Beyond the Switch: Lasting Effects of Informational Nudges on Online Grocery Shopping Behavior*

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Abstract

It is well documented in the literature that consumers exhibit persistence in their choices. This study explores how informational nudges can disrupt habitual choice in online grocery shopping. Utilizing data from a price comparison platform that provides real-time *"swap & save"* reminders of cheaper alternatives, we find significant and lasting effects on consumer choice. Shoppers who switched products after receiving a nudge were 19 percentage points more likely to choose the alternative product in future visits, with this effect persisting for up to 10 shopping trips. Our findings reveal that this sustained impact is not primarily driven by long-term cost savings. Instead, the informational nudges facilitate product discovery by expanding shoppers' consideration sets. Our analysis of underlying mechanisms suggest that habitual choices may not always be optimal, and that disruptions can lead to improved decision-making.

Keywords: Informational Nudges, Online Shopping, Product Swap, New Product Discovery, Long-term Effect

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1 Introduction

A large literature in marketing documents that consumers exhibit persistence in their choices, showing a higher likelihood of repurchasing products they have previously purchased (Keane 1997, Seetharaman et al. 1999, Dubé et al. 2008, 2009, 2010, Bronnenberg et al. 2012). Even when product outages force consumers to switch products, these changes are often temporary, with many reverting to their original choices shortly thereafter (Levine and Seiler 2023). This well-documented phenomenon in marketing is commonly attributed to factors such as habit formation (Figueroa et al. 2019), rational inattention (Sims 2003, Matějka and McKay 2015, Joo 2023), and the costs associated with searching for alternatives. Interestingly, persistence in choice is observed even in online shopping, where price discovery and product comparison are easier. Research shows that even mild preferences, combined with search frictions, can result in highly persistent choices (Morozov et al. 2021), often leading consumers to remain locked into suboptimal options.

In contrast to supermarket shopping, recent research on travel choices suggests that search frictions can be mitigated by encouraging exploration. For example, in the context of subway commuting, a strike that forced commuters to change their travel behavior resulted in them choosing more efficient routes, which reduced their travel time and costs even a week after the strike ended (Larcom et al. 2017). While one way to encourage exploration is to remove alternatives, better information provision, such as informational nudges, might be an alternative way to break inertia. By reducing search and switching costs, these nudges can expand consumers' consideration sets and help them discover options better suited to their needs.

In this study, we examine how informational nudges influence consumers' typically persistent product choices. Specifically, we investigate whether these nudges not only prompt initial exploration but also result in lasting changes to consumer preferences. Do consumers, after discovering new alternative products through nudges, continue to choose these alternatives when they return to the platform? How long do these effects, if present, persist?

To answer these questions, we collaborate with an online price comparison platform that aggregates products from major online supermarkets in Israel and sends real-time reminders to inform consumers of cheaper alternatives based on their algorithm. Specifically, when consumers add an item to their cart, they receive a "*swap & save*" reminder which suggests similar but cheaper products when available, allowing them to easily click on an alternative product and swap it into their cart. We constructed an extensive dataset of detailed shopping records of 6,382 shoppers in 2015. This dataset includes information on products, prices, quantities purchased, and switch behaviors for each shopping trip, which allows us to track

multiple shopping trips for the same shopper both before and after product switches.

Our goal is to investigate how informational nudges influence changes in consumer product choices through product swaps. We face two key challenges in analyzing the effects of these voluntary switches. First, the receipt of "*swap & save*" reminders depends on the products shoppers add to their carts and how those prices compare to alternatives. To address this, we adopt a quasi-experimental design following the guidelines provided by Goldfarb et al. (2022). We define the "treated" group as shoppers who received the "*swap & save*" reminder and swapped products, and we construct a control group that includes shoppers who purchased *the same initial product* but did not receive a reminder because a cheaper alternative was not available at the same supermarket within a nearby time window. This could either be because the cheaper alternative was out of stock, or it was no longer discounted – events independent of shopper decisions. We begin our analysis with a two-way fixed effects difference-in-differences (TWFE DID) model to compare switching behavior between treated and control groups, ensuring the parallel trends assumption holds. To account for treatment effect heterogeneity over time and across shoppers while addressing observed and unobserved characteristics, we also apply the staggered difference-in-differences (CS DID) method introduced by Callaway and Sant'Anna (2021). The second challenge is that product swaps are voluntary, conditional on receiving the reminders. To mitigate potential selection bias, we use an instrumental variable (IV) analysis, instrumenting for swapping products with having received a *swap & save* reminder.

Our analysis yielded several interesting findings. First, after shoppers switched to an alternative product, their probability of buying the alternative product that they swapped to increased by 19 percentage points, compared to those who never received the reminders. Moreover, this change in purchasing behavior persisted over time, lasting for up to ten purchase occasions after the initial swap. This indicates that the switches not only prompted immediate product changes but also had a durable impact on shopper behavior and preferences. We further explored the underlying mechanisms behind these long-term effects. While the swap reminders encouraged shoppers to switch to cheaper products, they did not lead to substantial cost savings in subsequent shopping trips. Interestingly, even shoppers who saved less showed a similar increase in post-swap purchase probability as those who saved more. This suggests that cost savings may not be the primary driver of the lasting effect. Instead, the swap reminders facilitated product discovery. Specifically, the reminders expanded shoppers' consideration sets by introducing products they had not previously purchased, which potentially better met their needs, leading them to continue purchasing those products. As expected, the effect of the swaps was stronger for shoppers who displayed weaker level of preference for the initial product.

Our study contributes to the stream of literature on state dependence in consumer shopping behavior (Dubé et al. 2008, 2009, 2010, Bronnenberg et al. 2012, Simonov et al. 2020, Bronnenberg et al. 2022, Levine and Seiler 2023). Previous research has predominantly focused on product switching triggered by unexpected external shocks, documenting effects that are typically transitory and dissipate over time. For example, Levine and Seiler (2023) demonstrate that households' purchasing behavior reverts to its pre-hurricane trajectory immediately after a hurricane. Similarly, Goldfarb (2006) examines internet denial of service (DoS) attacks by hackers and identifies a dissipating lock-in effect on consumers' future website visit choices. Our study differs in several key aspects. First, rather than focusing on external shocks that reduce options (e.g., stock-outs), we examine voluntary product switches prompted by informational nudges that reduced search or switching costs on online platforms thereby expanding the consumers' choice sets. These nudges potentially lead to better alignment between consumer needs and products. As a result, our findings offer insights into how platform design can drive persistent changes in consumer behavior. Second, while prior research often highlights transient effects, we observe that consumers who switch products continue purchasing the alternative over an extended period. Our analysis identifies a key mechanism: the reminders facilitate product discovery, which underpins these lasting changes in choice behavior. This discovery mechanism is akin to that identified in the context of public transportation by Larcom et al. (2017), who found that commuters who switched routes during a strike experienced reductions in travel time and costs even seven days after the strike had ended. Importantly, our data allow us to explore consumer behavior weeks beyond the initial switch, offering deeper insights into the durability of these changes.

Our study also relates to the literature on the effect of informational nudges on consumer choice. As a cognitive intervention, nudging can influence people's behavior by modifying the choice architecture without restricting options (Thaler and Sunstein 2008, Barløse et al. 2022). Previous research has demonstrated that nudges can be an effective alternative to more heavy-handed interventions across various applications. For instance, Ghose et al. (2024) shows that digital nudges in an online marketplace can stimulate product purchases. Zeng et al. (2023) found that social nudges can promote user-generated content on social network platforms. An emerging research stream investigating the effect of nudges in encouraging prosocial behaviors has found that nudges can significantly boost charitable behaviors and donations (Goswami and Urminsky 2016), and promote environmentally-friendly shopping behaviors (White et al. 2019, Von Zahn et al. 2024). We contribute to this stream of research in two ways. First, the informational nudges in our setting are issued at the point of search, offering a one-click option for "swap", which results in low switching costs and

makes it easier for consumers to change their purchase decisions. Second, we document the effect of the informational nudges both in the short term and long term. Commonly used interventions in supermarkets, such as price discounts, are often costly, prone to stockpiling, and yield only short-term results (Nijs et al. 2001, Hendel and Nevo 2006, Dubé et al. 2010). In contrast, the informational nudges in our setting are more cost-effective, easy to implement, and lead to lasting behavioral changes. Moreover, our exploration of the underlying mechanism suggests that cost savings are not the key decision-making factor; rather, product discovery plays a more significant role in the long-term. These results have important implications for platform design, consumer engagement, and new product introduction.

The remainder of the paper is organized as follows. In the next section, we discuss the institutional background. Section 3 describes the data, sample construction and presents descriptive evidence of shopper behavior on the platform. Section 4 presents the empirical strategies and results. Section 5 discusses the mechanisms, and Section 6 concludes.

