Behavioral Spillovers from Promoting Healthier Consumer Choices

Mathias Wagner Barløse
Aarhus University

Kfir Eliaz
Tel Aviv University

Neil Thakral
Brown University

Sarit Weisburd
The Hebrew University

October 2024*

Abstract

We examine a four-month-long randomized intervention that provided information about healthier alternatives when online grocery shoppers added certain less-healthy products to their baskets, leading to significant and persistent average increases in healthier purchases. Using machine learning techniques, we characterize consumers' direct responsiveness to the intervention and broader changes in behavior. More-responsive consumers make healthier purchases beyond the immediate scope of the intervention; less-responsive consumers engage in more active shopping behaviors, spending more time shopping and making cost-saving substitutions. These results highlight the capacity of information-based approaches to not only affect isolated consumer decisions but also shape behavior across multiple domains.

*Barløse: Department of Economics and Business Economics, Aarhus University (email: mathias@barlose.dk). Eliaz: Eitan Berglas School of Economics, Tel Aviv University (email: kfire@tauex.tau.ac.il). Thakral: Department of Economics, Brown University (email: neil_thakral@brown.edu). Weisburd: The Hebrew University Business School (email: sarit.weisburd@mail.huji.ac.il). We thank Chuqing Jin for helpful comments and discussions as well as Elior Cohen, Maya Fuks, and Isabella Kuhr for excellent research assistance. Special thanks to Bernard Feldman, Lev Muchnik, and Inbar Kinarty for their assistance with the data. We very much appreciate input received from seminar participants at Hebrew University (Econ) and Tel Aviv University (Coller). Research funding from the Pinhas Sapir Center and the Israel Science Foundation is gratefully acknowledged.

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 under-nutrition 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 USD (Cawley et al., 2021).

The predominant public policy response to promote healthier consumer choices is information provision. In particular, 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, contain "clear and actionable suggestions" such as "make half of 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 and Department of Health and Human Services, 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 customized and personally relevant nutritional information during shopping trips (Lowe, de Souza-Monteiro and Fraser, 2013).

This article uses comprehensive data from about 8,400 online shoppers to study a novel intervention that provides consumers with information when they add less-healthy versions of certain foods to their shopping carts. The intervention, which we refer to as "Swap and Be Healthy" (SABH), provides specific, actionable, brief health information at the time of decision-making. The intervention is *informative* (shoppers learn about the nutritional content of an item), *shopper-specific* (information relates 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 consequences of the SABH intervention for shopper behavior. Shoppers randomly assigned to the intervention group receive information on particular nutrients and alternative products when they add to their shopping basket one of 78 common food items that a registered dietitian identified as having healthier alternatives. 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 such as heart disease, stroke, Type 2 diabetes, some cancers, and chronic kidney disease" (NHMRC, 2015). As another example, Public Health England launched the "Change4Life Smart Swaps" TV advertising campaign in 2014 to encourage lower-fat and lower-sugar varieties of popular products (Wrieden and Levy, 2016).

[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,

Our raw data show clear evidence of a direct response among treated shoppers during the intervention period (Figure 1). While shoppers in both the treatment and control groups purchase the healthier varieties at a rate of about 22 percent before the intervention period, treated shoppers become 19 percent more likely to purchase these alternatives during the intervention period. Since treated shoppers during the intervention period only received SABH information when they add specific goods to their baskets, this information does not reach shoppers in roughly 90 percent of product categories on average. Thus, receiving SABH information on healthier alternatives tripled the demand for healthier products among shoppers receiving the nudge.[3]

About one-third of this response comes in the form of shoppers switching to directly adding healthier varieties to their shopping baskets, creating a spillover effect on shopping behavior after the completion of the intervention. In particular, we find a persistent change in consumption decisions after the intervention with a magnitude of about 80 percent of the direct effect on adding healthier varieties.

We then use the recently developed causal forest method (Athey and Imbens, 2016; Wager and Athey, 2018; Athey, Tibshirani and Wager, 2019) to examine how the intervention impacts various types of shoppers differently. This method identifies conditional average treatment effect (CATE) estimates based on covariates that best predict heterogeneous treatment effects. We use these estimates to characterize shoppers in the top and bottom quartiles of the distribution of responsiveness to the intervention. The shoppers most responsive to the intervention tend to exhibit a distinct profile. First, those who shop more often and purchase more products encounter a higher intensity of treatment and respond more to the intervention. Second, more-responsive shoppers exhibit less-healthy tendencies while also demonstrating some degree of nutritional awareness: they purchase more junk foods and are more likely to add junk foods just before checking out; but they are more likely to shop for

a 2017 national iodine intake survey revealed that 85 percent of pregnant women and 62 percent of school-age children have insufficient iodine levels, which puts adults at risk for thyroid disease and puts fetuses, infants, and children at risk of impaired neurocognitive development (Ovadia et al., 2017; Lazarus, 2020).

[3] We do not observe whether shoppers complement their weekly supermarket shopping with additional food purchases in smaller grocery shops or in restaurants. Because such purchases will be made after some time has elapsed since the shopping experience on the platform, it is likely that shoppers would not feel any urge to deliberately purchase unhealthy food to compensate for any healthy purchases they made on the platform.

produce before adding junk to their basket, and they have higher baseline demand for the healthier varieties of the experimental products. Third, they make decisions more quickly, allocating less time to evaluate each product, selecting fewer on-sale items, and making fewer changes in the supermarket they check out from.

A unique aspect of our dataset is that it allows us to examine the impact of the SABH intervention on behavior across other dimensions of the shopping trip. While the intervention promoted specific healthier alternatives, it also had effects on purchasing behaviors that extend beyond the immediate scope of the intervention. Shoppers who were more responsive to the intervention exhibited modest but discernible shifts toward other healthier purchasing behaviors: they purchase more-expensive products, with more fiber, lower levels of cholesterol, and buy less junk food. In contrast, shoppers who were less likely to have a direct response to the intervention also adjusted their behavior along other dimensions in response to the intervention: they purchased cheaper products, changed supermarkets more often, spent more time shopping, and purchased more junk food and products with higher levels of saturated fat. We discuss several possible mechanisms for these spillover effects, including guilt, skepticism, and cognitive load.

The remainder of the paper is organized as follows. After discussing the relevant literature, Section 2 describes the experimental design and the data and presents summary statistics on shopping behavior. Section 3 presents our estimates of the direct impacts of the intervention. Section 4 considers heterogeneous treatment effects and identifies shopper types who are most and least likely to be impacted by the intervention. Section 5 analyzes broader responses to the intervention, and Section 6 concludes.

Related 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).[4] 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.[5] 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 a novel intervention and detailed data but also characterizes the consumers who exhibit such compensatory effects. In addition, while previous theoretical (Nafziger, 2020), empirical (Medina, 2021; Trachtman, 2024), and experimental (Altmann, Grunewald and Radbruch, 2022) work proposes interpretations of behavioral spillovers based on scarce cognitive resources, our results go beyond the scope of mechanisms purely driven by attentional factors.

Our study also enriches the literature on the design of information interventions. We develop a novel information-provision intervention by combining insights about effective design from previous experiments. In the marketing literature, Lowe, de Souza-

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

[5] 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, 2024).

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.[6] 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).[7] 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 grocery 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; Avishai-Rizi and Reshef, 2024). Importantly, the few papers that consider the impacts of suggested product alternatives or default options (Huang et al., 2006; Coffino, Udo and Hormes, 2020; Van der Laan and Orcholska, 2022) do not analyze possible spillover effects (in contrast to us, those papers do not have the data that enables such analysis), and they also do not study the heterogeneity in response to the treatment (i.e., they do not characterize the attributes that are most predictive of high and low response to the treatment).[8]

[6] 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.

[7] Other recent work emphasizes that receiving information further in advance of making decisions can lead to healthier food choices (Belot, James and Spiteri, 2020; Brownback, Imas and Kuhn, 2021) or generally more forward-looking behavior (Thakral and Tô, 2020; Imas, Kuhn and Mironova, 2022; 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.

[8] 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).

Furthermore, in contrast to our work, the above studies do not track the participants both before and after the experiment (and hence, cannot evaluate the persistence of the treatment).

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

2 Swap and Be Healthy Intervention

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

2.1 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.

One of the core features of the platform 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 switch supermarkets 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.[9] 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.

2.2 The experiment

In collaboration with a registered dietitian, we identified 78 food items in 15 product 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 particular product categories that were chosen reflect popular food categories in Israel, but may not be as popular in other

[9] 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.

countries.[10] In addition, some of the unhealthy items and their healthier counterparts (e.g., whole and skim milk) also featured in previous studies that tried to promote healthier food choices (e.g., Van der Laan and Orcholska 2022). 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 over- 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 issues such as weight gain, obesity, type 2 diabetes, and heart disease.[11] 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.[12] Diets with a low glycemic index not only support the prevention of coronary heart disease in both diabetic and healthy individuals 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.[13]

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 (0.56 USD) 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.[14] Those in the treatment group encountered the SABH prompt every time they added one of the 78 designated less-healthy varieties to their basket (in contrast to the "Swap

[10] E.g., two of the most popular snacks in Israel are pretzels and puddings/flavored-yogurts: the former was worth 100 million NIS in 2011 (26 million USD), and the latter was worth 618 million NIS (165 million USD) in 2023 (Zeitan, 2011; Kadosh, 2024).

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

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

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

[14] For our analysis we focus on 8,463 shoppers who we observe making a purchase in the pre-intervention period. The pre-intervention data is necessary to classify different types of consumers.

and Save" feature which only appears if a shopper presses a button). 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 (as Appendix Figure 1 illustrates).

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.

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

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 possible substitutes, including the reason for the suggested 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.[15] We classify these characteristics into four domains: general features, price sensitivity, health preferences, and lifestyle factors (Sacco et al., 2017).

Consumers may exhibit stronger or weaker reactions depending on their shopping habits and tastes. Thus, we consider the following general pre-intervention behaviors:

[15]Thus, of the 14,282 consumers who made a purchase on the site during the intervention period, we exclude 5,819 shoppers who were not observed shopping prior to the intervention.

how much time shoppers spend on the site, how much time they spend on each product, how often they shop, and how often they remove products from their baskets.

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 on-sale products, and the tendency to select the supermarket that offers the lowest price for the shopping basket.

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 and degree of religiosity, 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. Our analysis thus incorporates the following lifestyle variables: purchasing products that have ultra-Orthodox (kosher) supervision, purchasing baby products, and frequency of trips on the site. 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 (163 USD) 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 consider the platform's recommendations for more cost-effective alternatives 2.5 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.[16] About 90 percent of shoppers have made a junk-food purchase in the pre-intervention period. 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 two distinct databases. In the *relevant purchases* database, the unit of analysis is a product purchase in a category that is relevant to the intervention, so that every purchase is either a "more-healthy" or "less-healthy" alternative. This provides an opportunity to answer the question of whether shoppers in the treated group purchase a healthier product conditional on shopping within a relevant category (or shopping at all). For this to have a causal interpretation, the intervention should not cause treated shoppers to avoid making purchases (e.g., to avoid the healthy nudge). On the other hand, if attrition does play a role, then part of the effect estimated from these data could be driven by selection. For example, an increase in healthier purchases may occur because less-healthy shoppers choose to avoid shopping on the site.

Our primary analysis uses a *balanced panel* dataset to circumvent issues related to attrition. Specifically, we construct a dataset that tracks purchase behavior in 125,715 shopper-category pairs (8,381 consumers who shopped during the intervention period across the 15 product categories) across the three time periods (pre-intervention, during the intervention, and post-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.[17] Using this panel structure, we can directly test for attrition by analyzing whether treated shoppers shopped less during the intervention period, or were less likely to use the site after the intervention period; we find no evidence for either of these forms of attrition (see Appendix Table 1). To investigate the nutritional implications of the intervention, we compiled an extensive dataset containing detailed

[16]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 Middle Eastern desserts.

[17]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.

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.[18] 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 collects this information from a variety of external sources.

A detailed nutritional breakdown per 100-gram serving of the typical product purchased by treatment and control shoppers before the intervention period appears in Table 4. 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. Throughout this paper we focus on the types of products shoppers purchase as opposed to an aggregate of the nutritional composition of the entire basket. The reason for this is that individuals could be stocking up on products or changing the number of products they purchase as a response to the intervention. In this case, purchasing more calories/fat at any given time does not necessarily imply a change in healthy behavior.

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 due to various factors discussed in Section 5.3.

