binned scatterplot of the relationship between the probability of purchasing the healthier alternative and the price difference, controlling for shopper and product category fixed effects. Price difference is defined as the difference between the price of the less healthy product and the healthier alternative. The sample in the top panel consists of shoppers randomly assigned to the treatment group, and the sample in the bottom panel consists of shoppers randomly assigned to the control group.

Table 1: List of experimental products and healthier alternatives

Product (Unit)	Healthier alternative	Price unhealthy	Price healthy
Canned corn (600 g)	No added sugar	10.30	7.40
Chocolate milk (1 L)	No added sugar	10.20	10.40
Yogurts (100 g)	No added sugar	9.40	11.10
Date honey (400 g)	No added sugar	8.20	13.90
Nuts (200 g)	No added sugar	17.20	15.70
Soy milk (1 L)	No added sugar	10.90	13.50
Jam (300 g)	No added sugar	10.10	16.50
Salt (200 g)	Low sodium	3.30	10.00
Salt (200 g)	Iodine fortified		5.70
Soy Sauce (400 g)	Low sodium	14.90	19.00
Soup powder (400 g)	Low sodium	14.40	16.60
Chocolate pudding (100 g)	Low sodium, more calcium	7.10	8.40
Pretzels (300 g)	Low sodium	11.80	8.30
Pretzels (400 g)	Low fat		11.80
Mayo (500 g)	Low saturated fat	11.60	11.30
3% milk (1 L)	1% milk (Low cholesterol)	6.20	5.80
Jasmine rice (1 kg)	Lower glycemic index	11.40	13.90
Persian rice (1 kg)	High fiber	9.20	8.40

Note: This table provides details on the consumer goods from the experiment. The first column lists the product that triggers a "Swap and Be Healthy" prompt when added to the shopper's basket along with its package size. The second column provides the nutrient information associated with the healthier alternative. The third and fourth columns contain the unit prices of the experimental product and the healthier alternative in NIS.

Table 2: Features with definitions

Panel A: General features	Definition
Shopping frequency	Number of baskets / Days between the first basket and the start of intervention
Basket purchase time	Average shopping time
Item purchase time	Average time it takes the consumer to add an item to basket
Products removed	Average fraction of added products removed from basket (Products removed / Products added)
Panel B: Price-related features	Definition
Average item price	Average price of the purchased items
Average basket price	Average price of the shopping trip
'Swap & Save' opened	Average number of 'Swap & Save' offers examined by shopper
On sale	Average fraction of products in basket bought at full price
Supermarket switches	Fraction of baskets that change supermarkets
Cheapest basket selected	Fraction of baskets checked out in the cheapest supermarket
Basket price premium	Average difference between the basket value and that of the cheapest supermarket
Panel C: Health-related features	Definition
Baseline demand for healthier variety	Number of healthier varieties purchased / Relevant products
Have ever added junk	Fraction of baskets that contain at least one junk item
Junk fraction	Number of junk items bought / All products
Produce fraction	Number of produce items bought / All products
Produce before junk	Fraction of baskets in which a sequence of produce is purchased before the first sequence of junk (if any)
Ended basket on junk	Fraction of baskets in which the last item is junk
Have ever added alcohol	Have ever added alcohol or cigarettes to basket
Alcohol/cigarettes fraction	Number of alcohol and cigarettes items bought / All products
Panel D: Lifestyle features	Definition
Contains ultra-Orthodox products	Have ever bought item identified as kosher
Contains baby products	Have ever bought items associated with having children

Note: This table lists groups of variables that enter the causal forest model. In addition to those listed, the model also includes variables for the fraction of products belonging to different consumption groups (fruit/vegetable, grain, dairy, protein, alcohol / cigarettes and non-food), nutrient composition (sugar, sodium, saturated fat, protein, cholesterol, iron), and product categories (see the list in Table 1). All values are computed using variables in the preintervention period. A sequence is defined as four consecutive products.