2 Institutional Background

Our data come from a well-established online supermarket platform that aggregates real-time information from major online supermarkets in Israel, including Bitan Wines, Mega, Rami Levy, Shufersal, and Victory. All shoppers view the same product layout simultaneously, without customization or filtering options. They can add items to their basket through direct search, a menu of product categories (e.g., dairy, fish, meat, produce), previous shopping orders, or favorite products.[1]

A unique feature of this platform is it enables users to compare prices for different products within a supermarket. It displays the price per unit for each item. When a shopper adds a product to their basket, a *swap & save* button appears if there are cheaper alternatives (based on unit price) available at the same supermarket. Clicking the button presents the shopper with a prompt (a "reminder") displaying up to three similar substitutes, enabling them to switch their initial product for a lower-priced alternative. Figure A1 provide examples of the *swap & save* button and the corresponding reminder.[2]

The platform's swap & save feature offers an opportunity to explore the effects of deviating from typical consumption patterns within a product category. Consider two shoppers with similar preferences and purchase histories who both add the same product to their online shopping basket at the same supermarket within a short time frame. Shopper A receives a reminder for cheaper alternatives due to a sale and opts for a cheaper option, replacing the

[1] See https://www.youtube.com/watch?v=octfR1gYEL0 for an illustration video in Hebrew.

[2] The platform uses a proprietary algorithm to identify cheaper close substitutes or quantity discounts.

original item. In contrast, Shopper B does not receive a reminder because the alternatives were either unavailable or not on sale, and thus purchases the initial product. Our analysis focuses on how Shopper A's future shopping behavior changes compared to Shopper B, who did not experience the alternative product due to the absence of the *swap & save* reminder.

Because products go on sale at different times, it is common for prices at the same supermarket to vary significantly from week to week. Consequently, a shopper who returns just a week later may encounter noticeably different prices (see Figure C4). Therefore, it is reasonable to assume that receiving a reminder is randomly determined, conditional on the shopping day and supermarket. However, a product switch depends on the consumer's decision to explore alternatives and swap to a new product. Comparing consumers who switch products to those who do not may lead to biased results. We will discuss this further in Section 4.

3 Data, Sample Construction and Descriptive Evidence

This section presents our main datasets. Section 3.1 provides an overview of the data, Section 3.2 details the sample construction, and Section 3.3 presents the measures of consumer buying behavior along with descriptive statistics.

3.1 Data

We focus on the mineral water category, observing a panel of 6,382 shoppers who made purchases in this category.[3] The data span between January 1st and December 31st 2015, and includes product and brand names, quantities purchased, prices paid, shopping dates, supermarket names, sale status, and whether a product was added from previous orders or favorite lists. The platform also provided an *Alternatives Database* with the top three alternative products for each item, allowing us to identify close substitutes for all purchases.

Additionally, the platform provided us with a *Swap Database* containing detailed product-trip level data for each event when a shopper clicked the *swap & save* button and viewed the reminder. This database includes the initially selected products, final purchases, and whether the shopper accepted the reminder and swapped. Thus, for events where a shopper clicked the *swap & save* button, we can observe the initial product added to the basket, the suggested alternative products, and the final purchase.

[3] We choose bottled mineral water because many consumers make frequent purchases in this category. The frequency of swaps in this category is 29%, which is slightly below the overall average swap rate of 36% across all categories.

These unique datasets allow us to track shoppers' initial preferences, the availability of cheaper substitutes, their swapping decisions, and their behavior across multiple shopping trips. For shoppers who did not click the *swap & save* button, we infer that they had the opportunity to do so if they purchased the same initial product on the same day another shopper clicked *swap & save* at the same supermarket (this is further discussed in Section 3.2).

Products. We define a water product as a combination of a brand and unique product ID, focusing on the 35 most purchased products in our sample. Table B1 lists the top 20 products ranked by market share, including brand names, market shares, price per liter (in dollars), and size.[4] The category is relatively concentrated, with the top five products holding a combined market share of 92.84%. The two leading products are Mineral Water Ein Gedi (6-pack of 2-liter bottles) with a 37.11% market share, and Mineral Water Neviot (6-pack of 1.5-liter bottles) with a 20.72% market share.

Prices. Table 1 summarizes the price per liter, along with the frequency, duration, and depth of promotions across products and supermarkets. Of the 35 products in the sample, 14 went on sale during the study period. For these 14 products, we calculate promotion frequency as the percentage of days a product is on sale relative to the total number of days it is sold during the sample period, while promotion duration is defined by the number of consecutive days a product stays on sale. Promotion depth is defined as the difference between the sale price and the average non-sale price, both in absolute terms and as a percentage. For products that went on sale, promotions lasted an average of about nine days, with sale prices approximately 22% below non-sale prices. Figure B1 depicts the distribution of promotion frequencies for the 10 products with the highest promotion frequency, ranging from 3.35% to 21.91%.

[4]Market shares are computed based on the total quantity sold, determined by multiplying the number of units sold by their size in liters.

Table 1: Summary Statistics of Prices and Price Promotions

	Mean	SD	p50	p25	p75
Price per liter ($)	1.289	1.057	1.042	0.338	1.930
Promotion Frequency (Percentage)	8.209	11.160	5.372	1.899	9.524
Promotion Duration (Days)	9.871	11.007	4.381	2	20.587
Promotion Depth ($)	-0.330	0.352	-0.216	-0.627	-0.048
Promotion Depth (Percentage)	-22.065	9.161	-23.430	-25.121	-14.875

Notes: This table reports summary statistics for prices and promotions. Price per liter is summarized at the product-supermarket-date level, while other variables are summarized at the product-supermarket level. Promotion related variables are conditional on the occurrence of a promotion.

Alternative Products and Initial Products. Table C1 in Appendix C lists the 10 most common swap product pairs across all supermarkets, along with their average prices. Two distinct price tiers emerge among these pairs: (1) More expensive small bottles, primarily Neviot and Mey Eden, and (2) Cheaper large 1.5-2 liter bottles, including Mey Eden, Ein Gedi, and Aqua Nova. We observe swaps within each group across all five supermarkets. The price per liter for alternative products is typically 10% to 20% lower than that of the original products. Figure C2 in Appendix C plots the distribution of cost savings from the swaps. Cost savings are calculated as the difference in price per liter between the initial product and the alternative product, divided by the price per liter of the initial product. The average (median) cost saving of swaps is 17.8% (19.2%). Figure C4 in Appendix C illustrates the weekly price series for these commonly swapped products at one supermarket, showing significant price variability over time within the same supermarket.

3.2 Sample Construction

Our analysis investigates how switching to an alternative product affects future shopping behavior. We classify shoppers as treated (**Swapped shoppers**) if they accepted a product swap for the initial item in their basket. Since the decision to view and accept the reminder is endogenous, it may influence differences in post-swap shopping behavior. Therefore, we also construct an expanded shopper group to include all shoppers exposed to a swap opportunity (**Exposed shoppers**), defined as those who received a *swap & save* button for a water purchase, regardless of whether they clicked it. These shoppers had the opportunity to see cheaper alternatives even if they did not utilize it. In our IV analysis, we utilize exposure to a *swap & save* button as an instrument for switching products. We also conduct an intention-to-treat (ITT) analysis that compares the behavior of exposed shoppers to unexposed shoppers. Finally, we classify control shoppers (**Unexposed shoppers**) as those

who purchased *the same initial product* within 30 days of an exposed shopper's purchase at the same supermarket when no cheaper alternative was available.

Below, we provide a detailed definition and explanation for how each of these three shopper groups are constructed. For clarity: let $J1$ denote the initial product, $J2$ the alternative product a shopper swapped to, e the swap event day, and s the supermarket.

Swapped shoppers. These shoppers viewed the reminder for the initial product ($J1$) they added to their basket on the swap event day e at supermarket s and decided to swap to an alternative product ($J2$). This group represents approximately 22% of the total shoppers (1,420 out of 6,382). Figure C1 plots the distribution of swaps per shopper in our sample. As illustrated, most shoppers did not swap, and among those who did, 78% (1,109 out of 1,420) swapped only once during the sample period.

Exposed Shoppers. This group includes shoppers who received a *swap & save* button for the initial product ($J1$) they added to their basket on the swap event day (e) at supermarket (s). It consists of three subgroups. The first two subgroups appear in the "*Swap Database*" and include shoppers who switched products (swapped shoppers) and shoppers who clicked the *swap & save* button to view cheaper alternatives but remained with their initial product choice. The last subgroup comprises shoppers who purchased the same initial product on the same day and at the same supermarket as a shopper who clicked the *swap & save* button, but did not click it themselves (and thus do not appear in the "*Swap Database*"). For shoppers in the second and third subgroups, the alternative product ($J2$) is defined as the one most frequently chosen by *swapped shoppers* who initially added product ($J1$) at supermarket (s) on swap event day (e).[5]

Unexposed shoppers. These shoppers purchased the same initial product ($J1$) at the same supermarket (s) as the *exposed shoppers* within a 60-day window centered around the swap event day (e-30, e+30), but did not receive the reminder because either the cheaper alternatives were unavailable or the price of the initial product was already the lowest among similar substitutes at that supermarket on that day. Specifically, the following criteria are applied to identify the *unexposed shoppers*:

(1) Same preference: purchases the same product as the initial products in the *exposed shoppers'* purchase.

