Retargeting Social Media Outreach for SNAP Take-up

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Abstract

In a California field experiment, I investigated the impact of a Facebook outreach campaign aimed at increasing enrollment in the Supplemental Nutrition Assistance Program (SNAP). The campaign used a promising marketing strategy known as "retargeting," where ads were delivered to a randomly selected subset of over 16,000 eligible non-participants who had nearly completed the SNAP application process, while a control group remained unaffected. Despite leveraging ad content developed in collaboration with non-profit and government partners, the campaign did not produce statistically or economically significant increases in enrollment, even when considering the extreme values of estimated confidence intervals.

JEL codes: M31; H75; I38

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The incomplete take-up of government benefit programs is a well-documented issue, with numerous studies identifying the pervasive barriers that prevent eligible individuals from enrolling (Currie, 2006). For instance, in 2019, only 70% of eligible households in California participated in CalFresh, the state's Supplemental Nutrition Assistance Program (SNAP), leaving nearly 2 million qualified households without needed assistance (USDA, 2019). At the same time, a body of work has evaluated various policies designed to improve the take-up of benefit programs, including direct-mail informational outreach and behavioral nudges (Finkelstein and Notowidigdo, 2019; Linos et al., 2022).

In the marketing domain, online retargeted advertising has proven effective in increasing engagement and sales among already interested customers, particularly those who have abandoned their online shopping carts (Lambrecht and Tucker, 2013; Sahni et al., 2019). This success raises an interesting question: Can the same retargeting strategy be effectively applied in the non-profit sector to increase the take-up of government benefit programs? Our study seeks to address this question by evaluating the impact of retargeted online advertisements on increasing SNAP enrollment among individuals who nearly completed the application process for CalFresh.

To conduct the experiment, I collaborated with non-profit and government partners. We began by identifying experimental groups from a sample of Los Angeles residents who had nearly completed an application through GetCalFresh.org (GCF), a user-friendly online CalFresh application platform managed by *Code for America* (CfA). Over half of all statewide CalFresh applications are submitted through GCF (Giannella et al., 2023). The individuals in this sample were deemed likely eligible for SNAP based on the household size and income information provided during the application process but had not completed the final document signing. This procedure resulted in a total sample of over 16,000 individuals. We then collected monthly enrollment outcomes for these experimental groups from administrative data provided by the Los Angeles County Department of Public and Social Services (LA DPSS), which included monthly snapshots of SNAP enrollment at the individual level. Over

75% of participants were successfully matched to LA DPSS administrative records, which encompass all individuals participating in any government benefit program in LA.

Over a three-month period, we delivered Facebook and Instagram advertisements to a randomly selected sample of the experimental group. Individuals were randomly assigned to one of four groups, each receiving a distinct ad. In developing these ads, we worked closely with communication specialists at LA DPSS and advertising managers at GCF, who were well-versed in the barriers to SNAP participation. Our objective was to refine and enhance our partners' existing advertisements, both to maintain consistency with their ongoing efforts—an important aspect for policy evaluation—and to effectively adapt these ads for an online platform.

The targeting process leveraged Facebook's "custom audience" tool, allowing us to deliver ads to our pre-selected group of individuals who had nearly completed the SNAP application process (i.e., "retargeted") by matching their demographic data to Facebook and Instagram user profiles. To ensure consistent ad exposure across the groups, we allocated the same per-person daily advertising budget. Approximately two-thirds of the treated groups viewed their assigned ad, with an average of 5.5 views per user, resulting in over 10,000 clicks per group. Additionally, 35% of participants viewed their assigned ad at least 15 times.

Despite the potential of online retargeting, our campaign did not yield economically or statistically significant impacts on SNAP take-up. Even at the upper bound of the estimated confidence interval, the cost per enrollee of this outreach reached $42, compared to $20 per enrollee achieved by Finkelstein and Notowidigdo (2019) through direct-mail outreach. Notably, enrollment in control groups increased by 0.6 percentage points over the sample period, indicating the challenges of measuring the impact of outreach using observational data.

It is important to recognize that this study represents a single implementation of a promising strategy. The lack of significant results does not rule out the potential effectiveness of online retargeted outreach in other non-profit contexts or with different execution strategies.

Different targeting methods or higher-quality ad executions have been found to yield vastly different outcomes (Wernerfelt et al., 2024), and these findings should be interpreted with this context in mind. However, the lack of impact observed in this specific case provides actionable information to organizations engaged in similar outreach efforts, helping them refine their approaches moving forward.

This study provides insights for both marketing and economics. It contributes to the marketing literature on evaluating online advertising through field experiments (Blake et al., 2015; Goldfarb and Tucker, 2011; Hoban and Bucklin, 2015; Kalyanam et al., 2018; Lewis and Reiley, 2014; Sahni, 2015) and expands the retargeting literature (Lambrecht and Tucker, 2013; Bleier and Eisenbeiss, 2015; Moriguchi et al., 2016; Sahni et al., 2019), which has predominantly focused on for-profit settings. Additionally, this study contributes to the economics literature on policies aimed at improving benefit program take-up (Finkelstein and Notowidigdo, 2019; Linos et al., 2022).[1] By testing the application of commercial retargeting techniques in a non-profit context, this study bridges an existing gap between these two fields, offering a novel perspective on the effectiveness of such strategies in promoting public benefit programs.

Moreover, this study contributes to the broader discourse on the effectiveness of online advertising in promoting pro-social and political behaviors (Kalla and Broockman, 2018; Aggarwal et al., 2023; Ho et al., 2023). The findings indicate that while online retargeted advertising has shown promise in for-profit contexts, this non-profit campaign failed to increase enrollments in government programs, despite using similar strategies and ad content as those used by non-profit and government partners. Although different execution may yield better results, this outcome raises questions about the effectiveness of these techniques in similar non-profit settings.

[1] See also Currie (2006); Linos et al. (2022); Giannella et al. (2023); Meckel (2020); Guyton et al. (2016); Bhargava and Manoli (2015); Manoli and Turner (2014); Armour (2018); Barr and Turner (2018); Allcott and Greenstone (2017); Bettinger et al. (2012); Daponte et al. (1999); Deshpande and Li (2019); Rossin-Slater (2013); Schanzenbach (2009).

1 Background

The Supplemental Nutrition Assistance Program (SNAP) is a means-tested program that ensures a minimum level of food consumption for eligible households (Finkelstein and Notowidigdo, 2019). In California, SNAP is known as CalFresh and is administered at the county level. This study focuses on Los Angeles, which has one of the highest SNAP caseloads in the US (Giannella et al., 2023).

To apply for CalFresh, individuals must submit an application and complete an in-person or phone interview. Applicants must provide identifying information in the application process, including Social Security Numbers, name, addresses, household size, and income. Applications can be submitted by mail, fax, telephone, in person, or online. Online applications are available through the county website or an online portal at GetCalFresh.org, a website administered by the non-profit organization Code for America. GetCalFresh (GCF) offers a streamlined, user-friendly, and digitally assisted SNAP enrollment process. After receiving applications, GCF forwards the applications to the appropriate CalFresh county offices and provides applicants additional support throughout the enrollment process. GCF receives roughly half of all SNAP applications in Los Angeles (Giannella et al., 2023), and applications are provided in English, Spanish, and Chinese.

2 Advertisement Design and Study Pre-Registration

The advertisements for this study were developed in collaboration with our non-profit and government partners, the Los Angeles Department of Public Social Services (LA DPSS) and GetCalFresh (GCF). Our goal was to adapt and enhance their existing outreach materials for digital platforms. Examples of their existing ads can be found in Appendix Figures D.1 and D.2.[2] We improved these ads by incorporating animations, highlighting benefit amounts, simplifying the design, and drawing on insights from the literature that highlights

[2]Many of these ads focused on COVID-19, as the experiment took place during the pandemic.

the different barriers to benefit program take-up (Currie, 2006).

