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

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A well documented phenomenon in the literature is that consumers exhibit persistence in their choices. This study explores whether informational nudges can disrupt persistent product choice in online grocery shopping. Leveraging data from a price comparison platform that provides real-time reminders of cheaper alternatives, we find significant and lasting effects on consumer choice. Shoppers who switched products after receiving a nudge were 20 percentage points more likely to choose the alternative product in future visits, with this effect persisting for up to 10 shopping trips. Our analysis suggests that this sustained impact is not driven by long-term cost savings but by product discovery facilitated by the informational nudges.

Key words: informational nudges; online shopping; product swap; new product discovery; long-term effect

1. Introduction

A large body of 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 consumers reverting to their original choices shortly thereafter (Levine and Seiler 2023). This well-documented phenomenon in marketing is commonly attributed to factors such as rational inattention (Sims 2003, Matějka and McKay 2015, Joo 2023), costs associated with searching for alternatives (Dubé et al. 2009),

* The author names are listed in alphabetical order. The authors thank Jura Liaukonyte and Stephan Seiler for their helpful comments.

and persistent brand preferences (Bronnenberg et al. 2012). Persistence in choice even occurs in online shopping, where price discovery and product comparison are easier (Chu et al. 2008, 2010, Chintagunta et al. 2012). Research shows that even mild preferences, combined with search frictions, can result in highly persistent choices (Morozov et al. 2021, Chintala et al. 2024), often leading consumers to remain locked in to suboptimal options.

In contrast with 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 another way to break inertia. By reducing search 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 in subsequent shopping trips? 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. This platform sends real-time reminders to inform consumers of cheaper alternatives. Specifically, when shoppers add an item to their cart, they receive a "swap & save" reminder that suggests similar but cheaper products, if available, allowing them to easily click on an alternative product and replace the initial one. These reminders, triggered solely by the availability of alternatives that are on sale, are applied universally to all platform users without personalization. We constructed an extensive dataset of detailed shopping records of 6,319 shoppers who made at least one purchase of mineral water on the platform in 2015. This dataset includes information on products, prices, quantities purchased, and switching behaviors for each shopping trip. It enables us to track multiple shopping trips for the same shopper both before and after instances where a product swap took place.

Our study aims to explore how informational nudges, specifically through "swap & save" reminders, influence consumer product choices via product swaps. We encounter three primary challenges in quantifying the causal effects of these switches. First, the reminder is applied universally to all users, and observed and unobserved factors can affect the consumer product choices after the swap. To effectively control for these factors among consumers and over time, we employ a quasi-experimental design as outlined by Goldfarb et al. (2022). We define the "treated" group as shoppers who received the "swap & save" reminder and subsequently swapped products. The control group comprises shoppers who never received the reminder, and purchased the *same initial product* but did not receive a reminder because a cheaper alternative was not available at the same supermarket and time. This "unavailability" of cheaper alternatives results from either stockouts or the end of discounts – events independent of shopper decisions. We then measure the difference in product choice between the treated and control groups before and after the product swaps using a Difference-in-Differences (DID) framework.

Second, we face the challenge of capturing heterogeneous treatment effects over time and across shoppers. The traditional two-way fixed effects Difference-in-Differences (TWFE DID) model assumes constant treatment effect across treated time and units. However, prior research indicates that if treatment effects vary across units or time, the model may assign negative weights, potentially leading to incorrect estimates (De Chaisemartin and d'Haultfoeuille 2020). To account for treatment effect heterogeneity, we apply the staggered Difference-in-Differences method introduced by Callaway and Sant'Anna (2021), hereafter referred to as CS DID.

The third challenge is that product swaps are voluntary, contingent upon receiving reminders. To address this endogeneity issue, we employ an instrumental variable analysis combined with Difference-in-Differences method (IV DID), following the approach of Angrist (1990), Finkelstein et al. (2012), Lundborg et al. (2014), and Hudson et al. (2017). Our instrument leverages the randomness of receiving a reminder, conditional on day of week and supermarket. In our setting, the "swap & save" reminder is triggered by the "availability" of cheaper alternatives during shopping trips. For example, for two similar shoppers who both added the same products to their shopping cart, one shopper will receive the reminder if a cheaper alternative is in stock, while the other will not if the alternative is out of stock or no longer on sale. Notably, shoppers who received and did

not receive the reminder exhibit similar product choice and shopping behavior before the reminder. Hence, we use receiving a "swap & save" reminder as an instrument for product swaps to estimate the local average treatment effect of swapping.

Our analysis yields several key findings. First, after shoppers switched to an alternative product in the mineral water category as a result of the reminders, their probability of buying this alternative product increased by 20 percentage points, compared with the control shoppers. Second, this change in purchasing behavior persisted over time, lasting for up to 10 purchases after the initial swap. This finding indicates that the switches not only prompted immediate changes but also had a longer term influence on shopper behavior. Third, this effect of product swaps on future behavior is also consistently observed across the 45 most-purchased product categories, which account for over 70% of all purchases on the platform. These results suggest that these nudges can effectively drive long-term changes in shopping behavior across a wide range of product categories.

We further explored the underlying mechanisms behind these long-term effects. While the reminders enabled shoppers to easily switch to cheaper products, they did not lead to substantial cost savings in subsequent shopping trips. Even shoppers who saved less showed a similar increase in post-swap purchase probability to those who saved more. This implies that cost savings may not be the primary driver of the lasting effect. Instead, the swap reminders may have facilitated product discovery. Specifically, the reminders expanded shoppers' consideration sets by introducing products they had not previously purchased and that potentially better met their needs, leading them to continue purchasing those products.

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 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 attacks by hackers and identifies a dissipating lock-in effect on consumers' future website visit choices.

Our study differs from the literature in two key ways. First, rather than focusing on external shocks that reduce options (e.g., stockouts), we examine voluntary product switches

prompted by informational nudges that reduce search or switching costs on online platforms and expand consumers' consideration sets. These nudges can 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, unlike the transient effects documented in prior research, we find that after switching, consumers continue purchasing the alternative product over an extended period. This persistence aligns with a product discovery mechanism facilitated by reminders that increase awareness of alternative product choices. This discovery mechanism is similar 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. We track shoppers over a longer period (weeks after the initial product switch) and find that shoppers continue to purchase the alternative product even when it is no longer significantly cheaper, indicating that this alternative product may better meet their needs.

Our study also relates to the literature on the effect of informational nudges on consumer choice. Nudges, as cognitive interventions, can influence behavior by altering 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 example, Ghose et al. (2024) show that digital nudges in an online marketplace can stimulate product purchases. Zeng et al. (2023) find 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 also shows 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 changing purchase decisions easier for consumers. Second, we document both short- and long-term effects of these nudges. Unlike traditional supermarket interventions, which are often costly and yield only short-term results (Nijs et al. 2001, Hendel and Nevo 2006, Dubé et al. 2010), the nudges in our study are more cost-effective, easy to implement, and result in lasting changes in consumer behavior. 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 run. These findings have important implications for platform design, new product introduction, and consumer engagement strategies.

2. Institutional Background

Our data come from a well-established price comparison 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, 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.

A unique feature of this platform is that it enables users to compare prices for different products in a supermarket. When browsing through products on the site, it displays the total price and price per unit (e.g., kg, liter) for each item. When shoppers add a product to their basket, a "swap & save" button appears if cheaper alternatives (based on unit price) are available at the same supermarket. Clicking the button presents the shoppers with a prompt (a "reminder") displaying up to three similar cheaper substitutes, enabling them to switch their initial product for a lower-priced alternative. Figure A1 in Appendix A provides examples of the "swap & save" button and the corresponding reminder.[1]

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 original item. In contrast, Shopper B does not receive a reminder, because the alternatives are 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 with Shopper B's, who was unaware of the alternative product because of the absence of the "swap & save" reminder.

Because products go on sale at different times, prices at the same supermarket can vary significantly from week to week. Consequently, shoppers who return even just a week later

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

are shopping in an environment with different prices. Thus, conditional on the supermarket and the day of the shopping trip, whether or not a shopper receives a reminder is plausibly random. However, a product switch depends on consumers' decisions whether or not to explore alternatives and swap to a new product. Comparing consumers who switch products with those who do not may lead to biased results. We discuss this issue further in Section 4.