[5]The average purchase rate of the most frequently chosen $J2$ conditional on $J1$ is 94.76%.

(2) Similar shopping environment: purchases at the same supermarket within a 60-day window around the *exposed shoppers'* purchase.

(3) Proxy unavailability: cheaper alternatives are either unavailable, or the initial product is the lowest-priced option among similar substitutes on that day at that supermarket.[6]

For *swapped shoppers* the swap event is defined as the first time they made a swap. For each *exposed shopper* who is not a *swapped shopper* we define the treatment event as the first time they had the opportunity to click on a *swap & save* button. For *unexposed shoppers*, the treatment event is defined according to the matched treated event. This allows us to create a normalized "purchase time" variable centered around the event time. This variable is set to 0 at the swap event, with negative values (e.g., -1, -2) for purchases made before the swap event and positive values (e.g., 1, 2) for those made afterward. Table 2 presents the number of shoppers in each subgroup, and further details on this sample construction process are described in Appendix B.

Table 2: Number of Shoppers in Each Group

Shopper Subgroups	Definition	Number of shoppers
Swapped shoppers	shoppers who received a reminder: swapped from their initial product to an alternative product.	1,420
Exposed shoppers	shoppers who received a reminder: swapped from their initial product to an alternative product; or viewed the reminder but did not swap; or did not view the reminder.	5,576
Unexposed shoppers	shoppers who did not receive a reminder: due to unavailability of alternatives; or the price of initial product is the lowest.	806

Notes: This table reports the definition and the number of shoppers in each subgroup.

We report summary statistics on shopper buying behaviors for all shoppers, as well as for the swapped, exposed, and unexposed shoppers, in Table C2. Panel A shows shopping behavior characteristics across all trips, while Panel B focuses on trips before any swap event. Water is a frequently purchased product among shoppers in our sample, with roughly 70% including it in their baskets. Shoppers across these groups show similar average spending per water purchase (around $5) and per basket (around $140), as well as similar time spent per trip. However, swapped shoppers use the platform more frequently, making approximately twice as many trips compared to unexposed shoppers. Our analysis accounts for this variation in platform usage.

[6]Instances where cheaper alternatives are unavailable are indicated by missing prices for the alternatives.

3.3 Shopper Buying Behavior

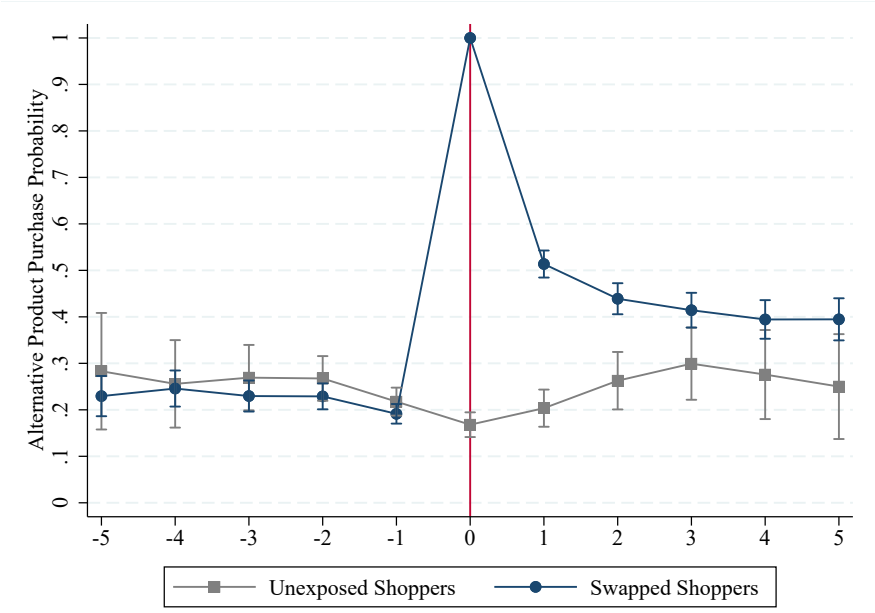
To analyze consumer shopping behavior and assess whether product switches influence subsequent purchases, we construct the following outcome measure:

Purchasing the alternative product. This variable indicates whether the product purchased by shopper i at a given purchase time (t) matches the alternative product ($J2$).[7]

$$\text{BuyAlternative}_{it} = \mathbf{1}\{j_{it} = J2_{ie}\}$$

Figure 1 illustrates the demand for the alternative product ($\text{BuyAlternative}_{it}$) across five purchase instances before and after the swap event, separately for swapped and unexposed shoppers. The swap event time is indicated by a red vertical line. Following the swap event, swapped shoppers significantly increased their probability of purchasing the alternative product compared to unexposed shoppers. The pre-treatment trends appear similar between swapped and unexposed shoppers, while the post-swap changes range from approximately 10 to 30 percentage points.

Figure 1: Evolution of Alternative Product Purchase Probability



Notes: The figure plots the average demand for the alternative product for *swapped shoppers* and *unexposed shoppers* over time. The red vertical line indicates the swap event. This is the purchase incidence where *swapped shoppers* switched from their initial product choice to the alternative product and *unexposed shoppers* purchased the same initial product at the same supermarket in this time period and were not exposed to any alternatives.

[7] For unexposed shoppers, the alternative product is defined as the alternative product of the exposed shopper they are matched with.

4 Empirical Strategy and Results

This section presents our empirical strategy and results. In the following subsection, we discuss the major empirical challenges and the solutions we implement to address them.

4.1 Identification Challenges and Solutions

Our panel dataset allows us to examine changes in shopping behavior of the swapped shoppers by comparing them to a relevant control group. We carefully define the control group (*unexposed shoppers*) as those with similar preferences, indicated by purchasing the same initial product at the same supermarket, within a similar time frame as the *swapped shoppers*. This comparison lends itself to a classic TWFE DID setup, which we use as the starting point for our analysis.

However, the observational nature of the data presents two key challenges for identifying treatment effects: (i) Shoppers accept reminders and swap at different times. This requires a method that accounts for the heterogeneity of treatment effects over time and across treated units, while aggregating individual effects into an average treatment effect (Goodman-Bacon 2021, De Chaisemartin and d'Haultfoeuille 2020, Callaway and Sant'Anna 2021, Borusyak et al. 2021). (ii) The decision to view the reminder and/or swap is endogenous. It may correlate with unobserved shopper characteristics, such as price sensitivity or expectations of better outcomes from swapping. To address these challenges, we employ both a staggered difference-in-differences (CS DID) model based on Callaway and Sant'Anna (2021), and an IV analysis based on Angrist et al. (1996), Finkelstein et al. (2012) in Section 4.2. Below, we provide an overview of how these methods address the identification challenges.

Challenge (i) of staggered swaps is addressed using the CS DID model, which computes treatment effects for each individual shopper who swapped, then aggregates them into an overall average treatment effect on the treated (ATT). This analysis addresses issues such as negative weighting of treatment effects in a classic two-way fixed effects difference-in-differences (TWFE DID) model, as discussed in Goodman-Bacon (2021), De Chaisemartin and d'Haultfoeuille (2020), Callaway and Sant'Anna (2021). This method is suitable in our setting as it has weaker assumptions regarding a) whether the parallel trends assumption holds after conditioning on covariates; and b) whether the possible aggregations of group-time average treatment effects are flexible, allowing treatment effect heterogeneity across cohort groups and time (Braghieri et al. 2022).

After applying this strategy, concerns may remain about endogeneity of the decision to view cheaper alternatives and/or to make a swap (Challenge (ii)). We address this challenge in two ways. First, the CS DID model partially mitigates some forms of endogeneity by

ensuring consistency against mis-specification of controls or omitted variables (Berman and Israeli 2022), and by matching on pre-trends between treated and control groups. Second, we conduct an instrumental-variable (IV) analysis including all *exposed shoppers* and *unexposed shoppers*. We then use the receipt of a reminder as an instrument for swapping products. This approach leverages the quasi-random factors that influence whether or not a shopper received the *swap & save* button–such as supermarket stock-outs and promotion strategies–rather than the endogenous decision to switch products. The IV analysis allows us to estimate the local average treatment effect of the product switch.

In the next section, we describe the specification and implementation of the aforementioned models in quantifying the impact of swapping products, as well as their results. In Section 4.3, we carefully assess the parallel trends assumption in the pre-swap period and examine how long the effect of a product switch persists across future shopping trips.