[18]The nutritional data for packaged items follow a standardized serving size of 100 grams, per Israeli packaging regulations.

3 Impact on demand for healthier alternatives

3.1 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 during that period). We model this outcome using the following difference-in-differences specification:

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

The parameter α_1 captures the direct effect of the SABH intervention on the share of healthier purchases during the intervention period, while α_2 captures the spillover effect on healthier purchases after the intervention period.[19] We add shopper fixed effects (θ_i), category fixed effects (δ_c), and time-period fixed effects (ρ_t) to account for any pre-existing differences in demand across shoppers as well as time trends in demand for healthier products. To capture changes in the demand for 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 2.3, adjusting standard errors for clustering at the shopper level.

Across all shopper-category pairs, the baseline probability of purchasing one of the healthy varieties of the intervention products is 4.2 percent. The probability of purchasing one of the healthy varieties during the intervention period increases to 5 percent (column 1 of Table 5 panel A). This corresponds to a 19 percent increase in the probability of purchasing a healthier product during the intervention period. The magnitude 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. We also find

[19] An alternative to this difference-in-differences specification would be to ignore the pre-intervention period. This requires balance between the treatment and control groups in the pre-intervention period, which holds in our data (Table 3), and gives similar results as expected. However, the difference-in-differences specification gives us the ability to conduct additional exercises that remove shoppers from the treatment group who did not receive SABH prompts.

similar magnitudes when estimating the effect for the first shopping trip during the intervention period and the first shopping trip in the post-intervention period (Appendix Table 2).

To shed light on how shoppers react to the intervention, we now consider the channel through which shoppers purchase healthier alternatives. Shoppers may either start directly adding healthy varieties to their baskets after learning about them, or they may continue to add unhealthy varieties and accept SABH prompts. Changing the set of products a shopper adds to their basket may lead to stronger spillover effects than relying on the SABH prompt to make healthier purchases. We find that the probability of directly adding a healthier alternative to one's basket increases from a baseline of 4.2 percent to 4.5 percent during the intervention period (columns 1–3 of Table 5 panel B). This corresponds to a 6.6 percent increase in the probability of adding the healthier variety during the intervention period. With a post-intervention effect on purchasing the healthier variety of about 5.2 percent (columns 1–3 of panel A), we can conclude that nearly 80 percent of the add-healthy response persists and provides an explanation for the increase in healthier purchases in the post-intervention period.

To facilitate the interpretation of these magnitudes, we also estimate Equation (1) using the *relevant purchases* dataset, in which each purchase of an experimental product corresponds to a separate observation, and the outcome variable is an indicator for purchasing the healthy variety of the experimental product over the unhealthy variety. This dataset removes the imputed zeros included in the balanced panel database when the shopper did not make any purchases during a particular period. At baseline, shoppers purchase less-healthy varieties about four times as often as they purchase the healthier alternatives. The share of healthy purchases among intervention products increases from 21 percent to 25 percent (columns 4 to 6 of Table 5 panel A), corresponding to a 19 percent increase relative to the baseline rate as in the balanced-panel analysis.

This aligns with the effect sizes discernible directly from plotting the data. Figure 2 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.[20] Shoppers in the treatment group are about 4 percentage points more likely to select the healthier alternative during the intervention period. An increase in purchases of healthier alternatives occurs regardless of whether

[20] Also see the data plotted at the daily level in Figure 1.

the healthier alternative has a price advantage over the less-healthy version, consistent with the results of our difference-in-difference analysis (Appendix Table 3). 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 relevant purchases analysis also provides similar estimates of the post-intervention effect and the share attributable to the increase in directly adding healthier varieties. We find a post-intervention effect on purchasing healthier varieties of about 5.6 percent (column 6 of Table 5 panel A, or Appendix Figure 2). Compared to the 7.5 percent increase in adding healthier varieties during the experiment period (columns 6 of Table 5 panel B), this amounts to a persistence rate of about 75 percent.

Alternative specifications

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 did 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: prior to the experiment, treatment group shoppers who never receive SABH prompts purchase healthy varieties in 27.8 percent of purchases involving experimental products, compared to only

21.7 percent for treatment group shoppers who receive at least one SABH prompt.

We run our analysis on this subsample of relevant shoppers. The estimated effect of being assigned to receive SABH information grows by 20 percent during the intervention period for this subsample (from 0.82 percentage points in Table 5 to 0.98 percentage points in Appendix Table 4) and by 60 percent after the intervention period (from 0.22 percentage points in Table 5 to 0.35 percentage points in Appendix Table 4). Imposing only restriction (i) does not materially change the effect sizes from those observed for the full sample (see columns 1 to 3 of Appendix Table 5), suggesting that the increase in magnitudes in Appendix Table 4 arises primarily due to the removal of shoppers who failed to receive the SABH prompts.[21] 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 5). Across all of these subsamples, the purchase rate of the healthier varieties remains significantly elevated after the intervention period ends.

3.2 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 view an 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:

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

[21] At the same time, removing shoppers who never received SABH prompts slightly decreases the estimates in the relevant purchases analysis. This is because the shoppers who never received SABH prompts are more likely to purchase the healthier varieties, as discussed earlier.

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 discussed previously, only treated shoppers who add the less-healthy product varieties to their shopping basket receive the SABH prompt. In other words, shoppers prone to making less-healthy choices will be more likely to receive the prompt. Since receiving the prompt is correlated with lower tendencies toward healthy decision-making, this would bias the OLS estimate of β_1 in the negative direction. 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 an 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 (columns 1 and 2) show.[22] Recall that shoppers do not 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

[22]We obtain highly precise first-stage estimates, mitigating potential weak instrument concerns.

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 3.1.

Indeed 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 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 (which is largely driven by the 9 percent of cases where 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.

4 Categorizing consumers by responsiveness to the intervention

4.1 Methodology for categorizing consumers

We use the causal forest methodology to estimate the heterogeneous treatment effects of the intervention. Specifically, this method allows us to estimate the conditional average treatment effect (CATE), defined as

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

where $y_{ic}(1)$ is the probability of selecting a healthier alternative product in category c for individuals with characteristics z in the treatment group and $y_{ic}(0)$ is this outcome for similar individuals in the control group. Note that Equation (3) without conditioning on $Z_i = z$ gives the population average treatment effect, which we estimated in Section 3 using a standard difference-in-differences approach. To estimate the conditional average treatment effect (CATE), we define a list of features (see Table 2) that may impact the decision to purchase healthier products. These features categorize consumers based on their shopping habits, thriftiness, healthiness, and demographic characteristics.[23]

The causal forest method for estimating the CATE involves partitioning the feature space, i.e., the collection of all possible values that our variables of interest can take, based on the criterion of minimizing the mean squared error (MSE) between predicted values and actual outcomes. We start by splitting our dataset into two parts: one for training the model, and the other for estimation. The algorithm then recursively partitions the observations of the training sample into subgroups, evaluating potential divisions to find the one that minimizes the MSE. Following this recursive partitioning, the model yields treatment effect estimates given the specific characteristics of each subgroup. By using separate subsets of the data for determining how to split the data and for estimating the treatment effect, following the "honest" estimation approach of Athey and Imbens (2016), this process allows us to circumvent overfitting and thus obtain unbiased estimates of the conditional average treatment effect (CATE). Extending from a single "causal tree" to a "causal forest" involves generating multiple trees, each based on different random splits of the dataset into training and estimation samples. We then average the estimates from these trees to obtain a more precise estimate of the treatment effect for each individual in our sample.

We run the causal forest to predict shoppers' decisions to purchase the healthier variety over the less-healthy variety in response to the SABH intervention. To do so, we use one observation per shopper per category during the intervention period from the relevant purchases sample used in the difference-in-differences analysis. If a shopper made multiple purchases within the same category, the outcome variable is the fraction of healthier varieties the shopper purchased in that category.

[23]Note that each feature is defined in the pre-intervention period. As we have a randomized controlled trial, we can assume unconfoundedness (see Athey and Imbens, 2016, p. 4).

4.2 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 following the approach outlined in the previous section. We label more-responsive shoppers (those most impacted by the intervention) as those with CATE estimates in the top 25 percent of the distribution, and less-responsive shoppers (those least impacted by the intervention) as those with CATE estimates in the bottom 25 percent. We report the differences in observed characteristics of more-responsive and less-responsive consumers in Table 7, which orders the features within each category (general, price-related, health-related, and lifestyle) by the (absolute value of the) percent difference between consumer types.[24]

Some features in Table 7 leverage the unique nature of our data, which tracks the order in which items were purchased—in particular, whether healthy food items was purchased before or after unhealthy ones. Including these features can potentially discover a novel relation between the dynamics of shopping—specifically, the sequence of "vice" vs. "virtue" items—and the likelihood of a shopper to be more responsive to nudges that try to steer them to healthier food choices. The motivation for considering this possible relation is partly motivated by studies of shopping behavior in the marketing literature - in particular, those analyzing the notion of "licensing." This refers to the idea that purchasing a "virtue" item such as healthy food raises a shopper's "self-concept," which then lowers the negative self-attributions associated with the purchase in a "vice" such as junk food (see Khan and Dhar 2006 and Hui, Bradlow and Fader 2009).

Consumers who shop more frequently on the site and have larger supermarket baskets in the pre-intervention period exhibit stronger responses to the intervention. This is reasonable since these consumers are more likely to shop during the intervention period and therefore receive the SABH nudge. Those most impacted by the intervention also appear to deliberate less about their purchases, as they spend less time choosing each item and less time shopping overall, make fewer swaps to alternative supermarkets, remove fewer items from their shopping baskets, and purchase fewer products on sale. In addition, more-responsive shoppers exhibit mixed levels of healthiness. On the

[24] This is calculated by taking the value of the difference divided by the average for the least-responsive shoppers. Thus, the first entry in each panel shows the largest percent difference (in absolute value) between the less-responsive and more-responsive groups.

one hand, they generally have less healthy tendencies, as they purchase more junk foods and are more likely to add junk foods just before checking out. On the other hand, they have higher baseline purchase rates of the healthier alternatives and are much more likely to shop for produce before adding junk to their basket. The typical profile of a consumer who is most responsive to the intervention is thus one who is time constrained and tends to make less-healthy choices but has some health-related inclination.

To illustrate the heterogeneity in the magnitude of responses to the intervention, we can replicate the IV analysis from Section 3.2 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 by a factor of 7 during the intervention period and by a factor of 1.5 after the intervention period (see columns 3 and 4 of the top panel of Appendix Table 6). The less-responsive group, by contrast, exhibits a decrease in healthier purchases. We can also apply this categorization of more-responsive and less-responsive shoppers to the difference-in-differences analysis in Section 3.1. When running the analysis on the more-responsive shoppers (top panel of Appendix Table 7), we observe a 54–75 percent increase in the probability of purchasing a healthier alternative during the intervention period and a 15–18 percent increase after the intervention period. In contrast, less-responsive shoppers, if anything, decrease consumption of healthier alternatives (bottom panel of Appendix Table 7). We find similar patterns when analyzing shoppers' decisions about directly adding healthier alternatives to their shopping baskets (Appendix Table 8).

5 Spillover effects on other behaviors

5.1 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 may change beyond the scope of the healthier alternatives from the experiment. 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 powerful method for variable selection and model regularization is 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 standardize each variable so that the magnitudes are comparable. 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 collected during the experiment period (Ludwig, Mullainathan and Spiess, 2019). The underlying logic behind this approach is that variables that emerge as significant predictors of treatment status during or after the intervention period reveal behavioral changes attributable to the treatment—i.e., spillover effects on products outside the direct scope 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.

5.2 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 these 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. We only consider products outside of the scope of the intervention when defining these measures.

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 (Table 8 and Appendix Table 12). We also consider three alternative specifications that each maintain the basic features but drop one of the additional sets of variables (Appendix Tables 9 to 11).

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 resulting in different sample splits for training and estimation) 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 8 (for effects during the intervention period) and Appendix Table 12 (for effects after the intervention period).

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 during the intervention period for the group that has the smallest direct response to the intervention are as follows: higher product prices during the intervention period are associated with a lower predicted probability of being in the treatment group, while more frequent supermarket switching and greater saturated fat purchases are associated with an increase in the predicted probability of being in the treatment group. The increase in supermarket switching and decrease in prices for less-responsive treated shoppers aligns well with their increase in time taken between adding items to their shopping baskets. These factors suggest that the intervention prompts the least-responsive group to reinforce their tendencies 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.