Table 3: Basket-level summary statistics

	Control	Treat	Difference	Std. err.
Panel A: General features				
Shopping frequency	2.0539	2.0728	0.0189	0.0504
Products removed / Products Added	0.0447	0.0430	-0.0017	0.0009
Panel B: Price-related features				
Average item price (NIS)	10.8608	10.8193	-0.0415	0.0499
Average basket price (NIS)	576.3705	577.8264	1.4558	5.6426
“Swap & Save” opened	0.0248	0.0253	0.0005	0.0011
On sale	0.0508	0.0524	0.0015	0.0016
Supermarket switches	0.1291	0.1259	-0.0032	0.0050
Cheapest basket selected	0.6105	0.6022	-0.0083	0.0091
Basket price premium	0.0355	0.0348	-0.0007	0.0013
Panel C: Health-related features				
Produce / All Products	0.2313	0.2295	-0.0018	0.0030
Healthy Products / Relevant Products	0.2023	0.2012	-0.0011	0.0060
Junk / All products	0.1244	0.1316	0.0072	0.0018
Have ever added junk	0.8819	0.8977	0.0158	0.0044
Ended basket on junk	0.1436	0.1499	0.0063	0.0043
Fraction of trips with produce before junk	0.2078	0.2017	-0.0061	0.0059
Alcohol/cigarettes fraction	0.0193	0.0201	0.0008	0.0009
Have ever added alcohol	0.6999	0.7308	0.0309	0.0098
Panel D: Lifestyle features				
Contains baby products	0.3840	0.3576	-0.0264	0.0105
Contains ultra-Orthodox products	0.2166	0.2078	-0.0089	0.0089
N	4225	4238		

Note: The table displays the average value of each of the variables that enter into the causal forest, along with their standard deviation. The difference is based on a regression where the variable is regressed on the treatment indicator and a constant. The standard deviation for the difference is from the same regression. The data is on the user level in the pre-intervention period and is based on 61,463 baskets.

Table 4: Summary of nutritional components

	Control	Treat	Difference
Total calories	91.9690	92.3170	0.347
	(36.7)	(36.9)	(0.286)
Sugar (g)	3.2200	3.1930	-0.027
	(2.31)	(2.31)	(0.018)
Sodium (mg)	0.2350	0.2380	0.003
	(0.327)	(0.316)	(0.002)
Saturated fat (g)	2.4210	2.4660	0.045
	(1.47)	(1.47)	(0.011)
Dietary fiber (g)	1.1500	1.1520	0.002
	(0.68)	(0.675)	(0.005)
Cholesterol (mg)	0.0130	0.0130	0
	(0.0101)	(0.0103)	(0)
Protein (g)	4.9100	4.9460	0.035
	(2.94)	(2.94)	(0.023)
Iron (mg)	0.7950	0.7790	-0.015
	(0.701)	(0.623)	(0.005)
N	32872	33342	

Note: The table displays the average value of each of the nutritional variables, along with their standard deviation, from the pre-intervention period. The standard error of the difference appears in parenthesis in the third column.

Table 5: Effect of SABH on healthy purchases—Difference in differences

	Full sample			Subsample		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.0002	-0.0002		0.0012	0.0012	
	(0.0012)	(0.0012)		(0.0014)	(0.0014)	
During experiment	-0.0098	-0.0098	-0.0098	-0.0119	-0.0119	-0.0119
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
After experiment	-0.0155	-0.0155	-0.0155	-0.0167	-0.0167	-0.0167
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
Treat × During experiment	0.0082	0.0082	0.0082	0.0098	0.0098	0.0098
	(0.0012)	(0.0012)	(0.0012)	(0.0014)	(0.0014)	(0.0014)
Treat × After experiment	0.0022	0.0022	0.0022	0.0035	0.0035	0.0035
	(0.0012)	(0.0012)	(0.0012)	(0.0014)	(0.0014)	(0.0015)
Outcome mean	0.0423	0.0423	0.0423	0.0449	0.0449	0.0449
Sample size	377145	377145	377145	283500	283500	283500
Category FE		X	X		X	X
Shopper FE			X			X