4.2 Effect of Swaps on Subsequent Purchase Behavior

In this section we estimate the impact of a product switch on subsequent demand for the alternative product. Our starting point is the classic TWFE DID model comparing shopping behavior of treated and control shoppers before and after the swap. We use the following specification:

$$\text{BuyAlternative}_{irt} = \beta_0 + \beta_1 \text{After}_t * \text{Swap}_i + \beta_2 \text{After}_t + \gamma_i + \gamma_r + \gamma_{d(t)} + \epsilon_{irt} \quad (1)$$

where After_t is equal to 1 when an observation occurs after the swap event $t = 0$.[8] Swap_i indicates whether shopper i is in the *swapped shoppers* subgroup. The coefficient β_1 captures the relative difference in purchasing behavior for *swapped shoppers* before and after the swap compared to *unexposed shoppers*—those who purchased the same initial product but were not exposed to the swap opportunity. The outcome variable, $\text{BuyAlternative}_{irt}$, equals 1 if shopper i purchased the alternative product at purchase time t (defined by their purchase at $t = 0$) and supermarket r, and 0 otherwise. We focus on purchases made up to five periods before and after the swap, and later we extend to ten periods before and after. γ_i, γ_r, and $\gamma_{d(t)}$ are the fixed effects for shopper, supermarket, and day-of-week, respectively. These fixed effects account for unobserved factors related to shoppers and supermarkets that could impact shopping behavior, such as differences in platform usage.

We begin by estimating the TWFE DID model, with the results presented in Column (1) of Table 3. The estimated coefficient, $\hat{\beta}_1$, is 0.213^{***}, indicating that the probability of purchasing the alternative product increased by 21.3 percentage points over the five

[8] We do not include observations at $t = 0$ to avoid artificially inflating the treatment effect.

post-swap purchase periods. The classic TWFE DID model estimates the ATT under the assumption that treatment effects are constant across time and treated units. However, the TWFE DID estimate is a weighted average of treatment effects across different treated units and periods. If treatment effects vary across units or time, the model can assign negative weights, leading to an estimate with an incorrect sign (De Chaisemartin and d'Haultfoeuille 2020). To account for the treatment effect heterogeneity, we apply the CS DID estimator introduced by Callaway and Sant'Anna (2021). Similar to a TWFE DID model, the CS DID model leverages pre-swap data to establish a baseline for comparing behavior between treated and control shoppers in the post-swap periods (After_t=1).[9] The key difference between estimating Equation 1 with a CS DID model and a traditional TWFE DID model lies in how the treatment effect, β_1, is calculated. The CS DID model estimates the effect for each treated shopper by comparing their behavior to that of a matched control shopper, and these individual effects are then aggregated to compute an overall treatment effect estimate.

We report the results from the CS DID model in Column (2) of Table 3. The estimate suggests that the probability of purchasing the alternative product increased by 24.6 percentage points over the five post-swap purchase incidences. This effect, which is very similar to that estimated with the TWFE DID model, represents a twofold increase compared to the baseline purchase rate of 20% for these products in the unexposed shoppers.

Instrumental Variables Analysis. One concern with the estimates reported in Columns (1) and (2) of Table 3, which focus on the treated group of *swapped shoppers*, is that the results may overstate the effect of the product swap if shoppers who take advantage of the *swap & save* opportunity are less prone to inertia than those in the control group (see discussions in Section 1 and Section 4.1 regarding the endogeneity of product swaps). To address this, we conduct an IV analysis, using whether the shopper receives the *swap & save* button as an instrument for the endogenous choice to switch products.

This IV strategy exploits the random assignment of *swap & save* buttons, conditioned on the shopping day of the week and supermarket. Figure C3 in Appendix C illustrates the price differences between the alternative and initial products for both *swapped shoppers* and *unexposed shoppers*. The figure reveals significant price fluctuations over time within a supermarket for the same product pairs. This indicates that a shopper purchasing the same product on different days at the same supermarket may encounter significantly different

[9] To ensure a sufficient number of control units for each swap event, we also include *exposed shoppers* who have not yet received a swap as controls prior to their first swap event, following the approach of Wang and Goldfarb (2017), Berman and Israeli (2022). By incorporating these not-yet-treated units into the control group, we increase the sample size and ensure a clean comparison between treated and untreated units over time. Our results remain robust even when using only the unexposed shoppers.

prices. As a result, the receipt of the *swap & save* button is primarily influenced by the random timing of promotions, which is beyond the control of shoppers. Thus, we construct an indicator variable (Reminder_i) that equals one if a shopper swapped, viewed the reminder but did not swap, or received the reminder without viewing it while shopping on the platform. To address the potential concern that variations in shopping behavior across different days (e.g., weekend shoppers may have more time and patience to search for deals, making them more likely to receive reminders) or differences in promotional strategies across supermarkets could violate the exclusion restriction, we include day-of-week and supermarket fixed effects, as well as shopper fixed effects, in the model.

Thus, we estimate Equation 1 on a sample that includes all *exposed shoppers* and *unexposed shoppers*. In the first stage, we use the receipt of the *swap & save* button ($\text{After}_t \times \text{Reminder}_i$) as an instrument for the interaction term $\text{After}_t \times \text{Swap}_i$, applying the following regression:

$$\text{After}_t \times \text{Swap}_i = \alpha_0 + \alpha_1 \text{After}_t \times \text{Reminder}_i + \beta_2 \text{After}_t + \gamma_i + \gamma_r + \gamma_{d(t)} + \epsilon_{irt} \quad (2)$$

The first-stage results in column (3) of Table 3 suggest that receiving a *swap & save* button at time $t = 0$ increases the probability of switching products by 29% (see the row labeled "First Stage Estimate"). The instrument passes the Cragg-Donald weak instrument test, with F-statistics of 551. The IV estimates reported in column (3) of Table 3 are very close to the TWFE DID and CS DID estimates, indicating that responding to the reminder to switch products raised the future purchase probability by 19.2 percentage points, compared to the TWFE and CS DID estimate of 21.3 and 24.6 percentage points.[10]

[10] In Appendix D, we focus on the direct effect of $\text{After}_t \times \text{Reminder}_i$ on the probability of purchasing the alternative product. This intention-to-treat (ITT) analysis provides a straightforward estimate for platforms to assess the overall impact of implementing this type of reminder.

Table 3: Effect of Swaps on Future Purchases of the Alternative Product

	(1) TWFE DID	(2) CS DID	(3) IV
$\text{After}_t \times \text{Swap}_i$	0.213***	0.246***	0.192***
	(0.017)	(0.017)	(0.037)
First Stage Estimate	–	–	0.291***
			(0.008)
Cragg-Donald Wald F statistic	–	–	550.923
Shopper FEs	Yes	Yes	Yes
Supermarket FEs	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes
N of Obs.	12,229	11,749	27,351

Notes: To avoid artificially inflating the treatment effect from swaps, the regressions exclude the treatment event. After_t indicates purchase times after the swap and Swap_i indicates whether a shopper swapped products. The average purchase probability of the alternative product for unexposed shoppers is 20%. Standard errors, clustered at the shopper level, are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3 Ensuring Parallel Trends

The causal interpretation of estimates in a difference-in-differences framework depends on the identifying assumption of conditional parallel trends between the treated and control group. To assess the validity of this assumption, we employ the following event study specification to analyze demand for the alternative product in the periods before and after the swap event.

$$\text{BuyAlternative}_{irt} = \sum_{\substack{t=-5 \\ t\neq 0}}^{5} \delta_t \, \text{Post}_t \times \text{Swap}_i + \gamma_i + \gamma_r + \gamma_{d(t)} + \epsilon_{irt} \tag{3}$$

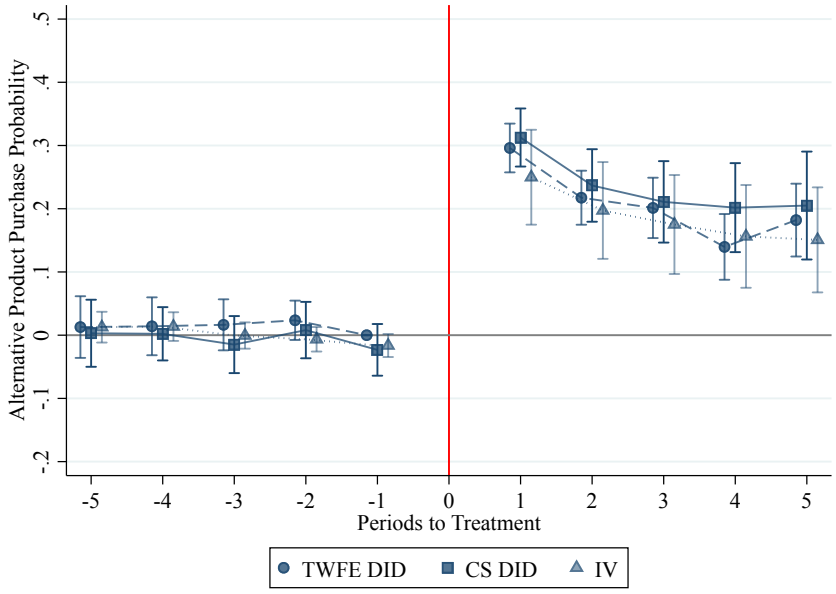
where Post_t are a set of indicator variables equal to 1 when an observation occurs at purchase time t surrounding the swap event $t = 0$. Swap_i indicates whether shopper i belongs to the *swapped shoppers* group. δ_t measures the difference in purchasing behavior between swapped shoppers and control shoppers at each purchase incidence t surrounding the swap. As in Equation 1, we include shopper, supermarket, and day-of-week fixed effects.