We observe some of these effects after the intervention period as well (Appendix Table 12). In particular, the least-responsive group continues to purchase less healthy products, as higher sugar and saturated fat levels after the intervention period are associated with a higher predicted probability of having received the treatment. This is consistent with certain purchase habits persisting over time. On the other hand, we find a more limited role for prices, supermarket switching, and time spent shopping in predicting treatment status after the intervention period. This suggests that the more active shopping behaviors observed during the intervention period arise as a consequence of the SABH prompts themselves, rather than persisting as a long-term change in shopping habits.

The group that has the largest direct response to the intervention, by contrast, exhibits a more consistent tendency toward making healthier choices. During the intervention period, across all specifications, we find that this group purchases products with more fiber, reduces cholesterol and saturated fat consumption, purchases fewer junk food items, and buys less alcohol and cigarettes. While we also see some evidence of increases in sodium, the overall patterns suggest that the intervention further encourages healthier purchasing decisions beyond the experimental products among the most-responsive group. Their purchases tend to have higher prices in response to the intervention, and they purchase more of the relatively pricey ultra-Orthodox products which they exhibit higher purchase rates for at baseline. Given their baseline tendency to purchase less-expensive products, we also observe an increase in "Swap and Save" offers opened and accepted, perhaps to counterbalance their increases in expenditure.

After the intervention period, the most-responsive group continues to exhibit healthier purchasing habits (Appendix Table 12). In particular, they purchase products with less saturated fat, more fiber, and less sugar. They also spend more on fruits and vegetables and buy less junk food. We do not find an important role for prices and "Swap and Save" offers in predicting treatment status after the intervention period, suggesting that these effects may result from the SABH prompts themselves, as was the case for the least-responsive group.

5.3 Mechanisms

We conclude by discussing potential mechanisms for both the direct effect of the intervention, whereby treated individuals purchased more of the healthier alternatives, and for why the group least responsive to the intervention exhibits a pattern of increased search behavior during the intervention period.

Information is one explanation for the direct positive effect of the intervention on the likelihood of purchasing healthier alternatives. The intervention itself serves as a source of new information, making shoppers aware of healthier or potentially more cost-effective alternatives. Another factor is the nudge itself, which may prompt individuals to respond to the introduction of an alternative product regardless of the reason. For those shoppers who choose the healthier alternative, we also observe spillovers to more-healthy purchasing behaviors (e.g., products with less saturated fat and cholesterol). Even if they do not ultimately choose the healthier option, this knowledge could prompt them to spend more time exploring their choices, resulting in the increased time spent shopping we observe in the data. These spillover effects are more consistent with an information effect than a direct response to observing alternatives without processing information.

The spillover effects observed among the least responsive shoppers can be driven by guilt (or internal conflict), skepticism, or cognitive overload. 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.[25] 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. To take a closer look at this mechanism, we identify more guilt-prone shoppers in our data as shoppers who in the pre-intervention period were more likely to add a junk-food product to their shopping basket and remove it prior to purchase. These shoppers may tend to exhibit spillovers driven by guilty emotions when they do not choose the healthier alternative suggested by the SABH prompt. When we divide the sample of least responsive shoppers into those who exhibit guilty behavior regarding unhealthy purchases in the pre-intervention period and those who do not, the "guilty types" appear to be driving the spillovers observed for this group. Specifically, Panel (a) of Figure 3, illustrates that it is these treated shoppers who are more

[25]Indeed Steenhuis (2009) and Gonzalez and Vitousek (2004) find that consuming fattening foods trigger feelings of guilt.

guilt-prone who spend less per product and are more likely to switch supermarkets during the intervention period.[26]

Skepticism could also play a role for those shoppers who are least likely to respond to the nudge by buying the healthier alternative. 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. The persistent decrease in purchases of the healthier alternatives among the shoppers least responsive to the intervention (Appendix Table 6) aligns with this mechanism.

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 duration we observe. To consider this mechanism more carefully, we split the sample of bottom shoppers across those that had higher and lower cognitive loads at the time of receiving the SABH nudge. We characterize shoppers as having a higher cognitive load during the intervention period if they had already received a "Swap and Save" nudge during their shopping trip prior to adding the product that triggers the SABH nudge for treated shoppers. These shoppers may be especially susceptible to spillovers driven by cognitive overload. In panel (b) of Figure 3, we find that treated shoppers who had received a "Swap and Save" nudge earlier on in their shopping trip spend more time selecting products, and were more likely to purchase cheaper product and swap supermarkets.

Cognitive overload and skepticism regarding possible manipulation by the shopping site could also drive attrition. Indeed, when running our difference-in-differences analysis on the balanced panel data (regarding the fraction of times the shopper purchases a relevant product—healthy or unhealthy—in a category out of all shopping trips during that period), we find significant attrition for the shoppers who responded least to the intervention. Specifically, we find that treated shoppers who were most responsive to the intervention were 13 percent more likely to purchase in categories

[26]We note that the magnitudes of the spillovers measured for guilty and non-guilty types do not average out to the results reported for the full sample of least-responsive shoppers in Table 8. The reason for this is that the penalty term in the lasso estimation results in a different set of variables being selected for each sample.

with the SABH than control shoppers (see columns 1–3 of Table 9), while shoppers who were least responsive to the SABH nudge decreased their purchase rate in these same categories by 18 percent (see columns 4–6 of Table 9).

6 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). As a recent article from Time Magazine (Hyman and Gutman, 2024) put it, "While front-of-package labeling on packaged foods is a crucial first step towards a healthier society, education and awareness alone will only get us so far. To drive even more significant change in the way most Americans eat, a change that will lead to a healthier population, we must also incentivize the production and widespread distribution of healthier alternatives. These alternatives—a packaged cookie with healthier ingredients, for instance—must be just as delicious, and readily available as those loaded with sugar."

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 reveals additional insights into consumer behavior. Machine learning analysis of the SABH intervention points to specific consumer types responding most favorably, notably those who shop frequently, make larger purchases, make decisions quickly, and have less healthy tendencies while demonstrating some health consciousness.

In addition, we observe behavioral shifts in shoppers that indicate 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' characteristics and 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.

References

ABC. 2012. "Foods that have hidden fat, sugar, salt." *https://abc7news.com/archive/8589311/*.

Altmann, Steffen, Andreas Grunewald, and Jonas Radbruch. 2022. "Interventions and cognitive spillovers." *The Review of Economic Studies*, 89(5): 2293–2328.

Araya, Sebastian, Andrés Elberg, Carlos Noton, and Daniel Schwartz. 2022. "Identifying food labeling effects on consumer behavior." *Available at SSRN 3195500*.

Arteaga, Felipe, Adam J Kapor, Christopher A Neilson, and Seth D Zimmerman. 2022. "Smart Matching Platforms and Heterogeneous Beliefs in Centralized School Choice." *The Quarterly Journal of Economics*.

Athey, Susan, and Guido Imbens. 2016. "Recursive partitioning for heterogeneous causal effects." *Proceedings of the National Academy of Sciences*, 113(27): 7353–7360.

Athey, Susan, Julie Tibshirani, and Stefan Wager. 2019. "Generalized random forests." *The Annals of Statistics*, 47(2): 1148–1178.

Avishai-Rizi, Or, and Oren Reshef. 2024. “Firms’ Anticipation and Adaptation to Changing Environments: Evidence from Nutritional Regulation.” *Working Paper*.

Balasubramanian, Siva K, and Catherine Cole. 2002. “Consumers’ search and use of nutrition information: The challenge and promise of the nutrition labeling and education act.” *Journal of marketing*, 66(3): 112–127.

Belot, Michèle, Jonathan James, and Jonathan Spiteri. 2020. “Facilitating healthy dietary habits: An experiment with a low income population.” *European economic review*, 129: 103550.

Bhargava, Saurabh, and Dayanand Manoli. 2015. “Psychological frictions and the incomplete take-up of social benefits: Evidence from an IRS field experiment.” *American Economic Review*, 105(11): 3489–3529.

Biban, Bianca Georgiana, and Corina Lichiardopol. 2017. “Iodine deficiency, still a global problem?” *Current health sciences journal*, 43(2): 103.

Brownback, Andy, Alex Imas, and Michael Kuhn. 2021. “Behavioral Food Subsidies.” *Available at SSRN 3422272*.

Bunten, Amanda, Lucy Porter, Jet G Sanders, Anna Sallis, Sarah Payne Riches, Paul Van Schaik, Marta González-Iraizoz, Tim Chadborn, and Suzanna Forwood. 2021. “A randomised experiment of health, cost and social norm message frames to encourage acceptance of swaps in a simulation online supermarket.” *PloS one*, 16(2): e0246455.

Buyalskaya, Anastasia, and Matthew Shum. 2020. “Self-Regulation Failures in the Field: Investigating Spillovers from Morning Exercise to Food Choice.” *Mimeo*.

Cadario, Romain, and Pierre Chandon. 2020. “Which healthy eating nudges work best? A meta-analysis of field experiments.” *Marketing Science*, 39(3): 465–486.

Cawley, John, Adam Biener, Chad Meyerhoefer, Yuchen Ding, Tracy Zvenyach, B Gabriel Smolarz, and Abhilasha Ramasamy. 2021. “Direct medical costs of obesity in the United States and the most populous states.” *Journal of Managed Care & Specialty Pharmacy*, 27(3): 354–366.

Cawley, John, Alex Susskind, and Barton Willage. 2020. “The impact of information disclosure on consumer behavior: evidence from a randomized field experiment of calorie labels on restaurant menus.” *Journal of Policy Analysis and Management*, 39(4): 1020–1042.

Cecchini, Michele, and Laura Warin. 2016. “Impact of food labelling systems on food choices and eating behaviours: a systematic review and meta-analysis of randomized studies.” *Obesity reviews*, 17(3): 201–210.

Chiou, Wen-Bin, Chao-Chin Yang, and Chin-Sheng Wan. 2011. “Ironic effects of dietary supplementation: illusory invulnerability created by taking dietary supplements licenses health-risk behaviors.” *Psychological science*, 22(8): 1081–1086.

Choinière, CJ, and A Lando. 2008. “Health and diet survey.” *Food and Drug Administration: Silver Spring, MD, USA*.

CHP. 2017. "Centre for Health Protection, Department of Health, The Government of the Hong Kong Special Administrative Region." https://www.chp.gov.hk/en/static/90037.html.

Coffino, Jaime A, Tomoko Udo, and Julia M Hormes. 2020. "Nudging while online grocery shopping: A randomized feasibility trial to enhance nutrition in individuals with food insecurity." *Appetite*, 152: 104714.

Crespo-Bellido, Mayra S, Stephanie K Grutzmacher, Yumie Takata, and Ellen Smit. 2021. "The Association Between Food-Away-From-Home Frequency and a Higher BMI Varies by Food Security Status in US Adults." *The Journal of Nutrition*, 151(2): 387–394.

De Witt Huberts, Jessie C, Catharine Evers, and Denise TD De Ridder. 2012. "License to sin: Self-licensing as a mechanism underlying hedonic consumption." *European Journal of Social Psychology*, 42(4): 490–496.

Dolan, Paul, and Matteo M Galizzi. 2014. "Because I'm worth it: a lab-field experiment on the spillover effects of incentives in health."

Dolan, Paul, and Matteo M Galizzi. 2015. "Like ripples on a pond: behavioral spillovers and their implications for research and policy." *Journal of Economic Psychology*, 47: 1–16.

Downs, Julie S, George Loewenstein, and Jessica Wisdom. 2009. "Strategies for promoting healthier food choices." *American Economic Review*, 99(2): 159–64.

Downs, Julie S, Jessica Wisdom, Brian Wansink, and George Loewenstein. 2013. "Supplementing menu labeling with calorie recommendations to test for facilitation effects." *American Journal of Public Health*, 103(9): 1604–1609.

Drake, Marshall, Fernando Payró, Neil Thakral, and Linh T Tô. 2022. "Bayesian Adaptive Choice Experiments." *Mimeo.*

Drake, Marshall, Neil Thakral, and Linh T Tô. 2022. "Wage Differentials and the Price of Workplace Flexibility." *Mimeo.*

Drichoutis, Andreas C, Rodolfo M Nayga, and Panagiotis Lazaridis. 2012. "Food away from home expenditures and obesity among older Europeans: are there gender differences?" *Empirical Economics*, 42(3): 1051–1078.

Ericson, Keith Marzilli, and David Laibson. 2019. "Intertemporal choice." In *Handbook of Behavioral Economics: Applications and Foundations 1.* Vol. 2, 1–67. Elsevier.