Note: The dependent variable is the fraction of times a shopper purchases the healthy rather than the unhealthy variety of the experimental product in a given category. Each observation corresponds to a shopper, product category, and time period (before, during, and after the intervention period). The "Full sample" in columns (1) to (3) consists of all shoppers who ever purchased at least one of the experimental products in any time period. The "Subsample" in columns (4) to (6) consists of shoppers who purchased at least one of the less healthy versions of the experimental products before the start of the experiment and excludes shoppers in the treatment group who never received the SABH prompt. Column (1) contains a treatment group indicator, time fixed effects (before, during, and after the intervention period), and their interactions. Column (2) adds product category fixed effects. Column (3) adds shopper fixed effects. Columns (4) to (6) are analogous. Standard errors reported in parentheses are adjusted for clustering at the shopper level.

Table 6: Effect of SABH on healthy purchases—IV estimates

	FS		IV		OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: During the experiment period						
Received SABH prompt			0.0876	0.0901	0.0643	0.0395
			(0.0120)	(0.0131)	(0.0036)	(0.0037)
Assigned to treatment × During	0.0910	0.0911				
	(0.0013)	(0.0013)				
Panel B: After experiment period						
Received SABH prompt			0.0221	0.0247	0.0188	-0.0057
			(0.0114)	(0.0132)	(0.0026)	(0.0027)
Assigned to treatment × After	0.0910	0.0911				
	(0.0013)	(0.0013)				
Outcome mean	0.0003	0.0003	0.0423	0.0423	0.0423	0.0423
Sample size	251430	251430	251430	251430	251430	251430
Category FE		X		X		X
Shopper FE		X		X		X

Note: The first pair of columns displays the first stage relationship between being assigned to the treatment and receiving a SABH prompt in a given product category. In this case, the dependent variable is an indicator for receiving at least one SABH prompt in a given category. The second pair of columns presents estimates of the impact of receiving an SABH prompt in a given product category on the fraction of healthier alternatives purchased in that category, using assignment to treatment as an instrument. The third pair of columns contains OLS estimates of the relationship between receiving an SABH prompt and the fraction of healthier alternatives purchased. In these cases, the dependent variable is the fraction of times a shopper purchases the healthy rather than the unhealthy variety of the experimental product in a given category. The sample consists of all shoppers who purchased at least one of the experimental products in any period. Within each pair of columns, the second specification adds product category and shopper-fixed effects. All standard errors reported in parentheses are adjusted for clustering at the shopper level.

Table 7: Summary statistics for most- and least-responsive shoppers

	Bottom	Top	Difference	Std. err.
Panel A: General features				
Shopping frequency	1.6036	2.5019	0.8983	0.1133
Products removed / Products Added	0.0488	0.0391	-0.0097	0.0016
Panel B: Price-related features				
Average item price (NIS)	11.0942	10.5973	-0.4969	0.0012
Average basket price (NIS)	537.8885	614.5083	76.6198	11.4130
"Swap & Save" opened	0.0246	0.0255	0.0009	0.0052
On sale	0.0596	0.0440	-0.0156	0.0058
Supermarket switches	0.1563	0.1001	-0.0562	0.0103
Cheapest basket selected	0.6096	0.6031	-0.0065	0.0162
Basket price premium	0.0357	0.0347	-0.0010	0.0022
Panel C: Health-related features				
Produce / All Products	0.2326	0.2283	-0.0043	0.0052
Healthy Products / Relevant Products	0.1853	0.2174	0.0321	0.0117
Junk / All products	0.1153	0.1403	0.0250	0.0031
Have ever added junk	0.8584	0.9199	0.0615	0.0081
Ended basket on junk	0.1234	0.1691	0.0457	0.0075
Fraction of trips with produce before junk	0.1124	0.2927	0.1803	0.0108
Alcohol/cigarettes fraction	0.0208	0.0187	-0.0021	0.0017
Have ever added alcohol	0.6170	0.8094	0.1924	0.0171
Panel D: Lifestyle features				
Buy baby product (indicator)	0.3568	0.3840	0.0272	0.0181
Contains ultra-Orthodox products	0.1712	0.2512	0.0800	0.0149

Note: The table displays the average value of each of the variables that enter into the causal forest, along with their standard deviation. The difference is based on a regression where the variable is regressed on the treatment indicator and a constant. The standard deviation for the difference is from the same regression. The data is on the user level in the pre-intervention period and is based on 61,463 baskets.