For the conditional parallel trends assumption to hold, the $\hat{\delta}_t$ estimates should not be statistically significant from zero in the pre-swap periods ($t < 0$). In Figure 2, we plot the estimated coefficients of $\hat{\delta}_t$ from estimating Equation 3 using the TWFE DID model. These estimates are shown as circles connected by a dashed line, along with their 95% confidence

intervals. The figure indicates that the parallel trends assumption is satisfied, as the pre-treatment estimates all include zero within their confidence intervals. The $\hat{\delta}_t$ estimates in the post-swap periods ($t \in \{1, \ldots, 5\}$) are positive and significant, showing a 30 percentage point increase in the demand for the alternative product in the first purchase post-swap. This substantial effect persists throughout the entire post-swap period, with *swapped shoppers* remaining 10 to 20 percentage points more likely to purchase the alternative product, even by their fifth purchase after the swap event. The event-study estimates from the CS DID method (denoted as squares connected by a solid line) closely align with those from the TWFE DID.

We present the event-study estimates from the IV estimation as triangle dots connected by a dotted line in Figure 2. In the event-study estimation, for each post-swap period indicator ($\text{Post}_t \times \text{Swap}_i$ for $t \in \{1, \ldots, 5\}$), we instrument with an indicator for each post period times receipt of reminder ($\text{Post}_t \times \text{Reminder}_i$ for $t \in \{1, \ldots, 5\}$). The event-study graph for the IV analysis shows that the post-swap coefficients remain significantly positive and stable. While the magnitude of the IV estimates is slightly smaller than the CS DID estimates, the differences are not statistically significant at the 5% level.

Figure 2: Effects of Swaps over Time

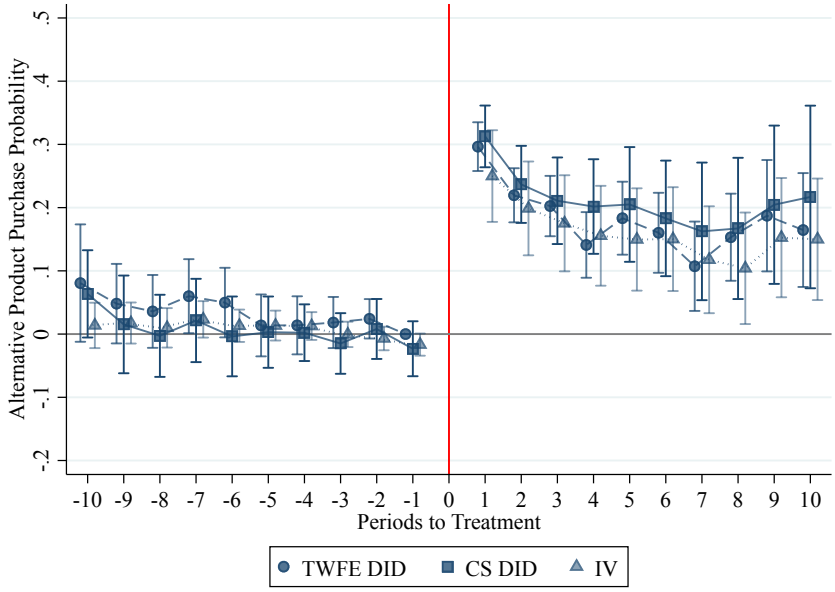


Notes: The figure plots event-study graphs from TWFE DID, CS DID and IV models. We omit the dots for the event. The red vertical line denotes the swap event time.

So far, we have demonstrated that after shoppers switch to alternative products, they are more likely to continue purchasing these products than unexposed shoppers. To test how long these effects last, we extend the pre- and post-swap periods to include ten purchase

times, and present the event study estimates in Figure 3. While the confidence intervals widen during these extended periods due to fewer observations, the treatment effects persist and remain relatively stable across all specifications.

Figure 3: Lasting Effects of the Swaps



Notes: The figure plots δ_t and their 95% confidence intervals estimated from Equation 3 extended to ten purchases before and after the swap. The red vertical line marks the treatment event time.

5 Exploring Mechanisms Behind the Lasting Effect

Our analysis so far suggests that shoppers who switch to an alternative product, continue to purchase this product at a higher frequency than *unexposed shoppers*, even ten periods later. In this section, we explore the possible mechanisms driving this lasting effect. Specifically, we test two hypotheses: (i) Did the swaps result in long-term cost savings, thereby helping consumers make more cost effective decisions in future shopping trips? (ii) Did the swaps facilitate product discovery, providing an opportunity for consumers to discover products that better meet their needs?

5.1 Cost Saving

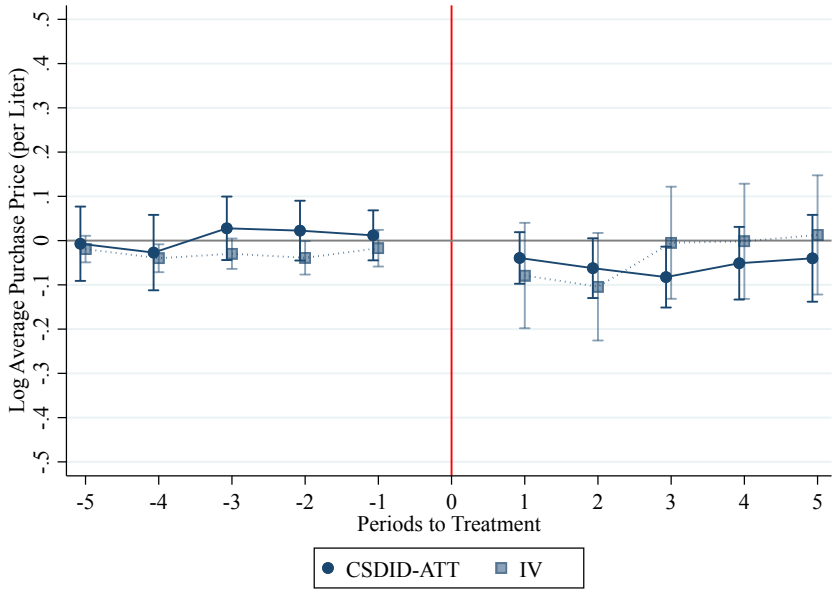
Swap reminders provide consumers with lower-cost alternatives, potentially leading to medium- to long-term savings. These savings may arise if the alternative product remains cheaper than the initial choice over future shopping periods or if the swap reduces inertia, encouraging shoppers to explore other cheaper water options in subsequent trips. If cost savings are

a primary driver of the effects, we would expect two possible outcomes: (1) shoppers who saved more during the swap event would be more likely to continue buying the alternative product in subsequent trips compared to those who saved less; (2) swapped shoppers would pay lower prices for water products in future purchases than those who were not exposed to the swap reminder.

To test possible outcome (1), we analyze the alternative product purchase probability post-swap among shoppers with varying levels of swap-day savings. Savings are calculated as the difference between the per-liter prices of the original and alternative products, with shoppers divided into high- and low-saving groups based on median savings (median savings in the sample is 19.2%). We estimate our IV model for each group separately, and find positive effects in both. A Wald test reveals no statistically significant difference between the two groups' coefficients, as shown by the p-values (see Panel (a) of Table 4). This finding suggests that shoppers with differing levels of cost savings equally increased their probability of purchasing the alternative product, and therefore, possible outcome (1) is not supported by the empirical evidence.

To test possible outcome (2), we estimate Equation 3, focusing on the outcome variable of log per-liter price paid for water. Using our CSDiD-ATT and IV specifications, we examine how the prices paid by swapped shoppers for water change after the swap event. The results, depicted in Figure 4, indicate no significant change in the prices paid by swapped shoppers post-swap. These results suggest that cost savings are likely not the primary driver of the lasting effects.

Figure 4: Purchase Price Comparison



Notes: This figure plots event study graphs from Equation 3 with the dependent variable as log average price per liter. The red vertical line indicates the treatment event time.

5.2 Product Discovery

Swap reminders may expand a consumer's consideration set by introducing products they have not previously purchased, potentially aligning better with their needs. If this is a key factor, we would expect a stronger long-term effect among first-time shoppers—those who switched to a new product—compared to repeat shoppers, who switched to an alternative they had previously purchased.