Finkelstein, Eric A, Felicia Jia Ler Ang, Brett Doble, Wei Han Melvin Wong, and Rob M van Dam. 2019. "A randomized controlled trial evaluating the relative effectiveness of the Multiple Traffic Light and Nutri-Score front of package nutrition labels." *Nutrients*, 11(9): 2236.

Finkelstein, Eric Andrew, Felicia Jia Ler Ang, and Brett Doble. 2020. "Randomized trial evaluating the effectiveness of within versus across-category front-of-package lower-calorie labelling on food demand." *BMC public health*, 20(1): 1–10.

Forwood, Suzanna E, Amy L Ahern, Theresa M Marteau, and Susan A Jebb. 2015. "Offering within-category food swaps to reduce energy density of food purchases: a study using an experimental online supermarket." *International Journal of Behavioral Nutrition and Physical Activity*, 12(1): 1–10.

Galizzi, Matteo M, and Lorraine Whitmarsh. 2019. "How to measure behavioral spillovers: a methodological review and checklist." *Frontiers in psychology*, 10: 342.

Gonzalez, Vivian MM, and Kelly M Vitousek. 2004. "Feared food in dieting and non-dieting young women: a preliminary validation of the Food Phobia Survey." *Appetite*, 43(2): 155–173.

Griffith, Rachel, Stephanie von Hinke, and Sarah Smith. 2018. "Getting a healthy start: The effectiveness of targeted benefits for improving dietary choices." *Journal of health economics*, 58: 176–187.

Guthrie, Joanne, Lisa Mancino, and Chung-Tung Jordan Lin. 2015. "Nudging consumers toward better food choices: Policy approaches to changing food consumption behaviors." *Psychology & Marketing*, 32(5): 501–511.

Herber, Stefanie P. 2018. "The role of information in the application for highly selective scholarships: Evidence from a randomized field experiment." *Economics of Education Review*, 62: 287–301.

Horgen, Katherine Battle, and Kelly D Brownell. 2002. "Comparison of price change and health message interventions in promoting healthy food choices." *Health Psychology*, 21(5): 505.

Hoxby, Caroline M, and Sarah Turner. 2013. "Informing students about their college options: A proposal for broadening the expanding college opportunities project."

Huang, Amy, Federica Barzi, Rachel Huxley, Gareth Denyer, Beth Rohrlach, Kathy Jayne, and Bruce Neal. 2006. "The effects on saturated fat purchases of providing internet shoppers with purchase-specific dietary advice: a randomised trial." *PLoS clinical trials*, 1(5): e22.

Hui, Sam K, Eric T Bradlow, and Peter S Fader. 2009. "Testing behavioral hypotheses using an integrated model of grocery store shopping path and purchase behavior." *Journal of consumer research*, 36(3): 478–493.

Hulshof, Casper D, and Ton De Jong. 2006. "Using just-in-time information to support scientific discovery learning in a computer-based simulation." *Interactive Learning Environments*, 14(1): 79–94.

Hyman, Mark, and Ron Gutman. 2024. "It's Time to Treat Sugar Like Cigarettes." https://time.com/6973208/sugar-america-transparency-essay/.

Imas, Alex, Michael A Kuhn, and Vera Mironova. 2022. "Waiting to choose: The role of deliberation in intertemporal choice." *American Economic Journal: Microeconomics*, 14(3): 414–440.

Jansen, Laura, Ellen van Kleef, and Ellen J Van Loo. 2021. "The use of food swaps to encourage healthier online food choices: a randomized controlled trial." *International journal of behavioral nutrition and physical activity*, 18(1): 1–16.

Kadosh, Nurit. 2024. "The Public is Paying More: The Dairy Market Grew Last Year by 9.2 percent." *Calcalist*. https://www.calcalist.co.il/shopping/article/ryek4ou7r.

Khan, Uzma, and Ravi Dhar. 2006. "Licensing effect in consumer choice." *Journal of marketing research*, 43(2): 259–266.

Kling, Jeffrey R, Sendhil Mullainathan, Eldar Shafir, Lee C Vermeulen, and Marian V Wrobel. 2012. "Comparison friction: Experimental evidence from Medicare drug plans." *The quarterly journal of economics*, 127(1): 199–235.

Koutoukidis, Dimitrios A, Susan A Jebb, José M Ordóñez-Mena, Michaela Noreik, Melina Tsiountsioura, Sarah Kennedy, Sarah Payne-Riches, Paul Aveyard, and Carmen Piernas. 2019. "Prominent positioning and food swaps are effective interventions to reduce the saturated fat content of the shopping basket in an experimental online supermarket: a randomized controlled trial." *International Journal of Behavioral Nutrition and Physical Activity*, 16(1): 1–14.

Lazarus, John H. 2020. "Iodine deficiency in Israeli pregnant women–a time for action." *Israel Journal of Health Policy Research*, 9(1): 1–3.

Loewenstein, George, Joseph Price, and Kevin Volpp. 2016. "Habit formation in children: Evidence from incentives for healthy eating." *Journal of health economics*, 45: 47–54.

Lowe, Ben, Diogo M de Souza-Monteiro, and Iain Fraser. 2013. "Nutritional labelling information: Utilisation of new technologies." *Journal of Marketing Management*, 29(11-12): 1337–1366.

Ludwig, Jens, Sendhil Mullainathan, and Jann Spiess. 2019. "Machine-learning tests for effects on multiple outcomes." *arXiv preprint arXiv:1707.01473*.

Medina, Paolina C. 2021. "Side effects of nudging: Evidence from a randomized intervention in the credit card market." *The Review of Financial Studies*, 34(5): 2580–2607.

Murray, Christopher JL, Aleksandr Y Aravkin, Peng Zheng, Cristiana Abbafati, Kaja M Abbas, Mohsen Abbasi-Kangevari, Foad Abd-Allah, Ahmed Abdelalim, Mohammad Abdollahi, Ibrahim Abdollahpour, et al. 2020. "Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019." *The Lancet*, 396(10258): 1223–1249.

Nafziger, Julia. 2020. "Spillover effects of nudges." *Economics Letters*, 190: 109086.

Nahum-Shani, Inbal, Shawna N Smith, Bonnie J Spring, Linda M Collins, Katie Witkiewitz, Ambuj Tewari, and Susan A Murphy. 2018. "Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support." *Annals of Behavioral Medicine*, 52(6): 446–462.

NHMRC. 2015. "Fat, Salt, Sugars and Alcohol." *https://www.eatforhealth.gov.au/food-essentials/fat-salt-sugars-and-alcohol*.

NIH. 2016. "New dietary guidelines urge Americans to eat less added sugars, saturated fat, and sodium." *https://www.nhlbi.nih.gov/news/2016/new-dietary-guidelines-urge-americans-eat-less-added-sugars-saturated-fat-and-so*

Olsho, Lauren EW, Jacob A Klerman, Parke E Wilde, and Susan Bartlett. 2016. "Financial incentives increase fruit and vegetable intake among Supplemental Nutrition Assistance Program participants: a randomized controlled trial of the USDA Healthy Incentives Pilot." *The American journal of clinical nutrition*, 104(2): 423–435.

Ovadia, Yaniv S, Jonathan E Arbelle, Dov Gefel, Hadassah Brik, Tamar Wolf, Varda Nadler, Sandra Hunziker, Michael B Zimmermann, and Aron M Troen. 2017. "First Israeli national iodine survey demonstrates iodine deficiency among school-aged children and pregnant women." *Thyroid*, 27(8): 1083–1091.

Polivy, Janet, C Peter Herman, and Traci McFarlane. 1994. "Effects of anxiety on eating: Does palatability moderate distress-induced overeating in dieters?" *Journal of Abnormal Psychology*, 103(3): 505.

Ponzo, Valentina, Marianna Pellegrini, Paola Costelli, Laura Vázquez-Araújo, Lucía Gayoso, Chiara D'Eusebio, Ezio Ghigo, and Simona Bo. 2021. "Strategies for reducing salt and sugar intakes in individuals at increased cardiometabolic risk." *Nutrients*, 13(1): 279.

Read, Daniel, and Barbara Van Leeuwen. 1998. "Predicting hunger: The effects of appetite and delay on choice." *Organizational behavior and human decision processes*, 76(2): 189–205.

Riches, Sarah Payne, Paul Aveyard, Carmen Piernas, Mike Rayner, and Susan A Jebb. 2019. "Optimising swaps to reduce the salt content of food purchases in a virtual online supermarket: A randomised controlled trial." *Appetite*, 133: 378–386.

Rizkalla, Salwa W, F Bellisle, and G Slama. 2002. "Health benefits of low glycaemic index foods, such as pulses, in diabetic patients and healthy individuals." *British Journal of Nutrition*, 88(S3): 255–262.

Sacco, Jocelyn, Heather G Lillico, Emily Chen, and Erin Hobin. 2017. "The influence of menu labelling on food choices among children and adolescents: a systematic review of the literature." *Perspectives in public health*, 137(3): 173–181.

Sacks, Gary, Kim Tikellis, Lynne Millar, and Boyd Swinburn. 2011. "Impact of 'traffic-light' nutrition information on online food purchases in Australia." *Australian and New Zealand journal of public health*, 35(2): 122–126.

Shin, Soye, Rob M van Dam, and Eric A Finkelstein. 2020. "The Effect of

Dynamic Food Labels with Real-Time Feedback on Diet Quality: Results from a Randomized Controlled Trial." *Nutrients*, 12(7): 2158.

Steenhuis, Ingrid. 2009. "Guilty or not? Feelings of guilt about food among college women." *Appetite*, 52(2): 531–534.

Sunstein, Cass R. 2013*a*. "Nudges.gov: Behavioral economics and regulation." *Oxford Handbook of Behavioral Economics and the Law (Eyal Zamir and Doron Teichman eds.)*.

Sunstein, Cass R. 2013*b*. *Simpler: The future of government.* Simon and Schuster.

Thakral, Neil, and Linh T Tô. 2020. "Anticipation and Temptation." *Mimeo.*

Thakral, Neil, and Linh T Tô. 2022. "Anticipation and Consumption." *Mimeo.*

Tibshirani, Robert. 1996. "Regression shrinkage and selection via the lasso." *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 58(1): 267–288.

Trachtman, Hannah. 2024. "Does promoting one healthy behavior detract from others? Evidence from a field experiment." *American Economic Journal: Applied Economics*, 16(2): 249–277.

Urbszat, Dax, C Peter Herman, and Janet Polivy. 2002. "Eat, drink, and be merry, for tomorrow we diet: effects of anticipated deprivation on food intake in restrained and unrestrained eaters." *Journal of abnormal psychology*, 111(2): 396.

Van der Laan, L Nynke, and Oliwia Orcholska. 2022. "Effects of digital just-in-time nudges on healthy food choice–a field experiment." *Food Quality and Preference*, 98: 104535.

Van Herpen, Erica, and Hans CM Van Trijp. 2011. "Front-of-pack nutrition labels. Their effect on attention and choices when consumers have varying goals and time constraints." *Appetite*, 57(1): 148–160.

Wager, Stefan, and Susan Athey. 2018. "Estimation and inference of heterogeneous treatment effects using random forests." *Journal of the American Statistical Association*, 113(523): 1228–1242.

WHO. 2000. "Obesity: preventing and managing the global epidemic."

Wilcox, Keith, Beth Vallen, Lauren Block, and Gavan J Fitzsimons. 2009. "Vicarious goal fulfillment: When the mere presence of a healthy option leads to an ironically indulgent decision." *Journal of Consumer Research*, 36(3): 380–393.

Wilson, Amy L, Elizabeth Buckley, Jonathan D Buckley, and Svetlana Bogomolova. 2016. "Nudging healthier food and beverage choices through salience and priming. Evidence from a systematic review." *Food Quality and Preference*, 51: 47–64.

