Ref. Ares(2023)1950875 - 17/03/2023

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 774548.

EC Framework Programme for Research and Innovation

Horizon 2020
H2020-SFS-2017-2-RIA-774548-STOP:
Science & Technology in childhood Obesity Policy

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Start date of project: 1st June 2018 Duration: 48 months

D5.4: Evaluation of the Long-term Impacts of the Drink Up campaign

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Version: Draft 2

Preparation date: 14/03/2023

Dissemination Level

PU	Public	☒
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

Abbreviation	Definition
PHA	Partnership for a Healthier America
MNI	Natural Marketing Institute
CITS	Controlled Interrupted Time Series
DiD	Difference-in-Difference
FIPS	Federal Information Processing Standard
DMA	Designated Market Areas
UPC	Universal Product Code

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1 Foreword

This report contains initial findings of a study undertaken in the context of the STOP project, aimed at assessing whether the short-term effects of the Drink-Up Campaign, reported in a previous STOP deliverable (Watson et al., 2022), have persisted in subsequent years. The STOP team is still reviewing and revising the methods and the data used in this study. Once the analysis is completed, the manuscript will be revised accordingly and prepared for submission to a suitable peer-review journal.

2 Introduction

Drink Up is a social marketing campaign launched in 2013 by the Partnership for a Healthier America (PHA) and President Obama's Administration to encourage Americans to drink more water. The guiding principle of the campaign was derived from the observation that much of public health campaigns to change food behaviour rely heavily on a methodology that utilizes focus groups as a representation of how and what an audience perceives is actually being communicated to them (Grier and Bryant, 2005). Focus group research aims to understand the conscious expression of how people might be encouraged to change their behaviour, and then generally deploys a loss-framed, as opposed to a gain-framed message to the target audience (O'Keefe and Jensen, 2008). These information campaign have not yet demonstrated strong change in food behaviour, despite sometime a strong awareness of the key messages of the campaign. Does the innovative approach of the drink Up campaign based on the assumption that most of a consumer's decisions are unconscious and motivated by a gain-framed message that positions the benefits of a behaviour and provides information regarding specific, actionable measures that a consumer can take to achieve that gain bring about stronger and more persistent food behaviour changes?

The main evaluation of the Drink Up campaign was on its impact on the exposure, the reach of and awareness to the campaign on television, and online, and to both static text and video of the campaign imagery, on traditional as well as social media. Public Health America completed this evaluation by measuring the impact of the campaign on bottled water purchases. A three percent increase in the purchase of bottled water among the test groups was found, with a four percent increase in the segment with the lowest socioeconomic status, after the first year of the campaign (2013-2014), compared with bottled water purchases in 2012. To the best of our knowledge, no academic evaluation of this campaign exists and only the short term effects on bottled water purchases were evaluated. We aimed to evaluate the long-term impacts of the Drink Up campaign on households' purchase behaviour of bottled water.

We acquire long-term data of households' purchases of bottled water and their demographics from Nielsen - a global market research firm based in the United States. In order to maximize effects, the campaign targeted three household segments who were more likely to receptive to the message of the campaign: the Well Beings, the Fence Sitters, and the Eat, Drink and Be Merrys (see characteristics in **Figure A.1** in **Appendix A**), among which the Fence Sitters were most targeted. These segments were developed by the Natural Marketing Institute (NMI), a Philadelphia-based company and Nielsen partner, which conducted a longitudinal survey of U.S. population attitudes toward health and segmented the population into five segments with underlying demographic characteristics. Since the sample size of each segment is small, our main analysis focuses on households from all segments. However, we also conduct analysis on Fence Sitters considering they were most exposed to the campaign.

We use both the Difference-in-Difference approach (DiD) and Controlled Interrupted Time Series approach (CITS) to causally evaluate the impact of the campaign. DiD is a widely used approach to evaluate causal effects of interventions in the literature due to its ability to control for time-invariant between-group differences and time-varying confounders under the common trend consumption (Wing et al., 2018, Lechner, 2011). While approaches can be used to ensure that trends between groups are as similar as possible, such as using synthetic controls, the assumption that trends are common is not verifiable using this approach; therefore, the estimate could be biased due to the violation of the assumption. In our study, because the Drink Up campaign was deployed at the national level, it is impossible to find clean control groups. As a result, the DiD approach could be susceptible to confounding due to the between-group differences. We, therefore, also apply the CITS approach to capture the causal effects of the campaign. The CITS design is becoming increasingly popular to be used for the evaluation of public health interventions (Bernal et al., 2017, 2018). It allows the common trend assumption to be verified and for differences in trends between groups to be adjusted for. In addition, it can control for contemporaneous events that occur around the intervention. However, the control groups in the CITS approach could introduce time-invariant between-group differences which might lead to biased estimate. Therefore, in order to robustly capture the casual effects of the campaign, both approaches are used in our analysis.

3 Method

3.1 Data source

We use households purchase data obtained from the Nielsen Homescan Consumer Panel from 2007 to 2016, five years before and three years after the launch of the Drink Up campaign. The Consumer Panel Data represents a longitudinal panel of approximately 60,000 U.S. households who continually provide information to Nielsen about their households, products they buy, as well as information of shopping trips and transactions. Nielsen Homescan panelists use in-home scanners or mobile app to record all of their purchases, from any outlet, intended for personal, in-home use.

Panelists in the consumer panel are demographically balanced and geographically dispersed. Demographic variables include household size, income, age, presence and age of children, employment, education, marital status, occupation, type of residence, and race. Geographic information available for each panelist includes their zip code, FIPS state and county codes, DMA code, Scantrack Market code (assigned by Nielsen), and region. Consumer Panel products include all Nielsen-tracked categories of food and non-food items, across all retail outlets in all U.S. markets. The product data are organized into Departments, Product Groups, Product Modules, and UPC Codes. Departments, Product Groups and Product Modules are all Nielsen defined codes, while UPC codes are defined by manufacturers. For each shopping trip, the information includes household, date, retailer code, store code, store zip code, and total dollars spent. Within a trip, detailed transaction information is reported for each product purchased (e.g., UPC code, quantity, price, deals, and coupons).

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3.2 Study 1 – Difference in Differences analysis

3.2.1 Group identification

We first apply a Difference in differences (DiD) approach to analyse impact of the Drink Up campaign. Since the campaign was deployed at the national level, we can only compare households that had different levels of exposure to the campaign.

Los Angeles County was highly exposed to the campaign. Local officials joined the campaign at the very start and were provided with research that helped them understand how members of their communities behaved when it came to drinking water and sweetened beverages, and they also learned how and where to reach these residents. We explore a couple of the control candidates including Philadelphia County, San Diego County, Maricopa County and San Francisco County. It turns out San Diego County is the most suitable control as the others either have small number of households in the Nielsen consumer panel or have a significantly different trend of purchases of bottled water compared to the trend in Los Angeles County.

3.2.2 Sample and variables

We exclude households with extreme monthly purchases of bottled water in both Los Angeles County and San Diego County since they could be measurement errors or reflect purchases for organizations rather than households. The extreme monthly purchases are defined to be above the 95^{th} percentile of monthly purchases of bottled water on average per household from 2007 to 2016 that was equal to 50.15 litre/year for both counties.

Regarding household demographics, we use the same ethnicity groups (White/Caucasian, Black/African American, Asian and Other) and marital status groups (Married, Widowed, Divorced/Separated) as defined in the consumer panel in our analysis. However, due to insufficient number of households in some demographic sub-groups, we aggregate lower-level demographic groups in the consumer panel into higher-level groups regarding the household income, household size, education and age. Specifically, we aggregate thirty-level income groups in the consumer panel into four groups: Low and Low-middle (household income below $30,000); Middle (between $30,000 and $49,999), Middle-high (between $50,000 and $99,999); High (above $100,000). The nine-level household size is aggregate into two groups as follows: small (family members between 1 and 3); Medium-large (4+). The consumer panel has education level of both male and female heads if the household has two heads, we select the higher education between two heads to represent the education level of the household. A six-level education groups are aggregated into three levels: Low (grate school, some high school and graduated high school), High (some college, graduated college), Higher (post college grad). The consumer panel also includes ages for both male and female heads if the household has two heads. The older age is selected to represent the age of the household in this case. We aggregate nine-level age groups into three groups: under 45, 45-64; 65+.

In **Table 1,** we report household demographic and socio-economic characteristics for the county of Los Angeles and the County of San Diego. There are 1071 households on average per year and 10710 households in total over the study period (2007 - 2016) in Los Angeles County compared to average 486 households per year and total 4860 households over the years in San Diego County. The distributions of age, household income, household size, education and marital status are very similar between two counties, while the percentage of white/caucasian households in Los Angeles (75%) is higher than that in San Diego (58%). The samples in two counties both have more married white/caucasian households in the middle-high income quartile and with age between 25-64, high education and smaller family size between 1-3 family members

Table 1: Household descriptive statistics

	Los Angeles	San Diego
Average number of households per year	1071	486
Household income, %		
Low and Lower-middle	16%	16%
Middle	21%	19%
Middle-high	40%	41%
High	23%	24%
Household size		
family members 1-3	80%	83%
family members 4+	20%	17%
Age, %		
Under 45	22%	20%
45-64	52%	52%
65+	26%	28%
Education, %		
Low	10%	10%
High	67%	68%
Higher	23%	22%
Ethnicity, %		
Asian	15%	8%
Black/African American	15%	7%
White/Caucasian	58%	75%
Other	12%	10%
Marital status, %		
Married	54%	58%
Single	25%	20%
Divorced/Separated	15%	15%
Widowed	6%	7%

Our analysis is based on each household's monthly purchases of bottled water. There are totally 204120 monthly observations over the study period. **Figure 1** shows the monthly purchases of bottled water per household over the study period at the county level. In general, the purchases trends are very similar in both pre-campaign and post-campaign periods. Although there are more purchases in Los Angeles than San Diego in the first year after the campaign, it could be a continuity of the previous higher trends over almost two years before the campaign. The trends in two counties return to be similar again after the first year of the campaign, which could imply that the Drink Up campaign does not have significant impact on households' purchases of bottled water in the long term.

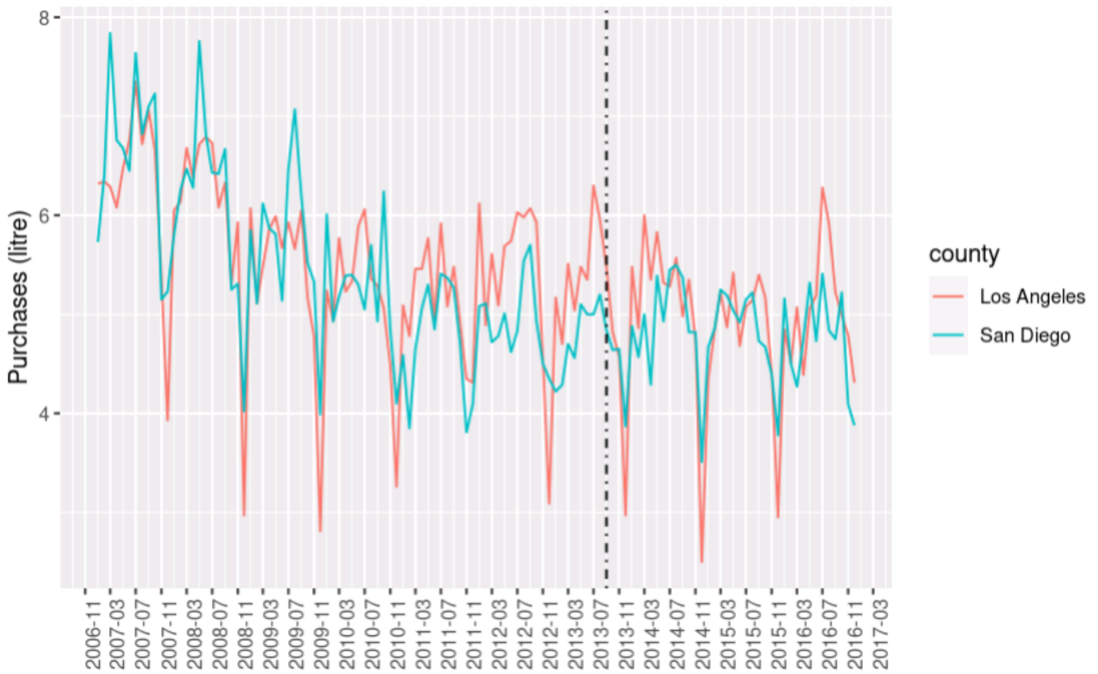

Figure 1 Average monthly purchases of bottled water per household from 2007 to 2016 by county

We explore whether the prices of bottled water drive the departure between the purchase trends in about two years before the campaign. **Figure 2** shows monthly sales weighted average prices of bottled water. It can be seen that the purchasing prices increase in the two-year pre-campaign period in San Diego is much higher than that in the Los Angeles, which would lead to lower purchases in San Diego than Los Angeles. In addition, we also explore whether differences in the number of retailer chains between two counties contributes to the departure between the purchase trends. The number of retail chains is proxied by the number of the retailer chains from which households purchase bottled water. As shown in **Figure 3,** the number of retail chains in Los Angeles increases over about two years before the campaign while it decreases in San Diego.

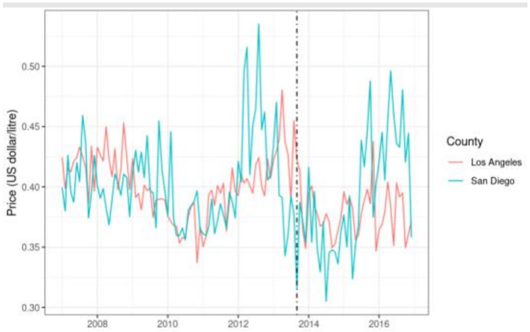

Figure 2 Monthly sales weighted average price

Figure 3 Monthly number of retailers chains

3.2.3 Difference-in-Difference model

In an effort to control for economic conditions and other policies, we apply the DiD model to exploit the causal effect of the Drink Up campaign at the households' purchases of bottled water. Specifically, we estimate the following equation:

$$y_{h,c,t} = \beta_0 + \beta_1\left(Group_{h,c} * \tau\right) + \beta_2 Group_{h,c} \ + \beta_3 t \ + \beta_4 X1_{h,c,t} + \beta_5 X2_{c,t} + \varepsilon_{h,c,t},$$

where $y_{h,c,t}$ indicates the quantity (in litre) of bottled water purchased by household h in county c at year/month t. $Group_{h,c}$ is a dummy variable that is equal to 1 if the household h is from Los Angeles County and zero otherwise. The time dummy τ is equal to one on or after the launch of the Drink Up campaign. $Group_{h,c} * \tau$ is the difference-in difference term. β_1 represents the effect of the campaign at households' purchases of bottled water. t are month-year dummies used to captured seasonality in purchases. The vector $X_{h,c,t}$ are demographic and socio-economic characteristics of household h in county c at month t, including household income, household size, age, education levels, ethnicity and marital status. The vector $X_{c,t}$ include county-level controls including prices of bottled water and numbers of retail chains.

3.2.4 Impact of the Drink Up campaign on a heavily targeted group ("Fence Sitters")

Since households in the segment of Fence Sitters were most exposed to the Drink Up campaign, we use the same method to investigate whether the campaign increased Fence Sitters' purchases of bottled water. In our analysis, Fence Sitters are households with middle-high income and age under 45. There are 256 Fence Sitters on average per year and 2560 in total over the study period in Los Angeles, and there are 106 Fence Sitters on average per year and 1060 in total in San Diego. Therefore, our analysis with Fence Sitters has 43440 monthly observations. As **Figure A.1** in Appendix A shows, the trends of monthly purchases by Fence Sitters in the two counties are both similar to the trends of monthly purchases by all households. As Fence Sitters in the two counties have similar demographic and socio-economic characteristics, we do not control for these characteristics in the analysis. However, the county-level prices of bottled water and numbers of retail chains are still used as controls in the analysis.

3.3 Study 2 – Controlled Interrupted Time Series analysis

3.3.1 Group identification

In addition to the San Diego group identified in study 1, we also use households purchasing juice-based drinks as a control based on the assumption that the Drink Up campaign does not have significant impact on households' purchases of juice-based drinks.

3.3.2 Sample and variables

We use the same sample as study 1 when the control are households in San Diego. When the control are households purchasing juice-based drinks in Los Angeles, we exclude households with extreme monthly purchases of juice-based drinks (above the 95th percentile, 21.41 litre/month). As a result, the sample for juice drinks includes1031 households. The sample for bottled water is the same as study 1, including 1071 households.

The analysis is based on households' monthly purchases of bottled water and/or juice drinks. There are totally 240 observations over the study period. As **Figure 4** shows, the trend of purchases of the juice drinks is very similar to the trend of the purchase of bottled water, suggesting that households purchasing juice-based drinks are a good control.

Figure 4 Average monthly purchases of bottled water and juice drinks per household in Los Angeles County from 2007 to 2016

3.3.3 Controlled Interrupted Time Series model

We also estimate the CITS model using both the San Diego control and Juice Drinks control to investigate the long-term impact of the Drink Up campaign. The CITS model is specified as follows:

$$y_{h,g,t} = \beta_0 + \beta_1 t + \beta_2 \tau + \beta_3 \tau * t + \beta_4 Group_g + \beta_5 Group_g * t + \beta_6 Group_g * \tau + \beta_7 Group_g * \tau * t + \varepsilon_{h,g,t},$$

where $y_{h,g,t}$ indicates the quantity (in litre) of drinks purchased by household h in group g at month t. t is the time since the start of the study. The time dummy τ is equal to one on or after September 2013, when the campaign was launched. $Group_g$ is equal to 1 if the household is from Los Angeles and zero if the household is from San Diego or juice drinks group. $\tau * t$, $Group_g * t$, $Group_g * \tau$ and $Group_g * \tau * t$ are all interaction terms used to capture the effects of the campaign.

β_0 represents the starting point of drinks purchases in controls, β_2 indicates the change in the level of drinks purchases in controls immediately following the launch of the Drink Up campaign, and β_3 represents the change in the slop of drinks purchases in controls after the initiation of the Drink Up campaign. β_4 represents the difference in the level (intercept) of drinks purchases between treatment and controls prior to the Drink Up campaign, β_5 represents the difference in the slope (trend) of drink purchases between treatment and controls prior to the Drink Up campaign. β_4 and β_5 play an important role in establishing whether the treatment and control groups are balanced on both the level and the trajectory of the outcome variable in the preintervention period. β_6

represents the difference between treatment and control groups in the level of drinks purchases immediately following the introduction of the Drink Up campaign compared with preintervention (difference-in-difference of levels), indicating the immediate causal effect of the Drink Up campaign, and β_7 represents the difference between treatment and control groups in the slope (trend) of the drinks purchases after initiation of the Drink Up campaign compared with the preintervention (difference-in-difference of slops), indicating the sustained effects of the Drink Up campaign.

3.3.4 Impact of the Drink Up campaign on a heavily targeted group ("Fence Sitters")

We also only target Fence Sitters to understand the long-term impact of the campaign using the CITS model. **Figure A.3** shows monthly purchases of bottled water and juice drinks on average per households in the segment of Fence Sitters. It can be seen that the trend of purchases of juice drinks is very similar to the trend of purchases of bottled water, suggesting that juice drinks could be a good control in the analysis.

4 Results

4.1 Results from the DiD analysis

Table 2 summarise model estimates with all households and Fence Sitters. The individual characteristics and county-level variables are added in the model step by step. The individual characteristics are not included in the model estimates with Fence Sitters. Both county fixed effects and time fixed effects are controlled for all the estimates. N is the number of the observations. It shows that the variable of interest DiD is not significant in all the cases, suggesting that the Drink Up campaign does not have long-term effects on households' purchases of bottled water. It's consistent with the finding from a descriptive comparison of purchase trends between the two counties.

Table 2 DiD estimates with all households and Fence Sitters

	All households			**Fence Sitters**	
DiD	0.068	0.078	0.028	-0.062	-0.310
	(0.544)	(0.483)	(0.810)	(0.768)	(0.140)
County FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y
Individual characteristics	N	Y	Y	-	-
County-level Covariates	N	N	Y	N	Y
N	204120	204120	204120	43440	43440

p value is reported in parentheses

4.2 Results from the CITS analysis

Table 3 report the impact the campaign on households' purchases of bottled water. The model estimates with all households and Fence Sitters are similar when the control group are households from San Diego. The positive and significant β_3 indicates that households in San Diego significantly increase purchases of bottled water after the campaign. It could be attributed to the campaign and/or other contributing factors associated with San Diego appearing around the launch of the campaign, which would suggest that our identification of the control group is biased. β_4 and β_5 are both significant, which means that there is significant difference in both the level and trend of pre-campaign purchases of bottled water between Los Angeles and San Diego. It is consistent with the plots of the estimated trends shown in **Figure A.4** and **Figure A.5**. The significant difference in the purchases trends between two groups suggested that the San Diego control is not able to control the unobservable time varying contributing factors to the change of purchases of bottled water. Both β_6 and β_7 are insignificant, suggesting households in Los Angeles neither significantly changed the purchases of bottled water immediately after the launch of the campaign nor in the long term after the campaign. However, the evidence could be limited by the significantly different pre-campaign purchases trends between two counties. From **Figure A.4** and **Figure A.5,** it also can be seen that increases in both the level and trend of purchases of bottled water in San Diego is higher than the that in Los Angeles after the launch of the campaign, which is in line with the negative values of β_6 and β_7. Similar findings can be found from estimates with juice drinks control, although pre-campaign purchases trends of bottled water and juice drinks are similar when the sample are all households.

Table 3 CITS estimates with San Diego control and Juice drinks control

	San Diego control		Juice drinks control	
	All Households	Fence Sitters	All Households	Fence Sitters
β_1	-0.03***	-0.46***	-0.0142***	-0.020***
	(0.000)	(0.000)	(0.000)	(0.000)
β_2	0.3933	-0.355	1.7333***	2.275***
	(0.145)	(0.383)	(0.000)	(0.000)
β_3	0.0139**	0.017**	-0.0023	-0.009
	(0.013)	(0.030)	(0.602)	(0.095)
β_4	0.6563***	0.873**	-0.0306	0.108
	(0.004)	(0.014)	(0.743)	(0.571)
β_5	0.0283***	0.046***	0.0062	0.022***
	(0.001)	(0.003)	(0.052)	(0.001)
β_6	-0.4752	-0.576	0.2116	0.188
	(0.175)	(0.254)	(0.491)	(0.642)
β_7	-0.0195	-0.021	0.0026	0.003
	(0.132)	(0.312)	(0.821)	(0.816)
N	240	240	240	240

p value is reported in parentheses; *** p <0.01; ** p <0.05; * p <0.1;

5 Robustness analysis

We also conduct the DiD analysis using yearly data in the same study period because smoother yearly purchases can reduce the potential effects of monthly shocks to the model estimates. In order to achieve compatibility, we use the same sample for both all households and Fence Sitters. The estimates are shown in **Table A.1** in **Appendix A**, suggesting no evidence of significant long-term impact of the campaign.

We also undertake the DiD analysis where we compare the households who were intensively exposed and less intensively exposed to the campaign in Los Angeles County. **Table A.2** shows the results using monthly and yearly data, indicating that the campaign has no significant long-term impact on households' purchases of bottled water.

6 Discussion

We do not find evidence showing the Drink Up campaign increased households' purchases of bottled water in the long run using different samples and models, which is consistent with the findings from literature on the effectiveness of social marketing campaigns on reducing SSBs consumption (Kraak et al., 2022, Truong et al., 2021) showing positive short-term evidence but limited evidence for long-term health outcomes. Lack of evidence that the short-term impacts of the Drink Up campaign shown elsewhere could be sustained in the longer-term suggests that a strong and consistent marketing strategy is required to ensure that similar campaigns have lasting impacts, especially considering that the effects of a campaign can be offset to some extent by the commercial marketing of unhealthy products. However, the analysis has some limitations: 1) as there is no data available measuring the consumption of tap water, we can only use the purchases of bottled water as a proxy for water consumption to quantitatively evaluate the impact of the campaign; 2) the campaign was operated at the national level, which makes it difficult to identify clean control groups for the DiD and CITS analysis, and thus the estimates could be biased. We can only compare purchase patterns between households intensively exposed and those less intensively exposed to the campaign. Future studies should focus on exploring more representative measurements of water consumption and alternative strategies to identify groups that were more exposed and less exposed to the campaign.

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Appendix A

Figure A.1. Summary of priority health and wellness segments.

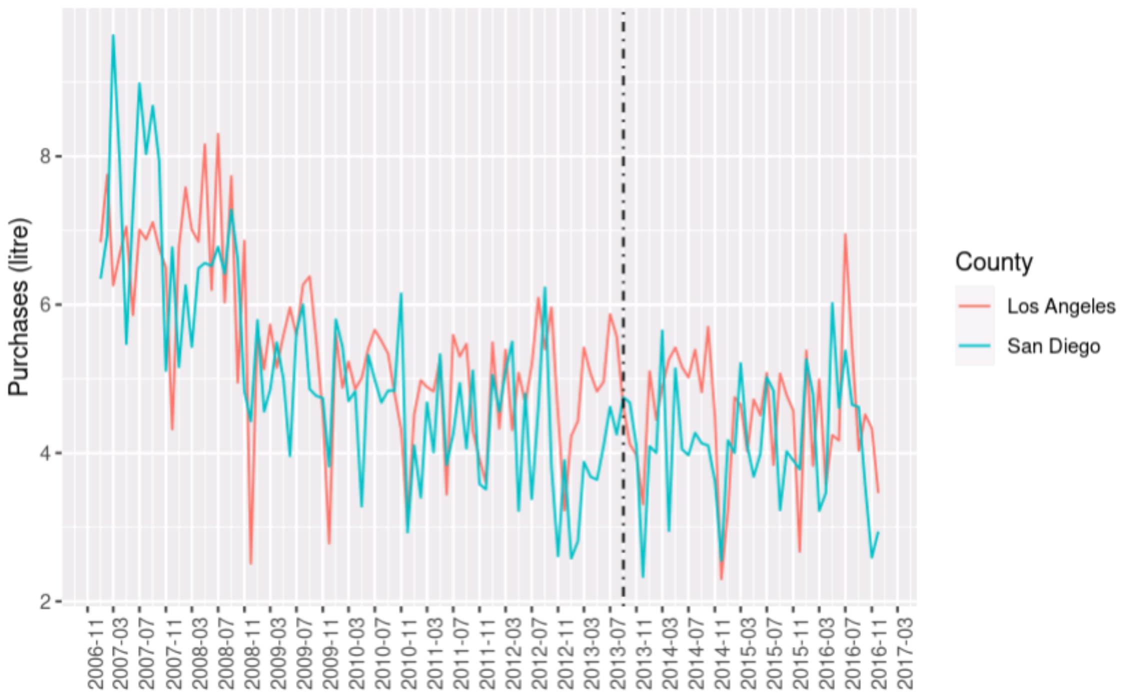

Figure A.2 Average monthly purchases of bottled water per household in Fence Sitters segment from 2007 to 2016 by county