To test this hypothesis, we compare the treatment effects for first-time and repeat shoppers by estimating the IV model separately for each group.[11] The results, presented in Panel (b-1) of Table 4, show a significantly positive and notably larger effect for first-time shoppers compared to repeat shoppers. This suggests that swaps may help consumers discover products that better meet their needs by highlighting similar, lower-priced alternatives.[12] It also indicates that swap reminders may disrupt consumer inertia and shift consumer preferences.

Additionally, shoppers with weaker preferences for the initial product may be more inclined to switch products. As suggested by Webb et al. (2024), a single, isolated shock has limited impact on switching behavior when consumer preferences are habitual and enduring.

[11] The first-time shoppers consists of 28.03% of the swapped shoppers.

[12] There might be a concern that the definition of first-time shoppers is highly correlated with those new to the shopping platform rather than new to the product. A robustness check, limiting the sample to shoppers who have been purchasing on the site for at least three months prior to the swap, yields consistent results.

To explore this, we compare the impact of swaps on shoppers with weaker versus stronger preferences for the initial product. We use the pre-swap purchase frequency of the initial product's brand as a proxy for preference strength, categorizing all shoppers into two groups: strong preference (above the median frequency) and weak preference (below the median). The median pre-swap purchase frequency of the initial product's brand is 61.80%. We then estimate our IV model separately for each group. The results, presented in Panel (b-2) of Table 4, show that shoppers with strong pre-swap preference for the initial brand are significantly less likely to continue purchasing the alternative product after the swap. In contrast, those with weaker preference exhibit a higher post-swap purchase probability for the alternative product, suggesting that swap reminders may have effectively shifted their preferences.

Table 4: Mechanisms behind the Long-Term Effect

	(1) Yes	(2) No	(3) Wald Test
Panel (a). High Cost Saving			
$\text{After}_t \times \text{Swap}_i$	0.190***	0.195***	0.007
	(0.039)	(0.042)	[0.932]
Number of Observations	13,444	15,810	
Cragg-Donald Wald F statistic	591.07	522.19	
Panel (b-1). Product Discovery			
$\text{After}_t \times \text{Swap}_i$	0.320***	-0.157***	48.165***
	(0.044)	(0.053)	[0.000]
Number of Observations	22,591	4,760	
Cragg-Donald Wald F statistic	300.521	461.74	
Panel (b-2). Strong Preference for Initial Brand			
$\text{After}_t \times \text{Swap}_i$	0.107	0.399***	9.457***
	(0.081)	(0.049)	[0.002]
Number of Observations	11,297	15,061	
Cragg-Donald Wald F statistic	167.91	271.43	

Notes: This table reports results for the mechanisms using our IV specification where the dependent variable is whether or not the alternative product was purchased. In panel (a) "High Cost Saving" is defined as "Yes" for shoppers where the swap resulted in above median cost savings and "No" otherwise. In panel (b-1) the "Product Discovery" is defined as "Yes" the shopper had never before purchased the alternative product and "No" otherwise. In panel (b-2) "Strong Preference for Initial Brand" is defined as "Yes" for shoppers with an above median purchase rate of the initial product brand pre-swap and "No" otherwise. Standard errors, clustered at the shopper level, are reported in parentheses in these first two columns. The third column presents Wald-test statistics assessing the equality of coefficients estimated in Columns (1) and (2), p-values for the statistics appear in square brackets. *** p<0.01, ** p<0.05, * p<0.1.

In summary, the long-term impact of product switching is primarily driven by product discovery and is moderated by the strength of preference for the initial product. We find no evidence that this effect is motivated by cost-saving incentives.

6 Discussion and Conclusion

This paper studies the long-term effects of informational nudges on consumer behavior in online grocery shopping. Specifically, we examine whether product swaps prompted by informational nudges toward cheaper alternatives have lasting effects beyond the initial swap events. Our unique shopper-level dataset enables us to estimate the effects of these swaps

and examine the underlying mechanisms.

Our analyses reveals that after switching to an alternative product, shoppers were more likely to continue purchasing the alternative product in subsequent trips, with this behavior persisting over time. Over the five shopping trips following the swap event, the likelihood of purchasing the alternative product increased by an average of 19 percent. Interestingly, although the nudges were triggered by the availability of cheaper products, they did not lead to significant cost savings in future shopping trips. Instead, they primarily facilitated product discovery by broadening shoppers' consideration sets and introducing them to previously unpurchased products that may better meet their needs.

These findings enhance our understanding of consumer shopping behavior on online platforms and offer insights for platform design in e-commerce settings. The lasting effect of swap reminders indicates that habitual purchasing patterns can be disrupted through well-timed, relevant and personalized information. The persistence of these changes suggests that consumers found value in the alternatives, likely due to better alignment with their needs or preferences rather than solely price considerations. In a different context, Larcom et al. (2017) observed that individuals often fail to make optimal decisions, but external shocks that force them to explore new options can help them discover better commuting routes. We observe similar patterns in the context of product choice. Our analysis of persistence and underlying mechanisms shows that habitual choices might not always be the best fit, and disruptions can lead to better decision-making. Additionally, we find that these reminders are particularly effective for shoppers with weaker preferences for their initial choice.

For platform design and e-commerce strategy, our results offer valuable insights. First, the findings highlight the power of personalized, real-time interventions in shaping consumer choices. Since cost savings were not the primary driver of sustained behavior change, platforms could emphasize product discovery and matching consumers with items that better suit their needs. Furthermore, our study suggests that informational nudges on online shopping platforms can effectively influence consumer choices or even preferences. Compared to heavy-handed and costly price discounts and promotions, informational nudges can effectively promote new product discovery and disrupt consumer inertia. They can also benefit smaller brands or new products by helping them gain market share, thereby fostering increased competition in the online marketplace. However, our study is limited to examining one type of informational nudge. A broader examination of various types of nudges could yield deeper insights for platform design, and we hope future research will further explore this area.

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Appendices

A Examples of Swaps on the Platform

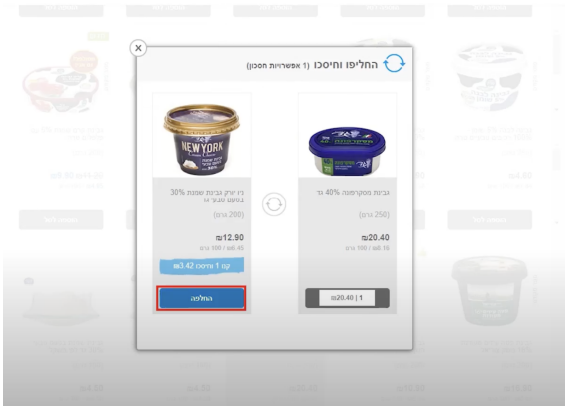
Panel (a) of Figure A1 displays an example of the *swap & save* button, and Panel (b) shows the reminder of a cheaper alternative if the shopper clicks the button.

Figure A1: Example of a Swap & Save Button and Reminder

(a) Swap & Save Button



(b) Cheaper Alternatives



B Sample Construction and Sample Details

Sample Construction. For each purchase exposed to reminders ("exposed purchase"), we match it with purchases by unexposed shoppers made at the same supermarket within a 60-day window before or after the "exposed purchase", ensuring the same initial product was bought. We then create a "purchase time" variable for all shoppers, normalized around the event time: this variable is set to 0 at the time of the first reminder or swap, with negative values (e.g., -1, -2) for purchases made before the event and positive values (e.g., 1, 2) for those after. For unexposed shoppers, the event time is defined according to the matched treated event.[13]

Sample Details. Table B1 presents the product and brand names in our sample, along with their quantity shares, promotion frequency, price per liter, and size. Figure B1 plots the promotion frequencies for the top 10 products with the highest frequency.

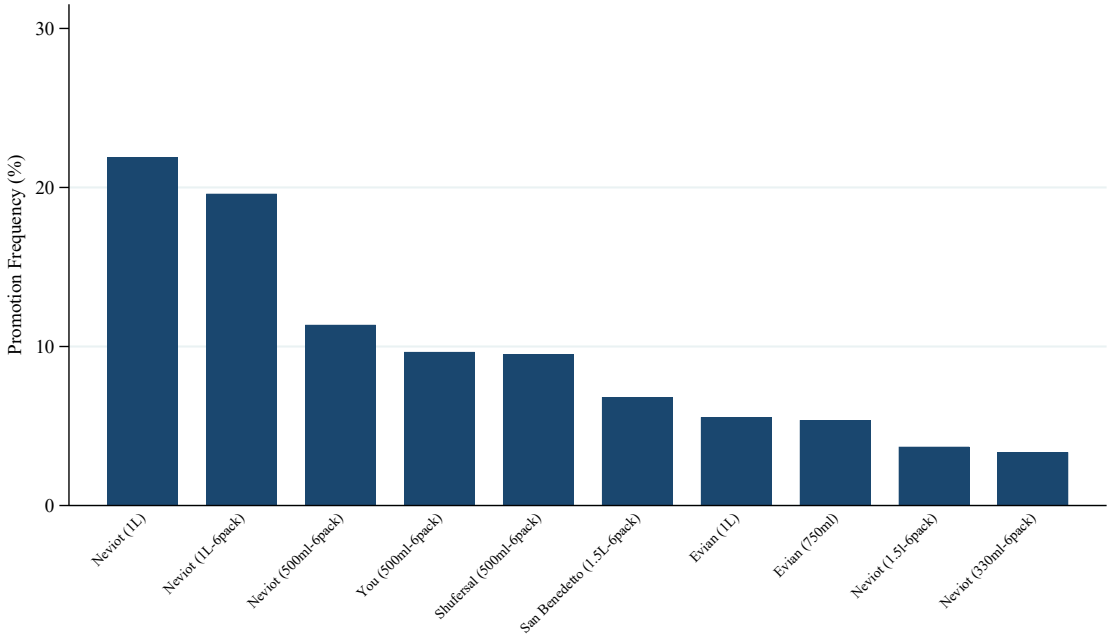
[13] A small number of shoppers made multiple purchases on the same day at the same supermarket. Given the short time lapse between these purchases, we treat them as a single trip. Consequently, the outcome variable is set to one if there is at least one purchase of the alternative product within that day.