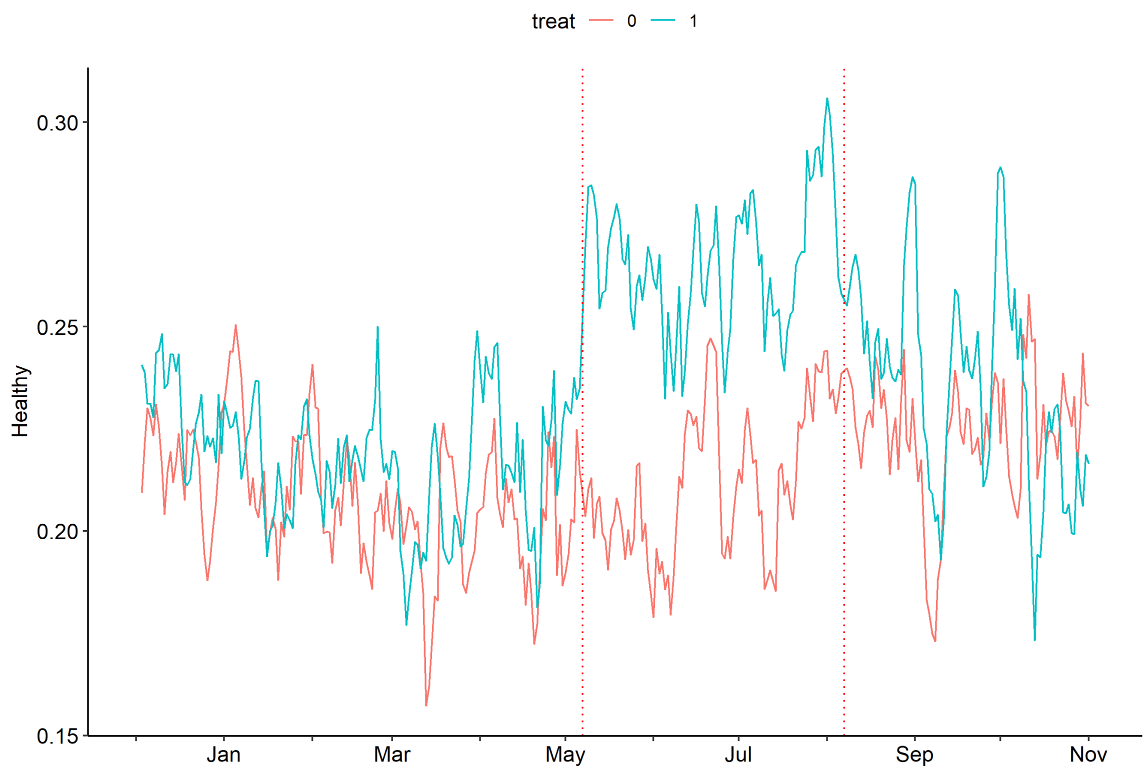
Wisdom, Jessica, Julie S Downs, and George Loewenstein. 2010. "Promoting healthy choices: Information versus convenience." *American Economic Journal: Applied Economics*, 2(2): 164–78.

Wrieden, Wendy L, and Louis B Levy. 2016. "'Change4Life Smart Swaps':

quasi-experimental evaluation of a natural experiment." *Public Health Nutrition*, 19(13): 2388–2392.

Zeitan, Avi. 2011. "A Big Change in the Pretzels Market." *Globes*. https://www.globes.co.il/news/article.aspx?did=1000642146.

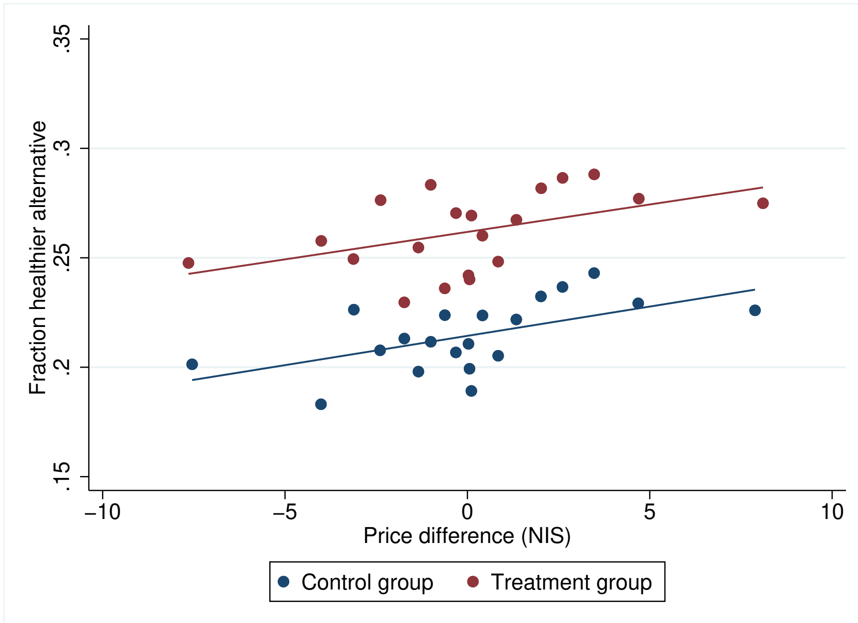
Figure 1: Effect of SABH: Event study



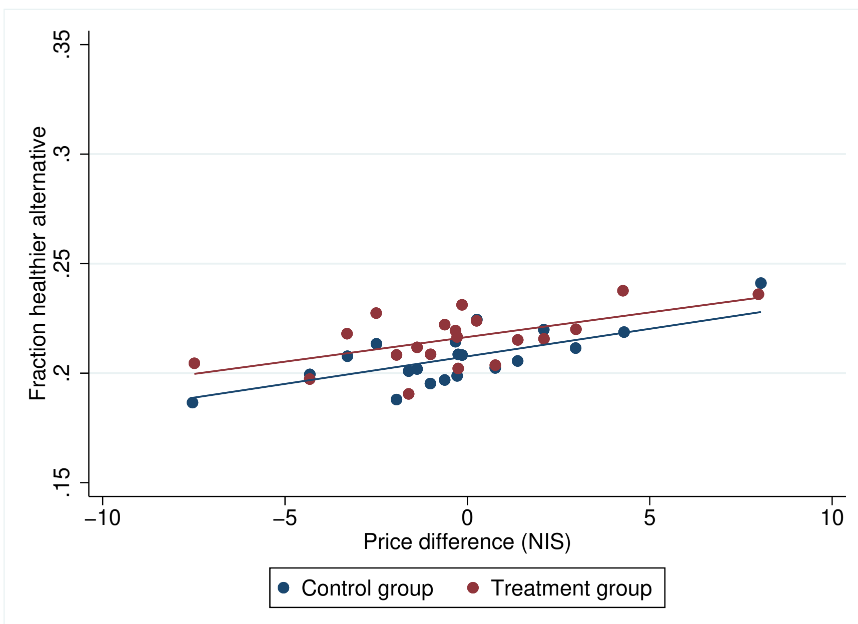
Note: This event study figure maps the five-day moving average of the fraction of healthy alternatives out of all relevant purchases for shoppers in the treatment and control groups.

Figure 2: Effect of treatment by price difference

(a) During intervention



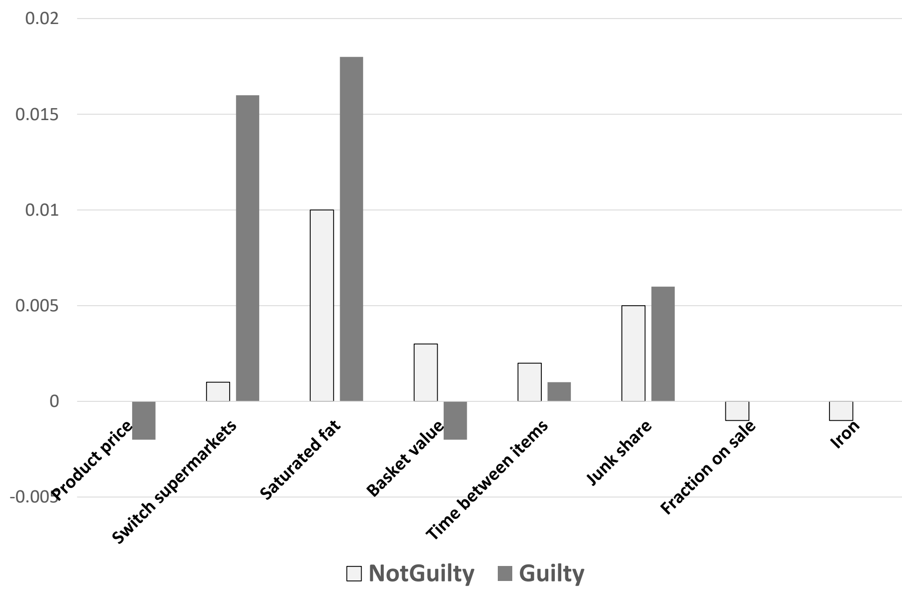
(b) Before intervention



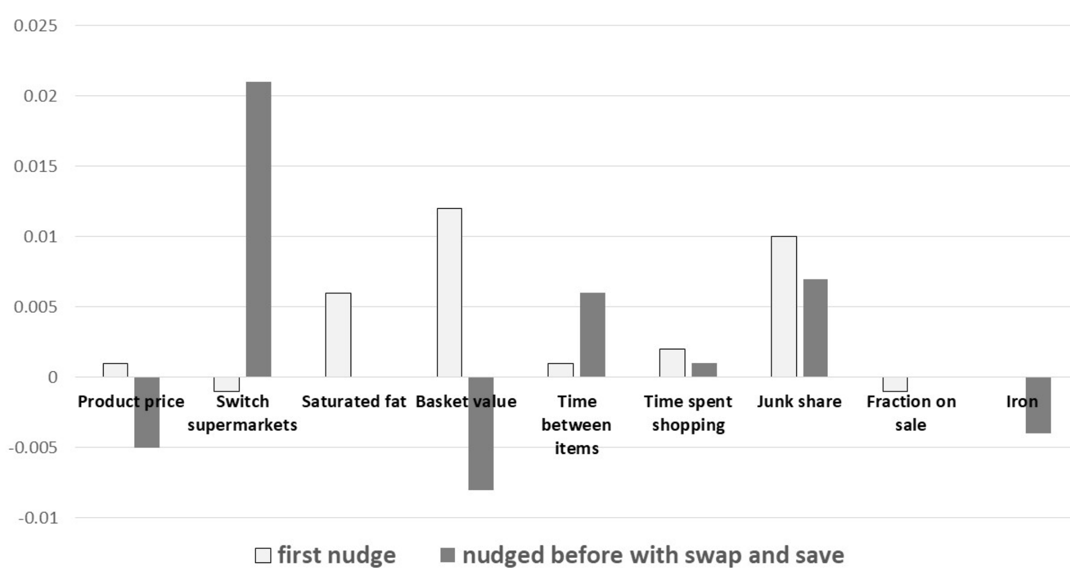
Note: Each panel shows a binned scatterplot of the relationship between the probability of purchasing the healthier alternative and the price difference, controlling for shopper and product category fixed effects. Price difference is defined as the difference between the price of the less healthy product and the healthier alternative. The sample in the top panel consists of shoppers during the 4 month intervention period, and the sample in the bottom panel consists of shoppers in the 6 months leading up to the intervention period.

Figure 3: Mechanisms Driving the Spillover Effect for Bottom Shoppers

(a) Guilty Types



(b) Cognitive Overload



Note: Each panel maps the LASSO estimates predicting spillover behaviors for the treatment group of bottom shoppers. Guilty types are defined as shoppers who in the pre-intervention period added junk-food products to their basket and removed them before purchase. Shoppers more prone to cognitive overload are defined as shoppers who already received a "Swap and Save" nudge prior to receiving the SABH nudge on this trip. In the top panel, the sample of bottom shoppers is split between those that are defined as guilty-types and those who are not, and in the bottom panel, this same sample is split across shoppers more and less likely to be responding to cognitive overload.

Table 1: List of experimental product categories 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	3.30	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	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 across the 15 product categories from the experiment (with rice classified as a single category). The first column lists the product category 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 average unit prices of the set of experimental products across multiple brands in that category and the healthier alternative in NIS.

Table 2: Features with definitions

Panel A: General features	Definition
Shopping frequency	Number of baskets per month
Basket purchase time	Average shopping time in minutes
Item purchase time	Average time it takes the consumer to add an item to basket in seconds
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 on sale
Supermarket switches	Fraction of baskets that change supermarkets
Cheapest basket selected	Fraction of baskets checked out in the cheapest supermarket
Basket price premium	Average fractional 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
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
Ever added alcohol/cigarettes	Fraction of baskets that contain at least one alcohol or cigarette item
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 pre-intervention period. A sequence is defined as four consecutive products.