Table 8: Effect of SABH on healthy purchases for most- and least-responsive shoppers—Difference in differences

	Full sample			Subsample		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Most-responsive shoppers						
Treat	0.0031	0.0031		0.0108	0.0108	
	(0.0019)	(0.0019)		(0.0024)	(0.0024)	
During experiment	-0.0221	-0.0221	-0.0221	-0.0247	-0.0247	-0.0247
	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0013)
After experiment	-0.0203	-0.0203	-0.0203	-0.0203	-0.0216	-0.0216
-0.0216						
	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0014)	(0.0014)
Treat × During the experiment	0.0224	0.0224	0.0224	0.0313	0.0313	0.0313
	(0.0019)	(0.0019)	(0.0019)	(0.0024)	(0.0024)	(0.0024)
Treat × After experiment	0.0044	0.0044	0.0044	0.0040	0.0040	0.0040
	(0.0019)	(0.0019)	(0.0019)	(0.0024)	(0.0024)	(0.0024)
Outcome mean	0.0476	0.0476	0.0476	0.0523	0.0523	0.0523
Sample size	171675	171675	171675	121410	121410	121410
Category FE		X	X		X	X
Shopper FE			X			X
Panel B: Least-responsive shoppers						
Treat	-0.0008	-0.0008		-0.0003	-0.0003	
	(0.0016)	(0.0016)		(0.0022)	(0.0022)	
During experiment	-0.0010	-0.0010	-0.0010	-0.0036	-0.0036	-0.0036
	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0013)
After experiment	-0.0113	-0.0113	-0.0113	-0.0129	-0.0129	-0.0129
	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0013)
Treat × During experiment	-0.0071	-0.0071	-0.0071	-0.0054	-0.0054	-0.0054
	(0.0017)	(0.0017)	(0.0017)	(0.0022)	(0.0022)	(0.0022)
Treat × After experiment	-0.0016	-0.0016	-0.0016	-0.0002	-0.0002	-0.0002
	(0.0017)	(0.0017)	(0.0017)	(0.0023)	(0.0023)	(0.0023)
Outcome mean	0.0348	0.0348	0.0348	0.0377	0.0377	0.0377
Sample size	171675	171675	171675	108450	108450	108450
Category FE		X	X		X	X
Shopper FE			X			X

Note: The sample in the top and bottom panels consists of shoppers who are in the top and bottom 25 percent, respectively, of the distribution of predicted responses to the treatment. See Table 5 for additional details regarding the specifications.

Table 9: Effect of SABH on healthy purchases for most- and least-responsive shoppers—IV estimates

	FS		IV		OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Most-responsive shoppers						
... during experiment period						
Received SABH prompt			0.3085	0.2709	0.1025	0.0680
			(0.0199)	(0.0228)	(0.0066)	(0.0068)
Assigned to treatment × During	0.0827	0.0828				
	(0.0021)	(0.0021)				
... after experiment period						
Received SABH prompt			0.0898	0.0526	0.0246	-0.0055
			(0.0189)	(0.0226)	(0.0043)	(0.0045)
Assigned to treatment × After	0.0827	0.0828				
	(0.0021)	(0.0021)				
Outcome mean	0.0003	0.0003	0.0476	0.0476	0.0476	0.0476
Sample size	114450	114450	114450	114450	114450	114450
Panel B: Least-responsive shoppers						
... during experiment period						
Received SABH prompt			-0.1321	-0.1181	0.0494	0.0348
			(0.0255)	(0.0283)	(0.0059)	(0.0061)
Assigned to treatment × During	0.0601	0.0602				
	(0.0015)	(0.0015)				
... after experiment period						
Received SABH prompt			-0.0405	-0.0266	0.0126	-0.0040
			(0.0232)	(0.0281)	(0.0042)	(0.0044)
Assigned to treatment × After	0.0601	0.0602				
	(0.0015)	(0.0015)				
Outcome mean	0.0002	0.0002	0.0348	0.0348	0.0348	0.0348
Sample size	114450	114450	114450	114450	114450	114450
Category FE		X		X		X
Shopper FE		X		X		X