Table B1: Summary Statistics of Main Products

Product	Brand	Quantity Share	Promotion Frequency	Price/L ($)	Size
Ein Gedi (6 pack)	Ein Gedi	37.11%	1.77%	0.23	2 liters
Neviot (6 pack)	Neviot	20.72%	3.70%	0.28	1.5 liters
Aqua Nova (6 pack)	Aqua Nova	16.01%	0.17%	0.20	2 liters
Mey Eden (6 pack)	Mey Eden	13.27%	0.80%	0.31	1.5 liters
Mey Eden Sport (6 pack)	Mey Eden	5.73%	1.20%	1.03	500 ml
Mey Eden Sport (6 pack)	Mey Eden	1.93%	1.85%	0.98	750 ml
San Benedetto (6 pack)	Sun Bendo	1.44%	2.68%	0.47	1.5 liters
Neviot Water-To-Go (6 pack)	Neviot	1.02%	5.55%	1.24	500 ml
Shufersal (6 pack)	Shufersal	0.83%	0.00%	0.30	1.5 liters
Neviot Water-To-Go (6 pack)	Neviot	0.74%	0.00%	1.05	755 ml
You (6 pack)	You	0.27%	5.37%	0.30	1.5 liters
Mey Eden Baby (6 pack)	Mey Eden	0.25%	0.73%	2.61	250 ml
San Benedetto (6 pack)	Sun Bendo	0.23%	0.00%	1.11	500 ml
Shufersal (6 pack)	Shufersal	0.17%	11.36%	1.01	500 ml
Neviot Baby (6 pack)	Neviot	0.14%	2.04%	2.00	330 ml
Neviot (1 pack)	Neviot	0.08%	21.91%	0.78	1 liter
You (6 pack)	You	0.02%	19.61%	0.98	500 ml
Spark (12 pack)	Spark	0.01%	0.00%	0.58	500 ml
You (1 pack)	You	0.01%	0.00%	0.29	1.5 liters
Opal (12 pack)	Opal	0.01%	0.00%	0.45	500 ml

Notes: This table presents summary statistics on the top 20 products based on quantity share ranking. Promotion frequency is calculated as the number of days when a product is on sale at a given supermarket divided by the total number of days it is sold the sample.

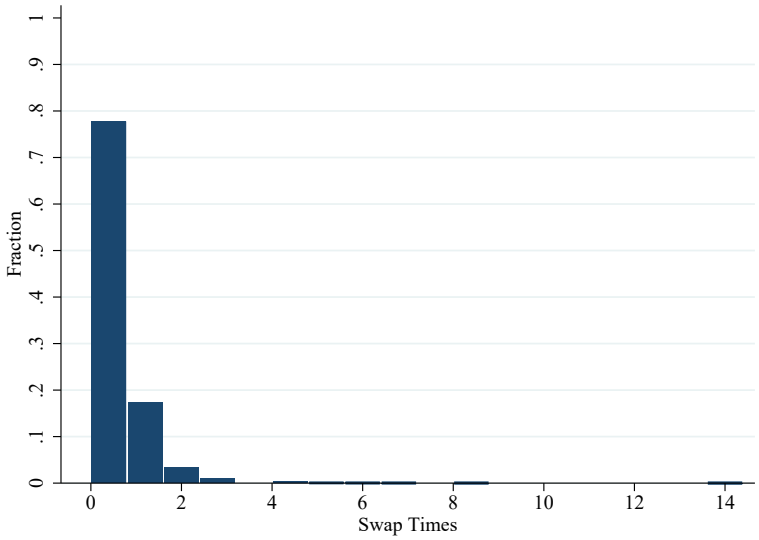
Figure B1: Promotion Frequency



Notes: This figure shows the promotion frequency for 10 products with the highest promotion frequency across the 5 supermarkets in our sample. Promotion frequency is calculated as the number of days a product is on sale at a supermarket divided by the total number of days sold in the sample period.

C Additional Descriptive Evidence

Figure C1: Number of Swaps per Shopper



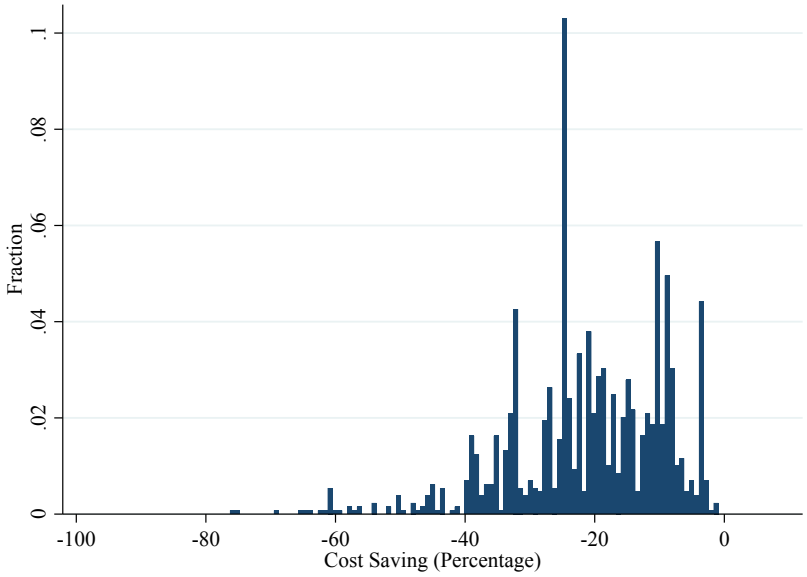
Notes: The figure depicts the distribution of number of swaps per shopper in the sample.

Table C1: Product Pairs of Top 10 Most Common Swaps

Initial Product	Initial Price	Alternative Product	Alternative Price	Price Difference	# of swaps
Ein Gedi 2 liter (6 pack)	0.267	Aqua Nova 2 liter (6 pack)	0.226	-0.041	326
Mey Eden 1.5 liter (6 pack)	0.347	Neviot 1.5 liter (6 pack)	0.291	-0.056	267
Neviot 1.5 liter (6 pack)	0.281	Aqua Nova 2 liter (6 pack)	0.209	-0.072	141
Mey Eden 1.5 liter (6 pack)	0.375	Ein Gedi 2 liter (6 pack)	0.284	-0.091	135
Neviot 1.5 liter (6 pack)	0.272	Ein Gedi 2 liter (6 pack)	0.223	-0.049	133
Neviot Water-To-Go 500 ml (6 pack)	1.169	Mey Eden Sport 500 ml (6 pack)	0.944	-0.225	128
Ein Gedi 2 liter (6 pack)	0.244	Neviot 1.5 liter (6 pack)	0.247	0.003	108
Mey Eden Sport 500 ml (6 pack)	0.993	Mey Eden Sport 750 ml (6 pack)	0.836	-0.157	85
Mey Eden Sport 500 ml (6 pack)	1.089	Neviot Water-To-Go 500 ml (6 pack)	0.896	-0.193	54
Aqua Nova 2 liter (6 pack)	0.211	Ein Gedi 2 liter (6 pack)	0.207	-0.004	52

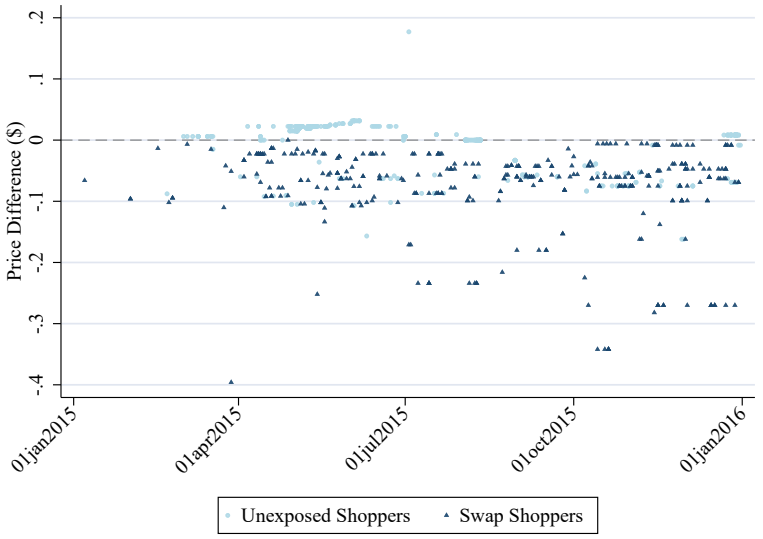
Notes: This table presents the top 10 most common product swaps across supermarket ranked by number of swaps. Price is price per liter in dollars. "# of swaps" represents the total number of swaps between the initial and the alternative product.