3. Data, Sample Construction, and Descriptive Evidence

3.1. Data

We focus on purchases of mineral water, observing a panel of 6,319 shoppers who made purchases in this category. This category was chosen because water is a staple product purchased by a wide range of consumers with a perceived high substitutability across brands.[2] The data span from January 1 to December 31, 2015, and include 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, enabling us to identify close substitutes for all purchases.

In addition, the platform provided 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 in which 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.

These unique datasets allow us to track shoppers' initial preferences, the availability of cheaper substitutes, shoppers' 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 the button at the same supermarket (we discuss this further in Subsection 3.2).

[2]Water is the 12th most purchased category out of 137 food categories included on the platform. The frequency of product swaps in this category is 29%, slightly below the overall average swap rate of 37% across all categories. For robustness, we later extend the analysis to include the 45 most-purchased categories on the site. These categories collectively account for over 70% of total purchases, with more than 50,000 purchases observed in each of them.

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 in Appendix B lists the top 20 products ranked by market share, including brand names, market shares, price per liter (in dollars), and size.[3] The category is relatively concentrated, with the top five products holding a combined market share of 93.65%. The two leading products are mineral water Ein Gedi (6-pack of 2-liter bottles), with a 38.14% market share, and mineral water Neviot (6-pack of 1.5-liter bottles), with a 21.08% 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, and we calculate promotion duration by the number of consecutive days a product stays on sale. Promotion depth captures 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 ten days, with sale prices approximately 22% below non-sale prices. Figure B1 in Appendix B depicts the distribution of promotion frequencies for the 10 products with the highest promotion frequency, ranging from 3.35% to 21.91%.

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: Price per liter is summarized at the product-supermarket-date level, while the other variables are summarized at the product-supermarket level. Promotion-related variables are conditional on the occurrence of a promotion.

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

Alternative Products and Initial Products. Table C1 in Appendix C lists the 10 most commonly swapped product pairs across all supermarkets, along with their average prices at the swap events. 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 C1 in Appendix C plots the distribution of cost savings from the swaps. We calculate cost savings as the absolute difference in price per liter between the alternative product and the initial product divided by the price per liter of the initial product. The average (median) cost saving of swaps is 21.1% (20.5%). Figure C2 in Appendix C illustrates the weekly price series for these commonly swapped products at one supermarket, highlighting significant price fluctuations over time within the same supermarket. These price discounts also appear evenly distributed throughout the year.

3.2. Sample Construction

Our analysis examines how switching to an alternative product influences future shopping behavior. We classify shoppers as **swapped shoppers** if they accepted a product swap for the initial product in their basket. To address the endogeneity of the decision to view and accept the reminder, we also define an expanded group of **exposed shoppers**, including all shoppers who received a "swap & save" button for a water purchase, regardless of whether they clicked it. In our IV analysis, we use exposure to the "swap & save" button—which is random after controlling for supermarket and shopping day—as an instrument for product switching. Finally, we define **unexposed shoppers** as those who never received a reminder, and purchased the *same initial product* within 60 days of an exposed shopper's purchase at the same supermarket when no cheaper alternative was available.

Subsequently, we provide a detailed explanation of how these 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. Swapped 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 of 6,319). Figure C3 in Appendix C plots the distribution of swaps per shopper in our sample. As illustrated, most shoppers did not swap, and of those who did, 78% (1,108 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 third subgroup comprises shoppers who purchased the same initial product on the same day and at the same supermarket as shoppers 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 ($J2$) represents the one most frequently chosen by *swapped shoppers* who initially added product ($J1$) at supermarket (s) on swap event day (e).[4]

Unexposed shoppers. Unexposed shoppers never received a reminder during our sample period, and purchased the same initial product ($J1$) at the same supermarket (s) as the *exposed shoppers* within a 60-day window centered on 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, we apply the following criteria to identify the *unexposed shoppers*:

(1) Same preference: they purchase the same products as the initial products in the *exposed shoppers'* shopping trip.

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

(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.[5]

For *swapped shoppers*, the swap event is 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*, we define

[4]The average purchase rate of the most frequently chosen $J2$ conditional on $J1$ is 94.73%.

[5]Instances in which cheaper alternatives are unavailable are indicated by missing prices for the alternatives.

the treatment event according to the matched treated event. This allows us to create a normalized "purchase time" variable centered around the event time. We set this variable 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 Appendix B provides further details on this sample construction process.

Table 2 Definition and Number of Shoppers in Each Group

Shopper Subgroups	Definition	Number of shoppers
Swapped shoppers	shoppers who received a reminder: viewed the alternatives in reminder & swapped from their initial product to an alternative product.	1,420
Exposed shoppers	shoppers who received a reminder: viewed the alternatives in reminder & swapped from their initial product to an alternative product; or viewed the alternatives in reminder but did not swap; or did not view the alternatives in 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.	743

We report summary statistics on shopper buying behaviors for all shoppers, as well as for the swapped, exposed, and unexposed shoppers, in Table C2 in Appendix C. Panel A shows shopping behavior characteristics across all trips, and Panel B focuses on trips before treatment event. Water is a commonly purchased category in our sample, appearing in about 69% of shopping trips. Shoppers in all groups exhibit similar average spending per water purchase (around \$6) and per basket (around \$145), as well as comparable average water product price, time spent per trip and fraction of on-sale products (excluding water). However, swapped shoppers use the platform slightly more frequently, with shorter intervals between trips compared to unexposed shoppers. Our analysis accounts for this variation in platform usage.

3.3. Shopper Buying Behavior

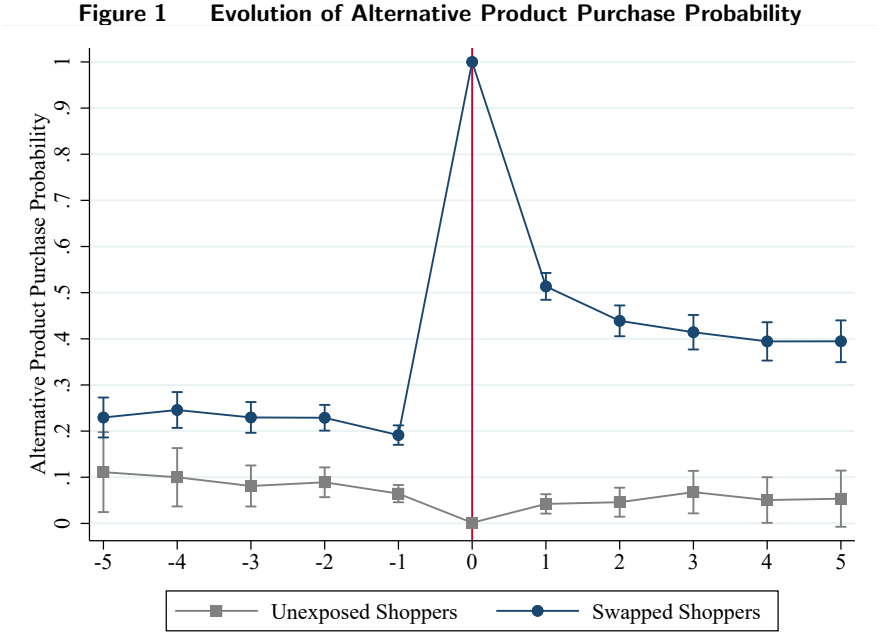
To analyze consumer shopping behavior and assess whether product switches influence subsequent purchases, we construct an outcome measure for purchasing the alternative product. This variable indicates whether the product in supermarket (r) purchased by shopper (i) at a given purchase time (t) matches the alternative product ($J2$).[6]

[6]For unexposed shoppers, the alternative product refers to the alternative product of the exposed shoppers with whom they are matched.

$$\text{BuyAlternative}_{irt} = \mathbf{1}\{j_{irt} = J2_{ire}\}$$

Figure 1 illustrates the demand for the alternative product ($\text{BuyAlternative}_{irt}$) across five purchase instances before and after the swap event, separately for swapped and unexposed shoppers. The swap event time is indicated by a vertical line. After the swap event, swapped shoppers significantly increased their probability of purchasing the alternative product compared with unexposed shoppers. The pre-swap trends between the two groups appear similar, while the post-swap difference is around 20 percentage points (a pre-swap gap of 10 percentage points, which widens to 30 percentage points after the swap).

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 vertical line indicates the swap event. This is the purchase incidence when *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 period and were not exposed to any reminders.