Note: The sample in the top and bottom panels consists of shoppers who are in the top and bottom 25 percent, respectively, of the distribution of predicted responses to the treatment. See Table 6 for additional details regarding the specifications.

Table 10: Spillover effects of SABH (Top and Bottom groups)

Bottom group		Top group	
Variable	Value	Variable	Value
Saturated fat	0.013	Swap & Saves opened	0.016
Switch supermarkets	0.012	Product price	0.008
Product price	-0.009	Dietary fiber	0.007
Time between items	0.005	Protein expenditure	-0.007
Iron	-0.003	Sodium	0.006
Fraction on sale	-0.002	Saturated fat	-0.005
Fruit share	-0.002	Child share	-0.004
Child expenditure	-0.002	Price diff. from most expensive	-0.002
Time spent shopping	0.001	Grain share	0.001
Junk share	0.001	Junk share	-0.001
Grain share	0.001	Junk expenditure	-0.001
Protein share	0.001	Fruit expenditure	-0.001
Junk expenditure	0.001	Cholesterol	-0.001
Basket value	-0.001	Basket value	0
Swap & Saves opened	0	Swap & Saves accepted	0
Swap & Saves accepted	0	Cheapest supermarket (indicator)	0
Price diff. from most expensive	0	Switch supermarkets	0
Cheapest supermarket (indicator)	0	Fraction on sale	0
Ended shopping on junk	0	Time between items	0
Nonfood share	0	Ended shopping on junk	0
Alc. & cig. share	0	Time spent shopping	0
Dairy share	0	Fruit share	0
Ultra-Orthodox share	0	Nonfood share	0
Child share	0	Alc. & cig. share	0
Fruit expenditure	0	Protein share	0
Alc. & cig. expenditure	0	Dairy share	0
Dairy expenditure	0	Ultra-Orthodox share	0
Grain expenditure	0	Alc. & cig. expenditure	0
Nonfood expenditure	0	Dairy expenditure	0
Protein expenditure	0	Grain expenditure	0
Ultra-Orthodox expenditure	0	Nonfood expenditure	0
Total calories	0	Ultra-Orthodox expenditure	0
Sugar	0	Child expenditure	0
Sodium	0	Total calories	0
Dietary fiber	0	Sugar	0
Cholesterol	0	Protein	0
Protein	0	Iron	0

Note:

Online Appendix

A Data Filtering Steps

1. Removing Baskets without a User ID:
   To maintain data integrity and traceability, we exclude all shopping baskets that lack a valid user ID. This ensures that each transaction in the data set can be associated with a unique user, allowing for the tracking of individual shopping patterns.

2. Removing Products without an Added Time:
   To enable temporal analysis and capture the dynamics of shopping behavior, we exclude products for which the time of addition to the basket is missing. This filtering step ensures that we have a complete timestamp for each product, facilitating time-series analyses.

3. Removing Products with Zero Purchases:
   We eliminate products that were added to baskets but were never actually purchased. This step ensures that the data set reflects only those items that were actively chosen and paid for by users, enhancing the accuracy of our analyses.

4. Removing Non-Relevant Stores:
   To focus on the most relevant data, we filter out transactions associated with stores that do not align with the research objectives.

5. Removing Items without a Price:
   To ensure accurate calculations of transaction values and prices paid by consumers, we remove items that do not have a listed price. This step guarantees that the data set contains consistent pricing information for all products.