Table 3: Basket-level summary statistics (Balance)

	Control	Treat	Difference	Std. err.
Panel A: General features				
Shopping frequency	2.1747	2.2254	0.0507	0.0488
Basket purchase time (min)	39.8257	39.5490	-0.2768	0.6717
Item purchase time (sec)	61.7673	60.4552	-1.3122	0.8296
Products removed	0.0488	0.0495	0.0007	0.0012
Panel B: Price-related features				
Average item price (NIS)	11.0957	10.8858	-0.2098	0.0770
Average basket price (NIS)	577.7015	570.9050	-6.7965	5.9117
"Swap & Save" opened	0.0227	0.0240	0.0012	0.0010
On sale	0.0551	0.0542	-0.0009	0.0018
Supermarket switches	0.1423	0.1398	-0.0024	0.0054
Cheapest basket selected	0.6138	0.6169	0.0030	0.0091
Basket price premium	0.0398	0.0393	-0.0006	0.0011
Panel C: Health-related features				
Produce fraction	0.2295	0.2315	0.0020	0.0032
Baseline demand for healthier variety	0.1943	0.1857	-0.0087	0.0060
Junk fraction	0.1236	0.1261	0.0026	0.0019
Ever added junk	0.8697	0.8721	0.0025	0.0056
Ended basket on junk	0.1486	0.1484	-0.0002	0.0047
Produce before junk	0.1864	0.1874	0.0009	0.0059
Alcohol/cigarettes fraction	0.0211	0.0209	-0.0002	0.0010
Ever added alcohol/cigarettes	0.6706	0.6770	0.0063	0.0101
Panel D: Lifestyle features				
Contains baby products	0.3485	0.3436	-0.0049	0.0103
Contains ultra-Orthodox products	0.1706	0.1826	0.0119	0.0082
Sample size	4272	4278		

Note: The data is at the user level in the pre-intervention period and is based on 61,463 baskets. 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 error for the difference is from the same regression.

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)
Sample size	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

	Balanced panel			Relevant purchases		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Buying a healthier alternative						
Treat	-0.0002	-0.0002		0.0105	0.0089	
	(0.0012)	(0.0012)		(0.0074)	(0.0071)	
During experiment	-0.0098	-0.0098	-0.0098	0.0070	0.0103	0.0061
	(0.0008)	(0.0008)	(0.0008)	(0.0040)	(0.0039)	(0.0035)
After experiment	-0.0155	-0.0155	-0.0155	0.0143	0.0137	0.0064
	(0.0008)	(0.0008)	(0.0008)	(0.0050)	(0.0049)	(0.0041)
Treat × During experiment	0.0082	0.0082	0.0082	0.0397	0.0388	0.0419
	(0.0012)	(0.0012)	(0.0012)	(0.0059)	(0.0057)	(0.0051)
Treat × After experiment	0.0022	0.0022	0.0022	0.0052	0.0054	0.0118
	(0.0012)	(0.0012)	(0.0012)	(0.0071)	(0.0069)	(0.0060)
Outcome mean	0.0423	0.0423	0.0423	0.2114	0.2114	0.2114
Panel B: Adding healthier alternative						
Treat	-0.0003	-0.0003		0.0104	0.0088	
	(0.0012)	(0.0012)		(0.0074)	(0.0071)	
During experiment	-0.0097	-0.0097	-0.0097	0.0072	0.0106	0.0063
	(0.0008)	(0.0008)	(0.0008)	(0.0040)	(0.0039)	(0.0035)
After experiment	-0.0154	-0.0154	-0.0154	0.0147	0.0141	0.0068
	(0.0008)	(0.0008)	(0.0008)	(0.0050)	(0.0049)	(0.0041)
Treat × During experiment	0.0028	0.0028	0.0028	0.0123	0.0114	0.0159
	(0.0012)	(0.0012)	(0.0012)	(0.0058)	(0.0055)	(0.0049)
Treat × After experiment	0.0022	0.0022	0.0022	0.0048	0.0050	0.0112
	(0.0012)	(0.0012)	(0.0012)	(0.0071)	(0.0069)	(0.0061)
Outcome mean	0.0422	0.0422	0.0422	0.2109	0.2109	0.2109
Sample size	377145	377145	377145	148524	148524	148524
Category FE		X	X		X	X
Shopper FE			X			X

Note: The sample consists of all shoppers who purchased at least one of the relevant products in any period. Columns (1) to (3) use a balanced panel data set in which each observation corresponds to a buyer, a product category, and a period (before, during and after the intervention period). The dependent variable in panel A is the fraction of times a customer purchases the healthy rather than the unhealthy variety of the relevant product in a given category. The dependent variable in panel B is the fraction of times a customer initially adds the healthy variety of the relevant product to the basket, rather than making a purchase. In columns (4) to (6), each purchase of a relevant product corresponds to a unique observation in the data. In panel A the dependent variable is an indicator of buying the healthy rather than the unhealthy variety of the experimental product. In panel B the dependent variable is an indicator for the initial addition of the healthy rather than unhealthy variety of the experimental product 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 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 shows the relationship of the first stage between being assigned to the treatment and receiving an SABH prompt in a given category of products. 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 that a consumer 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 relevant products in any period. Within each pair of columns, the second specification adds the 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

	Least	Most	Difference	Std. err.
Panel A: General features				
Shopping frequency	1.6444	2.4863	0.8419	0.1133
Products removed	0.0517	0.0426	-0.0091	0.0016
Item purchase time (sec)	64.7501	53.6439	-11.1062	0.7195
Basket purchase time (min)	39.7142	38.8999	-0.8143	0.7220
Panel B: Price-related features				
Supermarket switches	0.1580	0.1049	-0.0531	0.0103
On sale	0.0596	0.0457	-0.0139	0.0058
Average basket price (NIS)	540.8500	616.6166	75.7666	11.4130
Basket price premium	0.0353	0.0338	-0.0015	0.0022
Average item price (NIS)	11.0579	10.6083	-0.4496	0.0012
"Swap & Save" opened	0.0231	0.0238	0.0007	0.0052
Cheapest basket selected	0.6060	0.6074	0.0014	0.0162
Panel C: Health-related characteristics				
Produce before junk	0.1016	0.2699	0.1683	0.0108
Ended basket on junk	0.1218	0.1681	0.0462	0.0075
Ever added alcohol/cigarettes	0.6008	0.8006	0.1998	0.0171
Junk fraction	0.1135	0.1371	0.0235	0.0031
Baseline demand for healthier variety	0.1840	0.2159	0.0320	0.0117
Alcohol/cigarettes fraction	0.0203	0.0187	-0.0016	0.0017
Ever added junk	0.8606	0.9184	0.0577	0.0081
Produce fraction	0.2374	0.2320	-0.0054	0.0052
Panel D: Lifestyle features				
Contains ultra-Orthodox products	0.1652	0.2427	0.0775	0.0149
Buy baby product (indicator)	0.3485	0.3785	0.0300	0.0181
Sample size	1886	1886		

Note: The table displays the average pre-intervention characteristics of shoppers who are in the top (most responsive) and bottom 25 percent (least responsive), respectively, of the distribution of predicted responses to the treatment. The difference is based on a regression where the variable is regressed on the most responsive indicator and a constant. The standard error 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. The features are ordered within their feature category (general, price-related, health-related, and lifestyle) by the (absolute value of the) percent difference between consumer types.

Table 8: Effects of SABH on other behaviors, during intervention period (most- and least-responsive shoppers)

Least-responsive shoppers		Most-responsive shoppers	
Variable	Value	Variable	Value
Product price	-0.011	Ultra-Orthodox expenditure	0.012
Switch supermarkets	0.009	Dietary fiber	0.010
Saturated fat	0.004	Product price	0.008
Basket value	-0.002	Swap & Saves opened	0.007
Time between items	0.001	Cholesterol	-0.007
Time spent shopping	0.001	Junk share	-0.006
Ended shopping on junk	0.001	Sodium	0.005
Junk share	0.001	Price diff. from most expensive	-0.005
Fraction on sale	-0.001	Child share	-0.005
Iron	-0.001	Junk expenditure	-0.005
Swap & Saves opened	0	Child expenditure	-0.005
Swap & Saves accepted	0	Alc. & cig. expenditure	-0.004
Price diff. from most expensive	0	Switch supermarkets	-0.003
Price diff. from cheapest	0	Alc. & cig. share	-0.003
Fruit/vegetable share	0	Protein share	-0.003
Grain share	0	Iron	0.002
Nonfood share	0	Ultra-Orthodox share	-0.002
Alc. & cig. share	0	Protein expenditure	-0.002
Protein share	0	Saturated fat	-0.002
Dairy share	0	Swap & Saves accepted	0.001
Ultra-Orthodox share	0	Time spent shopping	-0.001
Child share	0	Total calories	-0.001
Junk expenditure	0	Time between items	0
Fruit/vegetable expenditure	0	Fraction on sale	0
Alc. & cig. expenditure	0	Basket value	0
Dairy expenditure	0	Price diff. from cheapest	0
Grain expenditure	0	Ended shopping on junk	0
Nonfood expenditure	0	Fruit/vegetable share	0
Protein expenditure	0	Grain share	0
Ultra-Orthodox expenditure	0	Nonfood share	0
Child expenditure	0	Dairy share	0
Total calories	0	Fruit/vegetable expenditure	0
Sugar	0	Dairy expenditure	0
Sodium	0	Grain expenditure	0
Dietary fiber	0	Nonfood expenditure	0
Cholesterol	0	Sugar	0
Protein	0	Protein	0

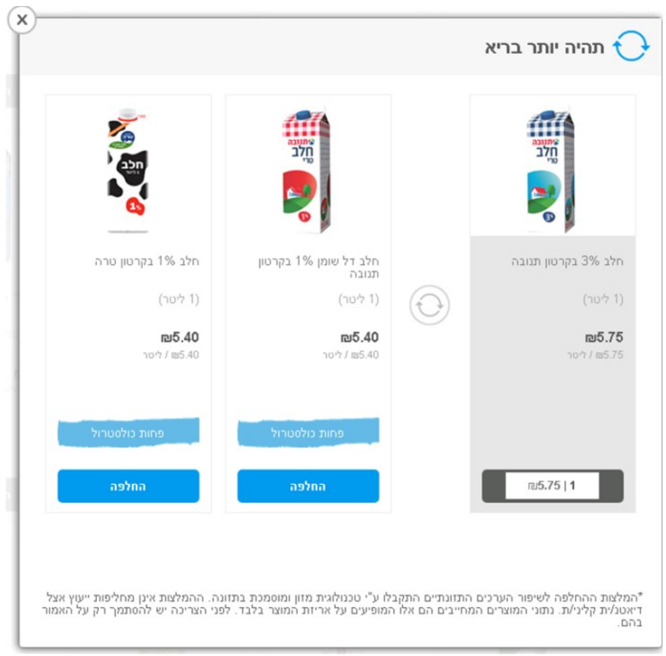
Note: This table presents the averages of the coefficients from running a LASSO regression 1,000 times to predict treatment status during the intervention based on the covariates listed above. Entries shaded in dark gray correspond to general- and price-related features, and entries shaded in light gray correspond to health-related features.