4. Empirical Strategy and Results

In this section, we quantify the causal effects of consumer product swaps on subsequent shopping behavior and address the three main empirical challenges mentioned in the Introduction: (1) confounding factors, both observed and unobserved, that may affect consumer product choices in addition to product swaps; (2) the heterogeneity of treatment effects

at varying times and across different shoppers; and (3) the endogeneity of the decision to swap products, conditional on receiving reminders. We outline our empirical strategies that tackle these challenges, starting with establishing a Difference-in-Differences (DID) framework and introducing a staggered DID model, followed by an Instrumental Variables (IV) approach. In Subsection 4.4, we evaluate and confirm the parallel trends assumption during the pre-swap period. Finally, in Subsection 4.5 we conduct two robustness checks: one extends our analyses of the persistence of product switching to longer future shopping trips (up to 10 trips), and the other broadens the analysis to a wider set of categories.

4.1. Difference-In-Differences Framework

To mitigate confounding factors, we employ a DID framework, leveraging the panel structure of our data to construct a suitable control group for each swapped shopper. The control group consists of *unexposed shoppers* who never received reminders (and hence never engaged in product swaps) but share similar preferences with their matched swapped counterparts. Specifically, these control shoppers purchased the same initial product at the same supermarket within a 60-day window. Their inclusion in the control group is determined by external factors—such as stockouts or the end of discounts—that rendered cheaper alternative products unavailable, circumstances that are independent of shopper decisions. We analyze the difference in product choices between the treated (swapped) and control (unexposed) groups before and after the product swaps in a base model using a TWFE DID framework:

$$\text{BuyAlternative}_{irt} = \beta_0 + \beta_1 \text{After}_t \times \text{Swap}_i + \beta_2 \text{After}_t + \Gamma_i + \Gamma_r + \Gamma_{d(t)} + \epsilon_{irt}, \qquad (1)$$

where After_t equals 1 for observations after the swap event $t = 0$,[7] and 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 with the control group. We focus on purchases made up to five periods before and after the swap, extending to 10 periods in Subsection 4.5. The terms Γ_i, Γ_r, and $\Gamma_{d(t)}$ represent fixed effects for shopper, supermarket, and day of week, respectively, accounting for unobserved factors that could influence shopping behavior.

[7] Observations at $t = 0$ are excluded from the analysis to avoid mechanically inflating the treatment effect.

The TWFE DID model results, presented in Column (1) of Table 3, show an estimated coefficient $\hat{\beta}_1$ of 0.213 ($p < 0.001$), indicating a 21.3 percentage point increase in the probability of purchasing the alternative product over the five post-swap purchase periods.

4.2. Staggered Difference-In-Differences

The TWFE DID model is widely used, with the assumption that treatment effects are constant across both time and treated units. However, if treatment effects vary, the model may assign negative weights, leading to incorrect estimates (De Chaisemartin and d'Haultfoeuille 2020). In our context, where shoppers swapped at different times, treatment effects are likely to vary. To account for this, we apply the Staggered Difference-In-Differences estimator introduced by Callaway and Sant'Anna (2021) (CS DID).

Similar to a TWFE DID model, the CS DID model uses pre-swap data to establish a baseline for comparing behavior between treated (swapped) and control (unexposed) shoppers in post-swap periods (After_t=1).[8] The key distinction lies in how the treatment effect, β_1, is estimated: the CS DID model calculates this effect by comparing the behavior of each treated shopper with matched controls and then aggregating these differences to provide an overall estimate.

Results from the CS DID model, presented in Column (2) of Table 3, indicate a 24.6 percentage point increase in the probability of purchasing the alternative product over the five post-swap purchase incidences. This effect, comparable to the TWFE DID estimate, represents a twofold increase compared to the baseline purchase rate of 10% for unexposed shoppers.

4.3. IV Analysis

The third challenge is the endogeneity of the product swap decision. Although the CS DID model partially addresses endogeneity by ensuring consistency against control misspecification or omitted variables and matching on pre-trends (Berman and Israeli 2022), concerns remain. For example, the swap decision may correlate with unobserved shopper characteristics, such as price sensitivity or expectations of better outcomes. To address this, we apply an IV analysis combined with the DID method (IV DID), following the

[8] To ensure sufficient number of control units for each swap event, we include *swapped shoppers* who have not yet swapped as controls before their first swap event, following Wang and Goldfarb (2017), Berman and Israeli (2022). This increases sample size and ensures a clean comparison over time. Results remain robust even when including only unexposed shoppers as the control group.

approach of Angrist (1990), Finkelstein et al. (2012), Lundborg et al. (2014), Hudson et al. (2017).

Our IV analysis uses receipt of the "swap & save" reminder as an instrument for the endogenous choice to switch products.[9] Denoting the endogenous variable as $F_{it} = \text{After}_t \times \text{Swap}_i$, we estimate the following two-stage model:

$$\begin{aligned} F_{it} &= \alpha_0 + \alpha_1 \text{After}_t \times \text{Reminder}_i + \alpha_2 \text{After}_t + \Gamma_i + \Gamma_r + \Gamma_{d(t)} + \nu_{irt} \\ \text{BuyAlternative}_{irt} &= \pi_0 + \pi_1 F_{it} + \pi_2 \text{After}_t + \Gamma_i + \Gamma_r + \Gamma_{d(t)} + \mu_{irt} \end{aligned} \tag{2}$$

The primary parameter of interest is the second-stage parameter π_1, identified if the instrument satisfies two conditions: (i) relevance, meaning receipt of the reminder is correlated with product switching; and (ii) independence, meaning receipt of the reminder is randomly assigned. Relevance is ensured by the institutional fact that the "swap & save" reminder is necessary for a product swap. Independence is ensured through the random timing of promotions which are beyond the control of shoppers, and the comparable shopping behaviors between exposed and unexposed shoppers, who are matched according to their product preference, shopping times and retailers. Appendix C provides further evidence of this condition. Figure C4 and Figure C5 illustrate that the swapped, exposed, and unexposed shopper groups exhibit a similar distribution of purchase shares across weeks of the year and days of the week. This suggests that their shopping patterns do not differ significantly, such as strategically timing purchases to take advantage of any potential discounts on certain days. Further, Panel B of Table C2 shows that exposed and unexposed shoppers are similar in their pre-treatment shopping behaviors, including metrics such as basket value, water product price, spending per purchase, time spent on each trip, and the fraction of on-sale products purchased per trip.[10] The difference between exposed and unexposed shoppers is how frequently they use the site, with unexposed shoppers having longer time gaps between trips than exposed shoppers. To account for this shopper characteristic difference, and further address potential concerns about variations in shopping

[9] The IV construction follows the logic used to identify *exposed shoppers* in Subsection 3.2. Specifically, we construct an indicator variable equal to one if a shopper swapped, viewed the reminder but did not swap, or received the reminder without viewing the alternatives.

[10] Regressing Reminder_i on pre-treatment shopping behavior averages (such as basket value, time spent on each trip, the fraction of on-sale products purchased, etc) yields coefficients that are close to zero and statistically insignificant.

behavior across different days of the week or differences in promotional strategies across supermarkets, we include day-of-week, supermarket, and shopper fixed effects in both model stages.[11]

The results from the IV model are reported in Column (3) of Table 3. The first-stage estimate α_1 suggests that receiving a "swap & save" reminder at time $t = 0$ increases the probability of switching products by 29.1% (see "First-Stage Estimate" row). The instrument passes the Cragg-Donald weak instrument test, with an F-statistic of 489. The second-stage estimate ($\hat{\pi}_1$) in Column (3) is close to TWFE DID and CS DID estimates. Responding to the reminder to switch products raised the probability of purchasing the alternative product in future purchases by 20.3 percentage points, which is comparable to the TWFE DID and CS DID estimates of 21.3 and 24.6 percentage points, respectively.[12]

4.4. Ensuring Parallel Trends

The causal interpretation of estimates in a DID framework relies on the assumption of conditional parallel trends between the treated and control groups. To assess this assumption, we use the following event study specification to analyze demand for the alternative product 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 is a set of indicator variables equaling 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, and δ_t measures the difference in purchasing behavior between swapped shoppers and control shoppers at each purchase time t. 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 appear as circles connected by a dashed line, along with their 95% confidence

[11] We also estimated a model with product-pair fixed effects or with price of the alternative product as a control, and get very similar estimates.

[12] In Appendix D, we examine the direct effect of receiving a reminder on the probability of purchasing the alternative product. This approach constitutes an intention-to-treat analysis, offering a straightforward estimate for platforms to evaluate the overall impact of implementing such reminders.

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

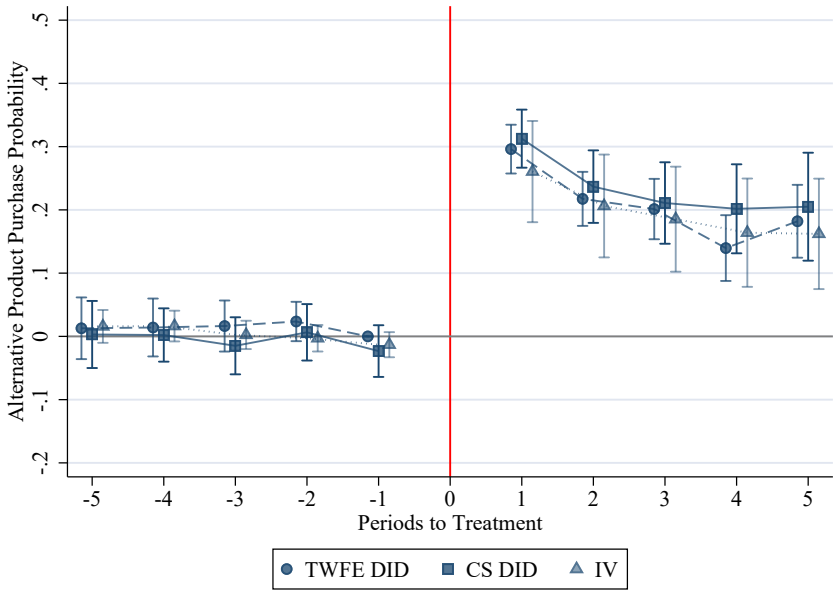
	(1) TWFE DID	(2) CS DID	(3) IV
$\text{After}_t \times \text{Swap}_i$	0.213***	0.246***	0.203***
	(0.017)	(0.017)	(0.039)
First-Stage Estimate (α_1)	–	–	0.291***
			(0.008)
Cragg-Donald Wald F statistic	–	–	489.205
Shopper FEs	Yes	Yes	Yes
Supermarket FEs	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes
N of Obs.	12,229	11,749	27,192

Notes: To avoid mechanically 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 TWFE DID analysis is run on all swapped and unexposed shoppers (Column (1)). The CS DID analysis is run on a smaller sample due to additional constraints on the matched pairs (Column (2)). The IV analysis is run on our full sample of exposed and unexposed shoppers (Column (3)). The average purchase probability of the alternative product for unexposed shoppers is 10% for all samples. Standard errors, clustered at the shopper level, are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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 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 than unexposed shoppers, 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 also conducted parallel trend test using the IV 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 multiplied by receipt of a reminder ($\text{Post}_t \times \text{Reminder}_i$ for $t \in \{1, \ldots, 5\}$). The estimates, shown as triangle dots connected by a dotted line in Figure 2, indicate insignificant pre-swap effects and positive, significant post-swap effects, with magnitudes closely matching those from TWFE DID and CS DID.

Figure 2 Effects of Swaps over Time



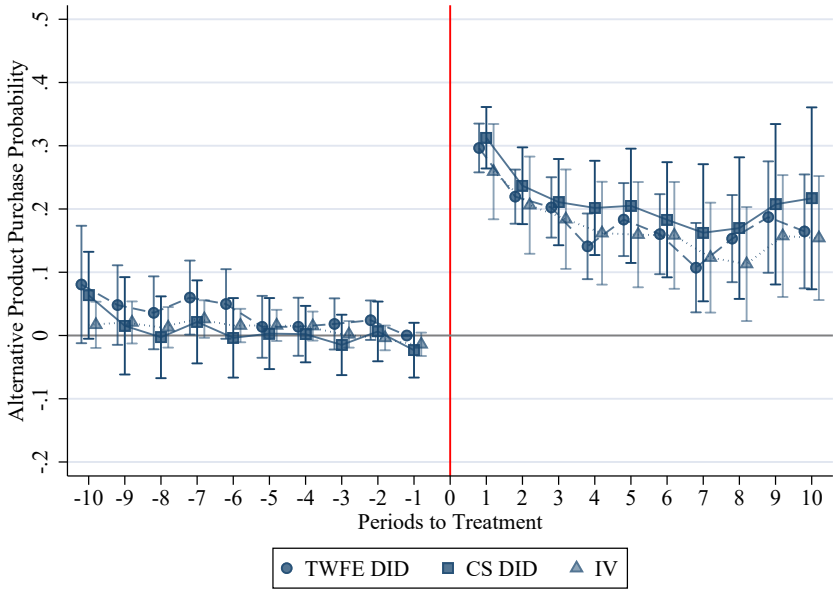
Notes: The figure plots δ_t and their 95% confidence intervals estimated from Equation 3 from the TWFE DID, CS DID, and IV models. The vertical line denotes the swap event time.

4.5. Robustness Checks

So far, we have shown that swapped shoppers are more likely to purchase the alternative products in subsequent shopping trips than unexposed shoppers. To examine the duration of these effects and whether they are unique to the water category, we perform two robustness checks in this section. First, we extend the pre- and post-swap periods to include 10 purchase incidences and present the event study estimates in Figure 3. Although confidence intervals widen over these extended periods due to fewer observations, the treatment effects remain persistent and relatively stable across all specifications. Second, we test the effects across multiple categories by estimating our IV model (Equation 2) for the 45 most-purchased categories in the dataset, which together account for over 70% of total

purchases. Figure 4 plots the coefficient ($\hat{\pi}_1$) for each category, along with their 95% confidence intervals. We estimate positive effects of swaps on future purchases of alternative product across many categories and find that, for 79.6% of categories, these effects are not significantly different from the 20% effect estimated in the water category. This suggests that the impact of swaps on future purchasing behavior is consistent across categories.

Figure 3 Lasting Effects of the Swaps

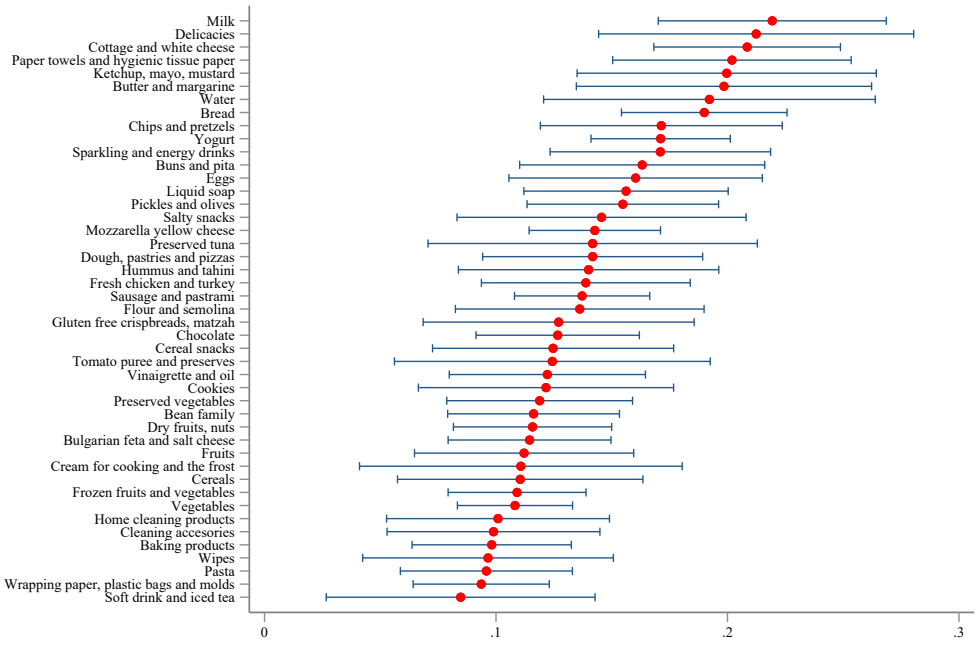


Notes: The figure plots δ_t and their 95% confidence intervals estimated from Equation 3 extended to 10 purchases before and after the swap. The vertical line marks the treatment event time.

5. Exploring Mechanisms Behind the Lasting Effect

Our analysis so far suggests that swapped shoppers continue to purchase the alternative product at a higher frequency than *unexposed shoppers*, even 10 periods later. In this section, we explore the possible mechanisms driving this lasting effect. Specifically, we test two hypotheses: (1) Did the swaps result in long-term cost savings, thereby helping consumers make more cost-effective decisions in future shopping trips? and (2) Did the swaps facilitate product discovery, providing an opportunity for consumers to discover products that may better meet their needs (e.g. a larger or smaller bottle, or a certain cap style)?

Figure 4 Effects of Swaps across Categories



Notes: This figure plots the IV estimates for the 45 most-purchased categories in the sample. The control and treated groups, as well as the variables, are constructed in the same manner as in the main IV model.

5.1. Cost Savings

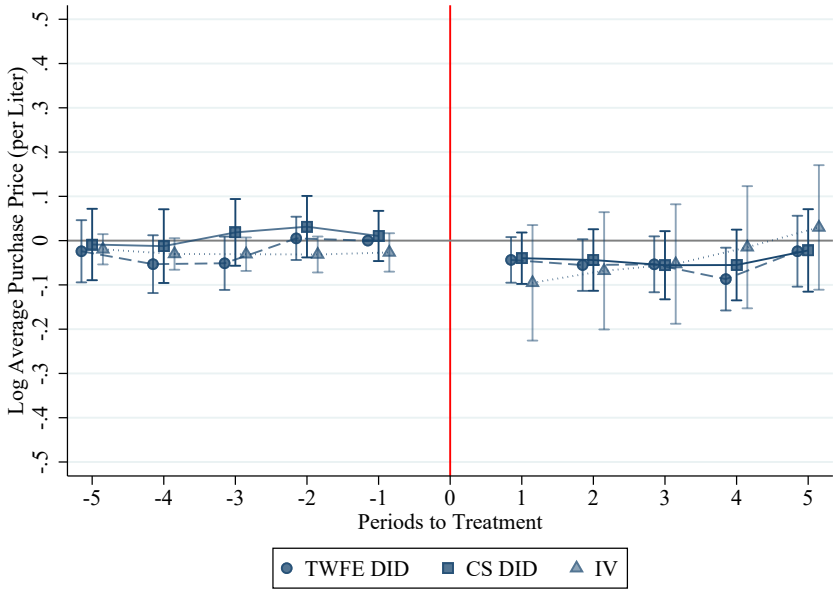
Swap reminders provide shoppers with lower-cost alternatives, potentially leading to medium- to long-term savings. These savings may arise if the alternative product remains less expensive than the initial choice in subsequent shopping trips or if the swap reduces inertia, prompting shoppers to consider other lower-cost water options in future trips. If cost savings are the primary driver of purchasing the alternative product more frequently, we would expect three possible outcomes: (1) shoppers who saved more during the swap event would be more likely to continue buying the alternative product on subsequent trips compared to those who saved less, (2) swapped shoppers would pay lower prices for water products on future trips than shoppers who were not exposed to the swap reminder, and (3) controlling for the price of the alternatives after the swap in the model would significantly attenuate the treatment effect of the swap.

To test outcome possibility (1), we analyze the probability of purchasing the alternative product after the swap event among shoppers with different levels of swap-event savings. We calculate swap-event savings as the absolute difference in price per liter between the alternative product and the initial product, divided by the price per liter of the initial

product. Shoppers are categorized into high- and low-savings groups based on the median savings achieved from a swap (20.5%).[13] Applying the IV model, we estimate the impact of the swap separately for each group (see Panel (a) of Table 4). We find that both the high- and low-savings groups exhibit a significant increase in their purchase rate of the alternative product after the swap. A Wald test confirms that there is no statistically significant difference between the behavior of the two groups. If the long-term changes in behavior were primarily driven by the magnitude of the discount, we would expect a larger response from shoppers who received greater discounts.

To test outcome possibility (2), we estimate Equation 3, using log per-liter price paid for water as the outcome variable. Figure 5 plots the event-study results from the TWFE DID, CS DID, and IV specifications. We do not find evidence of any significant change in the prices paid for water by swapped shoppers after the swap event. These results suggest that cost savings are not the primary driver of the observed lasting effects of a swap on the demand for the alternative product.

Figure 5 Purchase Price Comparison



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

[13]Control shoppers are split into high- and low-savings groups based on the classification of the matched treated shoppers.

To test outcome possibility (3), we estimate the TWFE DID, CS DID, and IV models including the price per liter of the alternative product as a control variable. We find that the treatment effect is still positive and significant and very similar to the estimates reported in Table 3 ($\beta_{\text{TWFE DID}} = 0.215$, $p < 0.001$; $\beta_{\text{CS DID}} = 0.248$, $p < 0.001$; $\beta_{\text{IV}} = 0.162$, $p < 0.001$). This suggests that the price of the alternative product is not the main driver of the lasting effect.

5.2. Product Discovery

Swap reminders may expand shoppers' 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 to find a stronger long-term effect among first-time adopters—those who switched to a new product—than among repeat buyers, who switched to an alternative they had previously purchased.

To test this hypothesis, we estimate the IV model separately for first-time adopters and repeat buyers.[14] The results, presented in Panel (b) of Table 4, show that first-time adopters drive the positive effect of swaps on future purchase rates of the alternative product, whereas repeat buyers exhibit no significant change in their post-swap purchase behavior. This suggests that swaps help these consumers discover products better suited to their needs by introducing them to options they may not have considered before. These findings indicate that swap reminders can play a key role in disrupting consumer inertia and shifting consumer preferences.

One concern about the results discussed above is that we do not observe the shopping choices outside of the platform. Thus, a shopper defined as a first-time adopter may be new to the platform, as opposed to the product. A robustness check restricting the sample to shoppers active on the platform for at least three months before the swap event, yields consistent results ($\beta_{\text{first-time adopters}} = 0.418$, $p < 0.001$, and $\beta_{\text{repeat buyers}} = -0.047$, $p > 0.1$; Wald test statistic $= 20.75$, $p < 0.001$).

6. Discussion and Conclusion

This study examines the lasting impact of informational nudges on consumer behavior in online grocery shopping. We find that after shoppers switch to a suggested cheaper alternative, they are significantly more likely to repurchase it in future trips - a persistence

[14] First-time adopters make up 72% of the swapped shoppers.

Table 4 Mechanisms behind the Long-Term Effect

	(1) Yes	(2) No	(3) Wald Test
Panel (a). High Cost Saving			
$\text{After}_t \times \text{Swap}_i$	0.132*	0.208***	0.710
	(0.075)	(0.050)	[0.399]
Number of Observations	12,753	14,439	
Cragg-Donald Wald F statistic	74.638	377.295	
Panel (b). Product Discovery			
$\text{After}_t \times \text{Swap}_i$	0.438**	-0.085	33.830***
	(0.047)	(0.077)	[0.000]
Number of Observations	9,478	17,569	
Cragg-Donald Wald F statistic	809.353	185.902	

Notes: This table reports results for the mechanisms using our IV specification. In Panel (a), "High Cost Saving" indicates "Yes" when shoppers' swap resulted in above-median cost savings and "No" otherwise. In Panel (b), "Product Discovery" indicates "Yes" if shoppers had never purchased the alternative product before and "No" otherwise. To ensure comparability in specification (b), we rematch control shoppers to swapped shoppers within group. Standard errors, clustered at the shopper level, are in parentheses in the 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 brackets.

*** p<0.01, ** p<0.05, * p<0.1.

that holds across extended time frames and diverse product categories. On average, the probability of purchasing the alternative increases by 20 percentage points over the next five trips, with similar effects observed over ten trips. The persistence of these changes suggests that shoppers may have found value in the alternatives, perhaps by better alignment with their needs or preferences. Despite being prompted by discount-based nudges, these shifts do not lead to long-term cost savings. Instead, nudges primarily act as a tool for product discovery, expanding shoppers' consideration sets. The effects are stronger for first-time buyers, highlighting the potential of nudges to shape consumer habits beyond a single purchase.

Our research offers insights for both the academic literature on state dependence and consumer inertia, as well as for retail and brand management strategies. First, a vast body of literature has documented consumer inertia and brand loyalty in both offline and online settings (Chintala et al. 2024), which can lead to persistent suboptimal choices. In a different context, Larcom et al. (2017) find that while consumers often fail to make optimal decisions, external shocks that push them to explore new options can lead to better outcomes, such as improved commuting routes. We demonstrate that it is similarly possible to break the inertia of shopping behavior through well-timed and relevant information. Moreover, these shifts can evolve into long-term change in purchase patterns, driven by a product discovery mechanism. These findings also connect to the effects of habit formation, where repeated interventions—such as prolonged stock-outs—alter product choices over time (Figueroa et al. 2019).

Second, these findings on effectively shifting persistent shopping patterns have important implications for the design of online retail platforms and e-commerce strategies. Unlike costly price discounts and promotions, which often yield only short-term effects, informational nudges can drive product discovery and disrupt consumer inertia more sustainably. By matching consumers with items that better suit their needs, platforms can increase long-term consumer satisfaction and engagement. Additionally, retailers and online platforms can leverage well-designed informational nudges to promote healthier food choices. In fact, research on the same platform has shown that similar nudges encouraging healthier options have had positive and lasting effects on healthy product choices (Barløse et al. 2022).

Third, our findings have significant implications for how brands can cultivate customer loyalty in online shopping. In traditional retail, brands often rely on in-store promotions, such as product displays, samples, and price discounts, to encourage customer switching. However, these strategies tend to have limited and short-lived effects (Nijs et al. 2001, Hendel and Nevo 2006, Dubé et al. 2010). In the context of online retail, establishing a presence in customers' baskets early on is even more critical (Dubé et al. 2009). This underscores the need for brands to carefully assess their strategies for introducing new products and promoting existing ones. Our results suggest that raising awareness and leveraging digital tools — such as informational nudges — will play an increasingly important role in affecting consumer choices.

Finally, our study has implications for competition in the retail industry. Prior research (Danaher et al. 2003, Guo and Wang 2024) shows that consumers tend to exhibit stronger brand loyalty in online shopping, making it more challenging for new entrants to establish a customer base. This dynamic can reduce market competition, enabling larger incumbents to raise prices and maintain higher markups while increasing barriers to entry. Our study connects with this literature and suggests that informational nudges can help small brands and new products gain traction, promoting greater competition in the online marketplace.

As with every study, ours has limitations that could serve as opportunities for future research. We focused solely on one type of informational nudge central to our application. A broader exploration of various nudge types could yield deeper insights into platform design. We hope our study sparks future research in this area.

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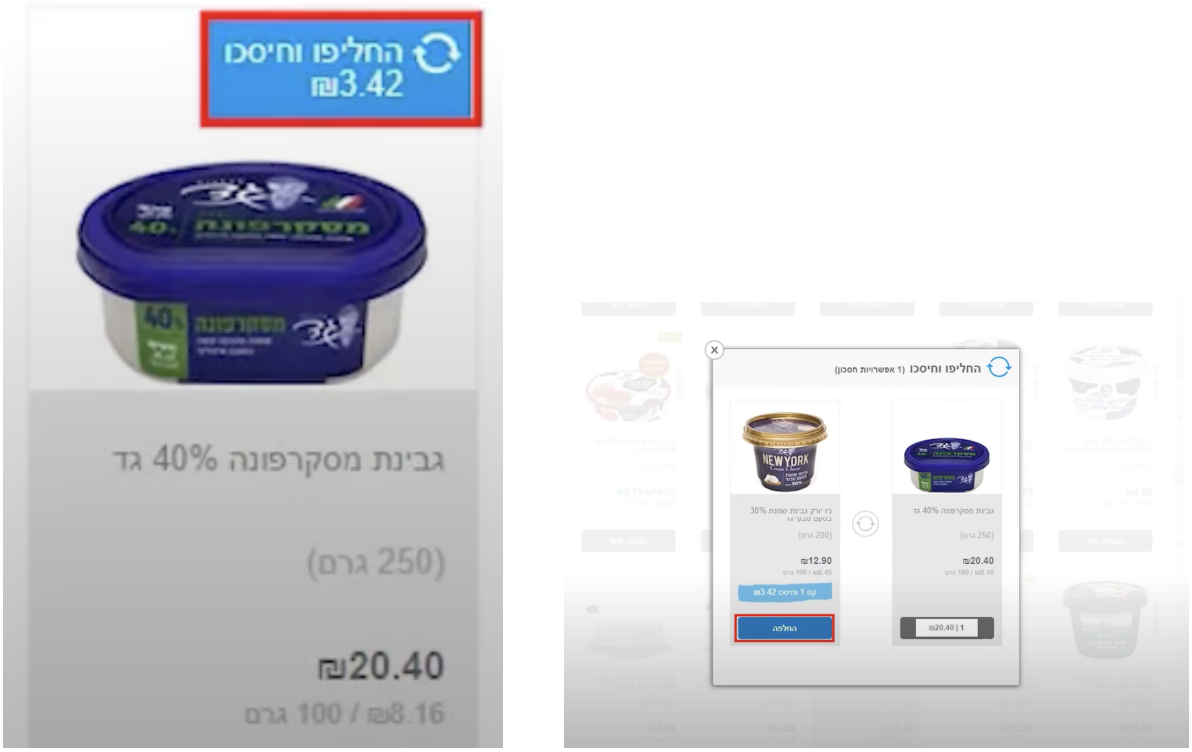
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Appendix

A. Examples of Swaps on the Platform

Figure A1 Example of a Swap & Save Button and Reminder



(a) Swap & Save Button (b) Reminder of Cheaper Alternatives

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

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 30-day window before and a 30-day window 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. We set this variable 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 made after. For unexposed shoppers, the event time is defined according to the matched treated event.[15]

[15] 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, we set the outcome variable to 1 if at least one purchase of the alternative product occurred on that day.

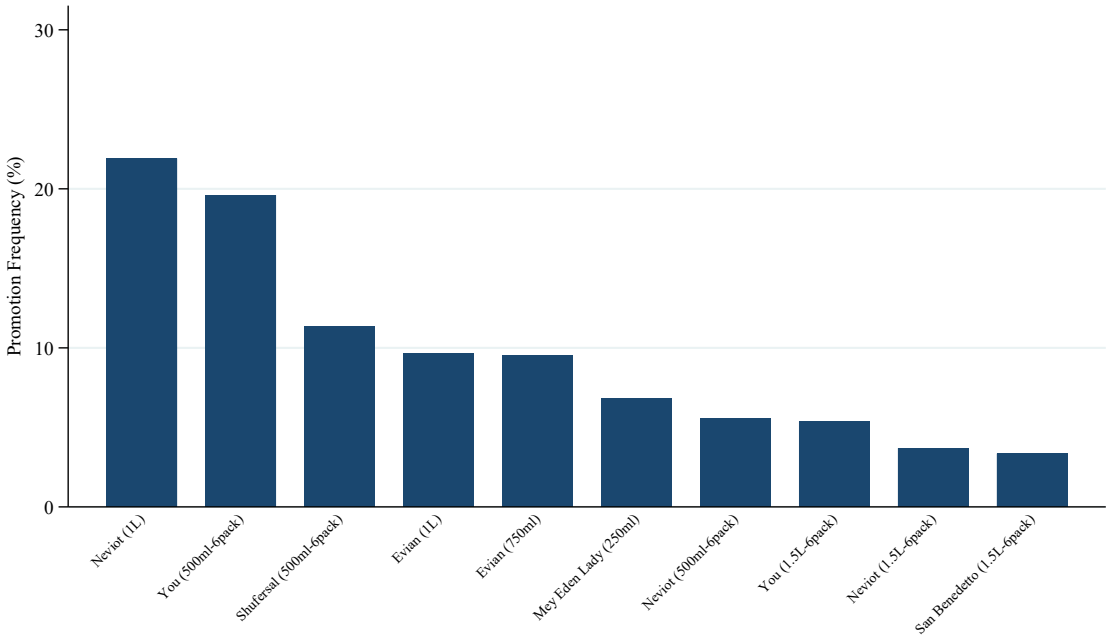
Sample Details. Table B1 presents the product and brand names in our sample, along with their quantity shares, promotion frequency, price per liter, and size. Figure B1 plots the promotion frequencies for the top 10 products with the highest frequency.

Table B1 Summary Statistics of Main Products

Product	Brand	Quantity Share	Promotion Frequency	Price/L ($)	Size
Ein Gedi (6 pack)	Ein Gedi	38.14%	1.77%	0.23	2 liters
Neviot (6 pack)	Neviot	21.08%	3.70%	0.28	1.5 liters
Aqua Nova (6 pack)	Aqua Nova	15.68%	0.17%	0.20	2 liters
Mey Eden (6 pack)	Mey Eden	13.42%	0.80%	0.31	1.5 liters
Mey Eden Sport (6 pack)	Mey Eden	5.33%	1.20%	1.03	500 ml
Mey Eden Sport (6 pack)	Mey Eden	1.71%	1.85%	0.98	750 ml
San Benedetto (6 pack)	Sun Bendo	1.19%	3.35%	0.46	1.5 liters
Neviot Water-To-Go (6 pack)	Neviot	0.91%	5.55%	1.24	500 ml
Shufersal (6 pack)	Shufersal	0.85%	0.00%	0.30	1.5 liters
Neviot Water-To-Go (6 pack)	Neviot	0.61%	0.00%	1.05	755 ml
You (6 pack)	You	0.25%	5.37%	0.30	1.5 liters
San Benedetto (6 pack)	Sun Bendo	0.22%	0.00%	1.11	500 ml
Mey Eden Baby (6 pack)	Mey Eden	0.21%	0.73%	2.61	250 ml
Shufersal (6 pack)	Shufersal	0.16%	11.36%	1.01	500 ml
Neviot Baby (6 pack)	Neviot	0.12%	2.04%	2.00	330 ml
Neviot (1 pack)	Neviot	0.07%	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	0.00%	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 in the sample period.

Figure B1 Promotion Frequency



Notes: This figure shows the promotion frequency for 10 products with the highest promotion frequency across all 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. Averages across supermarkets are plotted.

C. Additional Descriptive Evidence

Table C1 Product Pairs of Top 10 Most Common Swaps and their Prices at the Swaps

Initial Product	Initial Price	Alternative Product	Alternative Price	Price Difference	# of swaps
Ein Gedi 2 liter (6 pack)	0.231	Aqua Nova 2 liter (6 pack)	0.192	-0.039	325
Mey Eden 1.5 liter (6 pack)	0.304	Neviot 1.5 liter (6 pack)	0.242	-0.062	264
Neviot 1.5 liter (6 pack)	0.265	Aqua Nova 2 liter (6 pack)	0.189	-0.076	141
Mey Eden 1.5 liter (6 pack)	0.310	Ein Gedi 2 liter (6 pack)	0.223	-0.087	135
Neviot 1.5 liter (6 pack)	0.277	Ein Gedi 2 liter (6 pack)	0.219	-0.058	133
Neviot Water-To-Go 500 ml (6 pack)	1.287	Mey Eden Sport 500 ml (6 pack)	0.994	-0.293	128
Ein Gedi 2 liter (6 pack)	0.238	Neviot 1.5 liter (6 pack)	0.228	-0.010	99
Mey Eden Sport 500 ml (6 pack)	1.086	Mey Eden Sport 750 ml (6 pack)	0.890	-0.196	84
Mey Eden Sport 500 ml (6 pack)	1.172	Neviot Water-To-Go 500 ml (6 pack)	0.911	-0.261	54
Mey Eden 1.5 liter (6 pack)	0.309	Aqua Nova 2 liter (6 pack)	0.198	-0.111	46

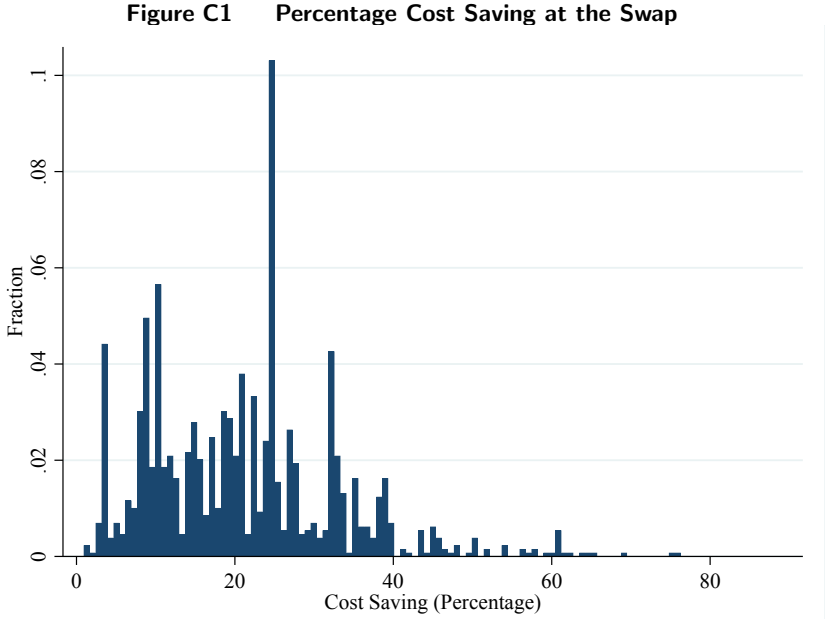
Notes: This table presents the top 10 most common product swaps across supermarkets, ranked by number of swaps. Price is measured as price per liter in dollars. Both the initial price and alternative price are prices at the swap events. '# of swaps" represents the total number of swaps between the initial and the alternative product.

Table C2 Summary Statistics on Shopper Buying Behaviors

	All Shoppers (N = 6319)	Swapped Shoppers (N = 1420)	Exposed Shoppers (N = 5576)	Unexposed Shoppers (N = 743)
Panel A. Entire Sample Period				
Weeks between Trips	5.980	5.715	5.773	7.602
	(5.119)	(4.990)	(4.793)	(6.964)
Basket Value ($)	146.886	144.963	146.851	147.151
	(64.355)	(57.089)	(64.261)	(65.104)
Water Product Price ($)	2.725	2.697	2.751	2.526
	(0.482)	(0.447)	(0.447)	(0.656)
Total Spending per Purchase ($) (Water)	6.187	6.077	6.335	5.072
	(4.578)	(4.277)	(4.638)	(3.925)
Trips with Water (%)	68.730	70.400	69.251	64.652
	(28.476)	(27.467)	(28.273)	(29.724)
Time Spent on Shopping Trip (Minutes)	29.587	30.975	29.625	29.303
	(15.414)	(15.178)	(15.204)	(16.917)
Fraction of On-sale Products Excluding Water (%)	6.186	6.468	6.208	6.026
	(7.696)	(7.826)	(7.583)	(8.503)
Panel B. Before Treatment				
Weeks between Trips	4.658	4.331	4.616	5.098
	(4.308)	(3.872)	(4.197)	(5.294)
Basket Value ($)	144.935	143.214	144.996	144.469
	(69.003)	(63.138)	(69.320)	(66.560)
Water Product Price ($)	2.699	2.697	2.721	2.532
	(0.580)	(0.537)	(0.550)	(0.749)
Total Spending per Purchase ($) (Water)	5.735	5.745	5.864	4.750
	(4.521)	(4.315)	(4.618)	(3.552)
Trips with Water (%)	67.642	68.714	67.963	65.125
	(32.682)	(32.282)	(32.624)	(33.047)
Time Spent on Shopping Trip (Minutes)	31.023	32.689	30.918	31.823
	(19.412)	(19.946)	(19.113)	(21.555)
Fraction of On-sale Products Excluding Water (%)	6.101	6.319	6.114	6.000
	(7.604)	(7.663)	(7.480)	(8.492)

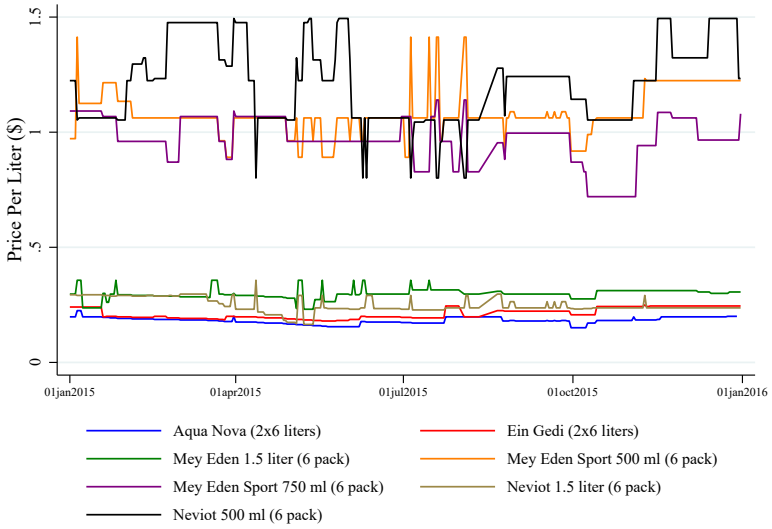
Notes: The averages are calculated at the shopper level for the entire period and for the period before the treatment. Water Product Price ($) measures the average unit price of the water product purchased per trip. Total spending per Purchase ($) (Water) is the total dollar amount spent on water per trip. Standard deviations are in the parentheses.

Figure C1 Percentage Cost Saving at the Swap



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

Figure C2 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.

Figure C3 Number of Swaps per Shopper

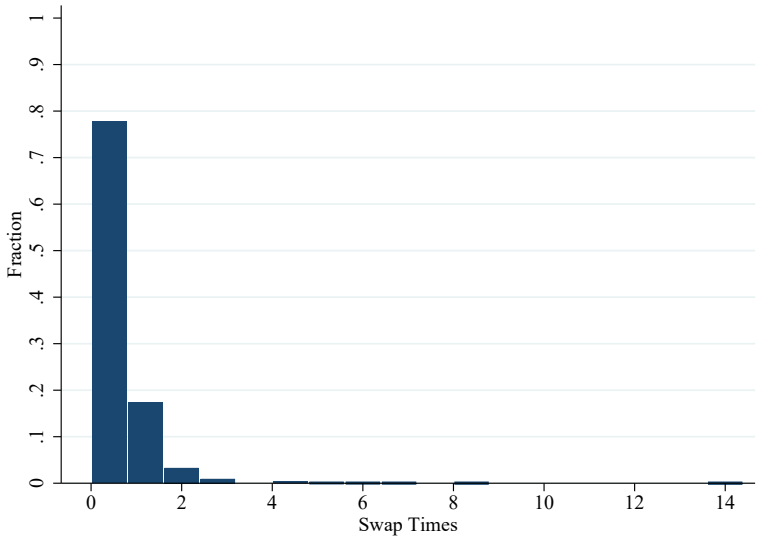
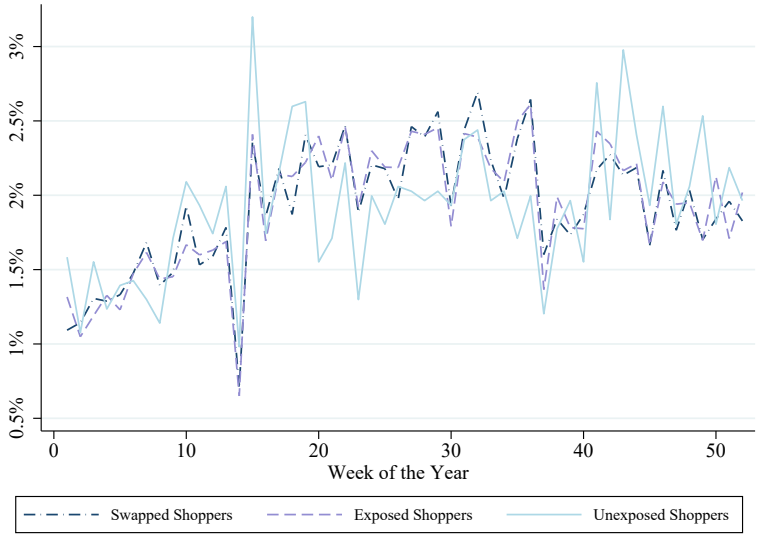
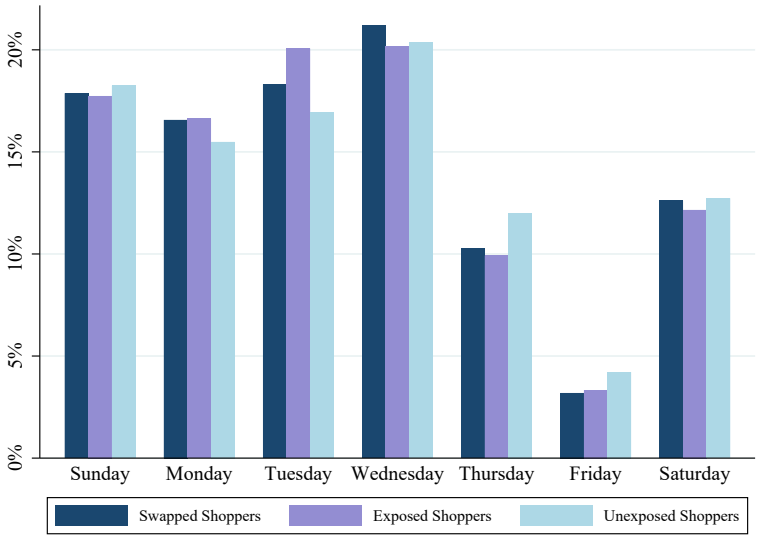


Figure C4 Share of Purchases by Weeks of the Year and Shopper Groups



Notes: The share of purchases is calculated as the number of purchases made by each shopper group (swap shoppers, exposed shoppers, and unexposed shoppers) in each week, relative to their respective total purchases of the year.

Figure C5 Share of Purchases by Day and Shopper Groups



Notes: The share of purchases is calculated as the number of purchases made by each shopper group (swap shoppers, exposed shoppers, and unexposed shoppers) in each day of the week, relative to their respective total purchases of the whole week.

D. The Effect of Informational Nudges

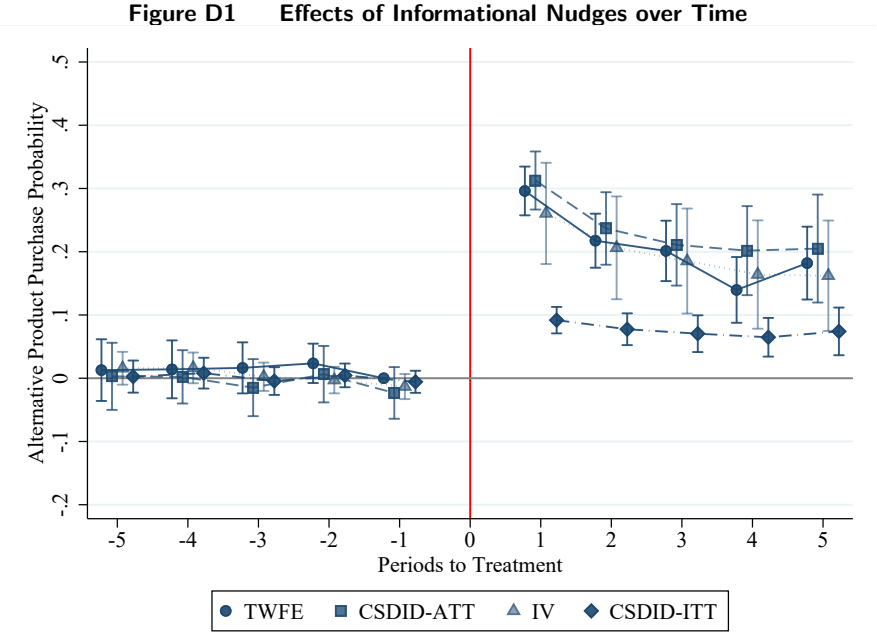
Our empirical analysis primarily focuses on estimating the implications of a product swap on future shopping behavior. While many factors, such as promotions or stockouts, can cause shoppers to switch products, in our context, the swap was prompted by an informational nudge: a "swap & save" reminder. We therefore have a unique opportunity to estimate how these types of nudges influence consumer choices, regardless of whether they lead to an actual product swap. To measure this, we conduct an intention-to-treat 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.[16] This approach also helps mitigate selection bias from the shopper's decision to accept, reject, or ignore the reminder.

We use the CS DID method to estimate the intention-to-treat effect, defining the treatment time as the first purchase incidence when a reminder is triggered. The control group consists of both *unexposed shoppers* and those who have not yet been treated. The results show that receiving the reminder increases the likelihood of purchasing the alternative

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

product by 7.8 percentage points ($\beta = 0.078, p < 0.01$), with the effect size being approximately one-third of the CS DID estimate (7.8% vs. 24.6%). Figure D1 illustrates the event study graph for the intention-to-treat estimates as diamond-shaped dots. Similar to Figure 2, the reminder effect remained stable following the treatment.

Figure D1 Effects of Informational Nudges over Time



Notes: The figure plots event-study graphs from the TWFE DID, CS DID-ATT, IV, and CS DID-ITT models. The vertical line denotes the treatment event time.