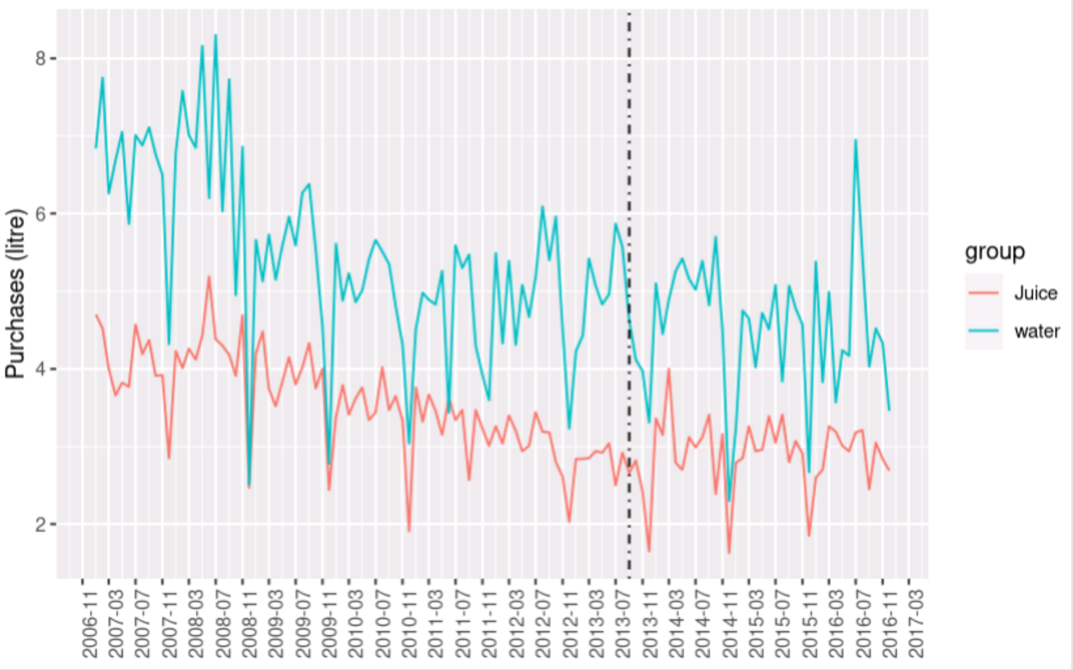

Figure A.3 Average monthly purchases of bottled water and juice drinks per household in Fence Sitters segment from 2007 to 2016 by county

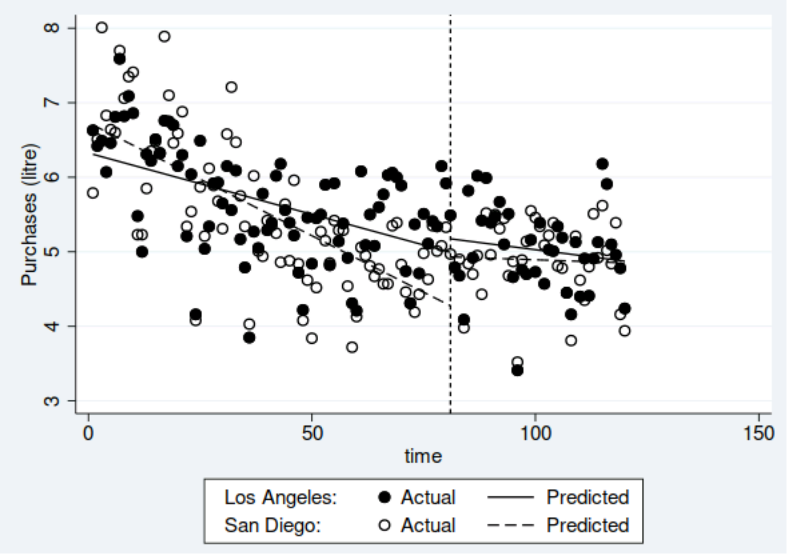

Figure A.4 Graph of the CITS estimate of monthly purchases of bottled water by all households in Los Angeles and San Diego

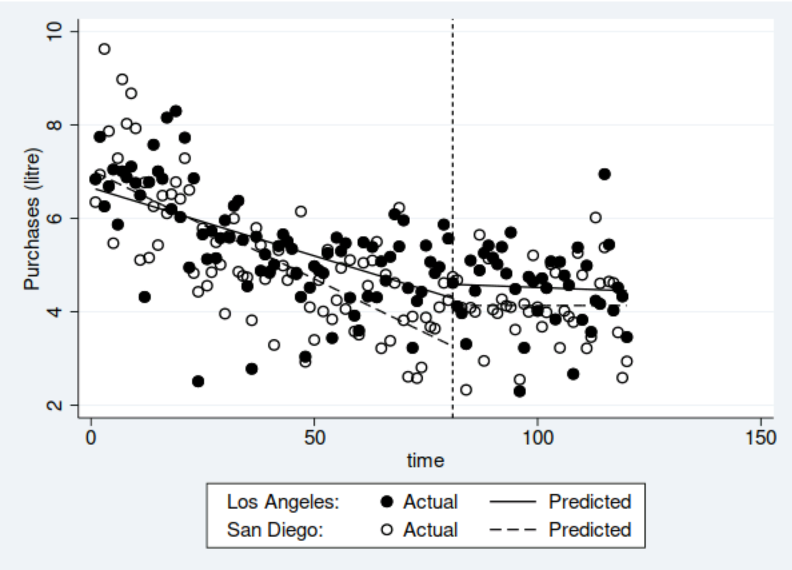

Figure A.5 Graph of the CITS estimate of monthly purchases of bottled water by Fence Sitters in Los Angeles and San Diego

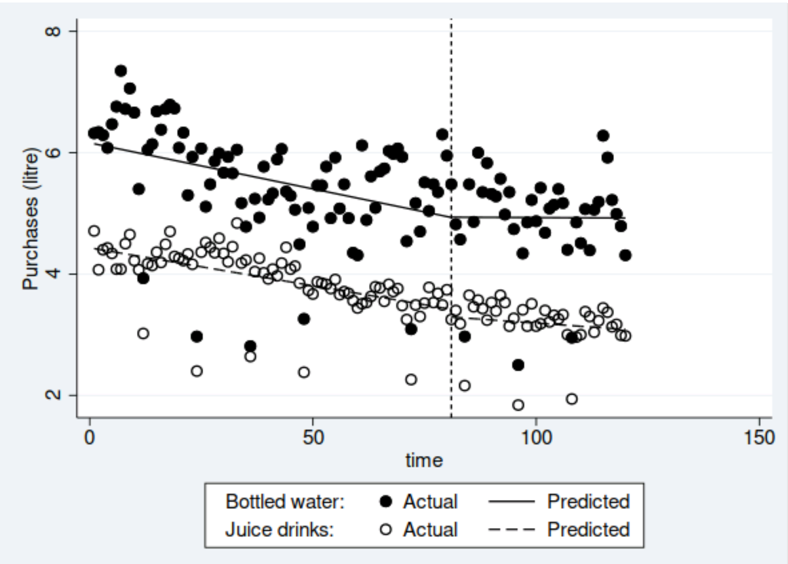

Figure A.6 Graph of the CITS estimate of monthly purchases of bottled water and juice drinks by all households in Los Angeles and San Diego

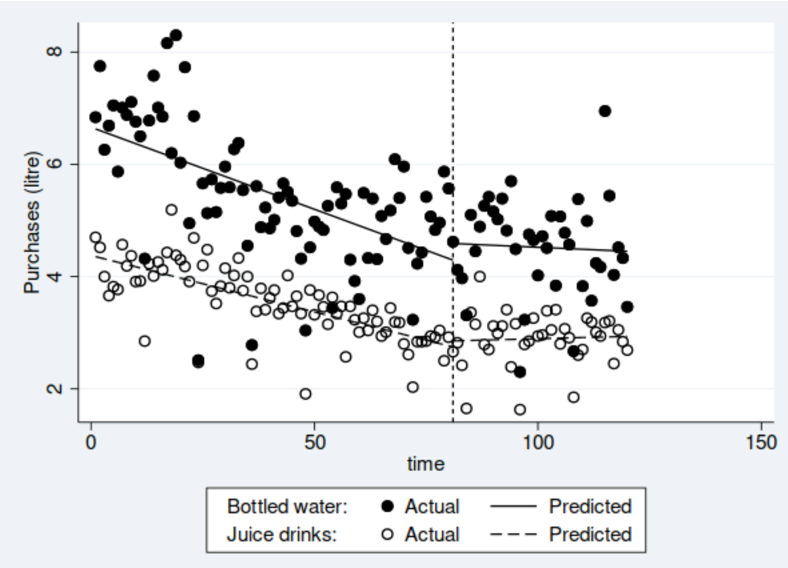

Figure A.7 Graph of the CITS estimate of monthly purchases of bottled water and juice drinks by Fence Sitters in Los Angeles and San Diego

Table A.1 DiD estimates using yearly data

	All households		Fence Sitters	
DiD	4.2989	3.249	-0.0265	4.428
	(0.4392)	(0.3961)	(0.9981)	(0.5696)
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Covariates	Y	N	Y	N
N	20412	20412	4344	4344

p value is reported in parentheses

Table A.2 DiD estimates with the control in Los Angeles

	Yearly purchases		Monthly purchases	
DiD	-2.082	0.2103	-0.0926	0.0737
	(0.796)	(0.9796)	(0.7744)	(0.8208)
County FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Covariates	Yes	No	Yes	No
N	9338	9338	110699	110699

p value is reported in parentheses