Figure C2: Percentage Cost Savings at the Swap



Notes: This graph plots cost saving of the swaps. Cost savings are calculated as the difference in price per liter between the initial product and the alternative product, divided by the price per liter of the initial product.

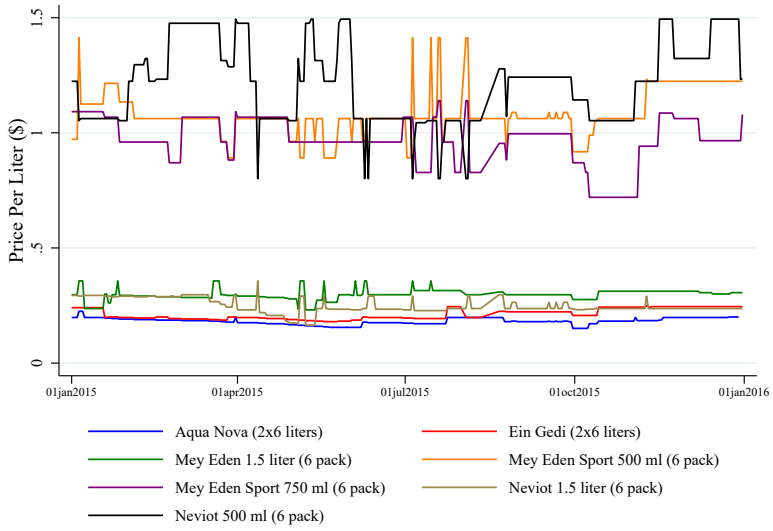
Figure C3: Price Difference for Swap and Unexposed Shoppers at a Supermarket



Notes: The price difference ($) is calculated as the price per liter of the alternative product minus the price per liter of the initial product. For the unexposed shoppers, the initial product is the product they purchase, and the alternative product is the alternative product of the treated shoppers that they are matched to.

Figure C4 plots price evolution over time for products of the most common swaps at one supermarket.

Figure C4: Price Series at a Supermarket



Notes: This figure plots price series for products of the most common swaps at one of the largest supermarkets in our sample. The price is (weekly) price per liter in dollars.

Table C2: Summary Statistics on Shopper Buying Behaviors

	All Shoppers (N = 6382)	Swapped Shoppers (N = 1420)	Exposed Shoppers (N = 5576)	Unexposed Shoppers (N = 806)
Panel A. Entire Sample Period				
Number of Trips	7.536	9.250	8.032	4.103
	(7.176)	(8.257)	(7.421)	(3.639)
Weeks between Trips	5.977	5.715	5.773	7.442
	(5.135)	(4.990)	(4.793)	(6.953)
Basket Value ($)	146.695	144.963	146.851	145.607
	(64.292)	(57.089)	(64.261)	(64.541)
Water Product Price ($)	2.722	2.697	2.734	2.524
	(0.481)	(0.447)	(0.612)	(0.636)
Spend per Purchase ($) (Water)	5.163	5.021	5.174	4.990
	(3.154)	(2.964)	(3.129)	(3.510)
Trips with Water (%)	68.715	70.400	69.251	64.866
	(28.501)	(27.467)	(28.273)	(29.828)
Time Spent in Each Shopping Trip (Minutes)	27.409	27.503	27.289	28.968
	(19.855)	(20.018)	(19.710)	(21.614)
Panel B. Before the Swap				
Number of Trips	3.130	4.057	3.291	2.004
	(3.491)	(4.664)	(3.641)	(1.816)
Weeks between Trips	4.660	4.331	4.616	5.082
	(4.305)	(3.872)	(4.197)	(5.202)
Basket Value ($)	144.687	143.214	144.996	142.509
	(68.886)	(63.138)	(69.320)	(65.742)
Water Product Price ($)	2.697	2.697	2.741	2.526
	(0.578)	(0.537)	(0.610)	(0.723)
Spend per Purchase ($) (Water)	5.005	4.973	5.027	4.719
	(3.257)	(3.130)	(3.257)	(3.247)
Trips with Water (%)	67.773	68.901	68.073	65.617
	(32.577)	(32.071)	(32.481)	(33.204)
Time Spent in Each Shopping Trip (Minutes)	26.237	26.848	26.147	27.653
	(19.105)	(19.239)	(18.984)	(20.873)

Notes: This table provides summary statistics for the shoppers. The averages are calculated at the shopper level for the entire period and for the period prior to the swap. Water Product Price ($) measures the average unit price of the water product purchased per trip. Spend per Purchase ($) (Water) is the total dollar amount spent on water per trip. Standard deviations are in the parenthesis.

D The Effect of Informational Nudges

Our empirical analysis primarily focus on estimating the implications of a product swap on future shopping behavior. While many factors, such as promotions or stock-outs can cause shoppers to switch products, in our context, the swap was prompted by an informational nudge – a *"swap & save"* reminder. It therefore provides a unique opportunity to estimate how these types of nudges impact consumer choices, regardless of whether they lead to an actual product swap. To measure this, we conduct an intention-to-treat (ITT) analysis on *exposed shoppers* who received the *swap & save* button, considering all shoppers based on their "assignment to treatment"—whether they received a reminder—regardless of whether they ultimately chose to switch.[14] This approach also helps mitigate selection bias from the shopper's decision to accept, reject, or ignore the reminder.

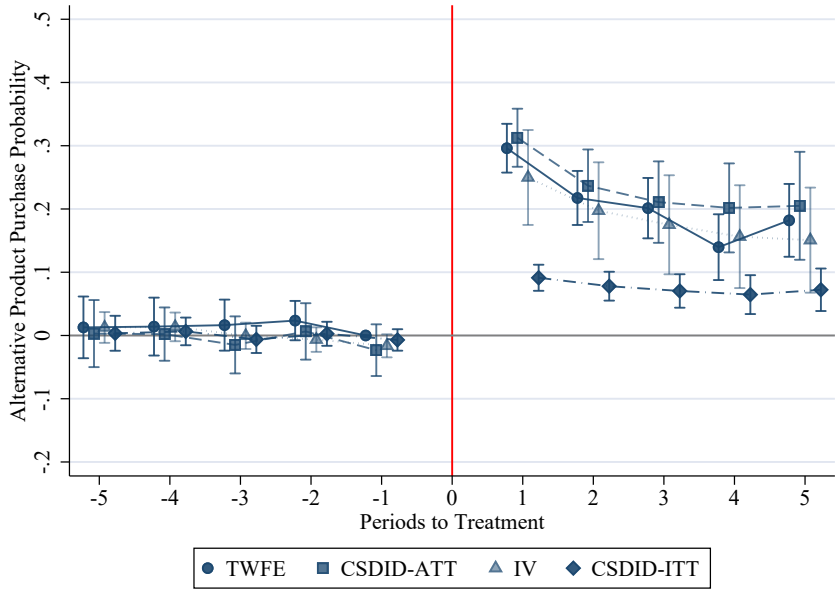
As in our main analysis, we apply the CS DID method to estimate the ITT effect, defining

[14] *Exposed shoppers* represent a broader group than *swapped shoppers*, including those who viewed the reminder without swapping, as well as those who received the *swap & save* button but did not click it. Details on the construction and composition of these groups are provided in Section 3.2 and Table 2.

the treatment time as the first purchase incidence where a shopper received a reminder. The control group includes both *unexposed shoppers* and those who have not yet received the treatment. The results indicate that receiving a reminder increases the likelihood of purchasing the alternative product by 7.8 percentage points ($\beta = 0.078, p < 0.01$), with the magnitude being approximately one-third of the CS DID estimate (7.8% compared to 24.6%).

Figure D1 presents the event-study results from the ITT analysis, depicted by diamond markers connected with a dashed line, alongside event-study plots from the TWFE DID, CS DID-ATT, and IV models. The ITT effect of the reminders remains significant up to five periods after the event, showing a 6 to 10 percentage point increase in the purchase rate of the alternative product throughout the post-event period.

Figure D1: Effects of the Swaps and Reminders



Notes: The figure plots event-study graphs from TWFE DID, CSDID-ATT, IV and CSDID-ITT models. We omit the dots for the event. The red vertical line denotes the treatment event time.