Table 9: Effect of SABH on purchasing in category—Difference in differences

	Most responsive			Least responsive		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.0034	-0.0034		-0.0030	-0.0030	
	(0.0065)	(0.0065)		(0.0048)	(0.0048)	
During experiment	-0.0993	-0.0993	-0.0993	0.0129	0.0129	0.0129
	(0.0042)	(0.0042)	(0.0042)	(0.0032)	(0.0032)	(0.0032)
After experiment	-0.1262	-0.1262	-0.1262	-0.0406	-0.0406	-0.0406
	(0.0044)	(0.0044)	(0.0045)	(0.0036)	(0.0036)	(0.0037)
Treat $\times$ During experiment	0.0358	0.0358	0.0358	-0.0241	-0.0241	-0.0241
	(0.0059)	(0.0059)	(0.0059)	(0.0046)	(0.0046)	(0.0046)
Treat $\times$ After experiment	0.0189	0.0189	0.0189	-0.0079	-0.0079	-0.0079
	(0.0063)	(0.0063)	(0.0064)	(0.0051)	(0.0051)	(0.0051)
Outcome mean	0.2827	0.2827	0.2827	0.1330	0.1330	0.1330
Sample size	84825	84825	84825	84825	84825	84825
Category FE		X	X		X	X
Shopper FE			X			X

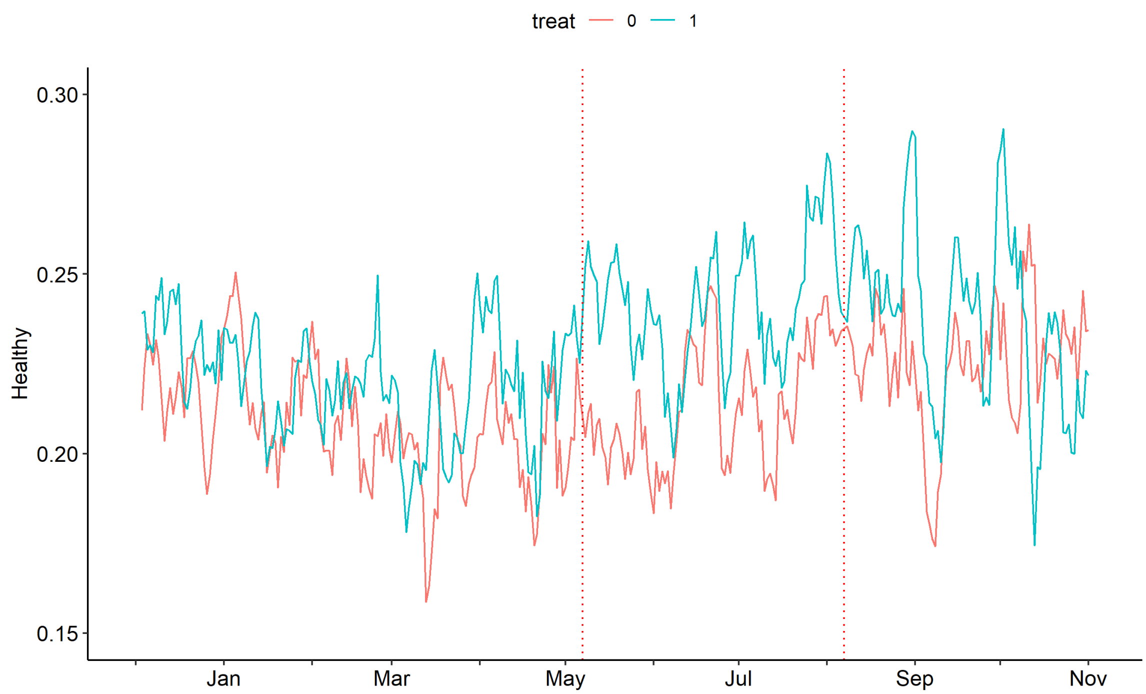
Note: The sample in columns (1) to (3) consists of shoppers who are in the top 25 percent of the distribution of predicted responses to the treatment, while the sample in columns (4) to (6) consists of shoppers in the bottom 25 percent of the distribution. Each observation corresponds to a shopper, product category, and time period (before, during, and after the intervention period). The dependent variable is the fraction of times a shopper purchases any product (healthy or unhealthy) in a given category. See Table 5 for additional details regarding the specifications.

Appendix Figure 1: 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.

Appendix Figure 2: Effect of SABH: Event study (add healthy)



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

Appendix Table 1: Effect of SABH on number of shopping trips—Difference in differences

	Intensive margin			Extensive margin		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.0686	0.0686		-0.0006	-0.0006	
	(0.0568)	(0.0568)		(0.0030)	(0.0030)	
During experiment	-1.0774	-1.0774	-1.0774	-0.0506	-0.0506	-0.0506
	(0.0280)	(0.0280)	(0.0283)	(0.0019)	(0.0019)	(0.0019)
After experiment	-1.2404	-1.2404	-1.2404	-0.0787	-0.0787	-0.0787
	(0.0299)	(0.0299)	(0.0303)	(0.0020)	(0.0020)	(0.0020)
Treat × During experiment	-0.0580	-0.0580	-0.0580	0.0008	0.0008	0.0008
	(0.0422)	(0.0422)	(0.0426)	(0.0026)	(0.0026)	(0.0027)
Treat × After experiment	-0.0635	-0.0635	-0.0635	-0.0002	-0.0002	-0.0002
	(0.0450)	(0.0450)	(0.0455)	(0.0028)	(0.0028)	(0.0028)
Outcome mean	1.8976	1.8976	1.8976	0.1930	0.1930	0.1930
Sample size	377145	377145	377145	377145	377145	377145
Category FE		X	X		X	X
Shopper FE			X			X

Note: This table reports difference-in-differences estimates of the effect of the treatment on the number of trips a shopper makes (columns 1 to 3) and on whether the shopper uses the platform at all (columns 4 to 6). See the balanced panel specification of Table 5 for additional details.

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

	Balanced panel			Relevant purchases		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.0003	-0.0003		0.0105	0.0089	
	(0.0012)	(0.0012)		(0.0074)	(0.0071)	
During experiment	-0.0265	-0.0265	-0.0265	0.0066	0.0024	-0.0057
	(0.0008)	(0.0008)	(0.0008)	(0.0060)	(0.0057)	(0.0051)
After experiment	-0.0305	-0.0305	-0.0305	0.0158	0.0133	0.0042
	(0.0008)	(0.0008)	(0.0009)	(0.0069)	(0.0066)	(0.0062)
Treat × During experiment	0.0047	0.0047	0.0047	0.0410	0.0440	0.0573
	(0.0012)	(0.0012)	(0.0012)	(0.0089)	(0.0085)	(0.0076)
Treat × After experiment	0.0020	0.0020	0.0020	0.0199	0.0195	0.0258
	(0.0012)	(0.0012)	(0.0012)	(0.0101)	(0.0096)	(0.0089)
Outcome mean	0.0429	0.0429	0.0429	0.2114	0.2114	0.2114
Sample size	372465	372465	372465	92331	92331	92331
Category FE		X	X		X	X
Shopper FE			X			X

Note: This table reports results analogous to Table 5 for the subsample consisting of only the first shopping trip in the during-experiment period and the first shopping trip in the after-experiment period in addition to the pre-experiment shopping trips.

Appendix Table 3: Effect of SABH on healthy purchases —Difference in differences (Heterogeneity by price)

	Balanced panel			Relevant purchases		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Healthy variety more expensive						
Treat	-0.0002	-0.0002		0.0070	0.0039	
	(0.0014)	(0.0014)		(0.0084)	(0.0076)	
During experiment	-0.0108	-0.0122	-0.0122	-0.0092	0.0059	0.0041
	(0.0010)	(0.0010)	(0.0011)	(0.0057)	(0.0051)	(0.0048)
After experiment	-0.0196	-0.0151	-0.0151	-0.0163	0.0138	0.0094
	(0.0011)	(0.0011)	(0.0011)	(0.0073)	(0.0066)	(0.0063)
Treat × During experiment	0.0080	0.0080	0.0080	0.0550	0.0519	0.0502
	(0.0015)	(0.0015)	(0.0015)	(0.0084)	(0.0077)	(0.0073)
Treat × After experiment	0.0025	0.0025	0.0025	0.0164	0.0148	0.0202
	(0.0015)	(0.0015)	(0.0016)	(0.0104)	(0.0097)	(0.0092)
Outcome mean	0.0442	0.0442	0.0442	0.2286	0.2286	0.2286
Sample size	251430	251430	251430	74373	74373	74373
Category FE		X	X		X	X
Shopper FE			X			X
Panel B: Healthy variety less expensive						
Treat	-0.0005	-0.0005		0.0141	0.0142	
	(0.0019)	(0.0019)		(0.0118)	(0.0117)	
During experiment	-0.0065	-0.0043	-0.0043	0.0246	0.0170	0.0094
	(0.0012)	(0.0012)	(0.0013)	(0.0060)	(0.0060)	(0.0048)
After experiment	-0.0070	-0.0118	-0.0118	0.0445	0.0142	0.0028
	(0.0014)	(0.0014)	(0.0014)	(0.0076)	(0.0077)	(0.0058)
Treat × During experiment	0.0087	0.0087	0.0087	0.0242	0.0252	0.0251
	(0.0018)	(0.0018)	(0.0019)	(0.0086)	(0.0085)	(0.0072)
Treat × After experiment	0.0020	0.0020	0.0020	-0.0051	-0.0036	0.0066
	(0.0020)	(0.0020)	(0.0021)	(0.0106)	(0.0106)	(0.0089)
Outcome mean	0.0372	0.0372	0.0372	0.1928	0.1928	0.1928
Sample size	125715	125715	125715	74151	74151	74151
Category FE		X	X		X	X
Shopper FE			X			X

Note: The sample in the top and bottom panels consists of products in which the suggested healthier alternative is more expensive and less expensive, respectively, than the less healthy variety. See Table 5 for additional details regarding the specifications.

Appendix Table 4: Effect of SABH on healthy purchases—Difference in differences (Subsample)

	Balanced panel			Relevant purchases		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.0012	0.0012		0.0008	-0.0003	
	(0.0014)	(0.0014)		(0.0075)	(0.0073)	
During experiment	-0.0119	-0.0119	-0.0119	0.0085	0.0118	0.0112
	(0.0009)	(0.0009)	(0.0009)	(0.0040)	(0.0039)	(0.0035)
After experiment	-0.0167	-0.0167	-0.0167	0.0144	0.0141	0.0117
	(0.0009)	(0.0009)	(0.0009)	(0.0050)	(0.0049)	(0.0041)
Treat $\times$ During experiment	0.0098	0.0098	0.0098	0.0318	0.0308	0.0308
	(0.0014)	(0.0014)	(0.0014)	(0.0061)	(0.0058)	(0.0052)
Treat $\times$ After experiment	0.0035	0.0035	0.0035	0.0059	0.0071	0.0085
	(0.0014)	(0.0014)	(0.0015)	(0.0073)	(0.0071)	(0.0063)
Outcome mean	0.0449	0.0449	0.0449	0.1941	0.1941	0.1941
Sample size	283500	283500	283500	134454	134454	134454
Category FE		X	X		X	X
Shopper FE			X			X

Note: This table reports results analogous to Table 5 for the subsample consisting 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.

Appendix Table 5: 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		-0.0007	-0.0007	
	(0.0013)	(0.0013)		(0.0012)	(0.0012)	
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 the balanced panel specification of Table 5 for additional details.

Appendix Table 6: 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			0.4077	0.3740	0.0989	0.0667
			(0.0217)	(0.0244)	(0.0078)	(0.0082)
Assigned to treatment × During	0.1262	0.1265				
	(0.0031)	(0.0031)				
. . . after experiment period						
Received SABH prompt			0.1251	0.0920	0.0203	-0.0085
			(0.0203)	(0.0231)	(0.0052)	(0.0055)
Assigned to treatment × After	0.1262	0.1265				
	(0.0031)	(0.0031)				
Outcome mean	0.0006	0.0006	0.0634	0.0634	0.0634	0.0634
Sample size	56550	56550	56550	56550	56550	56550
Panel B: Least-responsive shoppers						
. . . during experiment period						
Received SABH prompt			-0.3293	-0.3090	0.0199	0.0116
			(0.0284)	(0.0295)	(0.0060)	(0.0063)
Assigned to treatment × During	0.0784	0.0782				
	(0.0021)	(0.0021)				
. . . after experiment period						
Received SABH prompt			-0.0781	-0.0573	0.0112	-0.0030
			(0.0249)	(0.0291)	(0.0052)	(0.0054)
Assigned to treatment × After	0.0784	0.0782				
	(0.0021)	(0.0021)				
Outcome mean	0.0001	0.0001	0.0304	0.0304	0.0304	0.0304
Sample size	56550	56550	56550	56550	56550	56550
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.