6. Removing the Ketchup Category:

7. Removing the Schnitzel Category:

8. Removing the Sauce Tomato Category:

9. Removing Shopping from Smartphones:

Appendix Table 1: Effect of SABH on healthy purchases—Difference in differences (Subsamples)

	Unhealthy Pre			Non-List		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.0001	0.0001	0.0000	-0.0007	-0.0007	0.0000
	(0.0013)	(0.0013)	(0.0000)	(0.0012)	(0.0012)	(0.0000)
During experiment	-0.0119	-0.0119	-0.0119	-0.0097	-0.0097	-0.0097
	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
After experiment	-0.0167	-0.0167	-0.0167	-0.0147	-0.0147	-0.0147
	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
Treat × During experiment	0.0084	0.0084	0.0084	0.0080	0.0080	0.0080
	(0.0013)	(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0012)
Treat × After experiment	0.0027	0.0027	0.0027	0.0026	0.0026	0.0026
	(0.0013)	(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0012)
Outcome mean	0.0445	0.0445	0.0445	0.0373	0.0373	0.0373
Sample size	323370	323370	323370	350640	350640	350640
Category FE		X	X		X	X
Shopper FE			X			X

Note: The "Unhealthy Pre" subsample in columns (1) to (3) consists of shoppers who purchased at least one of the less healthy versions of the experimental products before the start of the experiment. The "Non-List" subsample in columns (4) to (6) consists of shoppers who did not begin their shopping trip with a pre-populated basket (i.e., from a pre-defined list or a previous basket). See Appendix Table 1 for additional details regarding the specifications.

Appendix Table 2: Effect of SABH on healthy purchases—Difference in differences (Relevant purchases)

	Full sample			Subsample		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.0105	0.0089	0.0000	0.0008	-0.0003	0.0000
	(0.0074)	(0.0071)	(0.0000)	(0.0075)	(0.0073)	(0.0000)
During experiment	0.0070	0.0103	0.0061	0.0085	0.0118	0.0112
	(0.0040)	(0.0039)	(0.0035)	(0.0040)	(0.0039)	(0.0035)
After experiment	0.0143	0.0137	0.0064	0.0144	0.0141	0.0117
	(0.0050)	(0.0049)	(0.0041)	(0.0050)	(0.0049)	(0.0041)
Treat × During experiment	0.0397	0.0388	0.0419	0.0318	0.0308	0.0308
	(0.0059)	(0.0057)	(0.0051)	(0.0061)	(0.0058)	(0.0052)
Treat × After experiment	0.0052	0.0054	0.0118	0.0059	0.0071	0.0085
	(0.0071)	(0.0069)	(0.0060)	(0.0073)	(0.0071)	(0.0063)
Outcome mean	0.2114	0.2114	0.2114	0.1941	0.1941	0.1941
Sample size	148524	148524	148524	134454	134454	134454
Category FE		X	X		X	X
Shopper FE			X			X

Note: The dependent variable is an indicator for purchasing the healthy rather than the unhealthy variety of the experimental product. Each purchase of an experimental product corresponds to a unique observation in the data. See Table 5 for additional details regarding the specifications.

Appendix Table 3: Spillover effects of SABH (Top and Bottom groups)—Removing nutrition variables

Bottom group		Top group	
Variable	Value	Variable	Value
Switch supermarkets	0.014	Swap & Saves opened	0.014
Fruit share	-0.007	Product price	0.006
Time between items	0.006	Protein expenditure	-0.006
Junk share	0.004	Child share	-0.003
Fraction on sale	-0.002	Grain share	0.002
Basket value	-0.002	Price diff. from most expensive	-0.002
Child expenditure	-0.002	Junk share	-0.001
Time spent shopping	0.001	Junk expenditure	-0.001
Grain share	0.001	Switch supermarkets	0
Protein share	0.001	Time between items	0
Junk expenditure	0.001	Fraction on sale	0
Product price	-0.01	Time spent shopping	0
Swap & Saves opened	0	Basket value	0
Swap & Saves accepted	0	Swap & Saves accepted	0
Price diff. from most expensive	0	Cheapest supermarket (indicator)	0
Cheapest supermarket (indicator)	0	Ended shopping on junk	0
Ended shopping on junk	0	Fruit share	0
Nonfood share	0	Nonfood share	0
Alc. & cig. share	0	Alc. & cig. share	0
Dairy share	0	Protein share	0
Ultra-Orthodox share	0	Dairy share	0
Child share	0	Ultra-Orthodox share	0
Fruit expenditure	0	Fruit expenditure	0
Alc. & cig. expenditure	0	Alc. & cig. expenditure	0
Dairy expenditure	0	Dairy expenditure	0
Grain expenditure	0	Grain expenditure	0
Nonfood expenditure	0	Nonfood expenditure	0
Protein expenditure	0	Ultra-Orthodox expenditure	0
Ultra-Orthodox expenditure	0	Child expenditure	0