The process involved first collecting the current advertisements used by LA DPSS and GCF. With the help of an LA DPSS advertising specialist, we created four new ads building on these materials. These drafts were then reviewed and edited by communications officials at LA DPSS and GCF employees specializing in digital outreach, leading to the final advertisements shown in Figure 1.

We targeted individuals who had nearly completed the SNAP application process—the "retargeting" audience—for two key reasons. First, this group allowed us to utilize demographic data from near-complete CalFresh applications, which could be linked to Facebook. Second, observational data from previous GetCalFresh Facebook campaigns showed that this type of audience had a lower cost-per-application (CpA) compared to other groups, with a CpA of $1.27 versus $1.76 for look-alike audiences. Additionally, existing literature highlights the promising potential of retargeting in the for-profit sector (Sahni et al., 2019).

Although this study was not pre-registered—originally intended as a pilot to identify effective ads among the retargeted population for a larger study—we believe the findings will be valuable to non-profit, academic, and government stakeholders. The results provide insights into designing policies for increasing take-up of government benefit programs through retargeted audiences and digital platforms.

3 Intervention Design and Data

During the intervention period spanning from November 26, 2021, to February 1, 2022, we conducted a study on the popular social media platforms Facebook and Instagram. This endeavor focused on a select sample of 16,510 individuals who had nearly completed the application process for the CalFresh program through GCF, having provided critical information such as Social Security Numbers (SSNs), dates of birth (DOBs), first and last names, and zip codes. This cohort was subsequently randomized into six distinct groups, each serving a unique purpose. The groups comprised two control groups, differentiated by language (English or Spanish), and four treated groups, including three English-language ads and one Spanish-language ad. The treated groups were served various infographic and textual content designed to engage the viewer.

Group 1, shown in Figure 1, received a reminder to finalize the CalFresh application, which presented the maximum benefit amount alongside a dynamic animated graphic. Group 2 received an advertisement encouraging participation by highlighting the potential nutritional and health benefits of enrolling in CalFresh. This ad featured an animated depiction of a shopping cart filled with nutritious foods. Group 3 received an advertisement confronting stigma, emphasizing the convenience and privacy of using CalFresh benefits on a mobile device at participating online retailers and disclosing the maximum benefit amount for a single-person household. Group 4's advertisement mirrored that of Group 2 but was tailored for a Spanish-speaking audience and included the maximum benefit amount in the main text. Group 5 was the English-speaking control group, and Group 6 was the Spanish-speaking control group. We included a separate Spanish-speaking control and treatment group because we were particularly interested in the impact of outreach on this demographic group.

Each English experimental group consisted of 3,555 randomly selected individuals, while a Spanish experimental group comprised 1,145 individuals, totaling 16,510 participants across the six groups. For each participant, we collected monthly enrollment snapshots over six months, resulting in 99,060 individual–month observations. To target the respective groups, the names, zip codes, and dates of birth of the individuals in each group were uploaded in separate group spreadsheets to Facebook's "Custom Audiences" feature.

The campaign was managed through Facebook's ad manager, which was configured to align with the protocols of previous online GCF campaigns (see Appendix A for more details on the ad manager setup). A uniform budget of $1,800 was allocated across the treatment groups during the three-month campaign, ensuring an equitable per-person per-day expenditure within each group. The reach of the intervention was broad: approximately 66% of the treated group members who were included in the spreadsheet upload received the ads at least once, experiencing an average of 5.5 views per person. Notably, a subset of 5,000 treated individuals out of the total 11,810 treated saw the ads a minimum of 15 times.

I collaborated with the Los Angeles Department of Public Social Services (LA DPSS) to gather enrollment outcomes for assessing the intervention. To gather outcomes from county administrative data, we shared essential individual details with LA DPSS, including names, dates of birth (DOB), Social Security Numbers (SSN), and zip codes. In return, LA DPSS conducted an internal cross-reference with their government program databases, linking the provided information with indicators of CalFresh participation for a given extract month. These extracts were conducted once a month during the months surrounding the intervention: from two months before to four months after.[3] The data returned by DPSS included SNAP participation status, a unique tracking number enabling cross-extract tracking of individuals, household size, and the monthly benefit amounts received.[4]

After the intervention, LA DPSS provided disposition codes that detailed the reasons for SNAP disenrollment. These codes were generated by SNAP caseworkers, and include reasons such as voluntary withdrawals, non-compliance with recertification, and changes in eligibility status.

Table 1 summarizes pre-intervention demographic characteristics of the individuals in the pooled, English, and Spanish samples. Characteristics include SNAP participation percentages (those we could not adequately screen before the experiment), the benefit totals for those previously enrolled, the household size, when available, and the percentage of households with a household size larger than three. Pre-intervention demographics of the

[3]The pre-intervention months comprised two data waves before the inception of the experiment, specifically on October 1, 2021, and November 2, 2021. These initial data snapshots served as baseline measurements to contextualize the subsequent effects of the intervention. Following the intervention's commencement, an additional four monthly data waves were gathered, capturing post-intervention insights. These waves occurred on December 1, 2021, January 1, 2022, February 1, 2022, and March 2, 2022.

[4]The augmented data returned by DPSS did not include the personally identifiable information that we provided to execute the linkage due to data privacy concerns.

samples from GCF applications, including age, household income, primary language, and race, were available at the time of intervention but are not available at the time of this writing; however, balance tests on these characteristics executed by the author and separately by a CfA employee revealed no significant differences between treatment and control groups across those demographics. Column 1 reports the summary statistics for the treatment and control groups together; Columns 2 and 3 report those for treatment and control groups, respectively; Column 4 reports the p-value from the t-test comparing treatment and control groups for the given outcome. Roughly 13% of individuals in the sample were already on SNAP, receiving, on average, a monthly benefit amount of $457. The average household size was one, with Spanish-speaking households, on average, having higher benefit amounts and larger household sizes. For all characteristics, we cannot reject equality across the two groups.

While groups 1-4 appear similar overall, Facebook's ad algorithm prioritizes individuals within each group for whom the ad is most relevant, potentially leading to systematically different subsets. This selection does not undermine the validity of the Intention-to-Treat (ITT) estimate for assessing the impact of online retargeting on SNAP take-up. However, it does complicate drawing conclusions about how different ads might affect a random sample of the population. Therefore, it is important to interpret the underlying mechanisms with caution, considering the potential influence of sample selection (Eckles et al., 2018).

4 Methodology

The first specification uses a standard Difference-in-Differences (DiD) specification to estimate the static effects of Facebook advertising on SNAP take-up. This strategy is given as follows,

$$Y_{i,t,e} = \gamma_i + \gamma_{t,e} + \beta_1 \cdot 1\{\text{Treated}\}_i \times 1\{\text{Post}\}_t + \varepsilon_{i,t,e}. \tag{1}$$

In this framework, the subscript t represents time in months since the start of the experiment, i identifies the individual, and e indicates if the individual speaks English (1) or not (0). The outcome $Y_{i,t,e}$ is binary, showing whether the individual is enrolled (1) or not (0) at time t. Other outcomes include whether the individual was disenrolled or not, and, if so, whether they withdrew their application and whether they re-enrolled. The model includes individual-specific (γ_i) and time-specific ($\gamma_{t,e}$) fixed effects. The term $1\{\text{Treated}\}_i \times 1\{\text{Post}\}_t$ allows for estimation of the impact of the intervention across the entire intervention among the treated groups (β_1). The coefficient β_1 measures the change in the likelihood of the outcome for the treated group relative to the controls. The term $\varepsilon_{i,t,e}$ accounts for unobserved variables that might affect the outcome. Standard errors are clustered at the individual level i.