Appendix Table 7: Effect of SABH on healthy purchases for most- and least-responsive shoppers—Difference in differences

	Balanced panel			Relevant purchases		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Most-responsive shoppers						
Treat	0.0042	0.0042		0.0384	0.0317	
	(0.0030)	(0.0030)		(0.0131)	(0.0125)	
During experiment	-0.0349	-0.0349	-0.0349	-0.0310	-0.0215	-0.0259
	(0.0019)	(0.0019)	(0.0019)	(0.0066)	(0.0063)	(0.0056)
After experiment	-0.0296	-0.0296	-0.0296	-0.0011	0.0029	-0.0033
	(0.0020)	(0.0020)	(0.0020)	(0.0083)	(0.0079)	(0.0067)
Treat × During experiment	0.0473	0.0473	0.0473	0.1253	0.1146	0.1163
	(0.0029)	(0.0029)	(0.0029)	(0.0098)	(0.0094)	(0.0086)
Treat × After experiment	0.0116	0.0116	0.0116	0.0348	0.0316	0.0316
	(0.0029)	(0.0029)	(0.0030)	(0.0122)	(0.0117)	(0.0104)
Outcome mean	0.0634	0.0634	0.0634	0.2166	0.2166	0.2166
Sample size	84825	84825	84825	54837	54837	54837
Panel B: Least-responsive shoppers						
Treat	-0.0016	-0.0016		-0.0209	-0.0161	
	(0.0021)	(0.0021)		(0.0185)	(0.0181)	
During experiment	0.0170	0.0170	0.0170	0.0713	0.0591	0.0594
	(0.0016)	(0.0016)	(0.0016)	(0.0103)	(0.0099)	(0.0091)
After experiment	-0.0056	-0.0056	-0.0056	0.0257	0.0158	0.0147
	(0.0016)	(0.0016)	(0.0016)	(0.0130)	(0.0125)	(0.0105)
Treat × During experiment	-0.0242	-0.0242	-0.0242	-0.0982	-0.0774	-0.0787
	(0.0022)	(0.0022)	(0.0023)	(0.0144)	(0.0140)	(0.0126)
Treat × After experiment	-0.0045	-0.0045	-0.0045	-0.0305	-0.0243	-0.0270
	(0.0023)	(0.0023)	(0.0023)	(0.0177)	(0.0172)	(0.0151)
Outcome mean	0.0304	0.0304	0.0304	0.2190	0.2190	0.2190
Sample size	84825	84825	84825	21760	21760	21760
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.

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

	Balanced Panel			Relevant Purchases		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Most-responsive shoppers						
Treat	0.0042	0.0042		0.0381	0.0312	
	(0.0030)	(0.0030)		(0.0131)	(0.0125)	
During experiment	-0.0344	-0.0344	-0.0344	-0.0303	-0.0209	-0.0251
	(0.0019)	(0.0019)	(0.0019)	(0.0065)	(0.0063)	(0.0056)
After experiment	-0.0293	-0.0293	-0.0293	-0.0005	0.0033	-0.0031
	(0.0020)	(0.0020)	(0.0020)	(0.0083)	(0.0079)	(0.0066)
Treat × During experiment	0.0358	0.0358	0.0358	0.0906	0.0802	0.0832
	(0.0028)	(0.0028)	(0.0028)	(0.0095)	(0.0090)	(0.0082)
Treat × After experiment	0.0115	0.0115	0.0115	0.0343	0.0314	0.0311
	(0.0029)	(0.0029)	(0.0029)	(0.0122)	(0.0117)	(0.0104)
Outcome mean	0.0630	0.0630	0.0630	0.2158	0.2158	0.2158
Sample size	84825	84825	84825	54837	54837	54837
Category FE		X	X		X	X
Shopper FE			X			X
Panel B: Least-responsive shoppers						
Treat	-0.0017	-0.0017		-0.0209	-0.0161	
	(0.0021)	(0.0021)		(0.0185)	(0.0181)	
During experiment	0.0167	0.0167	0.0167	0.0697	0.0577	0.0577
	(0.0016)	(0.0016)	(0.0016)	(0.0104)	(0.0100)	(0.0090)
After experiment	-0.0056	-0.0056	-0.0056	0.0257	0.0158	0.0150
	(0.0016)	(0.0016)	(0.0016)	(0.0130)	(0.0124)	(0.0104)
Treat × During experiment	-0.0264	-0.0264	-0.0264	-0.1150	-0.0945	-0.0941
	(0.0022)	(0.0022)	(0.0022)	(0.0142)	(0.0138)	(0.0123)
Treat × After experiment	-0.0044	-0.0044	-0.0044	-0.0310	-0.0246	-0.0278
	(0.0023)	(0.0023)	(0.0023)	(0.0177)	(0.0171)	(0.0151)
Outcome mean	0.0303	0.0303	0.0303	0.2190	0.2190	0.2190
Sample size	84825	84825	84825	21760	21760	21760
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 panel B for additional details regarding the specifications.

Appendix Table 9: Effects of SABH on other behaviors, during intervention period (most- and least-responsive shoppers)—Removing nutrition variables

Least-responsive shoppers		Most-responsive shoppers	
Variable	Value	Variable	Value
Product price	-0.010	Ultra-Orthodox expenditure	0.011
Switch supermarkets	0.008	Product price	0.008
Time between items	0.001	Swap & Saves opened	0.007
Time spent shopping	0.001	Price diff. from most expensive	-0.005
Ended shopping on junk	0.001	Junk share	-0.005
Junk share	0.001	Protein share	-0.005
Fraction on sale	-0.001	Child expenditure	-0.005
Basket value	-0.001	Child share	-0.004
Swap & Saves opened	0	Junk expenditure	-0.004
Swap & Saves accepted	0	Alc. & cig. expenditure	-0.004
Price diff. from most expensive	0	Switch supermarkets	-0.003
Price diff. from cheapest	0	Alc. & cig. share	-0.003
Fruit/vegetable share	0	Grain share	0.002
Grain share	0	Ultra-Orthodox share	-0.002
Nonfood share	0	Protein expenditure	-0.002
Alc. & cig. share	0	Swap & Saves accepted	0.001
Protein share	0	Time between items	0
Dairy share	0	Fraction on sale	0
Ultra-Orthodox share	0	Time spent shopping	0
Child share	0	Basket value	0
Junk expenditure	0	Price diff. from cheapest	0
Fruit/vegetable expenditure	0	Fruit/vegetable share	0
Alc. & cig. expenditure	0	Nonfood share	0
Dairy expenditure	0	Dairy share	0
Grain expenditure	0	Fruit/vegetable expenditure	0
Nonfood expenditure	0	Grain expenditure	0
Protein expenditure	0	Nonfood expenditure	0
Ultra-Orthodox expenditure	0	Dairy expenditure	0
Child expenditure	0	Protein expenditure	0

Note: This table presents the averages of the coefficients from running a LASSO regression 1,000 times to predict treatment status during the intervention based on the covariates listed above. The set of variables consists of those in Table 8, excluding nutrition variables. Entries shaded in dark gray correspond to general- and price-related features, and entries shaded in light gray correspond to health-related features.

Appendix Table 10: Effects of SABH on other behaviors, during intervention period (most- and least-responsive shoppers)—Removing expenditure variables

Least-responsive shoppers		Most-responsive shoppers	
Variable	Value	Variable	Value
Product price	-0.012	Dietary fiber	0.008
Switch supermarkets	0.009	Product price	0.006
Saturated fat	0.005	Junk share	-0.006
Basket value	-0.002	Child share	-0.006
Time between items	0.001	Swap & Saves opened	0.005
Time spent shopping	0.001	Cholesterol	-0.005
Price diff. from cheapest	0.001	Alc. & cig. share	-0.004
Ended shopping on junk	0.001	Sodium	0.003
Junk share	0.001	Switch supermarkets	-0.003
Protein share	0.001	Price diff. from most expensive	-0.003
Fraction on sale	-0.001	Protein share	-0.003
Iron	-0.001	Price diff. from cheapest	-0.002
Swap & Saves opened	0	Swap & Saves accepted	0.001
Swap & Saves accepted	0	Iron	0.001
Price diff. from most expensive	0	Saturated fat	-0.001
Fruit/vegetable share	0	Time between items	0
Grain share	0	Fraction on sale	0
Nonfood share	0	Time spent shopping	0
Alc. & cig. share	0	Basket value	0
Dairy share	0	Ended shopping on junk	0
Ultra-Orthodox share	0	Fruit/vegetable share	0
Child share	0	Grain share	0
Total calories	0	Nonfood share	0
Sugar	0	Dairy share	0
Sodium	0	Ultra-Orthodox share	0
Dietary fiber	0	Total calories	0
Cholesterol	0	Sugar	0
Protein	0	Protein	0

Note: This table presents the averages of the coefficients from running a LASSO regression 1,000 times to predict treatment status during the intervention based on the covariates listed above. The set of variables consists of those in Table 8, excluding expenditure variables. Entries shaded in dark gray correspond to general- and price-related features, and entries shaded in light gray correspond to health-related features.

Appendix Table 11: Effects of SABH on other behaviors, during intervention period (most- and least-responsive shoppers)—Removing share variables

Least-responsive shoppers		Most-responsive shoppers	
Variable	Value	Variable	Value
Product price	-0.011	Dietary fiber	0.008
Switch supermarkets	0.009	Ultra-Orthodox expenditure	0.007
Saturated fat	0.004	Product price	0.006
Time between items	0.001	Junk expenditure	-0.006
Time spent shopping	0.001	Child expenditure	-0.006
Ended shopping on junk	0.001	Swap & Saves opened	0.005
Fraction on sale	-0.001	Cholesterol	-0.005
Basket value	-0.001	Alc. & cig. expenditure	-0.004
Iron	-0.001	Sodium	0.003
Swap & Saves opened	0	Price diff. from most expensive	-0.002
Swap & Saves accepted	0	Protein expenditure	-0.002
Price diff. from most expensive	0	Swap & Saves accepted	0.001
Price diff. from cheapest	0	Iron	0.001
Junk expenditure	0	Switch supermarkets	-0.001
Fruit/vegetable expenditure	0	Total calories	-0.001
Alc. & cig. expenditure	0	Saturated fat	-0.001
Dairy expenditure	0	Time between items	0
Grain expenditure	0	Fraction on sale	0
Nonfood expenditure	0	Time spent shopping	0
Protein expenditure	0	Basket value	0
Ultra-Orthodox expenditure	0	Dist. from cheapest	0
Child expenditure	0	Ended on junk	0
Total calories	0	Fruit/vegetable expenditure	0
Sugar	0	Dairy expenditure	0
Sodium	0	Grain expenditure	0
Dietary fiber	0	Nonfood expenditure	0
Cholesterol	0	Sugar	0
Protein	0	Protein	0

Note: This table presents the averages of the coefficients from running a LASSO regression 1,000 times to predict treatment status during the intervention based on the covariates listed above. The set of variables consists of those in Table 8, excluding variables for the fraction of spending falling into specific categories. Entries shaded in dark gray correspond to general- and price-related features, and entries shaded in light gray correspond to health-related features.

Appendix Table 12: Effects of SABH on other behaviors, after intervention period (most- and least-responsive shoppers)

Least-responsive shoppers		Most-responsive shoppers	
Variable	Value	Variable	Value
Sugar	0.008	Price diff. from most expensive	-0.024
Basket value	-0.004	Saturated fat	-0.018
Grain share	-0.004	Time between items	-0.014
Sodium	-0.004	Child share	-0.012
Iron	-0.004	Dietary fiber	0.011
Alc. & cig. expenditure	-0.003	Protein	0.011
Alc. & cig. share	0.002	Fruit/vegetable expenditure	0.008
Cholesterol	0.002	Protein share	-0.007
Product price	0.001	Ultra-Orthodox expenditure	0.006
Time between items	0.001	Grain share	0.003
Protein share	0.001	Time spent shopping	-0.003
Ultra-Orthodox share	0.001	Swap & Saves accepted	-0.003
Saturated fat	0.001	Sugar	-0.003
Swap & Saves opened	-0.001	Price diff. from cheapest	0.002
Switch supermarkets	0	Grain expenditure	0.001
Fraction on sale	0	Sodium	0.001
Time spent shopping	0	Basket value	-0.001
Swap & Saves accepted	0	Junk share	-0.001
Price diff. from most expensive	0	Iron	-0.001
Price diff. from cheapest	0	Switch supermarkets	0
Ended shopping on junk	0	Product price	0
Junk share	0	Fraction on sale	0
Fruit/vegetable share	0	Swap & Saves opened	0
Nonfood share	0	Ended shopping on junk	0
Dairy share	0	Fruit/vegetable share	0
Child share	0	Nonfood share	0
Junk expenditure	0	Alc. & cig. share	0
Fruit/vegetable expenditure	0	Dairy share	0
Dairy expenditure	0	Ultra-Orthodox share	0
Grain expenditure	0	Junk expenditure	0
Nonfood expenditure	0	Alc. & cig. expenditure	0
Protein expenditure	0	Dairy expenditure	0
Ultra-Orthodox expenditure	0	Nonfood expenditure	0
Child expenditure	0	Protein expenditure	0
Total calories	0	Child expenditure	0
Dietary fiber	0	Total calories	0
Protein	0	Cholesterol	0

Note: This table presents the averages of the coefficients from running a LASSO regression 1,000 times to predict treatment status after the intervention period based on the covariates listed above. Entries shaded in dark gray correspond to general- and price-related features, and entries shaded in light gray correspond to health-related features.