Note:

Appendix Table 4: Spillover effects of SABH (Top and Bottom groups)—Removing expenditure variables

Bottom group		Top group	
Variable	Value	Variable	Value
Switch supermarkets	0.011	Swap & Saves opened	0.016
Saturated fat	0.011	Product price	0.008
Product price	-0.007	Dietary fiber	0.007
Time between items	0.003	Sodium	0.006
Fruit share	-0.002	Saturated fat	-0.005
Iron	-0.002	Cheapest supermarket (indicator)	-0.004
Time spent shopping	0.001	Child share	-0.004
Junk share	0.001	Price diff. from most expensive	-0.002
Fraction on sale	-0.001	Junk share	-0.002
Basket value	-0.001	Protein share	-0.002
Swap & Saves opened	0	Grain share	0.001
Swap & Saves accepted	0	Switch supermarkets	-0.001
Price diff. from most expensive	0	Cholesterol	-0.001
Cheapest supermarket (indicator)	0	Time between items	0
Ended shopping on junk	0	Fraction on sale	0
Grain share	0	Time spent shopping	0
Nonfood share	0	Basket value	0
Alc. & cig. share	0	Swap & Saves accepted	0
Protein share	0	Ended shopping on junk	0
Dairy share	0	Fruit share	0
Ultra-Orthodox share	0	Nonfood share	0
Child share	0	Alc. & cig. share	0
Total calories	0	Dairy share	0
Sugar	0	Ultra-Orthodox share	0
Sodium	0	Total calories	0
Dietary fiber	0	Sugar	0
Cholesterol	0	Protein	0
Protein	0	Iron	0

Note:

Appendix Table 5: Spillover effects of SABH (Top and Bottom groups)—Removing share variables

Bottom group		Top group	
Variable	Value	Variable	Value
Saturated fat	0.011	Swap & Saves opened	0.015
Product price	-0.006	Product price	0.007
Switch supermarkets	0.01	Protein expenditure	-0.007
Time between items	0.003	Dietary fiber	0.006
Time spent shopping	0.001	Sodium	0.005
Fraction on sale	-0.001	Saturated fat	-0.005
Child expenditure	-0.001	Price diff. from most expensive	-0.002
Iron	-0.001	Junk expenditure	-0.002
Basket value	0	Child expenditure	-0.001
Swap & Saves opened	0	Cholesterol	-0.001
Swap & Saves accepted	0	Switch supermarkets	0
Price diff. from most expensive	0	Time between items	0
Cheapest supermarket (indicator)	0	Fraction on sale	0
Ended shopping on junk	0	Time spent shopping	0
Junk expenditure	0	Basket value	0
Fruit expenditure	0	Swap & Saves accepted	0
Alc. & cig. expenditure	0	Cheapest supermarket (indicator)	0
Dairy expenditure	0	Ended shopping on junk	0
Grain expenditure	0	Fruit expenditure	0
Nonfood expenditure	0	Alc. & cig. expenditure	0
Protein expenditure	0	Dairy expenditure	0
Ultra-Orthodox expenditure	0	Grain expenditure	0
Total calories	0	Nonfood expenditure	0
Sugar	0	Ultra-Orthodox expenditure	0
Sodium	0	Total calories	0
Dietary fiber	0	Sugar	0
Cholesterol	0	Protein	0
Protein	0	Iron	0

Note: