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Abstract

Despite the growing popularity of alcohol-free product variants, little is known about the implications for alcohol sales. An analysis of household scanner data first provides descriptive evidence on how alcohol purchases change after households adopt alcohol-free beverages. Heavy alcohol buyers decrease their amount of alcohol purchased by approximately 6% (from 7,329 to 6,885 grams) in the first year post-adoption, suggesting partial substitution among those most at risk of alcohol harm. In contrast, light alcohol buyers increase their alcohol purchases by 80% (from 168 to 303 grams), raising concerns about greater consideration of alcoholic products in this group. In absolute terms, the reduction among heavy buyers (–444 grams) is more than three times the increase among light buyers (+135 grams). Second, the authors examine the implications of alcohol-free advertising on alcohol sales, a key topic of debate among policymakers and industry. While alcohol-free ads are associated with small increases in alcohol sales among light buyers, they decrease alcohol sales among heavy buyers. These findings highlight both opportunities and challenges for public health policy: targeted information about alcohol-free products may help reduce alcohol purchases among heavy alcohol buyers, but caution is needed to mitigate increases among light alcohol buyers.

Keywords: alcohol, public health, policy, alcohol-free beverages

The World Health Organization (WHO) attributes over 2.5 million deaths annually to alcohol, representing 4.7% of global mortality, with the highest rates occurring in Europe (WHO 2024b). Alcohol is considered the most harmful drug overall due to its wide-ranging negative effects on individuals and society (Nutt et al. 2010).[1] It causes seven types of cancer and contributes to nearly 750,000 new global cases annually, which is over 4% of all cancer cases (Rumgay et al. 2021). In the US, alcohol ranks among the top five preventable causes of death (NIAAA 2024). The economic cost of alcohol is also substantial, averaging 2.5% of GDP in high-income countries (Rehm et al. 2009). Although reducing alcohol harm counts among the UN Sustainable Development Goals (SDG Target 3.5; United Nations 2015), the global burden of alcohol-related harm has remained largely unchanged, and the 2030 reduction targets are unlikely to be met (WHO 2024b).

In this context, a relevant question is whether alcohol-free variants offer new opportunities to reduce alcohol purchases. Alcohol-free variants are typically defined as beverages with a maximum of 0.5% alcohol by volume (Legislation Act 2003; Miller, Pettigrew and Wright, 2011).[2] Alcohol-free beer, for example, has gained a substantial market share in Germany (14.3%), Spain (7.4%), Japan (6.5%), and France (5.6%). While shares have remained lower in the UK (1.7%) and the US (1.0%), they are likely to grow in the future (Best, 2025). However, the implications for alcohol sales remain unclear, as households may purchase alcohol-free products in addition to, rather than instead of, alcoholic ones. Critics caution that alcohol-free alternatives could even increase alcoholic purchases, while the industry argues they support harm reduction (McArdie 2023). In the absence of empirical research, and given that alcohol is an inherently addictive substance (Nutt et al. 2010), it

[1] To users, alcohol is considered the fourth most harmful substance after crack, heroin, and methamphetamine. To non-users, alcohol is the most harmful drug by a wide margin (Nutt et al. 2010).

[2] An example is "Heineken 0.0", the alcohol-free variant of the alcoholic "Heineken Original" product. The label "0.0" indicates the product has an ABV below 0.05%. Most alcohol-free beverages, including Heineken 0.0, still contain a small amount of alcohol. The alcohol content in alcohol-free beverages is similar to the naturally occurring alcohol content found in various foods. For instance, fruits like bananas can contain an ABV from 0.02% to 0.04%.

remains unclear whether and to what extent the adoption of alcohol-free beverages affects alcohol purchases.

Our manuscript contributes to this discussion by providing new empirical insights into how households' alcohol purchases change after the adoption of alcohol-free products.[3] It is well known that adopting a new product provides customers with new information that can lead to updated beliefs about product quality and shift demand preferences (e.g., Erdem and Keane 1996; Steenkamp and Gielens 2003).[4] However, prior studies offer mixed predictions on how demand for one product influences demand for related products, leaving the effect ambiguous a priori, especially in the context of health-related purchases (Keller and Guyt 2023; van Heerde, Srinivasan and Dekimpe 2010). On the one hand, adopting alcohol-free products could lead to more alcohol purchases due to incremental awareness of related alcoholic products, a mechanism observed in prior adoption research (Cleeren et al. 2016; Swaminathan et al. 2001). On the other hand, such adoption could lead to fewer alcohol purchases due to substitution (Aaker and Keller 1990). In this context, heavy alcohol buyers, who face the highest health risks and are of key concern among policymakers (Anderson et al. 2023; WHO 2024a), deserve particular attention.

In addition to information from new product adoption, our study also explores the effect of information obtained through advertisements of alcohol-free products on alcohol sales. Such ads now reach wide audiences, with alcohol-free ads accounting for around 10% of total TV ad spend in the beer category (Forbes, 2023; The Wall Street Journal, 2023). Proponents argue that these ads provide useful information about healthier variants (Drinks Ireland, 2023), while critics are concerned they may bring attention to alcoholic products (CNN 2024; Libération

[3] We focus on store purchases because data on purchases in restaurants or bars are unavailable. Two-thirds of all alcohol is bought from stores and consumed at home (Public Health England 2016).

[4] Post-adoption behavior depends on the initial experience rather than on expectations of repeat purchases (Steenkamp and Gielens 2003; Swaminathan et al. 2001; see 'Theoretical Background' for more details). While first-time purchase typically increases product knowledge, similar to prior adoption literature (e.g., Cleeren et al. 2016), we acknowledge the potential role of internal motivations as a limitation of our analysis (see 'Limitations and Future Research').

2023; SHAAP 2023; The Irish Times 2023; The Sunday Times 2023). Existing research on advertising shows positive and negative spillover effects, and no prior study has analyzed effects in the context of alcohol (Balachander and Ghose 2003; Erdem and Sun 2002; Shapiro et al. 2021). Meanwhile, policymakers face increasing pressure to regulate alcohol-free product advertising (Miller, Pettigrew, and Wright, 2021), but a lack of evidence on the direction of the effect complicates informed decision-making.

We rely on seven years of scanner data on household purchases at the SKU level in France from January 2015 to December 2021, obtained via Aimark, to answer these questions. We apply a staggered difference-in-differences estimator (Gardner 2022; Gardner et al. 2024; Proserpio et al., in press) to compare changes in alcohol sales before and after adopting alcohol-free products to changes in alcohol sales for households that did not adopt or have not yet adopted. Our findings show that, on an aggregate level, the adoption of alcohol-free products does not change the total alcohol amount purchased or alcoholic volume sales. Instead, total volume sales increase by an amount comparable to the average alcohol-free volume purchased by adopters. Thus, the average adopter appears to purchase alcohol-free beverages and alcoholic beverages without substantive changes in alcohol sales, indicating complementarity. We also find a small positive spillover effect of alcohol-free advertising on alcohol sales, indicating that alcohol-free ads do not merely increase alcohol-free product sales on an aggregate level.

However, our results also reveal that the effects of the adoption and advertising of alcohol-free beverages vary significantly between households depending on prior purchasing behavior. Regarding the effects of adoption, alcohol purchases *decrease* by approximately 6% (from 7,329g to 6,885g) in the first year after adoption among historically heavy alcohol buyers, indicating partial substitution. Among light buyers, alcohol purchases *increase* by 80% (from 168g to 303g), suggesting a positive spillover effect. In absolute terms, the reduction among heavy buyers (–444g) is more than three times the increase among light buyers (+135g). Additional analyses show that while the likelihood of purchasing alcohol among heavy buyers remains similar (i.e., from 83.2% to 80.7%), these buyers reduce their quantity when they purchase alcohol (–7%). Among light buyers, purchase likelihood (11.8% to 16.6%) and quantity purchased (+27%) increase. Our analysis of advertising spillovers aligns with this pattern. We find that the spillover effect is *positive* among light buyers, indicating that exposure to alcohol-free advertising positively influences sales of alcoholic beverages, while it is *negative* among heavy buyers. However, these spillover elasticities are relatively small (+0.018 among light and –0.025 among heavy buyers) compared to the direct elasticities of alcohol advertising on alcohol sales (+0.100 among light and +0.051 among heavy buyers).[5]

Our paper makes three main contributions to the literature. First, we provide novel empirical evidence that adopting alcohol-free products can substantively change households' alcohol purchases – a finding of considerable relevance to policymakers. Our findings support the interpretation that information about alcohol-free products, whether acquired through first-time adoption or advertising, *increases* the purchase of related alcoholic products among *lighter* alcohol buyers and *decreases* it for *heavier* buyers, who already purchase alcohol frequently and likely for a broader range of occasions. For both adoption and advertising, the desirable effects among heavy buyers are substantially larger than the undesirable effects among light buyers.

Second, our study highlights the importance of household heterogeneity in examining the effects of adopting healthier product variants. While prior adoption studies have focused on average effects across households (e.g., Cleeren et al. 2016), our results show that prior category purchase behavior can substantively impact this effect. Existing literature on advertising spillovers has focused on aggregate-level outcomes (e.g., Balachander and Ghose

[5] While these elasticities may appear small, their magnitude is consistent with recent meta-analytic research on advertising elasticities (Korkames, Stanley, and Stremersch, in press).

2003; Erdem and Sun 2002; Shapiro et al. 2021). Our findings highlight that such spillovers may differ, even in direction, based on households' prior purchasing behavior within the category.

Finally, our findings offer new insights for public policymakers. Prior research indicates that "sin taxes" on unhealthy products are less effective among heavy buyers due to stronger underlying preferences (e.g., sugary drink taxes; Dubois, Griffith and Connell 2020). In contrast, our results suggest that information-based strategies aimed at increasing consideration of otherwise comparable healthier (alcohol-free) variants may be a promising strategy to reduce unhealthier (alcoholic) purchases among heavy (alcohol) buyers. As such, targeted information interventions about healthier alcohol-free variants may complement existing policy tools to support public health objectives.

Theoretical Background

Effect of Adopting Alcohol-Free Products on Alcohol Purchases

Adoption refers to a household's first purchase of a product (Steenkamp and Gielens 2003; Swaminathan et al. 2001). Before adoption, consumers typically experience uncertainty and limited product knowledge. Adoption helps resolve this by providing new product information (Erdem and Keane 1996; Steenkamp and Gielens 2003). Adoption is often exploratory in the context of fast-moving consumer goods, as product quality can be difficult to assess without trial. Post-adoption behavior generally depends on the initial experience rather than expectations of repeat purchases (Steenkamp and Gielens 2003) because consumers learn more about products through adoption and may subsequently update their preferences (Erdem and Keane 1996). In our context, the first-time purchase of alcohol-free products can be seen as an information-generating event that may, in turn, influence purchases of related alcoholic products (Steenkamp and Gielens 2003; Swaminathan 2001).[6]

On the one hand, the adoption of alcohol-free products can positively impact demand for alcoholic products due to a (positive) *spillover effect*. Empirical research has primarily attributed positive spillover effects to increased awareness of related products. For instance, Swaminathan et al. (2001) find that adoption can generate positive spillovers for related products from a brand due to enhanced brand awareness stimulated by the adoption experience. Cleeren et al. (2016) further document that after households adopt low-fat chips, their overall purchases of regular-fat chips also increase. These findings suggest that adoption may increase consideration of related products, even those within the same category. More broadly, literature in the context of the introduction of entertainment products also suggests that newer offerings adopted by consumers (e.g., a new music album, movie sequels, movie adaptations of books) may increase demand for related offerings (e.g., older albums, preceding movies, books) due to increased awareness (Hendricks and Sorensen 2009; Hennig-Thurau, Houston and Heitjans 2009; Knapp, Hennig-Thurau and Mathys 2014).[7] As such, it is conceivable that alcohol-free product adoption leads to increased consideration of their alcoholic counterparts, resulting in more alcohol sales.

On the other hand, the adoption of alcohol-free products may reduce purchases of alcoholic products through a *substitution effect*. Substitution occurs when households at least partially replace alcoholic products with alcohol-free alternatives. Substitutes typically share a common usage context, whereby one product can fulfil similar needs and replace the other during specific consumption occasions (Aaker and Keller 1990). Alcohol-free products are

[6] Experience may also occur without purchasing in a grocery store (e.g., at a bar or restaurant). However, even in such cases, beginning to purchase still represents a relative, albeit weaker, increase in exposure.

[7] Spillovers may also be negative when the new product is unsuccessful, potentially reducing demand for related products (Swaminathan et al. 2001). However, this is unlikely to be a major mechanism in our context because (a) nearly all adopters (i.e., 98.4%) continue to purchase alcohol-free products beyond the adoption period, and (b) they do so at persistently high rates across the entire post-adoption period (i.e., 11.3% of post-adoption volume sales are alcohol-free). We provide further details on this in the empirical analysis.

unlikely to displace alcoholic products completely, as households may perceive unique benefits from the presence of alcohol (Shocker, Bayus and Kim 2004). However, advancements in de-alcoholization techniques over the past decade have significantly enhanced manufacturers' ability to approximate the quality and experience of traditional alcoholic products. As a result of adoption, households may come to view alcohol-free products as viable substitutes in certain contexts for which they would otherwise purchase alcohol, potentially leading to a decrease in alcohol purchases.

In sum, existing marketing literature points to the potential for both positive and negative effects of adoption on alcohol purchases. Because the direction of the effect in our context is unclear a priori, we leverage scanner data to generate new and socially relevant empirical evidence on the effect of alcohol-free product adoption on alcohol purchases (Golder et al. 2023).

Heterogeneity Between Heavy versus Light Alcohol Buyers

Although it is unclear whether adoption will lead to a positive spillover or a negative substitution effect, neither effect is likely to occur uniformly across households. Two main reasons lead to this assumption. First, the potential for a positive spillover should be greater when prior consideration of alcoholic beverages is lower, which varies with households' pre-adoption alcohol purchasing behavior. Among heavy buyers, alcohol is already highly accessible in memory and frequently purchased. While adoption of alcohol-free products may still offer additional exposure, diminishing returns reduce the likelihood that this leads to further increases in alcohol purchases. In contrast, light buyers have weaker associations with alcohol and a lower baseline of consideration. For these households, adoption may more meaningfully increase the salience of alcoholic products, which can translate into higher alcohol purchases. Thus, if positive spillover effects occur, they are more likely among light than heavy buyers.

Second, the potential for partial substitution may equally depend on prior alcohol purchases. Heavy buyers are more likely to purchase alcohol for a broader set of occasions, creating a greater scope for alcohol-free products to partially replace alcoholic beverages. As such, the potential for reductions in alcohol purchases might be greater in this group. In contrast, light buyers may purchase alcohol for fewer occasions, limiting substitution opportunities for existing occasions. As such, any negative effects on alcohol purchases are more likely to emerge among heavier than light buyers.

Effect of Advertising Alcohol-Free Products on Alcohol Purchases

Product advertising can affect demand for related, non-advertised products (Balachander and Ghose 2003; Erdem and Sun 2002). Advertising spillover effects are typically explained by associative network theory (Anderson, 1983; Collins and Loftus, 1975), which suggests that advertising cues activate linked nodes in consumers' memory. In our context, advertising alcohol-free products may trigger associations with related alcoholic products, increasing their salience among households (Alba and Chattopadhyay 1986).

Although the underlying salience mechanism is well established, the effect of increased salience for alcohol-free products on demand for alcoholic products remains unclear. Prior empirical evidence is mixed, with similar ambiguities as in the adoption literature. While some studies find positive spillovers, with advertising for one product increasing demand for non-advertised products from the same brand (Balachander and Ghose 2003; Erdem and Sun 2002), others report negative effects, indicating decreased demand for related products (Sullivan 1990). More recently, Shapiro et al. (2021) found that advertising can produce positive and negative spillovers across a wide set of brands, suggesting that contextual factors influence the direction of the effect.[8]

[8] Shapiro and colleagues (2021) focus on estimating the effect of product advertising on sales of the advertised product but include advertising for other products by the brand as a control variable ("affiliated (sub)brands"). Results for this control variable show that product advertising can increase and decrease demand for non-advertised products from the same brand (Appendix B in Shapiro et al. 2021).

Given the lack of prior research on advertising spillovers in the context of alcohol, the expected direction is ambiguous. However, spillovers from adoption and advertising may operate through similar information mechanisms. Thus, if alcohol-free product adoption increases consideration of alcoholic products, advertising for alcohol-free variants may similarly increase alcohol sales. Conversely, if adoption results in substitution, information advertising may also reduce alcohol purchases (Lattin and McAlister, 1985; Shocker, Bayus, and Kim, 2004).

Empirical Evidence on Adopting Alcohol-Free Products and Alcohol Purchases

To investigate how alcohol purchases change after households adopt alcohol-free products, we analyze seven years of household scanner data from France. We leverage that only a subset of households adopted alcohol-free beverages during our sample period, which enables us to compare changes in alcohol sales among adopters to those of a control group of non-adopting households. The main objective of our analysis is to explore how alcohol purchases differ between adopters and nonadopters after adoption.

Data and Sample

We use scanner data on household purchases at the stock-keeping unit (SKU) level in France from January 2015 to December 2021, obtained via Aimark (aimark.org) and originating from YouGov (formerly GfK). A key advantage of the French household scanner data is that it includes Alcohol by Volume (ABV) information at the SKU level. Because households typically do not purchase in the alcohol category weekly, our unit of analysis is the household month. Our sample consists of households that remained active in the panel for at least two consecutive calendar years between 2015 and 2021. We consider a household active in a given month if it records at least one purchase in any food or beverage category. Alcohol-free products are those with an ABV not exceeding 0.5%, a common legal limit for a beverage to be marketed as alcohol-free (European Commission 2022).

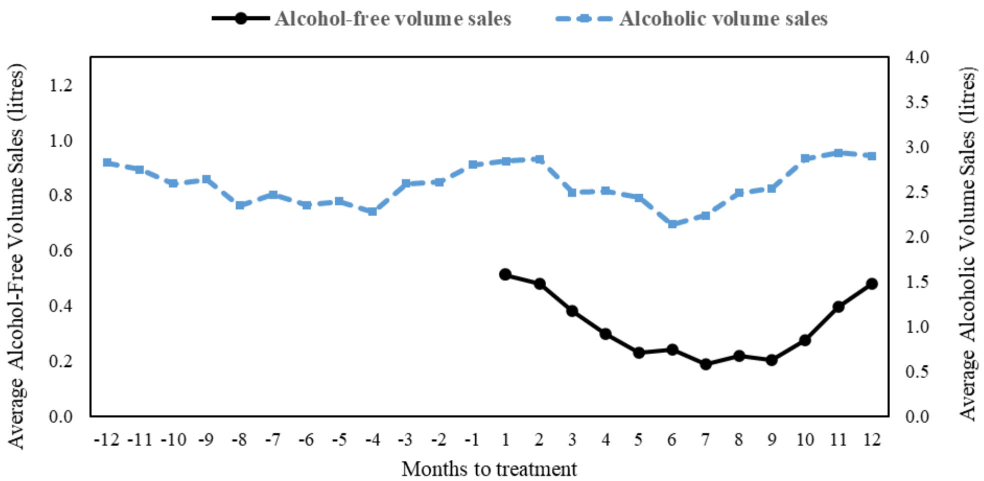
Adopters are defined as households that do not purchase any alcohol-free beverages in the beer, wine, or spirits categories during their first 12 months of observation in the panel but began doing so in any of these categories at any point thereafter (N = 1,736). Table 1 illustrates the adoption of alcohol-free beverages across time, indicating that adoption is most likely during the summertime. Across all years, 822 adoptions, or nearly 50%, occur in May, June, and July. Similar to prior studies that examine the impact of adoption using a difference-in-differences (DID) framework, adoption does not imply exclusive use of the adopted offering (e.g., Ananthakrishan, Proserpio and Sharma 2023, Gu and Kannan 2021, Maesen and Ang 2025, Manchanda, Xie, and Youn 2008). However, most adopters continue purchasing alcohol-free products within our sample, with only 27 out of 1,736 adopters (1.6%) not repurchasing beyond the adoption month.

Table 1. Number of Adopters Across Time

Month	2016	2017	2018	2019	2020	2021	**Total**
January	13	4	10	6	12	13	**58**
February	19	12	19	11	8	8	**77**
March	21	18	19	13	9	9	**89**
April	30	21	28	10	20	31	**140**
May	47	66	38	22	25	22	**220**
June	61	79	60	47	30	32	**309**
July	49	59	53	53	46	33	**293**
August	41	47	50	33	31	17	**218**
September	11	27	24	13	11	11	**97**
October	7	21	13	12	11	6	**70**
November	12	12	16	7	4	3	**54**
December	20	20	20	18	22	10	**110**
Total	**331**	**386**	**350**	**245**	**229**	**195**	**1,736**

Figure 1 further illustrates sustained demand for alcohol-free beverages among adopting households throughout the first year after adoption. On average, alcohol-free products account for about 11% of the volume purchased (in liters) across all post-adoption months, with this share remaining high throughout post-adoption months. While Figure 1 illustrates an apparent decrease in demand for several months post-adoption, this decrease applies to both alcoholic and alcohol-free beverages. As such, it likely reflects seasonal variation in overall category demand. Since adoption predominantly occurs during the summer, the six-month post-adoption point coincides with the winter months for most adopters, when overall beverage demand tends to be lower. We account for this effect in our empirical analysis. Finally, non-adopters are households that never purchased any alcohol-free beverages during the observation period (N = 3,154).

Figure 1. Average alcohol-free and alcoholic volume sales purchased among adopters



Measures

Our primary dependent variable, *total alcohol amount*, is defined as the total quantity of alcohol (in grams) purchased by household *h* in month *t*. This measure accounts for purchases across SKUs in the beer, spirits, and wine categories. Unlike volume-based sales metrics, this measure accounts for variations in alcohol content across SKUs. Following prior research using standardized alcohol metrics (Brick 2006, p.1279), we calculate the alcohol amount for each SKU_i as follows:

(1) $SKU\_Alcohol\_Amount_i = (SKU\_mL_i \times SKU\_\%ABV_i \times 0.79)/100$

In Equation 1, SKU_mL_i indicates the volume (in milliliters) of SKU i, $SKU\_\%ABV_i$ is the alcohol by volume (in percentage), and 0.79g/mL is the standard approximation for the gravity of alcohol (Bricks 2006). For example, a 500mL bottle of beer with 5.5% ABV contains approximately 21.7g of alcohol [(500 × 5.5 × 0.79)/100 = 21.725]. We then calculate the *total alcohol amount* as the sum of pure alcohol (in grams) across all beer, wine, and spirits SKUs purchased by household *h* in month *t*. For example, if a household purchases a 500mL bottle of beer with 5.5% ABV (21.725g of alcohol) and a 700mL bottle of wine with 12.5% ABV (66.360g of alcohol) in month *t*, the total alcohol amount purchased equals 88.085g.

Alcoholic volume sales are defined as the total volume (in liters) of alcoholic beer, spirits, and wine beverages purchased by household *h* in month *t*. *Alcohol-free volume sales* are defined as the total volume (in liters) of alcohol-free beer, spirits, and wine beverages purchased by household *h* in month *t*. Finally, *total volume sales* are defined as the sum of alcoholic and alcohol-free volume sales of household *h* in month *t*. For example, if a household purchases 5 liters of alcoholic beer and 2 liters of alcohol-free beer, the total volume sales equal 7 liters. Table 2 summarizes all measures and descriptive statistics of the variables across all households and observations in our sample (N = 239,692).

Table 2. Measures and summary statistics

Variables	Operationalization	M	SD	Min	Max
Total alcohol $amount_{ht}$	The total amount of pure alcohol (grams) purchased by household *h* in month t	169.49	379.86	0	6,753.27
Alcoholic volume $sales_{ht}$	The total volume of alcoholic products (liters) purchased by household *h* in month *t*	2.07	4.80	0	146.00
Alcohol-free volume $sales_{ht}$	The total volume of alcohol-free products (liters) purchased by household *h* in month *t*	0.06	0.59	0	58.20
Total volume $sales_{ht}$	The sum of alcoholic and alcohol-free volume (liters) purchased by household *h* in month *t*	2.13	4.87	0	146.00

Notes. Summary statistics across all households and observations in our sample (N = 239,692).

Model-Free Evidence

Figure 2 presents the monthly averages of our measures for one year before and one year after adoption across all adopters. As can be seen, on an aggregate level, the average monthly total alcohol amounts remain comparable before (207.3g) and after (211.2g) adoption. Adopters, on average, purchase 0.33L of alcohol-free beverages per month post-adoption. However, this does not appear to impact alcohol sales, which remain comparable (2.55L vs. 2.60L). Instead, adopting alcohol-free beverages increases total volume sales from 2.55L to 2.92L. Thus, although alcohol-free product sales account for approximately 11% of total volume sales after adoption (0.33/2.92 = 0.1130), the average adopter appears to purchase alcohol-free beverages and alcoholic beverages without substantive changes in alcohol sales.

Figure 2. Averages one year before and after adoption among adopters

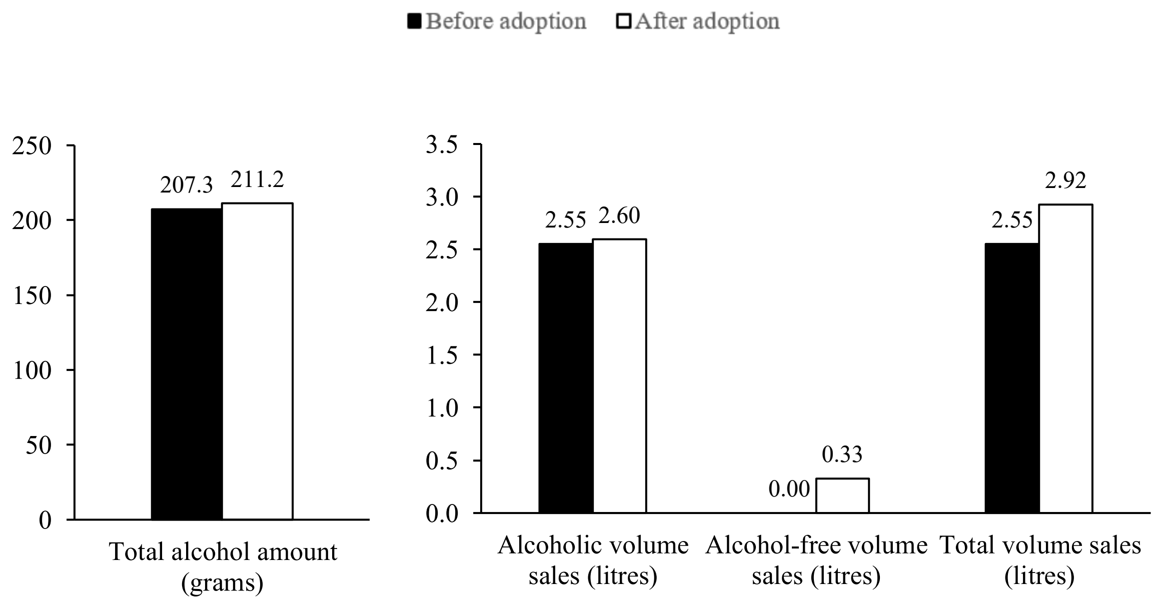
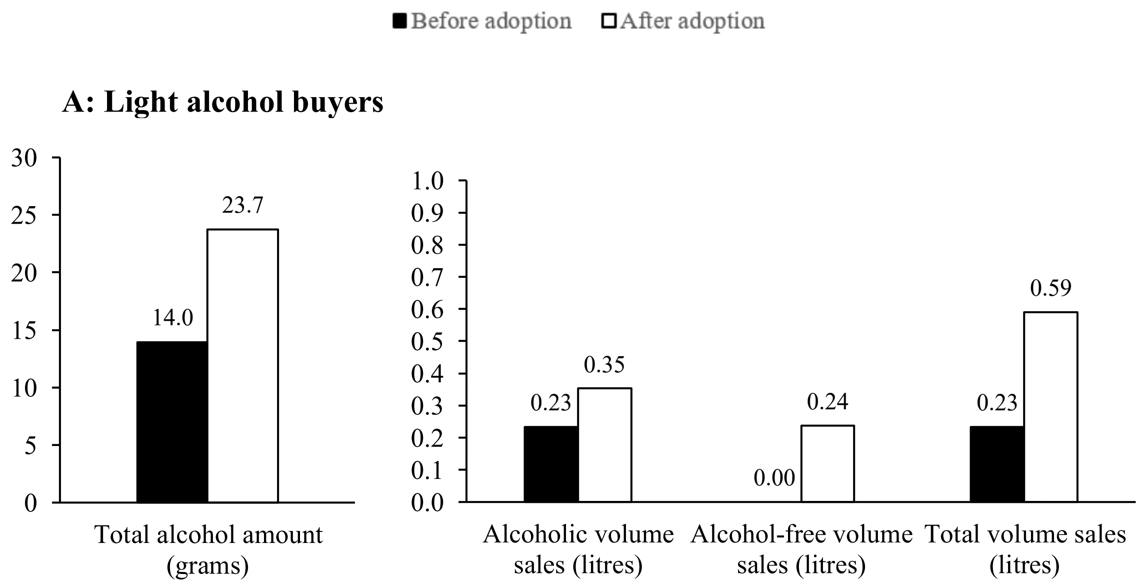


Figure 3 presents the same averages as Figure 2 but separately for light (Panel A), moderate (Panel B), and heavy (Panel C) alcohol buyers. Households are categorized based on their average monthly total alcohol amount (in grams) purchased before adoption. Following common practice, we define light and heavy buyers as those in the bottom and top quartiles, respectively (e.g., Bies, Bronnenberg and Gijsbrechts 2021; Liaukonytė, Tuchman and Zhu

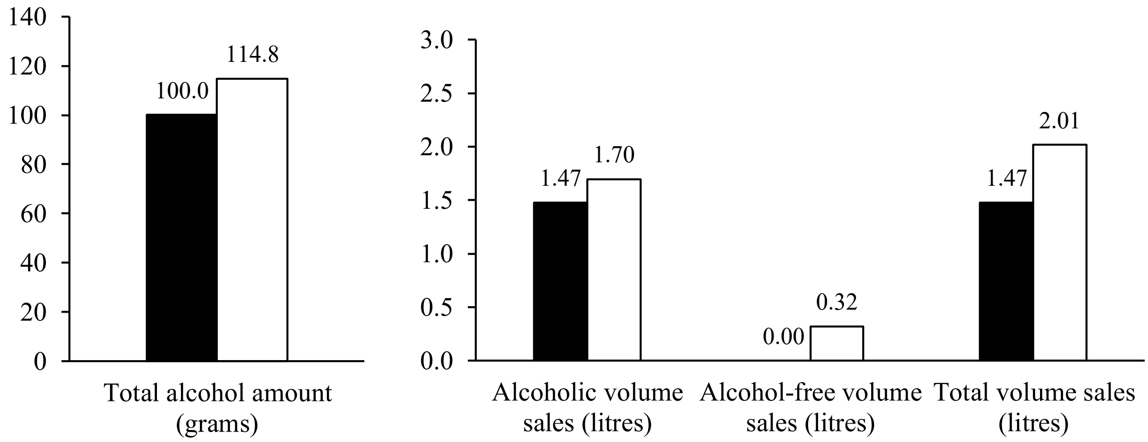
2023; Sokolova, Seenivasan and Thomas 2020). Light alcohol buyers purchase below the 25th percentile (< 30.3g). Moderate alcohol buyers fall between the 25th and 75th percentiles (≥ 30.3g and ≤ 219.0g), and heavy alcohol buyers exceed the 75th percentile (> 219.0g).

Alcohol-free volume sales post-adoption are somewhat higher among heavier buyers, averaging at 0.24L for light buyers (N = 441), 0.32L for moderate buyers (N = 856), and 0.44L for heavy buyers (N = 439). More interestingly, alcohol amounts *increase* among light (+9.7g from 14.0 to 23.7) and moderate (+14.8g from 100.0 to 114.8) buyers after adoption, as does their alcoholic volume sales (+0.12L and +0.23L, respectively). In contrast, alcohol purchases *decrease* among heavy buyers (–24g from 610.8 to 586.8 and –0.39L). Furthermore, the decrease in alcoholic volume sales among heavy buyers (–0.39L) is of similar magnitude as their increase in alcohol-free volume sales (+0.44L), resulting in no substantive change in total volume sales.

Figure 3. Averages one year before and after adoption among adopters (light, moderate, and heavy alcohol buyers)



B: Moderate alcohol buyers



C: Heavy alcohol buyers

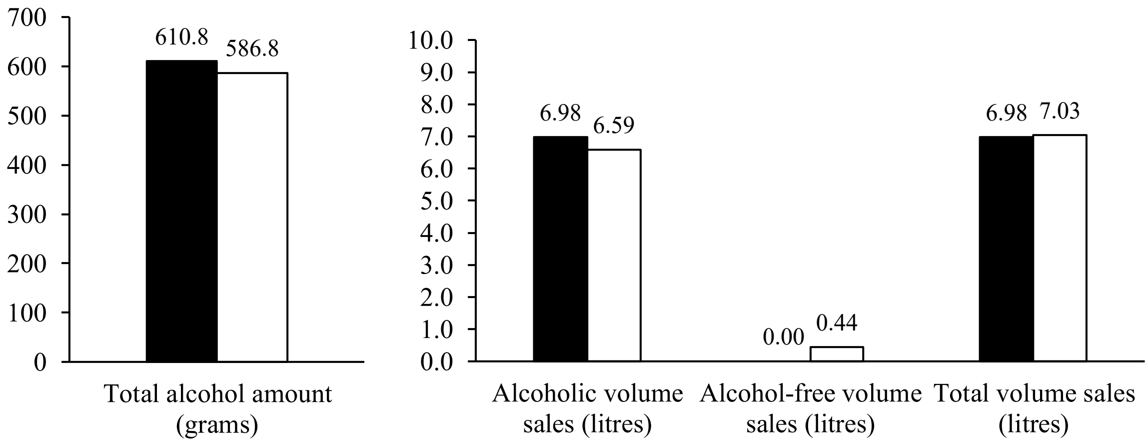


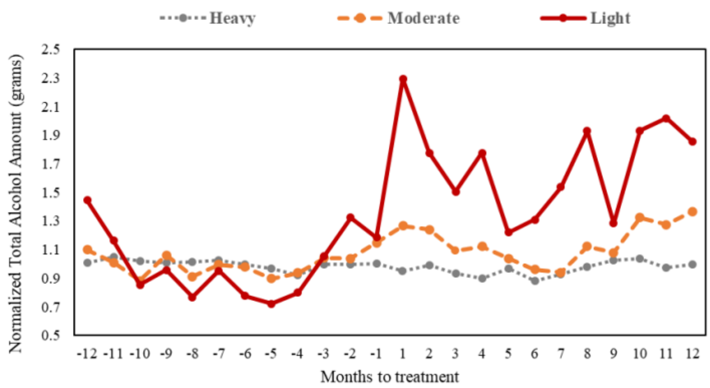
Figure 4, Panel A, shows the normalized average total alcohol amounts over time. To facilitate comparison across groups with differing baseline levels, alcohol amounts are normalized by each group's pre-adoption average (i.e., pre-adoption averages equal one within each group). Post-adoption averages are 1.70 for light buyers, 1.15 for moderate buyers, and 0.96 for heavy buyers, again indicating an increase among light and moderate buyers and a decrease among heavy buyers.[9] Panel B shows that although heavy buyers purchase more alcohol-free products than light and moderate buyers, post-adoption trends are similar across all groups. This finding suggests that the decrease in alcohol purchases among heavy buyers is unlikely to reflect a disappointment effect about alcohol-free products (Swaminathan et al.

[9] These trends and numbers should be interpreted cautiously due to potential differences between adopters and non-adopters in pre-adoption trends.

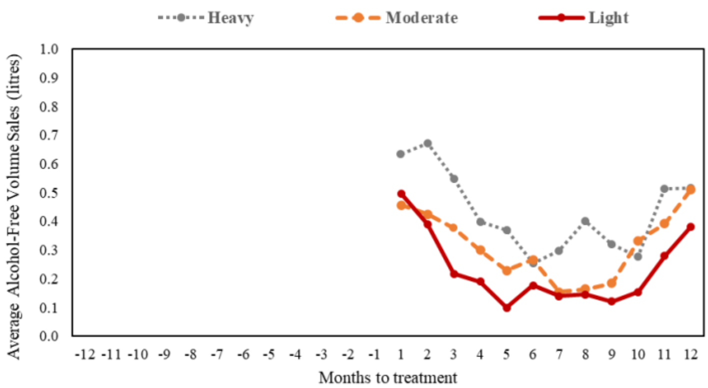
2001), which would have led to a drop in alcohol-free purchases among heavy buyers but not in the other groups.

Figure 4. Comparison between light, moderate, and heavy alcohol buyers across time

A: Normalized Average Total Alcohol Amount (grams)



B: Average Alcohol-Free Volume Sales (liters)



Difference-in-Differences Model

We use a difference-in-differences (DID) specification to estimate the impact of alcohol-free product adoption on alcohol sales. Specifically, we compare changes in alcohol sales before and after adopting alcohol-free products to changes in alcohol sales for households that did not adopt or have not yet adopted. We apply five distinct strategies to address potential challenges that arise in identifying this effect:

First, households decide when to adopt and this adoption decision could be influenced by unobserved variables, which may result in potential selection bias. We include household fixed effects to capture time-invariant differences across households (e.g., socio-demographics) and time-fixed effects to control for common demand shocks across households (e.g., seasonality, national advertising).

Second, our staggered DID model is estimated using a control group of households, including those who have not yet adopted. This further helps mitigate concerns about potential unobservable differences between adopters and non-adopters because earlier adopters are more likely to share unobservable characteristics with later adopters than with never adopters (Proserpio et al., in press).[10]

Third, we exclude the month of adoption from our analysis to mitigate potential simultaneity bias with adoption and to facilitate an understanding of the impact on post-adoption purchases (e.g., Gu and Kannan 2021; Iyengar, Park and Yu 2022).

Fourth, DID estimates may be biased when treatment effects are heterogeneous in staggered adoption settings. To address this, we adopt a two-stage DID (2SDID) estimation approach proposed by Gardner (Gardner 2022; Gardner et al. 2024; see Proserpio et al., in press, for an application in marketing). The key benefit is that this estimator can outperform alternative staggered estimators in settings with many small cohorts, as in our context (Table 1).[11] The estimator also scales well (Proserpio et al., in press), enabling us to estimate effects across multiple outcome variables and household segments efficiently. The 2SDID approach consists of two steps:

$$(2) \qquad Y_{it} = \alpha_i + \delta_t + \varepsilon_{it}$$

$$(3) \qquad \hat{Y}_{it} = \beta_1 \text{After}_{it} + \upsilon_{it}$$

We first regress each outcome variable Y_{it} for household *h* at month *t* on individual (α_i) and time (δ_t) fixed effects using the sample of untreated observations. Next, we subtract the

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[10] We find no evidence of diverging parallel trends before adoption between adopting and non-adopting households (see Results), enabling us to identify effect among the treated (ATT).

[11] Note that cohort sizes become even smaller when estimating the effects for light vs. heavy alcohol buyers.

estimated household and time effects from Y_{it} to obtain adjusted outcomes ($\widehat{Y}_{it} = Y_{it} - \widehat{\alpha}_i - \widehat{\delta}_t$). Finally, we regress these adjusted outcomes ($\widehat{Y}_{it}$) on the treatment indicator $After_{it}$, which equals one after household *i* adopted alcohol-free beverages, and zero otherwise.[12] Under the parallel trends assumption, this approach identifies the overall average treatment effect on the treated (ATT), even in the presence of treatment-effect heterogeneity (Gardner 2022; Gardner et al. 2024). Standard errors are clustered at the household level (Goldfarb, Tucker and Wang 2022).

Fifth, to assess whether treatment heterogeneity is affecting the results, we also estimate a Two-Way Fixed Effect (TWFE) model:

$$(4) \qquad Y_{it} = \beta_1 After_{it} + \alpha_i + \delta_t + \varepsilon_{it}$$

In Equation 4, Y_{it} is the outcome measure for household *i* at month *t*, $After_{it}$ is the treatment indicator, α_i are household fixed effects, and δ_t are month-year fixed effects.

Difference-in-Differences Results

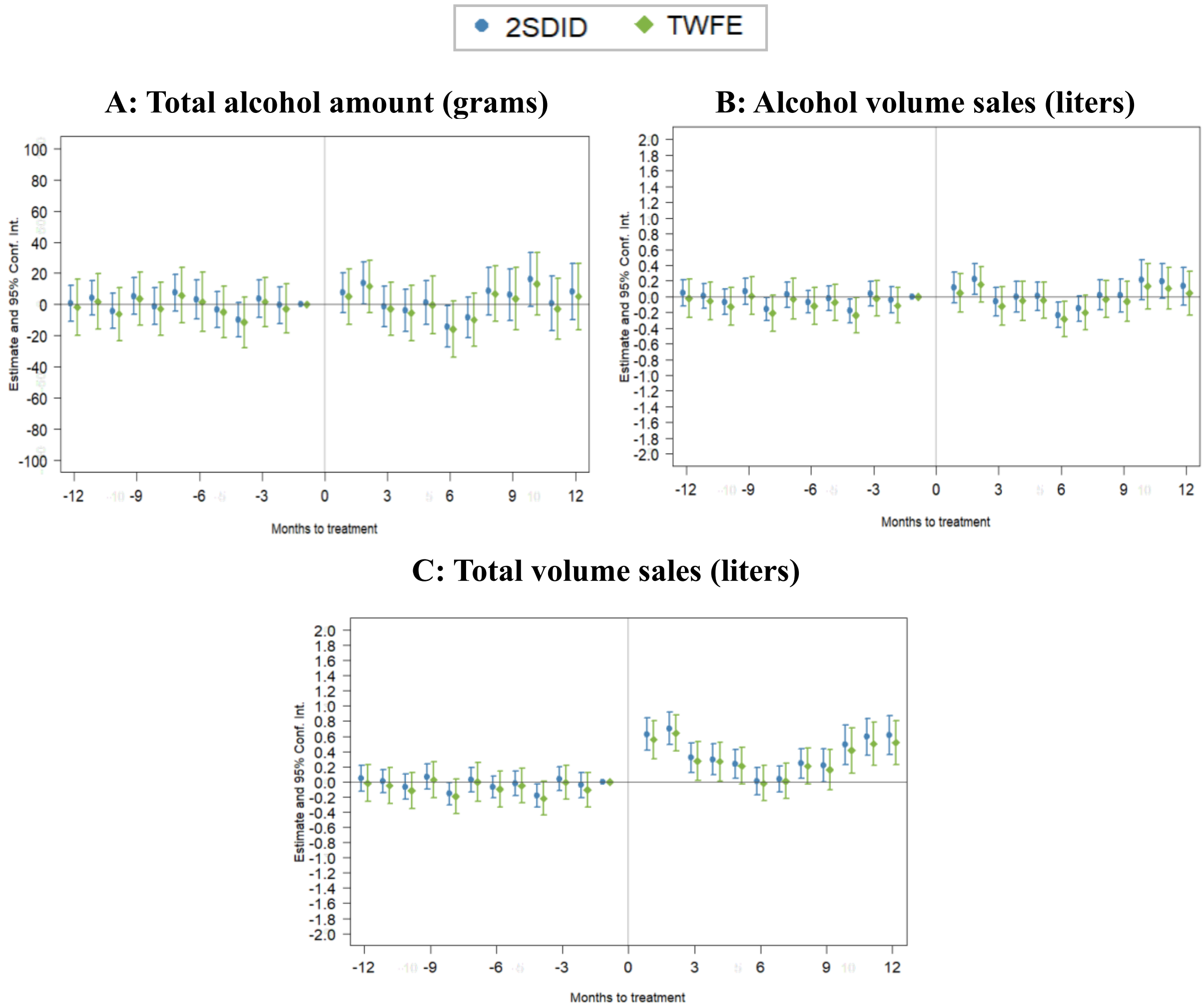
Parallel trends assumption

We first analyze whether adopters and non-adopters exhibited similar pre-adoption behavior. Figure 5 plots the estimates from both the 2SDID and the TWFE model. Three results are noteworthy: First, the estimates are close to zero for all outcomes pre-adoption, supporting the parallel trends assumption. Conditional on the fixed effects, there are no significant differences in alcohol purchases between adopters and non-adopters, suggesting that selection effects are not a major concern in estimating the average effect of treatment on the treated (ATT). Second, after adoption, there are no significant changes in total alcohol amount or alcoholic volume sales. However, there is a noticeable increase in total volume sales. These findings align with the model-free evidence in Figure 2, suggesting that demand for alcohol-free beverages among adopters does not significantly alter alcohol demand, at least not for the

[12] We implemented the estimator using the did2s package in R.

average adopter. Third, the post-adoption pattern in Panel C aligns with Figure 1, indicating positive effects when the demand for alcohol-free products is high. The results are similar across the 2SDID and TWFE approaches, suggesting that staggered adoption is not a major concern in our analysis.

Figure 5. Comparison of pre-adoption outcomes among adopters and non-adopters



Average treatment effect

Table 3 presents the average treatment effects on the treated (ATT) for the 2SDID and TWFE models across all available post-treatment periods. Consistent with Figure 5, adoption does not change the total alcohol amount (+3.492g, p = .497) nor alcoholic volume sales (+.065L, p = .296), but total volume sales increase by +0.390L (p < .0001). This increase in total volume sales is comparable to the average alcohol-free volume sales among adopters (0.33L). The TWFE model indicates a similar effect size of +0.374L ($p < .0001$). Table 3 also reports the pre-adoption means, indicating a relative average increase in total volume sales of 15.71% (0.390 / 2.482 = 0.1571).[13]

Table 3. DID estimates of the impact of the adoption of alcohol-free products

	Total Alcohol Amount (grams)	Alcoholic Volume Sales (liters)	Total Volume Sales (liters)
2SDID	3.492	.065	.390
	(5.147)	(.062)	(.067)
	$p = .497$	$p = .296$	$p < .0001$
TWFE	1.975	.055	.374
	(4.462)	(.054)	(.058)
	$p = .658$	$p = .306$	$p < .0001$
Pre-Adoption Mean	205.061	2.482	2.482

Notes. Estimates reflect the effect of $After_{it}$. All models include household and month-year fixed effects. Standard errors in parentheses are clustered at the household level. The total number of observations is 239,692. Pre-Adoption Mean is the average among adopters across all available pre-adoption months.

Heterogeneity between heavy and light alcohol buyers

To explore potential heterogeneity among different customer groups, we estimate the DID model separately for light, moderate, and heavy alcohol buyers. Web Appendix A contains the plots comparing pre-adoption behavior among adopters and non-adopters, indicating no diverging pre-trends in any of the groups. Table 4 reports the average treatment effects, revealing substantial heterogeneity across these groups. Among light and moderate alcohol buyers, we observe increases in total alcohol amounts purchased after adoption: +16.506 g for light buyers ($p < .0001$) and +24.692 g for moderate buyers ($p < .0001$). Correspondingly, we observe increases in alcoholic volume sales of +0.203L ($p < .0001$) and +0.342L ($p < .0001$) for light and moderate alcohol buyers, respectively. Total volume sales (alcoholic and alcohol-

[13] These pre-adoption means are calculated across all available pre-adoption months in the estimation sample, making them slightly different from those presented in the Model-Free Evidence, which were calculated based on a 12-month pre-adoption window. Note that alcoholic and total volume sales are the same prior to adoption by default, as there are no alcohol-free product sales among adopters before adoption.

free combined) rise by +0.437L ($p < .0001$) for light buyers and +0.665L ($p < .0001$) for moderate buyers. In contrast, we observe fewer alcohol purchases among heavy alcohol buyers after adoption. Specifically, the total alcohol amount purchased decreases by –52.293g ($p =$ .012), and alcoholic volume sales decrease by –0.633L ($p = .006$). We find no significant change in total volume sales among heavy alcohol buyers (–.125L, $p = .372$).

To better understand the relative impact, Table 4 also reports the pre-adoption means among adopters across all pre-adoption months. Our analysis shows a substantial relative *average* increase in total alcohol amount purchased: approximately +128.7% for light alcohol buyers (16.506g / 12.826g = 1.287) and +25.2% for moderate alcohol buyers (24.692g / 98.07g = 0.252). In contrast, heavy alcohol buyers experience a smaller relative decrease of –8.5% (52.293g / 611.727g = 0.085). However, it is important to note that the pre-adoption means vary substantially across these groups. While the relative increases among light (+128.7%) and moderate (+25.2%) alcohol buyers appear large, and the relative decrease among heavy alcohol buyers (–8.5%) relatively smaller, the absolute decrease among heavy buyers (–52.293g) is more than three times larger than the absolute increases among light buyers (+16.506g) and twice larger than the absolute increase among moderate (+24.592g) buyers.

To better understand effects over time, which are of interest to policymakers, we also calculate the cumulative change across the first 12 months following adoption using the 2SDID estimates (Web Appendix A), indicating that effects are not short-lived. Table 5 shows that among heavy alcohol buyers, total alcohol amounts decrease by –444.101g ($p < .0001$) in the first year after adoption. In contrast, light and moderate buyers experience increases of +224.780g ($p < .0001$) and +135.514g ($p < .0001$), respectively. Table 5 further shows that adoption changes alcohol amounts purchased across the first year by approximately –6% among heavy buyers (from 7,329g to 6,885g), +19% among moderate buyers (from 1,200g to 1,425g), and +80% among light buyers (from 168g to 303g). Despite these shifts, light buyers remain light buyers, and heavy buyers remain heavy buyers. Similar to the effects on total alcohol amount (in grams), total alcoholic volume sales (in liters) decrease by –6.339L ($p < .0001$) among heavy buyers but increase by +1.735L ($p < .0001$) and +3.309L ($p < .0001$) among light and moderate buyers. Consistent with our prior results, we observe no significant change in cumulative total volume sales among heavy buyers (–1.139L, $p = .328$). In contrast, light and moderate buyers show significant increases of +4.528L ($p < .0001$) and +7.100L ($p < .0001$), respectively.

Robustness Checks

Despite our main analysis including household fixed effects, it is conceivable that our classification of households into light versus heavy buyers could be confounded by household size. Additionally, we do not observe who does and does not consume alcohol within households, and cannot fully rule out the possibility that unobserved changes in household composition could be correlated with both the adoption of alcohol-free products and alcohol demand. To address these concerns, we first reestimate our models by dividing the outcome variables by the number of adults in the household and reclassifying households into heavy versus light buyers based on alcohol amounts purchased *per adult*. In doing so, we leverage survey data with information on household composition where available. Because this results in a substantially smaller subset of households (N = 2,864) compared to our main analysis (N = 4,890), we report this as a robustness check. Second, we restrict the sample to single-adult households only (N = 1,167). Despite the smaller sample sizes, we find a similar pattern of results. Full details on the sample, estimation, and results are provided in Web Appendix B.

Table 4. Estimates on the impact of the adoption of alcohol-free products for light, moderate, and heavy alcohol buyers

	Total Alcohol Amount (grams)			Alcoholic Volume Sales (liters)			Total Volume Sales (liters)		
	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers
2SDID	16.506	24.692	–52.293	.203	.342	–.633	.437	.665	–.216
	(2.7152)	(4.040)	(20.862)	(.029)	(.066)	(.229)	(.047)	(.073)	(.241)
	$p < .0001$	$p < .0001$	$p = .012$	$p < .0001$	$p < .0001$	$p = .006$	$p < .0001$	$p < .0001$	$p = .372$
TWFE	14.123	22.228	–49.102	.174	.319	–.563	.407	.621	–.125
	(2.139)	(3.392)	(17.406)	(.025)	(.054)	(.193)	(.040)	(.061)	(.203)
	$p < .0001$	$p < .0001$	$p = .005$	$p < .0001$	$p < .0001$	$p = .004$	$p < .0001$	$p < .0001$	$p = .537$
Pre-Adoption Mean	12.826	98.07	611.727	.209	1.421	6.885	.209	1.421	6.885

Notes. Estimates reflect the effect of $After_{it}$. All models include household and month-year fixed effects. Standard errors in parentheses are clustered at the household level. Pre-Adoption Mean is the average among adopters across all pre-adoption months in the sample.

Table 5. Cumulative effects among light, moderate, and heavy alcohol buyers one year after adoption

	Total Alcohol Amount (grams)	Alcoholic Volume Sales (liters)	Total Volume Sales (liters)
Light Alcohol Buyers	135.514	1.735	4.528
	(13.795)	(.192)	(.277)
	$p < .0001$	$p < .0001$	$p < .0001$
Moderate Alcohol Buyers	224.780	3.309	7.100
	(25.952)	(.422)	(.457)
	$p < .0001$	$p < .0001$	$p < .0001$
Heavy Alcohol Buyers	–444.101	–6.339	–1.139
	(92.173)	(1.128)	(1.164)
	$p < .0001$	$p < .0001$	$p = .328$
Pre-Adoption Sum			
Light	167.567	2.810	2.810
Moderate	1,200.429	17.699	17.699
Heavy	7,329.088	83.799	83.799

Notes. Estimates reflect cumulative effects across the first 12 months post-adoption. Pre-adoption sum is the cumulative value on the dependent variable across 12 months immediately before adoption among adopters, averaged across adopters.

Additional Analyses

Incidence vs. Quantity

We further examine whether adoption affects the likelihood of purchasing alcohol (incidence) and/or the conditional purchase amounts (quantity). To do so, we estimate separate effects of adoption on incidence and conditional quantity. Incidence is a binary variable equal to 1 if a household purchases any alcohol in a given time period and 0 otherwise. Conditional quantity reflects how much alcohol households purchase when incidence equals 1, measured in grams and liters, as defined in our main analysis (Table 2). We estimate a logistic regression model with household and time-fixed effects for incidence, and estimate the same 2SDID model for the quantity outcomes, but now conditional on incidence equalling 1.

Table 6. Estimates on the impact of adoption on alcoholic purchase incidence and conditional alcohol quantities

	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers
Incidence	.438 (.073) $p < .0001$	.090 (.040) $p = .023$	–.177 (.086) $p = .039$
Conditional Total Amount of Alcohol in Grams (when incidence equals 1)	29.761 (7.577) $p < .0001$	35.533 (5.934) $p < .0001$	–48.348 (21.056) $p = .027$
Conditional Total Alcoholic Volume Sales in Liters (when incidence equals 1)	.171 (.181) $p = .347$	.544 (.093) $p < .0001$	–.583 (.247) $p = .018$
Pre-Adoption Mean			
Incidence	.118	.440	.832
Conditional Total Amount in Grams	109.018	222.975	735.471
Conditional Total Volume in Liters	1.773	3.231	8.277
Marginal Effect			
Incidence	.048 (.009) $p < .0001$	.019 (.008) $p = .023$	–.025 (.013) $p = .046$

Notes. Estimates reflect the effect of $After_{it}$. All models include household and month-year fixed effects. Standard errors in parentheses are clustered at the household level. Pre-adoption means are averages among adopters across all pre-adoption months in the sample, conditional on incidence for the quantity variables (grams and liters).

Table 6 reports the pre-adoption means, estimation results, and the marginal effects for the incidence models. Among heavy buyers who purchase alcohol in 83.2% of time periods before adoption, we observe a substantively small decrease in incidence after adoption of 2.5 percentage points ($p = .046$), indicating heavy alcohol buyers largely continue purchasing alcohol with similar frequency after adoption. However, when they purchase alcohol, they buy –0.583L less on average ($p = .018$), a 7.0% reduction relative to their pre-adoption average (0.583 / 8.277 = 0.070). Similarly, they purchase –48.348g less alcohol ($p = .027$), a 6.6% reduction (48.348 / 735.471 = 0.066). Thus, while heavy alcohol buyers remain similarly likely to buy alcohol, they lower their purchase amounts when doing so, resulting in lower overall alcohol purchases.

Table 6 also highlights a difference in how alcohol purchases increase among light versus moderate alcohol buyers. Light buyers purchase alcohol in 11.8% of pre-adoption periods, but this increases by +4.8 percentage points after adoption ($p < .0001$). Among moderate buyers who purchase alcohol in 44.0% of pre-adoption periods, the increase is only +1.9 percentage points ($p = .023$). However, conditional on incidence, the increase in purchase quantities appears larger among moderate than light buyers: alcoholic volume increased by +0.171L ($p = .347$) among light buyers but by +0.544L ($p < .0001$) among moderate buyers. These additional results suggest that while adoption increases alcohol purchases in both groups, light buyers appear more likely to increase purchase frequency than moderate buyers. This finding is consistent with the notion that adoption increases consideration of alcoholic products, especially when baseline consideration is lower.

Soft drinks

Although alcohol-free variants are typically marketed as part of their respective alcohol categories, one may wonder about potential effects on outside goods such as soft drinks. We therefore re-estimate our 2SDID model using total volume sales (in liters) for soft drinks as the dependent variable. Table 7 indicates there are no significant changes in soft drink sales among light (+0.123L, $p = .246$), moderate (+0.244L, $p = .222$), or heavy alcohol buyers (–0.234L, $p = .504$).

Table 7. DID estimates on the impact of the adoption of alcohol-free products on soft drinks

	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers
Soft Drink Volume Sales (liters)	.123 (.246) $p = .616$	.244 (.200) $p = .222$	–.234 (.351) $p = .504$
Pre-Adoption Mean	4.223	5.078	7.405

Notes. Estimates reflect the effect of $After_{it}$. All models include household and month-year fixed effects. Standard errors in parentheses are clustered at the household level. Pre-Adoption Mean is the average among adopters across all pre-adoption months in the sample.

Empirical Evidence on Advertising Alcohol-Free Products and Alcohol Purchases

To understand the effect of alcohol-free ads on alcohol sales, we estimate a market response model that leverages our panel dataset alongside institutional details of national ad buying to mitigate potential endogeneity concerns (Herhausen, Van Heerde, Ludwig and Grewal, 2025; Shapiro et al. 2021). This approach can offer insights less readily obtained from experiments (Korkames, Stanley and Stremersch, in press) and avoids ethical challenges associated with randomly exposing individuals to potentially harmful alcohol-related advertising.

Data and Sample

We obtained weekly brand-level national advertising data from Kantar in France, covering advertising spending for alcohol-free and alcoholic products in the beer category over the six-year period from January 2016 until December 2021. We focus on the beer category because alcohol-free product availability and advertising were most developed in this category during our sample period.[14]

National advertising decisions are made for specific brands at the weekly level for the entire country.[15] Therefore, we conduct our analysis at the brand-week level, which enables us to leverage variation in weekly ad spending across brands to identify the advertising effect of interest. Since Kantar's advertising data captures alcohol-free versus alcoholic advertising per brand on a weekly basis, we aggregate the household purchase data into alcoholic versus alcohol-free sales for each brand per week.[16] To mitigate potential bias from changes in

[14] Note that advertising data are unavailable through our data provider (Aimark). The data are purchased from Kantar Media, which requires a more limited scope than the household scanner data.

[15] To the best of our knowledge, major beer brands tend to rely on national ads, and no data source provides local advertising for the French market. For instance, French television advertising was national between 2015 and 2020 due to regulatory constraints. Although targeted television ads became possible in 2021, operational constraints (e.g., required household equipment upgrades and consumer consent) limited its adoption to less than 15% of households by December 2021 (RTL 2021). Moreover, such targeted advertising primarily benefited regional brands, whereas the beer category is dominated by major national brands (Cross-Kovoor, 2023).

[16] Store-level scanner data are not available through Aimark. Similar to prior advertising work (e.g., Hanssens et al. 2014; van Ewijk, Stubbe, Gijsbrechts, and Dekimpe 2021), we aggregate across households to the brand level. We decided not to analyze the data at the household level due to the sparsity of the data at the household-brand-week level. Instead, we consider heterogeneous effects by aggregating across different types of households.

household composition over time, we use households that remained active in the panel throughout the entire sample period, with active defined as recording at least one purchase every two months in any food or beverage category (N = 5,526).

Our sample includes all major brands with a market share of at least three percent in volume sales (in liters) across the sample period, resulting in the top 12 beer brands. These brands account for 93% of all alcohol-free advertising spending in the category, and 82% of all alcohol advertising. While we cannot disclose brand-level ad spending or category-level spending patterns over time, these brands invested substantially in alcohol-free advertisements, with €189 million spent on alcohol-free ads compared to €717 million on alcohol ads across the sample period. Thus, approximately 21% of total advertising was allocated to alcohol-free products.

Of the 12 brands, 9 offer alcohol-free products during our sample period. These 9 brands invested in both alcohol-free and alcoholic product advertising, with each of these brands allocating at least €586,000 to alcohol-free ads and at least €8.1 million to alcohol ads. Regarding sales, our sample covers 23 thousand liters of alcohol-free beer and 373 thousand liters of alcoholic beer. Each brand recorded a minimum of 4.3 thousand liters of alcoholic beer and 1.2 thousand liters of alcohol-free beer sales.

Regulatory Setting

Regulation in France prohibits alcohol-free ads from promoting alcoholic products (Amazon Ads 2025). Thus, any spillover effects are not due to alcohol-free ads featuring alcoholic products. While alcohol advertising is permitted through most channels (such as radio, outdoor, magazines, and online), it is banned on television and in cinemas. However, observed spillover effects are unlikely to reflect attempts by brands to circumvent these bans via alcohol-free product advertising because there was no alcohol-free beer advertising in cinemas during our sample period. Additionally, 8 of the 9 brands did not use television to advertise their alcohol-free products. While one brand ran a single TV campaign that aired for three consecutive weeks in 2018, this accounts for only 1.6% of the total alcohol-free ad spend in our sample.

Measures

Our primary dependent variable is alcoholic volume sales ($Sales\_Alc_{bt}$), measured as the total volume of alcoholic products (liters) sold by brand *b* in week *t*, summed across all households active throughout our entire sample period (N = 5,526). We also estimate our advertising effects on total volume sales ($Total\_Volume\_Sales_{bt}$), measured as the sum of alcoholic and alcohol-free volume (liters) sold by brand *b* in week *t.* Additionally, we report the effect on alcohol-free volume sales ($Sales\_Alcfree_{bt}$), the total volume of alcohol-free products (liters) sold by brand *b* in week *t*.

Our two primary independent variables are the advertising of alcohol-free and alcoholic products. To measure the long-term sales effects of alcohol-free and alcoholic advertising, we use an advertising stock specification widely used to capture long-term advertising effects parsimoniously (e.g., Guitart and Stremersch 2021; Shapiro et al. 2021). We define advertising stock as follows:

(5) $$Advstock\_Alcfree_{bt} = \lambda \; Advstock\_Alcfree_{bt-1} + Adv\_Acfree_{bt}$$

(6) $$Advstock\_Alc_{bt} = \lambda \; Advstock\_Alc_{bt-1} + Adv\_Alc_{bt}$$

$Adv\_Alcfree_{bt}$ and Adv_Alc_{bt} denote the advertising expenditures (in euros) for alcohol-free and alcoholic products by brand b in week t, respectively. The parameter λ represents the carryover parameter estimated through a grid search. We use the observed value in the first week of our sample to initialize the stock variable (Burmester et al., 2015; Guitart and Stremersch, 2021). We estimate λ through a grid search over the interval [0, 0.99] in increments of 0.01 and select the model with the highest adjusted R^2 (Bayer et al., 2020;

Van Ewijk, Gijsbrechts and Steenkamp 2022).[17] Since advertising carryover may differ between alcohol-free and alcoholic ads, we allow λ to vary, yielding optimal carryover parameters of 0.49 for alcohol-free advertising and 0.73 for alcoholic advertising. The larger carryover for alcoholic products aligns with their maturity in the market and typically lower informational value compared to newer alcohol-free products. Additionally, the relatively large degree of carryover for alcoholic products is consistent with magnitudes in the existing literature (e.g., 0.75 in Burmester et al. 2015; 0.89 and 0.91 in Dinner, van Heerde and Neslin 2014; 0.80 in Guitart and Stremersch 2021; 0.90 in Shapiro et al. 2021).

Model Specification

Basic Model Structure

Our main objective is to measure the effects of alcohol-free and alcoholic advertising on the sales of alcoholic products. To achieve this, we model sales at the brand-week level using a regression model. We then supplement this model with fixed effects and brand-time varying controls. The basic model structure is:

$$(7) \qquad Y_{bt} = \delta_1 \, Advstock\_Alcfree_{bt} + \delta_2 \, Advstock\_Alc_{bt} + \varepsilon_{bt}$$

Y_{bt} is the natural logarithm of the outcome variable for brand b in week t. We consider three outcome variables: alcoholic volume sales, total volume sales, and alcohol-free volume sales. $Advstock\_Alcfree_{bt}$ and $Advstock\_Alc_{bt}$ represent the natural logarithm of advertising stock for alcohol-free (Equation 5) and alcoholic advertising (Equation 6), respectively.[18]

Endogeneity

A potential concern when estimating advertising elasticities using observational data is the endogeneity of advertising decisions. Managers may decide on advertising spending

[17] This grid search was performed using the full model, including all control variables (Equation 8).

[18] To avoid taking the logarithm of zero, we added a small number (.001) to both the outcome and advertising stock variables.

based on anticipated demand, which can introduce bias if unobserved factors influencing demand and advertising are omitted from the model.

To mitigate endogeneity concerns, we follow prior advertising research and use a rich set of fixed effects and control variables, assuming that the residual variation is quasi-random (e.g., Shapiro et al., 2021). Prior empirical research suggests that this approach is adequate due to the institutional details of the national ad-buying process, as brands do not vary week-to-week advertising in response to demand shocks (e.g., Becker, Wiegand and Reinartz 2018). National ads are purchased through negotiations between advertisers and media outlets and are typically secured and scheduled well in advance (Shapiro et al. 2021). This approach is also well-suited for our context, which involves multiple brands and outcome variables, where identifying strong and valid instruments for advertising is typically not feasible (Shapiro et al. 2021). Furthermore, since major national brands rely on national ads in France, targeting is unlikely to drive heterogeneous results across households. We account for six key factors that could confound the relationship between advertising and sales. Below, we detail these sources and the corresponding measures to address them.

First, there may be differences in advertising decisions between brands. For example, larger brands with higher demand might engage in more advertising. To address this, we include brand fixed effects (η_b), which capture time-invariant, brand-specific characteristics that may influence advertising and demand.

Second, advertising spending may be influenced by predictable fluctuations in demand, such as increased advertising expenditures during peak seasonal demand periods like summer. To control for this, we include month-of-year fixed effects (υ_m).

Third, although advertising spending for major brands is unlikely to adjust dynamically in response to demand shocks (Becker et al. 2018; Shapiro et al. 2021), overall category demand and advertising spending could still be influenced by external factors, such as predictable long-term shifts in economic conditions or alcohol purchases (e.g., due to the COVID-19 pandemic after it started or gradually growing alcohol-free adoption rates). We use quarter-year fixed effects to mitigate this concern while ensuring sufficient residual variation (ρ_{qy}).

Fourth, brands may base their advertising decisions on prices. For instance, they may increase advertising during periods with lower prices to maximize the impact on sales. To account for this, we include time-varying price controls at the brand level: $Price\_Alcfree_{bt}$, which represents the average (volume market share-weighted) paid price per equivalent unit across all alcohol-free SKUs for brand *b* in week *t*, and $Price\_Alc_{bt}$, which represents the corresponding paid price for alcoholic SKUs.[19]

Fifth, brands may also base their advertising decisions on competitors' advertising and price. Therefore, we include $Comp\_Advstock\_Alcfree_{bt}$ and $Comp\_Advstock\_Alc_{bt}$, which represent the advertising stock based on total advertising expenditures of all competing brands (i.e., including those with a market share below 1%). The carryover parameters for these variables are again estimated using a grid search, yielding an optimal carryover parameter of 0.31 for competitor alcohol-free ads and 0.53 for competitor alcoholic ads. Additionally, we control for weighted competitor prices through $Comp\_Price\_Alcfree_{bt}$ and $Comp\_Price\_Alc_{bt}$, which are based on all SKUs from all brands in the category. The weights are equal to the percentage of volume sales (in liters) that each competing SKU represents over the entire sample period.

Finally, the introduction of an alcohol-free variant by a brand may have a direct impact on alcohol sales. To account for this, we include a step dummy variable, $Has\_Alcfree_{bt}$, which equals one after the first-time introduction of an alcohol-free variant and zero before. Since 8 of the 9 brands introduced an alcohol-free variant for the first time

[19] The paid price is the price net of any promotions. The French household scanner data do not include information on regular prices. Promotion data (discounts, feature, display) and store-level data were not available through Aimark.

during our sample period, this dummy variable captures the baseline shift in alcohol sales associated with its introduction. Note that this implies that we estimate the effects of the alcohol-free advertising and price variables in interaction with this dummy (i.e., $Alv\_Alcfree_{bt} \times Has\_Alcfree_{bt}$ and $Price\_Alcfree_{bt} \times Has\_Alcfree_{bt}$).

Final Model and Estimation

In summary, we estimate the following model:

$$(8)\ Y_{bt} = \delta_1\, Advstock\_Alcfree_{bt} \times Has\_Alcfree_{bt} + \delta_2\, Advstock\_Alc_{bt} + \delta_3\, Price\_Alcfree_{bt} \times Has\_Alcfree_{bt} + \delta_4\, Price\_Alc_{bt} + \delta_5\, Comp\_Advstock\_Alcfree_{bt} + \delta_6\, Comp\_Advstock\_Alc_{bt} + \delta_7\, Comp\_Price\_Alcfree_{bt} + \delta_8\, Comp\_Price\_Alc_{bt} + \delta_9\, Has\_Alcfree_{bt} + \eta_b + \upsilon_m + \rho_{qy} + \varepsilon_{bt}\ ,$$

where Y_{bt} and the own and competitor advertising and pricing variables are log-transformed. As a result, δ_1 and δ_2 approximate the elasticities of alcohol-free and alcoholic advertising stock on the outcome variables. These estimates measure the total percentage change in current and future alcohol-free and alcohol sales resulting from a one-percent increase in current alcohol-free and alcohol advertising.

The variables $Advstock\_Alcfree_{bt}$ and $Price\_Alcfree_{bt}$ are mean-centered based on their post-introduction values so that the coefficient of $Has\_Alcfree_{bt}$ (δ_9) captures the effect of introduction at average levels of post-entry alcohol-free advertising and price. Standard errors are clustered at the brand level.

Equation 8 is estimated on a dataset containing 3,744 observations (12 brands × 312 weeks = 3,744). Table 8 presents the summary statistics for the variables included in our analysis across all observations.[20] Table 9 reports the correlations (all below 0.4), suggesting that multicollinearity is not a major concern.

[20] Alcohol-free products are commonly priced similarly or higher than their alcoholic counterparts. This pricing can, in part, be attributed to the additional production processes and costs involved in brewing alcohol-free beer, such as the de-alcoholization process and the use of additional ingredients to achieve the desired taste and aroma (LowBeers, 2023).

Table 8. Descriptive statistics

Variable	M	SD	Min	Max
Sales_Alc$_{bt}$ (liters)	99.953	102.120	2.330	744.597
Total_Volume_Sales$_{bt}$ (liters)	102.459	104.780	5.450	753.597
Sales_Alcfree$_{bt}$ (liters)[a]	2.506	5.371	.000	46.000
Adv_Alcfree$_{bt}$ (euros)[a]	15,326.650	112,491.200	.000	1,819,456.000
Adv_Alc$_{bt}$ (euros)	151,988.900	365,966.300	.000	4,350,235.000
Price_Alcfree$_{bt}$ (euros/liter)[a]	2.604	.406	1.532	4.212
Price_Alc$_{bt}$ (euros/liter)	2.473	.464	1.471	3.689
Comp_Adv_Alcfree$_{bt}$ (euros)	121,214.700	187,542.600	.000	2,098,570.000
Comp_Adv_Alc$_{bt}$ (euros)	1,326,774.000	1,405,343.000	.000	11,633,050.000
Comp_Price_Alcfree$_{bt}$ (euros/liter)	2.431	.419	1.421	4.755
Comp_Price_Alc$_{bt}$ (euros/liter)	2.366	.477	1.378	4.112
Has_Alcfree$_{bt}$ (0/1)	.296	.441	.000	1.000

[a] Because not all brands offer alcohol-free products in all weeks, these descriptives are calculated across weeks when alcohol-free products are available to households (N = 1,114).

Table 9. Correlations

	1	2	3	4	5	6	7	8
1. Adv_Alcfree$_{bt}$								
2. Adv_Alc$_{bt}$	.358							
3. Price_Alcfree$_{bt}$	.003	−.064						
4. Price_Alc$_{bt}$	.048	−.083	.338					
5. Comp_Adv_Alcfree$_{bt}$	.392	.102	−.023	−.002				
6. Comp_Adv_Alc$_{bt}$	.260	.094	−.021	.000	.378			
7. Comp_Price_Alcfree$_{bt}$	−.053	−.007	.103	.012	−.020	−.036		
8. Comp_Price_Alc$_{bt}$	−.074	.055	−.129	−.291	.022	.051	.197	
9. Has_Alcfree$_{bt}$	.006	.183	.000	−.168	.024	.020	.083	.183

Model Results

Average effects on alcoholic and total volume sales

Table 10 reports the effects of alcohol-free and alcoholic advertising on alcoholic volume sales (Column A) and total volume sales (Column B) on an aggregate level. Because both sales and advertising variables are log-transformed, the estimates approximate elasticities. The elasticity of alcohol-free ads on alcohol sales is positive. Specifically, a 1% increase in alcohol-free advertising stock is associated with a 0.010% increase in alcohol sales ($p <$ .001). Consequently, doubling alcohol-free advertising corresponds to an estimated 1% increase in alcohol sales. This finding suggests that, on average, alcohol-free advertising has a positive but relatively small impact on alcohol sales. We also observe a positive effect on total volume sales with an elasticity of 0.012 ($p < .001$).

As expected, alcoholic advertising also has a positive effect on alcohol sales. A 1% increase in alcoholic advertising stock is associated with a 0.079% increase in alcoholic total volume sales ($p < .001$). This direct effect of alcohol advertising is notably larger in magnitude than the spillover effect of alcohol-free advertising on alcohol sales, suggesting that alcoholic advertising plays a substantively more important role in boosting alcohol sales than alcohol-free advertising. The effect on total volume sales is also positive, with an elasticity of 0.086 ($p < .001$).

While the effect sizes of the price controls should be interpreted with caution due to potential price endogeneity, lower own alcohol prices increase alcohol sales (–2.688, $p < .001$). Lower alcohol-free prices are also associated with decreased alcohol sales (.462, $p < .001$). None of the competitors' pricing or advertising variables show statistically significant associations with the outcome variables at the 5% level. Consistent with our adoption analysis, on an aggregate level, introducing an alcohol-free variant has no impact on alcoholic volume sales (.032, $p = .397$) but is associated with increased total volume sales of about 10% (.096, $p < .011$; exp(0.096)-1 = 0.101).

Table 10. Estimates on the impact of alcohol-free advertising on alcoholic and total volume sales (Eq.8) (*all households*)

	A: Alcoholic Volume Sales (liters)	B: Total Volume Sales (liters)
Focal advertising variables		
$Adv\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.010 (.003)	.012 (.003)
	$p < .001$	$p < .001$
Adv_alc_{bt}	.079 (.008)	.086 (.009)
	$p < .001$	$p < .001$
Control variables		
$Price\_alc_{bt}$	–2.688 (.158)	–2.680 (.157)
	$p < .001$	$p < .001$
$Price\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.462 (.10)	.390 (.097)
	$p < .001$	$p < .001$
$Comp\_Adv\_alcfree_{bt}$	.010 (.005)	.009 (.005)
	$p = .058$	$p = .090$
$Comp\_Adv\_alc_{bt}$	.045 (.071)	.046 (.070)
	$p = .522$	$p = .509$
$Comp\_Price\_alcfree_{bt}$	.119 (.319)	.120 (.317)
	$p = .710$	$p = .705$
$Comp\_Price\_alc_{bt}$	.388 (.255)	.390 (.253)
	$p = .128$	$p = .123$
$Has\_Alcfree_{bt}$	.032 (.038)	.096 (.037)
	$p = .397$	$p = .011$
Brand FE	Yes	Yes
Month-of-year FE	Yes	Yes
Quarter-year FE	Yes	Yes
Adj. R^2	.813	.818

Notes. The table reports estimates from Eq.8 (N = 3,744) and clustered standard errors at the brand level between parentheses.

Heterogeneity between heavy and light alcohol buyers

To explore the role of prior alcohol purchases, we re-estimate our model (Eq. 8) but now separately for light, moderate, and heavy alcohol buyers. To preclude reverse causality concerns, we categorize households based on their total alcoholic volume sales (in liters) during an initialization period of the calendar year immediately prior to the start of our sample (i.e., 2015).[21] Like our adoption analysis, we categorized light alcohol buyers as those

[21] Although alcohol purchase behavior may change over time, group membership remains largely stable at the household level. Among the 1,213 heavy alcohol buyers in 2015, 91% remained heavy alcohol buyers in 2021, with similarly high persistence among light (83%) and moderate (89%) buyers. Furthermore, our earlier analysis showed that adoption of alcohol-free products does not lead to light (heavy) buyers becoming heavy (light) buyers. As a robustness check, we re-estimated our model after classifying households based on their alcohol purchases across the entire period (2016-2021), yielding similar results (see Robustness Checks).

who purchased below the 25th percentile (< 0.41 liter). Moderate alcohol buyers fall between the 25th and 75th percentiles (≥ .41 liter and ≤ 5.01 liters), and heavy alcohol buyers exceed the 75th percentile (> 5.01 liters). Similar to our aggregate analysis, we estimate all models using observations from January 2016 until December 2021.

Table 11 presents the estimation results for Equation 8. Column A shows the results using *alcoholic* volume sales as the dependent variable, separately for light, moderate, and heavy buyers. Column B shows the results for *total* volume sales (i.e., the sum of alcoholic and alcohol-free). Four key insights emerge:

First, the spillover elasticity of alcohol-free ads on alcohol sales is positive for light alcohol buyers (.018, $p < .001$) but negative for heavy buyers (–.025, $p < .001$). For moderate buyers, the effect is also positive but notably smaller (.004, $p = .066$). This result implies that a 1% increase in a brand's alcohol-free ads is associated with a .018% increase in alcohol sales among light buyers but a .029% decrease among heavy buyers. Doubling alcohol-free advertising corresponds to an estimated 1.8% increase in alcohol sales among light buyers and a 2.5% decrease for heavy buyers. Thus, consistent with the adoption analysis, this indicates that exposure to alcohol-free product information is linked to higher alcohol sales among light buyers but lower alcohol sales among heavy buyers.

Second, Table 11 (column A) reports the direct effects of alcohol ads on alcohol sales. The estimated elasticities are positive across all groups, with a larger effect observed among light buyers (.100, $p < .001$) than among heavy buyers (.051, $p < .001$). This difference likely reflects higher baseline awareness and potential diminishing returns of advertising among heavy alcohol buyers. More importantly, the spillover effects of alcohol-free advertising are again substantively smaller in magnitude than the direct effects of alcohol advertising in all groups. This result suggests that in a context where alcohol ads are allowed, alcohol advertising appears to be a more important policy concern than alcohol-free advertising.

Third, column B (Table 11) reports the effects on total volume sales, capturing how brand advertising influences overall demand for the brand across alcoholic and alcohol-free products. We observe a positive effect among light buyers (.019, p <.001) but no effect among heavy alcohol buyers (–.002, p = .491). This finding is consistent with the adoption analysis, indicating that information about alcohol-free products generates positive spillovers among light buyers. In contrast, among heavy buyers, it encourages substitution from alcoholic to alcohol-free products without affecting overall brand-level demand.

Fourth, own alcohol prices emerge as a key determinant of alcohol demand in all buyer groups. Lower alcohol-free prices are especially associated with lower alcohol sales among heavy alcohol buyers (.389, p = .005). Competitor pricing and advertising again have limited impact (e.g., 9 out of the 12 of the competitor estimates have a p-value above .05). Consistent with the adoption and advertising findings, the introduction of an alcohol-free variant by a brand is associated with large relative increases in sales of their alcoholic variant among light buyers (.996, p < .001), and smaller relative decreases alcohol sales among heavy alcohol buyers (–.202, p < .001).

Table 11. Estimates on the impact of alcohol-free advertising on alcoholic and total volume sales (Eq.8) (*heterogeneity between heavy and light alcohol buyers)*

	A: Alcoholic Volume Sales (liters)			B: Total Volume Sales (liters)		
	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers
Focal advertising variables						
$Adv\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.018 (.004)	.004 (.002)	–.025 (.007)	.019 (.004)	.004 (.002)	–.002 (.005)
	$p < .001$	$p = .066$	$p < .001$	$p < .001$	$p = .057$	$p = .491$
Adv_alc_{bt}	.100 (.011)	.119 (.045)	.051 (.008)	.098 (.011)	.108 (.035)	.049 (.008)
	$p < .001$	$p = .008$	$p < .001$	$p < .001$	$p = .002$	$p < .001$
Control variables						
$Price\_alc_{bt}$	–2.292 (.199)	–2.820 (.518)	–2.642 (.172)	–2.264 (.193)	–2.311 (.414)	–2.475 (.139)
	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$
$Price\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.382 (.271)	.733 (.616)	.389 (.140)	.561 (.248)	.552 (.479)	.343(.120)
	$p = .158$	$p = .234$	$p = .005$	$p = .024$	$p = .250$	$p = .004$
$Comp\_Adv\_alcfree_{bt}$	–.005 (.005)	–.001 (.004)	.006 (.003)	.005 (.005)	.001 (.003)	.002 (.002)
	$p = .332$	$p = .955$	$p = .034$	$p = .331$	$p = .967$	$p = .387$
$Comp\_Adv\_alc_{bt}$	–.041 (.008)	–.034 (.020)	–.045 (.044)	–.040 (.008)	–.026 (.017)	–.056 (.040)
	$p < .001$	$p = .093$	$p = .304$	$p < .001$	$p = .121$	$p = .153$
$Comp\_Price\_alcfree_{bt}$	.195 (.013)	.139 (.375)	.158 (.238)	.178 (.012)	.176 (.305)	.151 (.208)
	$p < .001$	$p = .711$	$p = .507$	$p < .001$	$p = .565$	$p = .468$
$Comp\_Price\_alc_{bt}$	.324 (.020)	.469 (.507)	.375 (.380)	.321 (.020)	.431 (.422)	.250 (.161)
	$p < .001$	$p = .355$	$p = .323$	$p < .001$	$p = .307$	$p = .121$
$Has\_Alcfree_{bt}$	.996 (.041)	–.053 (.098)	–.202 (.051)	1.123 (.038)	.019 (.084)	–.104 (.042)
	$p < .001$	$p = .591$	$p < .001$	$p < .001$	$p = .820$	$p = .013$
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.664	.622	.558	.683	.653	.616

Notes. Table reports estimates from Eq.8 (N = 3,744) and clustered standard errors at the brand level between parentheses.

Effects on alcohol-free volume sales

Table 12 presents results from estimating Eq.8 using alcohol-free volume sales as the dependent variable for all buyers and the three groups separately. Note that these estimates are based on a subset of the sample in which a given brand had an alcohol-free product available (N = 1,114) and should be interpreted cautiously. The results indicate that alcohol-free ads have a positive effect on alcohol-free purchases across all buyer groups: light (.350, $p = .007$), moderate (.032, $p = .027$), and heavy buyers (.152, $p = .001$). Furthermore, the magnitude of this 'intended' effect is larger than the 'unintended' spillover effects on alcohol sales (Table 12).

Table 12. Estimates on the impact of alcohol-free advertising on alcohol-free volume sales

	All Buyers	Light Alcohol	Moderate Alcohol	Heavy Alcohol
Focal advertising variables				
$Adv\_alcfree_{bt}$	.081 (.013)	.350 (.100)	.032 (.014)	.152 (.047)
	$p < .001$	$p = .007$	$p = .027$	$p = .001$
Adv_alc_{bt}	.025 (.005)	.083 (.044)	–.028 (.149)	.078 (.018)
	$p < .001$	$p = .092$	$p = .851$	$p < .001$
Control variables				
$Price\_alc_{bt}$	1.187 (.204)	1.215 (.734)	1.438 (.418)	.697 (.515)
	$p < .001$	$p = .098$	$p = .001$	$p = .176$
$Price\_alcfree_{bt}$	–1.369 (.553)	–1.615 (.579)	–1.992 (.519)	–1.125 (.026)
	$p = .013$	$p < .001$	$p < .001$	$p < .001$
$Comp\_Adv\_alcfree_{bt}$	–.220 (.144)	–.052 (.009)	–.006 (.003)	–.005 (.003)
	$p = .128$	$p < .001$	$p = .057$	$p = .070$
$Comp\_Adv\_alc_{bt}$	–.017 (.029)	–.061 (.055)	–.026 (.364)	.018 (.025)
	$p = .551$	$p = .302$	$p = .943$	$p = .475$
$Comp\_Price\_alcfree_{bt}$	.867 (.476)	.405 (.173)	.296 (.122)	.410 (.245)
	$p = .067$	$p = .044$	$p = .015$	$p = 094$
$Comp\_Price\_alc_{bt}$	.275 (.662)	.379 (.570)	.293 (.777)	–.120 (.191)
	$p = .678$	$p = .971$	$p = .706$	$p = .530$
Brand FE	Yes	Yes	Yes	Yes
Month-of-year FE	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes
Adj. R^2	.862	.868	.765	.762

Notes. The table reports estimates from Eq.8 (N = 1,114) and clustered standard errors at the brand level between parentheses.

Robustness Checks

To assess the robustness of our findings, we conducted two additional analyses. First, to preclude reverse causality concerns, our main analysis classified households into light vs. heavy buyers based on an initialization period (2015). As a robustness check, we re-estimate our model by classifying households based on averages across the entire sample period used for estimation (2016 – 2021). The effect sizes and significance levels remain consistent with our main findings (see Web Appendix C, Tables WC1, WC2 and WC3). Second, we examine whether competing brands may affect our advertising spillover effect by introducing an alcohol-free variant. Specifically, alcohol brands may adjust their advertising when they anticipate a competitor launch. Our main model already includes quarter-year fixed effects, which captures quarterly differences in availability across time. However, we also reestimate our model by including the number of competitor brands offering an alcohol-free variant as a control variable. This variable is not statistically significant in any of our estimated models, and the direction and magnitude of our main estimates remain comparable (see Web Appendix C, Tables WC4, WC5, and WC6).

Discussion

Households increasingly adopt alcohol-free products, and alcohol brands have invested heavily in advertising them. These trends have led to an ongoing debate among policymakers and industry stakeholders regarding the potential implications for alcohol sales. Our study addresses this issue by using seven years of scanner data to describe how the adoption and advertising of alcohol-free products are related to alcohol sales. Additionally, we investigate heterogeneity between light and heavy alcohol buyers. Our findings contribute to the existing literature on adopting healthier variants and the advertising spillover literature by highlighting the importance of accounting for household heterogeneity and offering new insights for policymakers on the effects of alcohol-free product information on alcohol purchases.

Theoretical Implications

First, previous adoption research has found that adopting healthier alternatives can increase demand for their unhealthier counterparts (Cleeren et al. 2016). Our study provides additional nuance to this effect by outlining the moderating role of household prior purchasing behavior, specifically whether households were heavy or light buyers of the unhealthier variant before adoption. While we observe a positive effect on demand for the unhealthier product for light and moderate buyers, the effect turns negative among the most vulnerable group, heavy buyers of the unhealthy variant. For this group, adoption of the healthier alternative is associated with a *decrease* in demand for the unhealthier version. This suggests that positive spillovers are less likely among households that already frequently purchase the unhealthier product, as they are likely already highly aware and inclined to consider the unhealthier variant. Instead, heavy buyers appear to purchase the healthier variant as a substitute for certain occasions, resulting in partial substitution.

Second, prior research on advertising spillovers has shown that advertising one product can affect demand for other non-advertised products from the same brand both positively and negatively (Balachander and Ghose 2003; Erdem and Sun 2002; Shapiro et al. 2021; Sullivan 1990). These studies have examined advertising spillover effects at the aggregate level across households. Our research identifies prior purchasing behavior as a household-level factor impacting the magnitude and direction of advertising spillovers. Specifically, we find that spillover effects vary depending on whether households are light or heavy buyers of the non-advertised product. Among light buyers, our results are consistent with associative network theory, suggesting that advertising increases the salience of the brand, which in turn spills over to non-advertised products by the same brand. In contrast, for heavy buyers where baseline salience is already high, our results are consistent with these households perceiving more substitution opportunities, leading to a negative advertising spillover effect. This indicates that spillover effects of the same advertisement can be positive and negative**,** depending on prior purchase behavior.

Implications for Marketing Stakeholders

For policymakers, our findings offer novel and timely evidence to inform the ongoing debate about regulating the marketing of alcohol-free beverages. While the industry proposes that alcohol-free beverages are potential harm-reduction tools, public health experts have raised concerns about unintended spillover effects (Miller, Pettigrew, and Wright, 2021). In particular, there are growing concerns about whether advertising alcohol-free variants may inadvertently reinforce the salience of alcohol brands and, in turn, their alcoholic products (The Irish Times 2023; The Sunday Times 2023). As a result, regulators face growing pressure to implement stricter legislative measures on alcohol-free product advertising. In Norway, for example, advertising alcohol-free beer is banned if the brand also sells alcoholic beer (SHAAP 2024). In the UK, some local authorities, such as Sheffield, have begun implementing similar bans on advertising of alcohol-free products on their billboards (Beeson 2024). Several other countries are considering similar measures. In March 2025, Alcohol Action Ireland (AAI) launched a campaign titled *"Time to Close the L0.0phole, Minister,"* calling for marketing restrictions on alcohol-free products (Bowers 2025). Likewise, India is considering prohibiting ads for products viewed as brand extensions that share characteristics of alcohol brands (Kalra 2024).

In this context, our research provides novel real-world empirical evidence on how the adoption and advertising of alcohol-free products relate to alcohol purchases. Notably, we find that heavy alcohol buyers tend to purchase alcohol-free variants as partial substitutes for alcoholic products, and that alcohol-free advertising reduces alcohol purchases in this group. As a result, banning alcohol-free ads may be suboptimal, as information about alcohol-free products may serve as an effective tool to reduce alcohol purchases. Furthermore, policymakers face challenges in implementing informational interventions encouraging alcohol-free product adoption due to concerns that such efforts may backfire. Our study offers novel evidence supporting the potential value of a targeted trial in which heavy drinkers are incentivized to consider alcohol-free alternatives. This may be a particularly useful complementary policy tool because interventions like "sin taxes" have been found to be less effective among heavy (vs. light) buyers due to stronger underlying preferences (e.g., sugary drink taxes; Dubois, Griffith and Connell 2020).

Despite these potential benefits, caution is warranted when providing information about alcohol-free variants to lighter buyers. In this group, alcohol-free products appear to complement, rather than substitute, alcoholic beverages, with evidence of a positive spillover effect wherein total alcohol purchases increase. Accordingly, alcohol-free ads are not only related to higher sales of alcohol-free products in this group but also to higher alcohol sales. This pattern suggests that alcohol-free ads may enhance brand salience among those with initially lower levels of brand salience, spilling over to the alcoholic counterpart. This finding aligns with the concern that alcohol-free advertising by alcohol brands may have an undesirable effect (e.g., Critchlow, Moodie, and Houghton, 2023). Still, our evidence suggests it does not emerge among the most vulnerable group of heavy alcohol buyers. Furthermore, the magnitude of the undesirable effect is relatively small and, in absolute terms, smaller than the reduction in alcohol sales observed among heavy buyers. Nonetheless, policymakers should consider targeting their interventions to heavy alcohol buyers rather than to light alcohol buyers.

From a managerial standpoint, our results imply that alcohol brands stand to gain from marketing alcohol-free products due to increased sales on an aggregate level. Our findings suggest that alcohol brands can leverage their advertising to shift purchases from alcoholic variants to alcohol-free variants among heavy buyers without any negative impact on primary demand. This presents a win for public health without sales losses for the brand among its most frequent buyers. Responsible alcohol brands should consider that their alcohol-free advertisements may also encourage alcohol sales among lighter buyers, and could consider targeting their ads to heavy users where possible to mitigate the potential harm of these ads.

Conclusion

In the 1970s, policymakers decided to significantly regulate the advertising of tobacco products, starting with Nixon's Public Health Cigarette Smoking Act in 1969. In the following decades, public attitude towards smoking shifted considerably and today cigarettes are largely considered harmful by the majority of the population. Today, similar discussions are in place regarding regulating alcoholic beverages and their advertising, with new questions arising in a context with alcohol-free variants. Our research integrates into this larger debate by providing insights into the nuanced relationship between alcohol-free product marketing and purchase behavior of alcoholic products.

While our findings provide some answers to these questions, more nuanced analysis is needed. For example, field studies with randomized information about alcohol-free products would be worthwhile to implement to further identify the causal effects on alcohol purchase behavior, particularly among heavy users. This would also enable researchers to consider the potential influence of unobserved factors such as internal motivations, which our observational analysis cannot fully rule out. Future studies could also examine how variation in advertising content influences the direction and magnitude of spillover effects among heavy versus light alcohol buyers and how to design alcohol-free ads that do not lead to positive spillovers among lighter alcohol buyers (e.g., through health warnings about alcohol in alcohol-free ads). We hope that our work provides additional motivation to address these issues.

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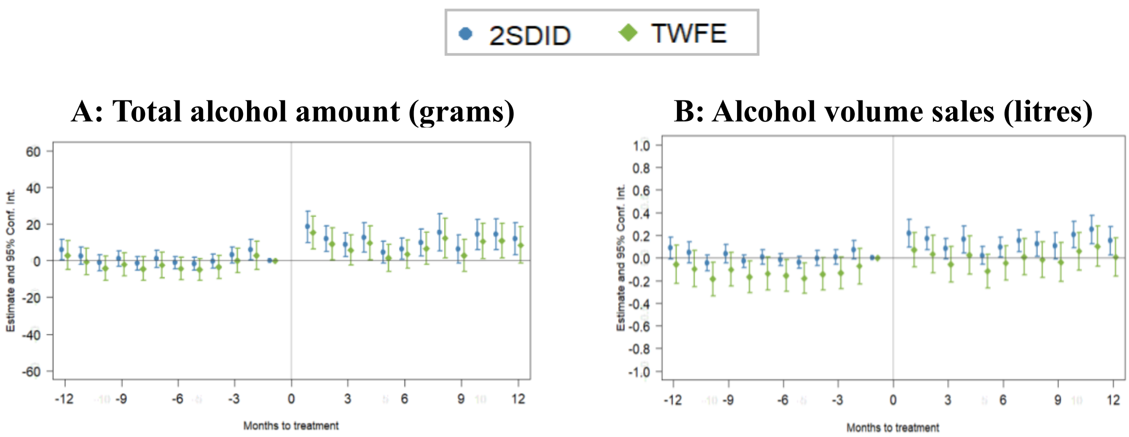
Web Appendix A: Event study plots for light, moderate, and heavy alcohol buyers

We report the event study plots for light (Fig. WA1), moderate (Fig. WA2) and heavy (Fig. WA3) alcohol buyers. None of the figures indicate diverging trends between adopters and non-adopters, supporting the parallel trends assumption within each group. Overall, the 2SDID model tends to yield smaller pre-adoption level differences compared to the TWFE model. For example, in Panel B of Figure WA1, the 2SDID estimates show no notable level differences before adoption, whereas the TWFE show a slight difference. However, the post-pre differences are nonetheless similar across both estimators.

We advise caution in interpreting the significance of the period-specific effects because the subgroup analyses are based on fewer households which do not purchase alcohol every time period, with more limited period-specific variation and larger standard errors. Tables 4 and 5 in the main text show that both the average and cumulative treatment effects are statistically significant across all three outcome metrics for light and moderate alcohol buyers. For heavy alcohol buyers, the effects on total alcohol amount and alcoholic volume sales are significant, whereas the effect on total volume sales is not. The point estimates in Figures WA1, WA2, and WA3 support these findings.

Figure WA1. Event study plots – light alcohol buyers



C: Total volume sales (litres)

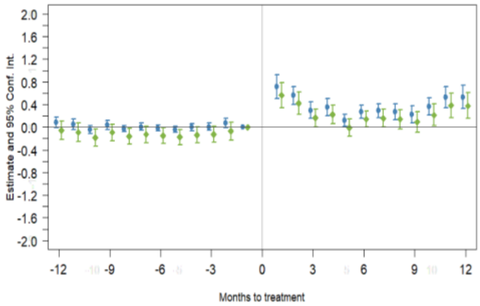
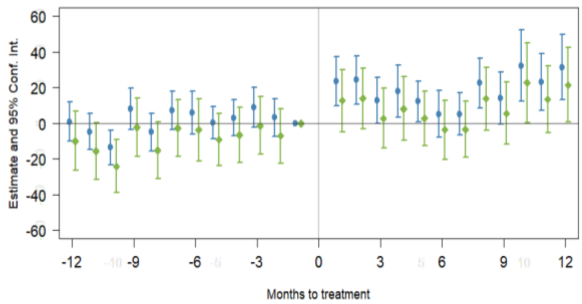
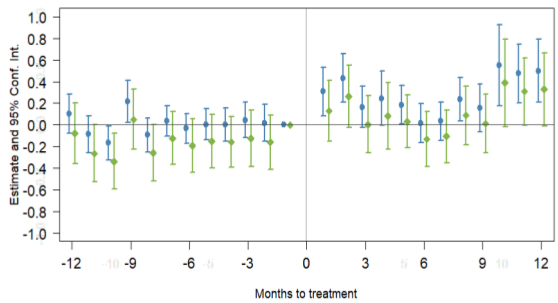


Figure WA2. Event study plots – moderate alcohol buyers

A: Total alcohol amount (grams)



B: Alcohol volume sales (litres)



C: Total volume sales (litres)

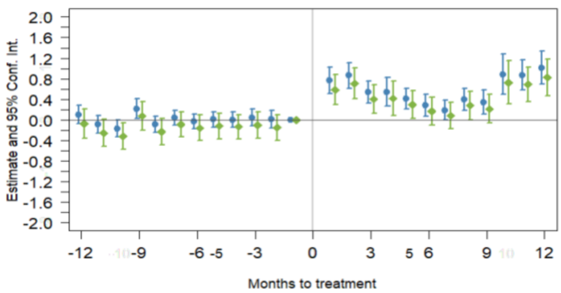
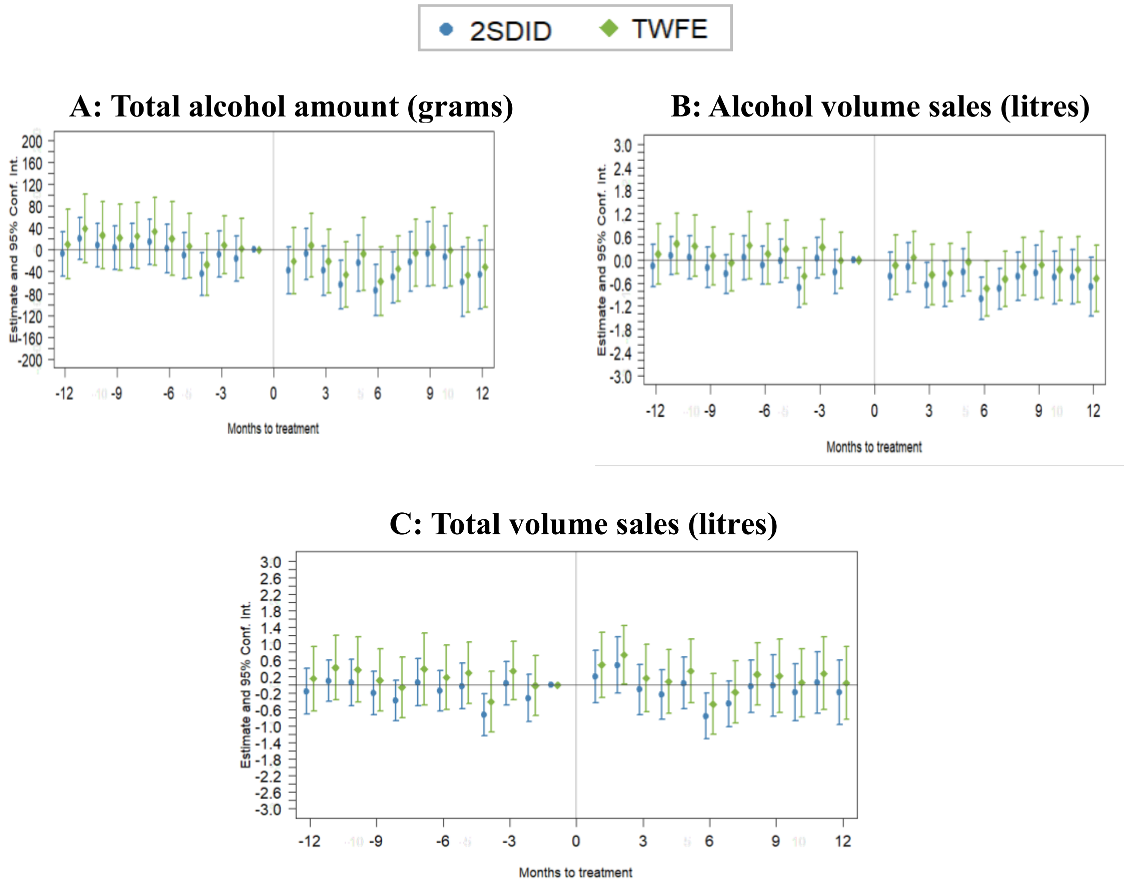


Figure WA3. Event study plots – heavy alcohol buyers



Web Appendix B: Robustnes checks – Adoption analysis

To address potential concerns related to household size, we first rerestimate our models after dividing the outcome variables by the number of adults in each household, and classify households into heavy or light buyers based on alcohol amounts purchased *per adult*. Second, we restrict the sample to single-adult households.

Alcohol demand per adult in households

We leverage survey data containing information on household composition. We select households that responded to the household composition questions at least once during the sample period and for whom household size remained constant in case of multiple survey responses by the same household. This yields a sample of 2,864 households. Most of these households consist of either one adult (N = 1,167) or two adults (N = 1,355), with a smaller number of of households with three (N = 240) or four adults (N = 102). In the survey, adults are defined as individuals aged 16 years or older.

As expected, when defining light versus heavy based on total household demand for alcohol, the correlation between the number of adults in a household and being classified as a light buyer is negative ($\rho = -.20$), while the correlation with being a heavy buyers is positive ($\rho = .16$). These correlations are rather weak, mitigating concerns about household size as a major confounding factor in our main analysis. To further address this concern, we divide the three outcome measures by the number of adults in each household, such that they reflect demand *per adult* rather than per household. We then reclassify housholds into light, moderate, and heavy buyers based on demand per adult. As a result, the correlations between the number of adults and being classified as a light ($\rho = -.03$) or heavy ($\rho = -.04$) buyer become negligible. We subsequently restimate our 2SDID model using the total alcohol amount, alcoholic volume sales, and total volume sales *per adult* as the dependent variables, as well as the revised classifiction of households into the three groups.

Table WB1 presents the results. We again observe positive effects over the first 12 months following adoption on total alcohol amount and alcoholic volume sales among light and moderate alcohol buyers, and negative effects among heavy buyers. Consistent with our main analysis, total volume sales increase among light and moderate buyers, but show no significant change among heavy buyers. As expected, the absolute magnitudes of the estimates in Table WB1 are smaller because they reflect per-adult level changes. However, the underlying averages prior to adoption are also lower once adjusted for household size such that in relative terms the effect sizes remain comparable to those in our main analysis. Specifically, adoption is associated with changes in alcohol amounts purchased of approximately –7% among heavy buyers (vs. –6% in the main analysis), +14% among moderate buyers (vs. +19%), and +97% among light buyers (vs. +80%).

Table WB1. Robustness check – alcohol demand per adult in household

	Total Alcohol Amount (grams)	Alcoholic Volume Sales (liters)	Total Volume Sales (liters)
Light Alcohol Buyers	80.843	.996	2.439
	(10.235)	(.140)	(.193)
	$p < .0001$	$p < .0001$	$p < .0001$
Moderate Alcohol Buyers	90.273	1.179	2.948
	(17.376)	(.264)	(.288)
	$p < .0001$	$p < .0001$	$p < .0001$
Heavy Alcohol Buyers	–290.421	–2.449	.004
	(73.738)	(.932)	(.946)
	$p < .0001$	$p = .009$	$p = .997$
Pre-Adoption Sum			
Light	83.535	1.384	1.384
Moderate	657.138	9.654	9.654
Heavy	4,369.617	49.758	49.758

Notes. Estimates reflect cumulative effects across the first 12 months post-adoption. Pre-adoption sum is the cumulative value on the dependent variable across 12 months immediately before adoption among adopters, averaged across adopters.

Single-adult households

Dividing the outcome variables by the number of adults may still introduce bias if, for example, one of the adults in the households consumers little to no alcohol. To address this concern, we conduct a second robustness check by restricting the sample to households with only one adult. This restriction further reduces the sample size to 1,167 households. Within this subsample, 381 households are adopters, containing 89 adopting light buyers, 203 moderate buyers, and 89 heavy buyers.

Table WB2 reports the results. Despite the small sample sizes, we reassuringly again observe similar results: –10% in alcohol amounts purchased among heavy buyers, +14% among moderate buyers, and +96% among lighters buyers.

Table WB2. Robustness check – single-adult households

	Total Alcohol Amount (grams)	Alcoholic Volume Sales (liters)	Total Volume Sales (liters)
Light Alcohol Buyers	74.160	.986	2.127
	(18.622)	(.278)	(.361)
	p < .0001	*p* = .0004	*p* < .0001
Moderate Alcohol Buyers	93.229	1.221	3.104
	(38.524)	(.566)	(.625)
	p = .016	*p* = .031	*p* < .0001
Heavy Alcohol Buyers	–549.181	–5.295	–1.556
	(148.907)	(2.016)	(2.045)
	p = .0002	*p* = .009	*p* = .447
Pre-Adoption Sum			
Light	77.229	1.191	1.191
Moderate	676.109	10.023	10.023
Heavy	5,115.86	61.226	61.226

Notes. Estimates reflect cumulative effects across the first 12 months post-adoption. Pre-adoption sum is the cumulative value on the dependent variable across 12 months immediately before adoption among adopters, averaged across adopters.

Web Appendix C: Robustness checks – Advertising analysis

Alternative household classification

Tables WC1, WC2 and WC3 report the estimation results when classifying households into light, moderate vs. heavy alcohol buyers based on averages across the entire sample period used for estimation (2016–2021).

Table WC1. Estimates on the impact of alcohol-free advertising on alcoholic and total volume sales (Eq.8) (*all households*, ***using alternative household classification***)

	A: Alcoholic Volume Sales (liters)	B: Total Volume Sales (liters)
Focal advertising variables		
$Adv\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.012 (.003)	.015 (.004)
	p < .001	*p < .001*
Adv_alc_{bt}	.084 (.008)	.080 (.008)
	p < .001	*p < .001*
Control variables		
$Price\_alc_{bt}$	–2.700 (.143)	–2.690 (.140)
	$p < .001$	$p < .001$
$Price\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.480 (.095)	.405 (.092)
	$p < .001$	$p < .001$
$Comp\_Adv\_alcfree_{bt}$	.012 (.005)	.010 (.005)
	$p = .058$	$p = .090$
$Comp\_Adv\_alc_{bt}$	.040 (.065)	.043 (.064)
	$p = .532$	$p = .512$
$Comp\_Price\_alcfree_{bt}$	.130 (.300)	.122 (.298)
	$p = .710$	$p = .705$
$Comp\_Price\_alc_{bt}$	.400 (.230)	.395 (.228)
	$p = .120$	$p = .118$
$Has\_Alcfree_{bt}$	.035 (.038)	.098 (.035)
	$p = .395$	$p = .010$
Brand FE	Yes	Yes
Month-of-year FE	Yes	Yes
Quarter-year FE	Yes	Yes
Adj. R^2	.806	.811

Notes. The table reports estimates from Eq.8 (N = 3,744) and clustered standard errors at the brand level between parentheses.

Table WC2. Estimates on the impact of alcohol-free advertising on alcoholic and total volume sales (Eq.8) (***using alternative household classification)***

	A: Alcoholic Volume Sales (liters)			B: Total Volume Sales (liters)		
	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers
Focal advertising variables						
$Adv\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.020 (.004)	.007 (.002)	–.022 (.007)	.022 (.004)	.007 (.002)	–.001 (0.005)
	$p < .001$	$p = .070$	$p < .001$	$p < .001$	$p = .062$	$p = .497$
Adv_alc_{bt}	.104 (.012)	.116 (.044)	.052 (.009)	.098 (.014)	.095 (.035)	.048 (.009)
	$p < .001$	$p = .009$	$p < .001$	$p < .001$	$p = .003$	$p < .001$
Control variables						
$Price\_alc_{bt}$	–2.100 (.220)	–2.600 (.600)	–2.450 (.190)	–2.050 (.210)	–2.250 (.470)	–2.300 (.160)
	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$
$Price\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.420 (.310)	.650 (.680)	.370 (.160)	.600 (.270)	.500 (.520)	.300 (.140)
	$p = .180$	$p = .250$	$p = .010$	$p = .030$	$p = .300$	$p = .010$
$Comp\_Adv\_alcfree_{bt}$	–.010 (.007)	–.002 (.005)	.008 (.004)	.008 (.006)	.000 (.004)	.003 (.003)
	$p = .200$	$p = .955$	$p = .060$	$p = .250$	$p = .980$	$p = .450$
$Comp\_Adv\_alc_{bt}$	–.050 (.010)	–.030 (.018)	–.060 (.050)	–.045 (.009)	–.020 (.015)	–.060 (.045)
	$p < .001$	$p = .100$	$p = .250$	$p < .001$	$p = .200$	$p = .200$
$Comp\_Price\_alcfree_{bt}$	.160 (.180)	.120 (.400)	.140 (.250)	.150 (.170)	.160 (.350)	.130 (.220)
	$p = .360$	$p = .760$	$p = .580$	$p = .380$	$p = .620$	$p = .550$
$Comp\_Price\_alc_{bt}$	.280 (.030)	.410 (.550)	.350 (.450)	.300 (.025)	.400 (.400)	.240 (.180)
	$p < .001$	$p = .380$	$p = .400$	$p < .001$	$p = .350$	$p = .200$
$Has\_Alcfree_{bt}$	1.000 (.050)	–.050 (.100)	–.200 (.060)	1.100 (.040)	.020 (.090)	–.100 (.045)
	$p < .001$	$p = .590$	$p < .001$	$p < .001$	$p = .820$	$p = .020$
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.656	.618	.551	.680	.644	.605

Notes. Table reports estimates from Eq.8 (N = 3,744) and clustered standard errors at the brand level between parentheses.

Table WC3. Estimates on the impact of alcohol-free advertising on alcohol-free volume sales (***using alternative household classification***)

	All Buyers	Light Alcohol	Moderate Alcohol	Heavy Alcohol
Focal advertising variables				
$Adv\_alcfree_{bt}$	.089 (.014)	.360 (.095)	.038 (.015)	.158 (.049)
	$p < .001$	$p = .007$	$p = .027$	$p = .001$
Adv_alc_{bt}	.028 (.005)	.088 (.043)	–.025 (.152)	.082 (.018)
	$p < .001$	$p = .090$	$p = .850$	$p < .001$
Control variables				
$Price\_alc_{bt}$	1.120 (.230)	1.240 (.780)	1.400 (.430)	.680 (.540)
	$p < .001$	$p = .095$	$p = .002$	$p = .180$
$Price\_alcfree_{bt}$	–1.300 (.600)	–1.580 (.620)	–1.970 (.530)	–1.140 (.032)
	$p = .018$	$p < .001$	$p < .001$	$p < .001$
$Comp\_Adv\_alcfree_{bt}$	–.210 (.155)	–.050 (.010)	–.008 (.004)	–.002 (.004)
	$p = .185$	$p < .001$	$p = .057$	$p = .100$
$Comp\_Adv\_alc_{bt}$	–.020 (.035)	–.060 (.060)	–.030 (.400)	.020 (.030)
	$p = .570$	$p = .302$	$p = .943$	$p = .475$
$Comp\_Price\_alcfree_{bt}$	.800 (.480)	.420 (.180)	.280 (.120)	.380 (.260)
	$p = .095$	$p = .045$	$p = .015$	$p = 094$
$Comp\_Price\_alc_{bt}$	.310 (.720)	.390 (.600)	.310 (.800)	–.115 (.200)
	$p = .670$	$p = .970$	$p = .710$	$p = .530$
Brand FE	Yes	Yes	Yes	Yes
Month-of-year FE	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes
Adj. R^2	.851	.862	.763	.753

Notes. The table reports estimates from Eq.8 (N = 1,114) and clustered standard errors at the brand level between parentheses.

Alcohol-free products by competing brands

Tables WC4, WC5 and WC6 report the estimation results when including the number of competitor brands offering an alcohol-free variant ($Comp\_has\_alcfree_{bt}$).

Table WC4. Estimates on the impact of alcohol-free advertising on alcoholic and total volume sales (Eq.8) (*all households)*

	A: Alcoholic Volume Sales (liters)	B: Total Volume Sales (liters)
Focal advertising variables		
$Adv\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.010 (.004)	.012 (.003)
	p < .001	*p < .001*
Adv_alc_{bt}	.077 (.008)	.081 (.008)
	p < .001	*p < .001*
Control variables		
$Price\_alc_{bt}$	–2.600 (.170)	–2.610 (.168)
	$p < .001$	$p < .001$
$Price\_alcfree_{bt} \times Has\_alcfree_{bt}$	.445 (.110)	.375(.108)
	$p < .001$	$p < .001$
$Comp\_Adv\_alcfree_{bt}$	.008 (.005)	.007 (.005)
	$p = .060$	$p = .095$
$Comp\_Adv\_alc_{bt}$	.050 (.070)	.048 (.069)
	$p = .520$	$p = .505$
$Comp\_Price\_alcfree_{bt}$	.125 (.330)	.118 (.328)
	$p = .708$	$p = .702$
$Comp\_Price\_alc_{bt}$	.375 (.250)	.380 (.248)
	$p = .125$	$p = .122$
$Has\_alcfree_{bt}$	.030 (.040)	.095 (.038)
	$p = .400$	$p = .012$
$Comp\_Has\_alcfree_{bt}$	.030 (.018)	.025 (.015)
	$p = .460$	$p = .520$
Brand FE	Yes	Yes
Month-of-year FE	Yes	Yes
Quarter-year FE	Yes	Yes
Adj. R^2	.801	.798

Notes. The table reports estimates from Eq.8 (N = 3,744) and clustered standard errors at the brand level between parentheses.

Table WC5. Estimates on the impact of alcohol-free advertising on alcoholic and total volume sales (Eq.8)

	A: Alcoholic Volume Sales (liters)			B: Total Volume Sales (liters)		
	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers	Light Alcohol Buyers	Moderate Alcohol Buyers	Heavy Alcohol Buyers
Focal advertising variables						
$Adv\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.020 (.004)	.006 (.002)	–.023 (.007)	.021 (.004)	.006 (.002)	–.002 (0.005)
	$p < .001$	$p = .070$	$p < .001$	$p < .001$	$p = .060$	$p = .495$
Adv_alc_{bt}	.103 (.012)	.115 (.044)	.054 (.009)	.101 (.012)	.112 (.036)	.046 (.009)
	$p < .001$	$p = .009$	$p < .001$	$p < .001$	$p = .003$	$p < .001$
Control variables						
$Price\_alc_{bt}$	–2.100 (.215)	–2.700 (.560)	–2.550 (.170)	–2.120 (.200)	–2.200 (.410)	–2.430 (.145)
	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$	$p < .001$
$Price\_alcfree_{bt} \times Has\_Alcfree_{bt}$	.420 (.290)	.710 (.590)	.330 (.150)	.550 (.245)	.530 (.450)	.320 (.130)
	$p = .160$	$p = .230$	$p = .010$	$p = .030$	$p = .250$	$p = .004$
$Comp\_Adv\_alcfree_{bt}$	–.002 (.007)	.000 (.006)	.010 (.004)	–.003 (.007)	.003 (.004)	.005 (.003)
	$p = .780$	$p = .996$	$p = .060$	$p = .650$	$p = .880$	$p = .350$
$Comp\_Adv\_alc_{bt}$	–.045 (.009)	–.028 (.018)	–.050 (.050)	–.042 (.009)	–.022 (.016)	–.060 (.045)
	$p < .001$	$p = .100$	$p = .300$	$p < .001$	$p = .200$	$p = .153$
$Comp\_Price\_alcfree_{bt}$	.225 (.180)	.135 (.375)	.200 (.250)	.180 (.140)	.120 (.300)	.130 (.200)
	$p = .210$	$p = .720$	$p = .450$	$p = .200$	$p = .650$	$p = .520$
$Comp\_Price\_alc_{bt}$	.310 (.022)	.440 (.500)	.370 (.430)	.360 (.020)	.410 (.420)	.255 (.161)
	$p < .001$	$p = .360$	$p = .380$	$p < .001$	$p = .350$	$p = .121$
$Has\_Alcfree_{bt}$	.950 (.050)	–.040 (.100)	–.220 (.060)	1.100 (.040)	.021 (.080)	–.090 (.040)
	$p < .001$	$p = .700$	$p < .001$	$p < .001$	$p = .800$	$p = .020$
$Comp\_has\_alcfree_{bt}$	.023 (.013)	.018 (.011)	.027 (.014)	.020 (.012)	.015 (.010)	.018 (.016)
	$p = .480$	$p = .520$	$p = .470$	$p = .500$	$p = .550$	$p = .580$
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.660	.615	.549	.680	.650	.568

Notes. Table reports estimates from Eq.8 (N = 3,744) and clustered standard errors at the brand level between parentheses.

Table WC6. Estimates on the impact of alcohol-free advertising on alcohol-free volume sales

	All Buyers	Light Alcohol	Moderate Alcohol	Heavy Alcohol
Focal advertising variables				
$Adv\_alcfree_{bt}$	.072 (.013)	.335 (.090)	.030 (.013)	.145 (.044)
	p < .001	*p* = .007	*p* = .027	*p* = .001
Adv_alc_{bt}	.023 (.005)	.080 (.042)	–.030 (.150)	.072 (.017)
	p < .001	*p* = .092	*p* = .851	*p* < .001
Control variables				
$Price\_alc_{bt}$	1.120 (.225)	1.260 (.760)	1.420 (.440)	.710 (.520)
	p < .001	*p* = .095	*p* = .001	*p* = .176
$Price\_alcfree_{bt}$	–1.340 (.560)	–1.600 (.590)	–1.980 (.530)	–1.130 (.028)
	p = .015	*p* < .001	*p* < .001	*p* < .001
$Comp\_Adv\_alcfree_{bt}$	–.215 (.150)	–.048 (.010)	–.007 (.003)	–.006 (.003)
	p = .150	*p* < .001	*p* = .057	*p* = .070
$Comp\_Adv\_alc_{bt}$	–.015 (.030)	–.060 (.055)	–.025 (.365)	.020 (.024)
	p = .551	*p* = .302	*p* = .943	*p* = .475
$Comp\_Price\_alcfree_{bt}$	.820 (.490)	.395 (.180)	.290 (.125)	.420 (.250)
	p = .083	*p* = .060	*p* = .020	*p* = 094
$Comp\_Price\_alc_{bt}$	.265 (.640)	.370 (.580)	.280 (.790)	–.130 (.195)
	p = .690	*p* = .980	*p* = .720	*p* = .530
$Comp\_has\_alcfree_{bt}$	.030(.016)	.022 (.014)	.015 (.010)	.028 (.018)
	p = .480	*p* = .530	*p* = .620	*p* = .550
Brand FE	Yes	Yes	Yes	Yes
Month-of-year FE	Yes	Yes	Yes	Yes
Quarter-year FE	Yes	Yes	Yes	Yes
Adj. R^2	.860	.853	.761	.752

Notes. The table reports estimates from Eq.8 (N = 1,114) and clustered standard errors at the brand level between parentheses.