We also employ an event-study methodology to capture the potential dynamic effects of the intervention over time. The method is described by the equation:

$$Y_{i,t,e} = \gamma_i + \gamma_{t,e} + \sum_{t \neq -1} \beta_t \cdot 1\{\text{Treated}\}_i \times 1\{\text{Months Since Start} = t\}_t + \varepsilon_{i,t,e}. \tag{2}$$

In this framework, the subscripts and variables are the same Equation 1, with the exception of the interaction term. The term $\sum_{t \neq 0} \beta_t \cdot 1\{\text{Treated}\}_i \times 1\{\text{Months since Start}\}_t$ allows for estimation of the impact of the intervention at each period among the treated groups ($\sum_{t \neq -1} \beta_t$). The coefficients β_t measure the change in the likelihood of the outcome for the treated group at various times t, with the month before the intervention $t = -1$ serving as a reference point. Standard errors are clustered at the individual level i. For both specifications, a separate analysis assesses the impacts of the intervention on Spanish-speaking participants alone to identify potential heterogeneous effects.

Lastly, for our power calculations in Appendix B, we include a series of straightforward statistical mean comparisons between treatment and control groups for each month following the start of the intervention.

5 Results

Table D.1 Panel A, row (i), suggests that the intervention did not significantly alter SNAP take-up. Further, the breakdown by language groups in Panels B and C indicates no substantial impact on either English or Spanish speakers, highlighting the intervention's limited static effect across these demographics.

However, a closer look at the dynamic effects, estimated with Equation 2 and illustrated in Figure 2, offers some nuance.[5] The first-month post-intervention showed a significant, albeit temporary, decrease in SNAP enrollment by two percent (0.3 pp) in the pooled sample, an effect that intensified but lost statistical significance in subsequent months. For an exploratory and speculative analysis of the mechanisms driving these potential negative impacts, see Appendix C.

Notably, enrollment in the control group rose by 5% (0.6 pp) during the study, highlighting the difficulty of assessing the causal impact of outreach efforts using observational data. For example, Facebook campaign metrics may overstate the impacts of outreach. Additionally, some studies rely on cross-treatment comparisons of outreach efforts to gauge the overall efficacy of certain outreach approaches relative to others. However, it is possible that outreach does not significantly increase take-up among any treated groups, even if some treatments perform better than others.

6 Back-of-the-Envelope Calculation

A back-of-the-envelope calculation rules out cost-effectiveness. The estimated impact of the outreach on SNAP take-up among prior non-enrollees was -0.0003, with a standard error of 0.002. At the upper bound of the 95% confidence interval (0.0036), the cost per enrollee

[5] Figure D.3 illustrates the estimates for all treatment groups separately.

would still be $42. By contrast, Finkelstein and Notowidigdo achieved a cost of $20 per enrollee by serving direct-mail informational outreach to seniors.

7 Discussion

We conducted a field experiment in California to evaluate the impact of online retargeted outreach on SNAP enrollment. Over 16,000 individuals were randomized into various treatment and control groups, with the analysis drawing on administrative datasets to assess program participation. The results indicate that the outreach did not lead to economically or statistically significant increases in SNAP take-up.

However, this study represents just one implementation of a promising strategy. The lack of significant results should not be seen as conclusive evidence against the potential effectiveness of online retargeted outreach. Different execution strategies or applications in other non-profit contexts could yield markedly different outcomes. Additionally, SNAP-eligible individuals in California might be desensitized to SNAP outreach, possibly due to previous similar online outreach initiatives by GCF, raising questions about whether such outreach efforts might be more effective in other states or regions. Despite the prior campaigns, the current outreach achieved a high level of ad engagement, with over 10,000 ad clicks per treatment group, suggesting that the content resonated with the audience.

An exploratory, post hoc analysis highlights broader questions about the socio-political dynamics that influence responses to government benefit program outreach. Further research is needed to better understand these associations and their implications for future outreach efforts.

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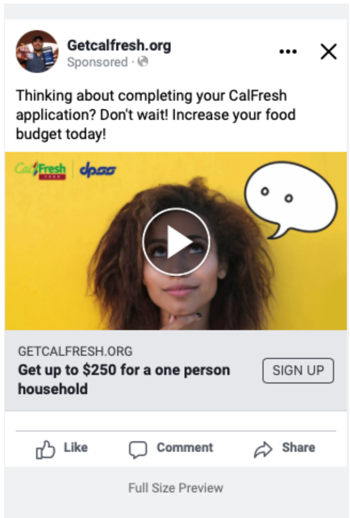
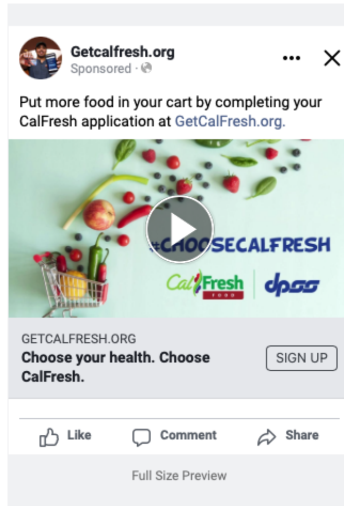
Figures and Tables

Figure 1: Treatment Advertisements By Group

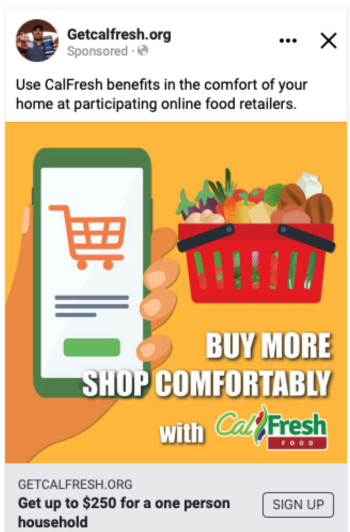
Group 1: Information



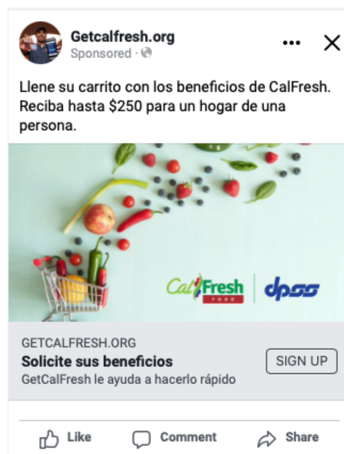
Group 2: Information



Group 3: Stigma

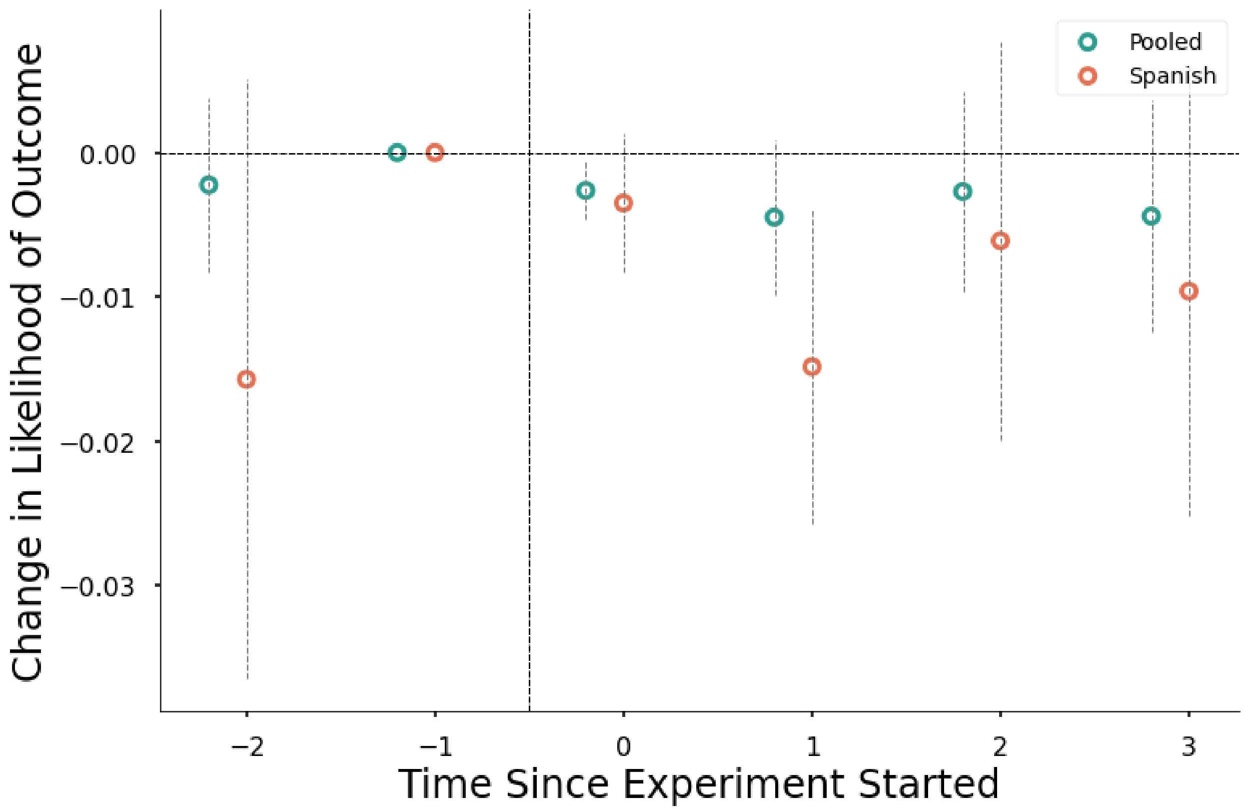


Group 4: Spanish Translation



Note: The figure provides our outreach treatments by group. Group 1, information intervention, includes a reminder and a specific likely benefit dollar amount. Group 2, information, provided a reminder appealing to the health benefits of being able to afford healthy, fresh produce with CalFresh. Group 3, stigma, emphasizes the potential to use CalFresh privately by ordering from online retailers and avoiding using the EBT card in public. Group 4, is a Spanish-translated advertisement, similar to Group 2, providing information and a benefit dollar amount.

Figure 2: Event Study: Change in Overall SNAP Enrollment



Note: The figure presents the coefficients obtained from estimating Equation 2 for the enrollment outcome across our entire sample. It illustrates the temporal evolution of enrollment in SNAP by the pooled sample and the Spanish group, separately, relative to control groups, with a reference period at $t = -1$. 95% confidence intervals are provided.

Table 1: Sample Characteristics and Balance Test

	Combined	Treatment	Control	p–value
A: Overall Sample				
SNAP Participant (%)	0.13	0.13	0.12	0.14
Benefit Amount	457.48	460.64	449.06	0.40
Household Size	1.19	1.18	1.22	0.15
Household Size $>$ 3 (%)	0.17	0.18	0.16	0.24
Observations	16510	11810	4700	
B: English Sample				
SNAP Participant (%)	0.14	0.14	0.14	0.94
Benefit Amount	444.46	449.90	428.35	0.13
Household Size	1.17	1.17	1.17	0.88
Household Size $>$ 3 (%)	0.16	0.17	0.14	0.26
Observations	14220	10665	3555	
C: Spanish Sample				
SNAP Participant (%)	0.09	0.10	0.09	0.20
Benefit Amount	574.36	592.83	552.20	0.41
Household Size	1.42	1.36	1.48	0.15
Household Size $>$ 3 (%)	0.27	0.32	0.22	0.09
Observations	2290	1145	1145	
Estimated Eligible (%)	100	100	100	-

Note: The table provides summary statistics for the outreach sample in the month before the intervention, providing those of both the treatment and control groups separately, as well as t-tests comparing the treatment and control groups for each outcome. Data come from LA County DPSS enrollee data. Only observations from the month before the experiment are included.

Appendix Material

A Facebook Campaign Setup

The ad campaign setup adhered closely to the protocols established in previous Facebook outreach efforts by GetCalFresh (GCF). Using GCF's funded Facebook business ad account, I created the campaign, ad sets, and individual ads. For the campaign, I selected the auction buying type and chose "reach" as the objective. This approach was intended to show the ad to as many people in the target audience as possible, minimizing Facebook's tendency to selectively target subgroups that might be more responsive to ads. This ensured broad exposure within the treatment groups.

Although optimizing for conversions, such as SNAP applications submitted through the website, might have been a more effective strategy for increasing take-up, we were unable to implement this option. Just before the campaign's launch, Facebook restricted GCF's ability to track and optimize for conversions due to the sensitive demographic data involved, particularly given the focus on potentially vulnerable populations (e.g., low-income individuals). These restrictions are commonly applied to organizations engaging in advertising classified by Facebook under the categories of "social issues, elections, or politics."

We opted not to use campaign budget optimization to ensure an equal distribution of funds across all ad sets. The daily budget was fixed to be the same for Groups 1-3, while Group 4, being smaller, received the same per-person daily budget as the other groups. Ads were set to display at all times of the day for all groups, consistent with previous campaigns. The attribution settings were left at their default levels.

The campaign was scheduled to begin on November 25, 2021, at 11:59 PM. In the ad set audience controls, we used the custom audiences we previously uploaded corresponding to each group-advertisement combination. We selected Facebook's recommended ad placement options, including devices. Within each ad set (four different sets for the four groups), I identified the GCF Facebook page and manually uploaded the corresponding ad copy and creative assets assigned to each group. We used the single image or video format. The appearance of the ads is illustrated in Figure 1. The primary text, headline, and description of the ads were configured as shown in Figure 1, with a "Sign Up" call to action. The destination website was GetCalFresh.org, the landing page for the CalFresh application process, and we tracked link clicks using a previously activated GCF web pixel.

B Power Calculations

Following (Duflo et al., 2007), I calculate the minimum detectable effect (MDE) for a simple model comparing the means of the treatment and control groups using data from the post-intervention periods. The MDE is given by:

$$\text{MDE} = \left(t_{1-\kappa} + t_{\frac{\alpha}{2}}\right) \times \sqrt{\frac{\sigma^2}{P(1-P) \times N}}$$

In this equation, $t_{1-\kappa}$ represents the critical value from the t-distribution corresponding to the desired power level, set at 0.8. The term $t_{\frac{\alpha}{2}}$ denotes the critical value from the t-distribution associated with the significance level, set at 0.05 for a two-tailed test. The variable σ^2 stands for the variance of the outcome variable, which is 0.11, calculated empirically from the control group. The term P is the proportion of the sample assigned to the treatment group, which is 0.715 . Finally, N is the total sample size, set at 16,510.

Using these parameters, the MDE is calculated to be 0.016. For context, the estimated impact of the intervention on take-up rates, based on a simple comparison of means between the treatment and control groups during the first three months of the intervention, results in values of 0.0042 (p-value = 0.474) for month 1, 0.0061 (p-value = 0.302) for month 2, and 0.0039 (p-value = 0.503) for month 3. When analyzing the intervention's impact on take-up rates among prior non-enrollees with the smaller sample size of 14,347, the MDE increases slightly to 0.018, with corresponding mean comparisons of 0.0002 (p-value = 0.941) for month 1, 0.0006 (p-value = 0.849) for month 2, and -0.0006 (p-value = 0.852) for month

3.

Given the significantly reduced sample size in the following exploratory analyses, it is important to interpret the results with caution. When examining the impact of the intervention on SNAP participation among prior enrollees, the MDE is 0.047. The mean comparisons for this group are -0.028 (p-value = 0.04) for month 1, -0.012 (p-value = 0.471) for month 2, and -0.017 (p-value = 0.39) for month 3. Additionally, for the analysis of the intervention's impact on enrollment rates among prior enrolled Spanish speakers, the MDE is substantially higher at 0.148, with mean comparisons of -0.09 (p-value = 0.015) for month 1, -0.053 (p-value = 0.251) for month 2, and -0.038 (p-value = 0.45) for month 3.

These findings suggest that the latter two analyses—particularly those focused on prior enrollees and Spanish speakers—may be statistically underpowered.

C Exploratory Analyses

In this section, I conduct a series of exploratory post-hoc analyses to inform future research directions and to form hypotheses explaining the potential decrease in take-up from our outreach intervention. Due to the post hoc nature of these analyses and the limited statistical power of our design to test these hypotheses, the findings in this section remain speculative and require further investigation.

C.1 Enrollment by Pre-Intervention Demographics

When gathering the experimental groups for targeting, we noticed a substantial portion of the individuals listed Spanish as their primary language. Thus, we integrated a spanish-speaking arm in the experiment with a spanish-translated advertisement. The Spanish-speaking subgroup saw a significant 15-percent (1.5 pp) reduction in enrollment in the second month of the intervention, although this estimate is not statistically different from the pooled estimate. This decrease gradually diminished, losing statistical significance over time. The corresponding raw share of enrolled individuals by treatment group and primary language is plotted in Figure D.4. This finding highlights potential socio-policitcal factors that may impact how individuals perceive outreach materials.

Due to the lack of personally identifiable administrative data, we couldn't exclusively target individuals not currently enrolled in SNAP.[6] Consequently, 13% of the sample was already enrolled in SNAP before the intervention. Thus, another way individuals differed, was whether they were already on CalFresh before the experiment started. Consequently, we differentiated our analysis between those previously enrolled in SNAP and prior non-enrollees. Table D.1, rows (ii) and (iii), presents the static estimates from Equation 1 for both sets, indicating a minor and insignificant decrease in SNAP take-up and disenrollment among both language groups. Disenrollment among Spanish speakers was proportionately higher than among English speakers, though not statistically different, while neither group showed statistically significant impacts.

Figure D.5 shows the dynamic impacts of digital outreach by estimating Equation 2 for prior enrollees and prior non-enrollees separately.[7] Panel (a) illustrates a negligible decline in enrollment for prior non-enrollees, whereas Panel (b) reveals a statistically significant increase in disenrollment among prior enrollees during the first two months of 2–3 percentage points. It is important to note that these estimates are speculative as our experimental design is not sufficiently powered to detect such effects for this small subsample. We observe a more substantial increase in disenrollment in the Spanish-speaking group, although this subsample is extremely small and the impact could be driven by statistical noise. Table D.2 details the reasons for disenrollment, with the most-cited reasons being documentation, verification, and recertification issues. Figure D.7 plots the raw share of enrolled individuals by treatment group and prior enrollment status.

[6]This limitation arose from relying on a retargeted audience who had nearly completed applications on GetCalFresh.org (GCF) rather than on administrative data. As a result, we couldn't verify SNAP enrollment status beyond GCF, as we lacked access to personally identifiable information (PII) from LA DPSS records. Instead, we used anonymized tracking IDs from LA DPSS to monitor enrollment trends across treatment groups.

[7]Figure D.6 illustrates the estimates for all treatment groups separately.

C.2 Drivers of Decreased Take-Up

The observed initial increase and subsequent decline in SNAP disenrollment prompted an investigation into the underlying causes. It is possible that the campaign caused confusion and led to temporary disenrollments, followed by individuals rejoining the program. Alternatively, some disenrollments might be permanent, potentially due to the outreach inadvertently stigmatizing participation or other reasons prompting individuals to exit the program.

To explore these hypotheses, I separately estimate Equations 1 and 2 for previously enrolled individuals, focusing on their rates of active withdrawals and re-enrollments. The static estimates, detailed in Table D.1 rows (iv) and (v), suggest a negligible increase in withdrawals across the sample, with a notable rise in withdrawals in the Spanish group. Lastly, Panel A, row (v) shows a marginally significant uptick in re-enrollments, suggesting that nearly 39% of initial disenrollments could be attributed to temporary lapses, possibly due to misconceptions introduced by the outreach campaign.

Figure D.8 further dissects these results by providing the dynamic estimates from Equation 2.[8] Panel (a) shows a significant temporary increase in withdrawals of 0.4 percentage points in the first month, indicating that some participants proactively opted out of SNAP in response to outreach. This response was especially marked for Spanish speakers—though it was not statistically significant and represented only two cases among Spanish speakers, with a near two-percentage-point increase in withdrawals.

Panel (b) shows a significant uptick in re-enrollments of 1.5 percentage points three months into the experiment, covering nearly 40% of those who initially disenrolled. These re-enrollments suggest potential confusion caused by outreach. This confusion may have led individuals to take actions that resulted in a temporary lapse in benefits. Figure D.10 plots the raw number of prior enrollees withdrawing and/or re-enrolling by treatment group across the study period.

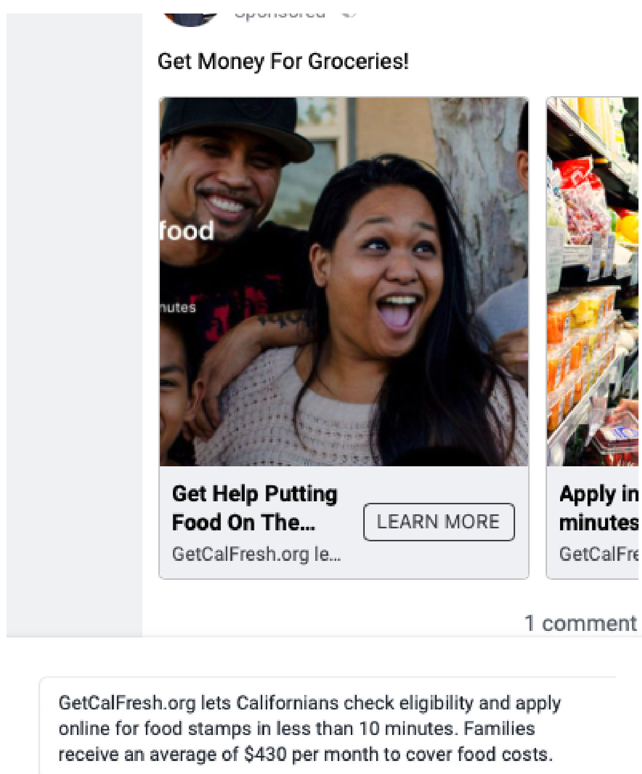
[8] Figure D.9 illustrates the estimates for all treatment groups separately.

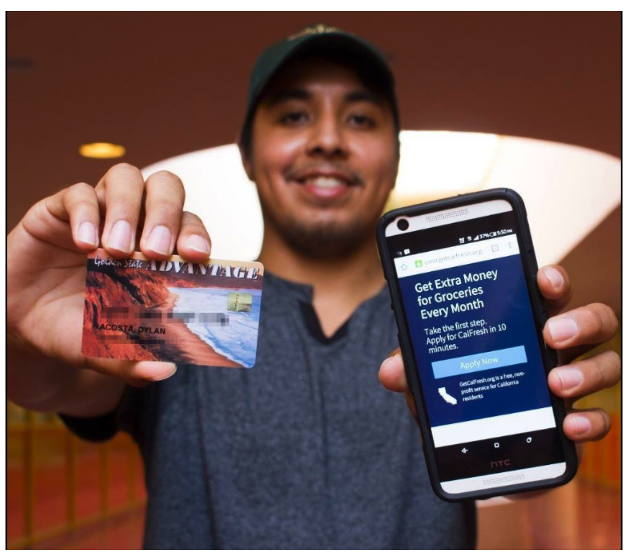
D Supplemental Figures and Tables

Appendix Figure D.1: Previous LA DPSS Advertisements

These advertisements represent those already used by LA DPSS, with some specifically addressing COVID-19 due to the timing of our intervention during the pandemic. Our objective was to enhance and expand upon the existing advertisements provided by our partners.

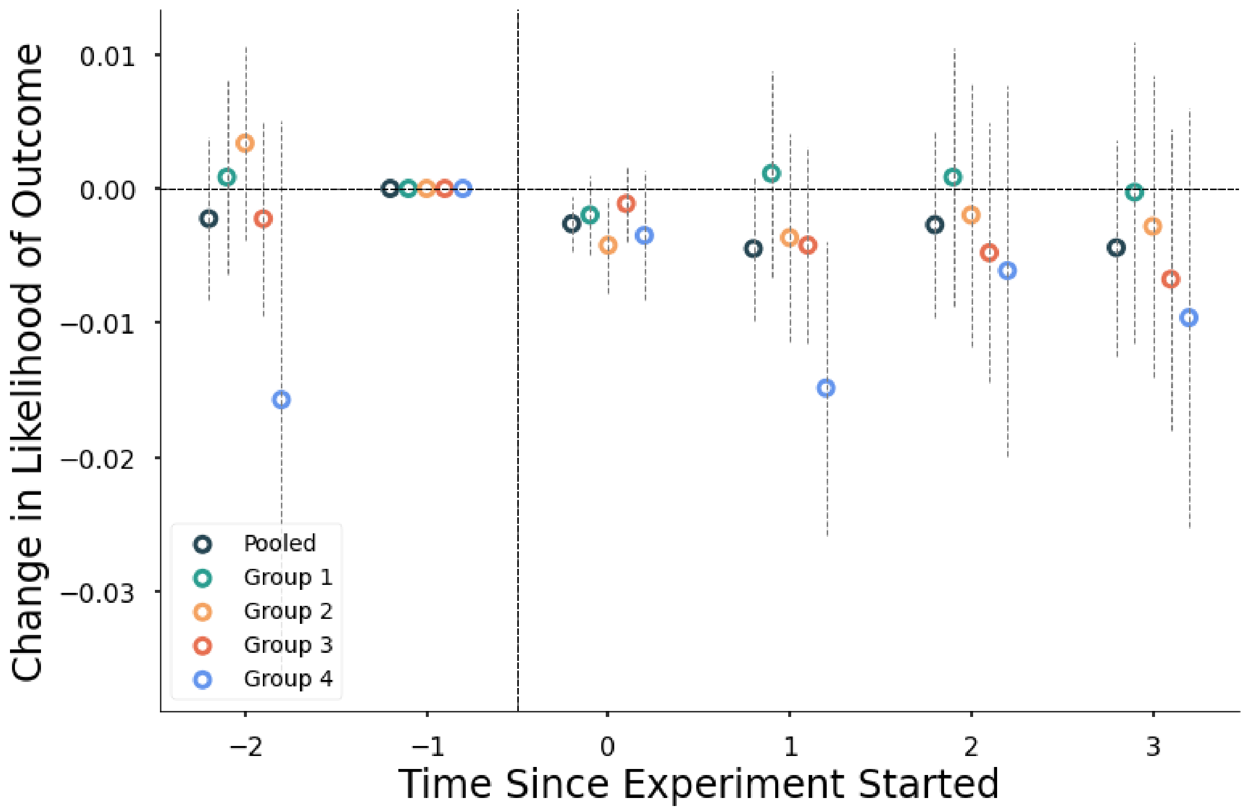
Appendix Figure D.2: Previous GCF Advertisements





These advertisements represent those already used by GetCalFresh. Our objective was to enhance and expand upon the existing advertisements provided by our partners.

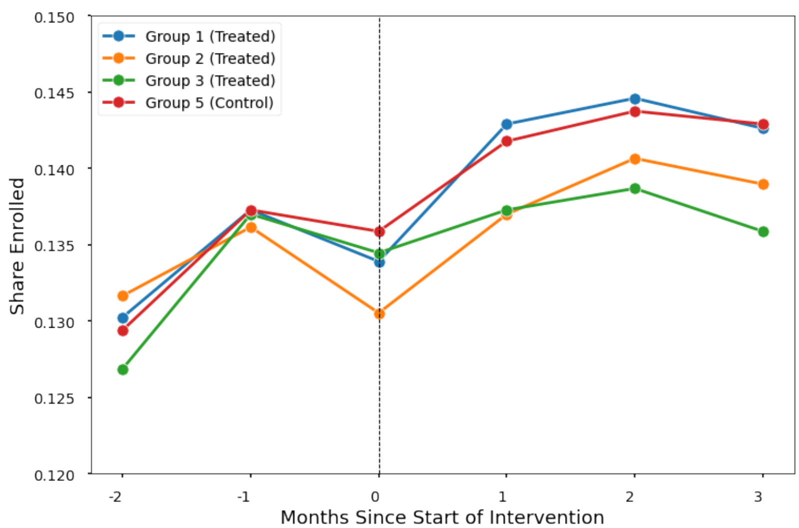
Appendix Figure D.3: Event Study: Change in Overall SNAP Enrollment



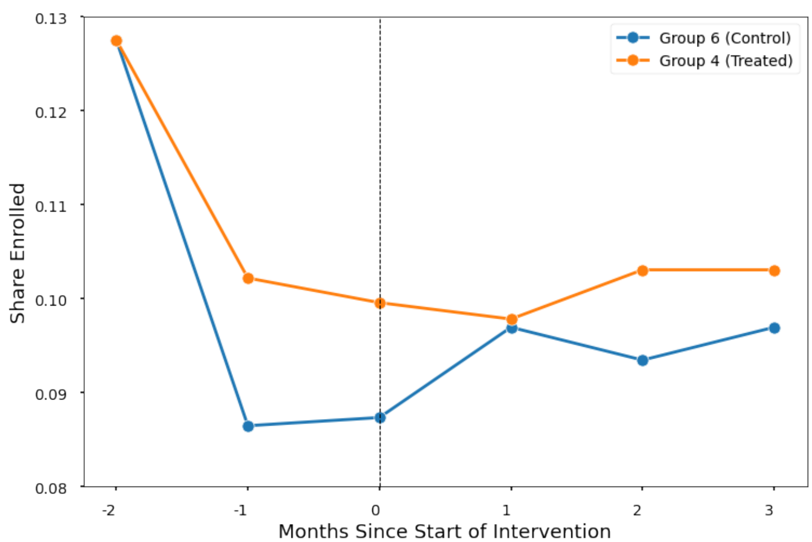
Note: The figure presents the coefficients obtained from estimating Equation 2 for the enrollment outcome across our entire sample. It illustrates the temporal evolution of enrollment in SNAP of the pooled sample and Groups 1–4 (see Figure 1), separately, relative to control groups, with a reference period at $t = -1$. 95% confidence intervals are provided.

Appendix Figure D.4: Raw Trends: Share Enrolled by Treatment Group and Primary Language

(a) English-Speaking



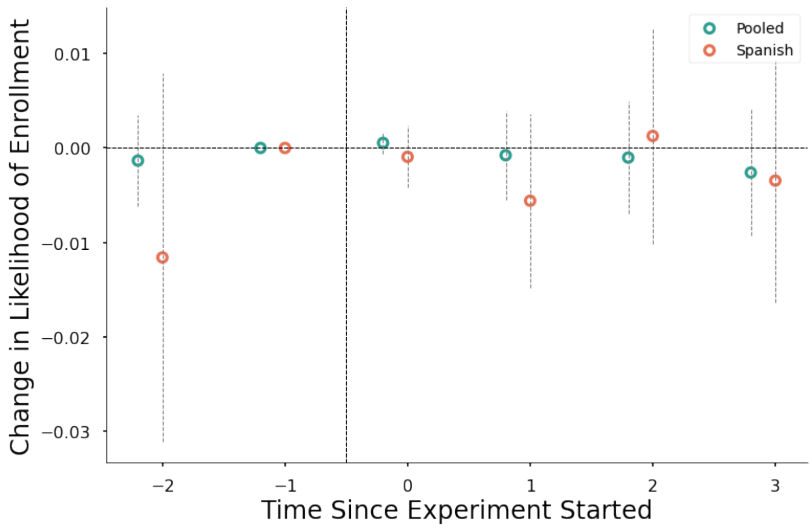
(b) Spanish-Speaking



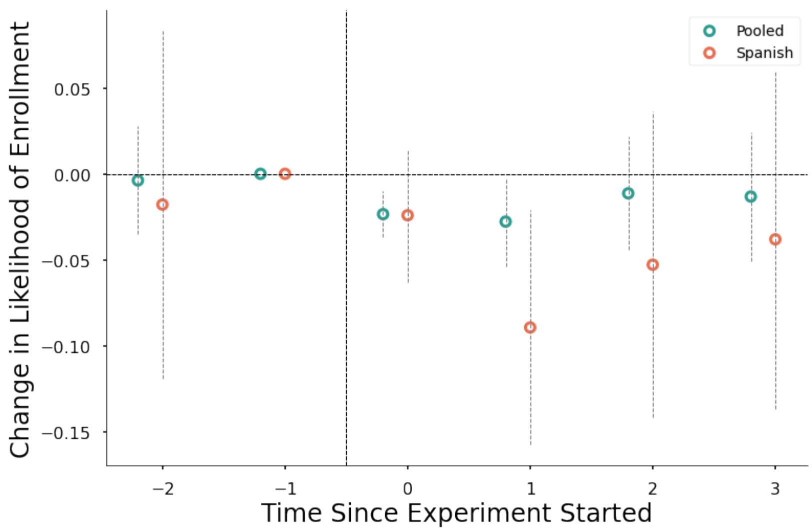
Note: The figure presents the raw share of individuals enrolled in SNAP by treatment groups and primary language across the study period. Groups 1–4 are the treatment groups and groups 5 and 6 are the controls.

Appendix Figure D.5: Event Study: Enrollment Effect Conditional on Initial Status

(a) Prior Non-Enrollees



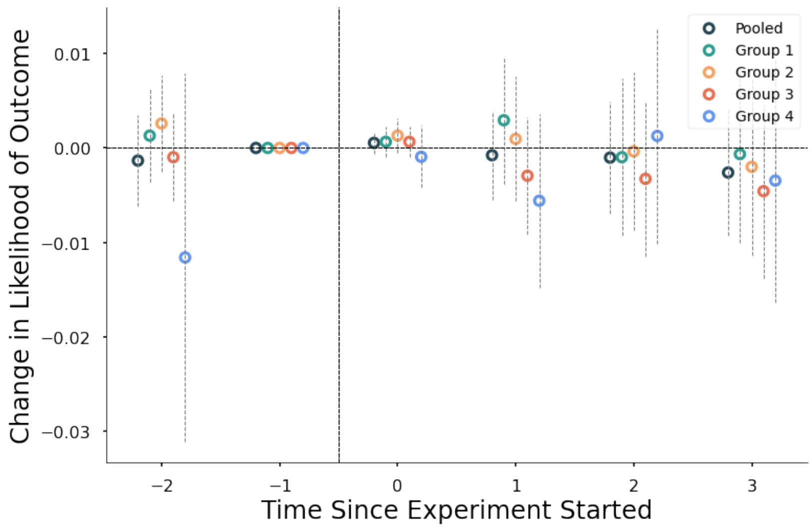
(b) Prior Enrollees



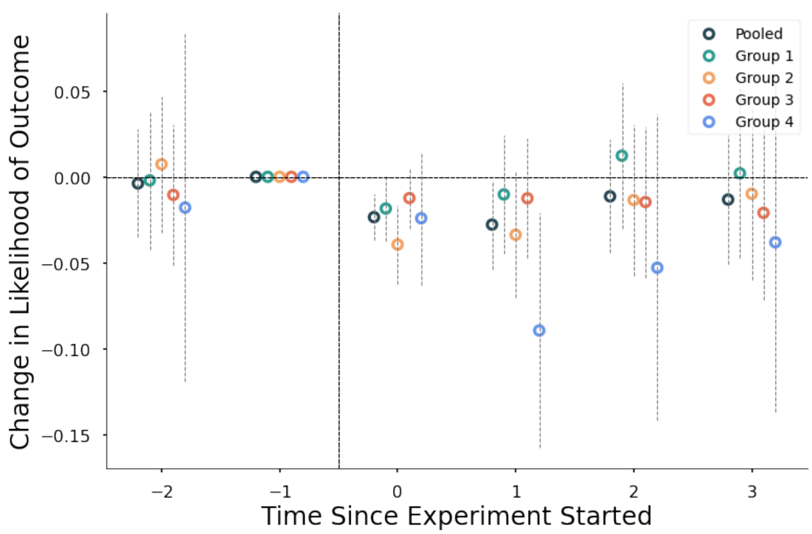
Note: The figure presents the coefficients obtained from estimating Equation 2 for the enrollment outcome, separately for prior enrollees and prior non-enrollees in the pooled and Spanish groups. It illustrates the temporal evolution of SNAP enrollment by prior enrollment status relative to control groups, with a reference period at $t = -1$. Panel (a) presents the event-study estimates for changes in the likelihood of enrollment among prior enrollees (in the given intervention month), while panel (b) presents estimates for the changes in enrollment of individuals who were previously enrolled in SNAP. 95% confidence intervals are provided.

Appendix Figure D.6: Event Study: Enrollment Effect Conditional on Initial Status

(a) Prior Non-Enrollees



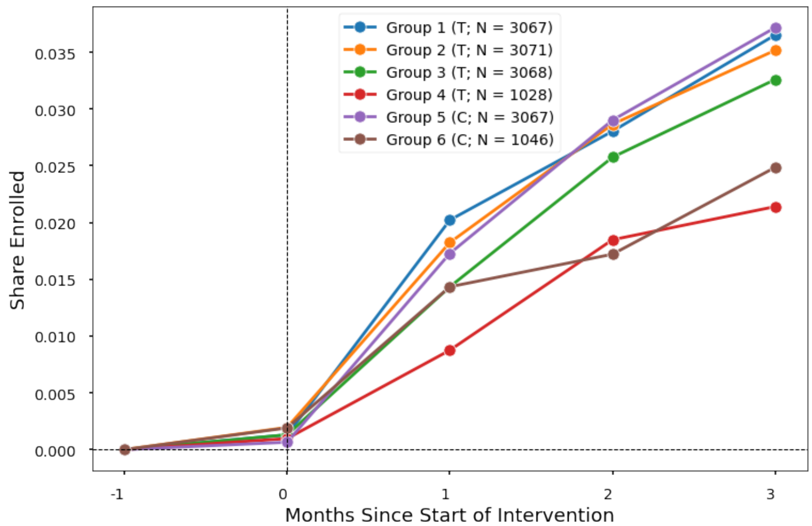
(b) Prior Enrollees



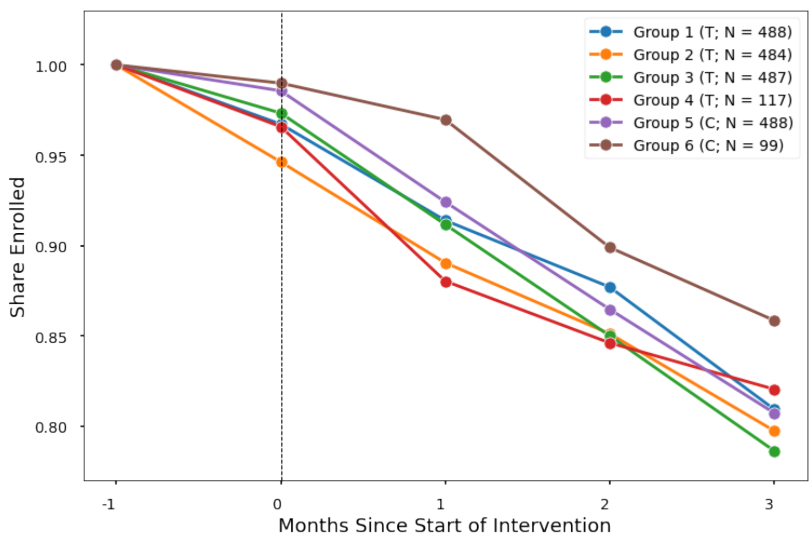
Note: The figure presents the coefficients obtained from estimating Equation 2 for the enrollment outcome, separately for prior enrollees and prior non-enrollees in the pooled and Spanish groups. It illustrates the temporal evolution of SNAP enrollment by prior enrollment status of the pooled sample and Groups 1–4 (see Figure 1), separately, relative to control groups, with a reference period at $t = -1$. Panel (a) presents the event-study estimates for changes in the likelihood of enrollment among prior enrollees (in the given intervention month), while panel (b) presents estimates for the changes in enrollment of individuals who were previously enrolled in SNAP. 95% confidence intervals are provided.

Appendix Figure D.7: Raw Trends: Share Enrolled by Treatment Group and Prior Enrollee Status

(a) Prior Non-Enrollees



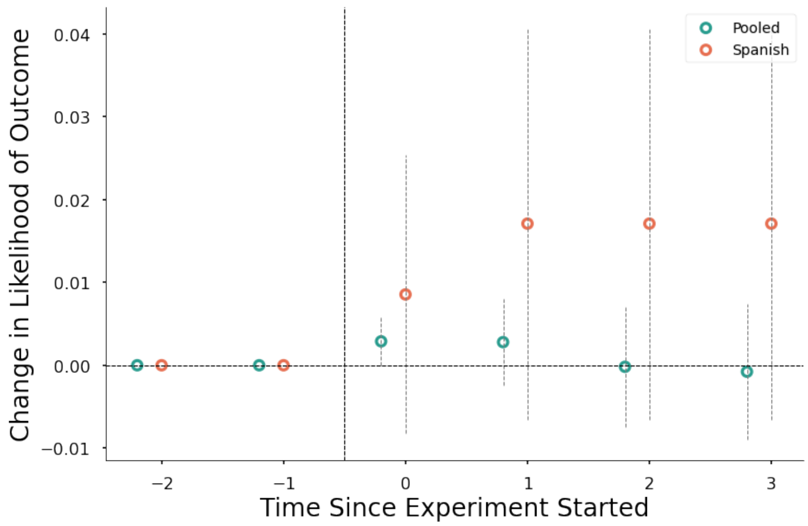
(b) Prior Enrollees



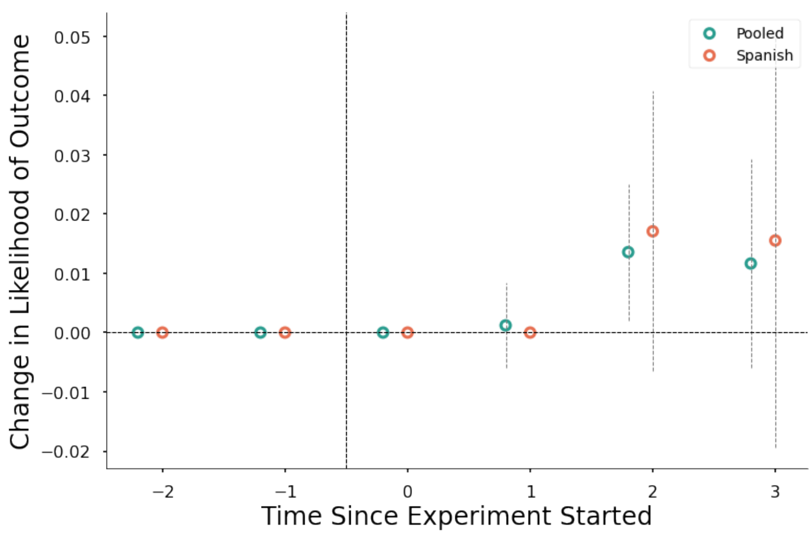
Note: The figure presents the raw share of individuals enrolled in SNAP by treatment groups and prior enrollee status across the study period. Groups 1–4 are the treatment groups, and groups 5 and 6 are the controls. The reported value of "N" represents the number of unique individuals in each group rather than the number of individual–month observations. The letters "T" and "C" indicate whether the groups are treatment or controls. Enrollee status is determined in the month prior to the start of the intervention.

Appendix Figure D.8: Event Study: Reason for Disenrollment (Stigma vs. Confusion)

(a) Withdrew from SNAP



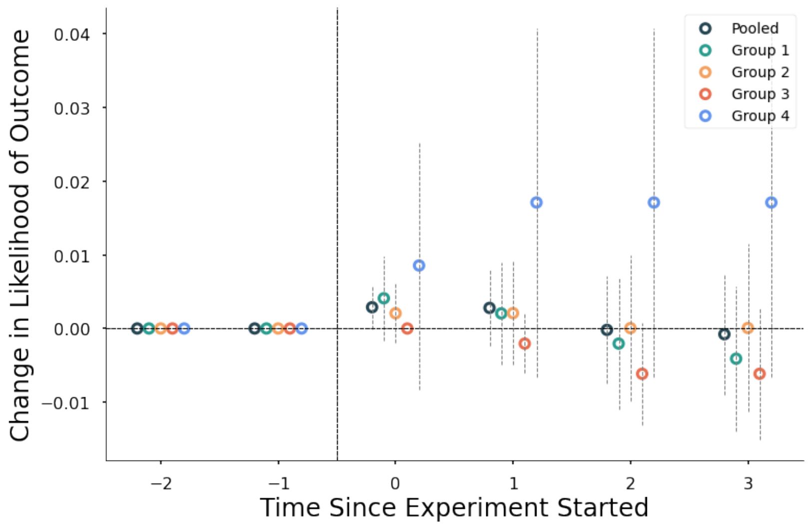
(b) Lapse Followed by Re-Enrollment



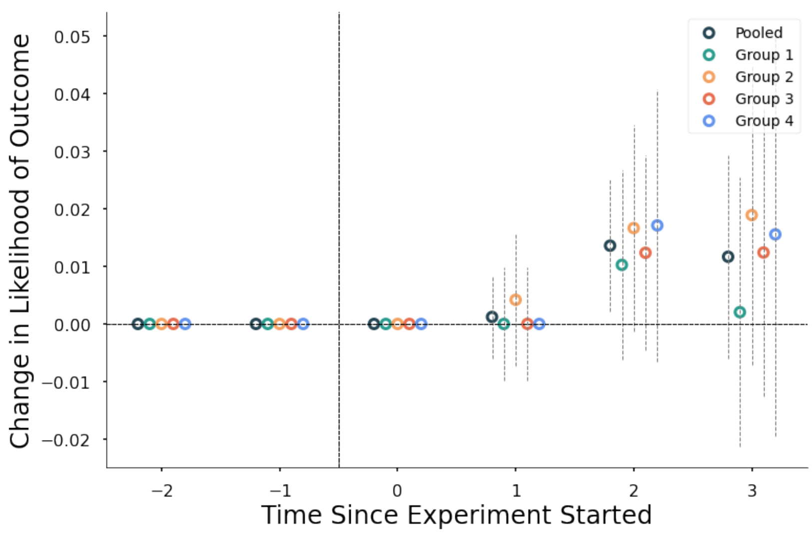
Note: The figure presents the coefficients obtained from estimating Equation 2 for the withdrawal and re-enrollment outcomes among prior enrollees, separately for the pooled and Spanish groups. It illustrates the temporal evolution of these outcomes relative to control groups, with a reference period at $t = -1$. Panel (a) presents the event-study estimates for changes in the likelihood of SNAP withdrawal among prior enrollees (in the given intervention month), while panel (b) presents estimates for the likelihood of re-enrollment among individuals who were previously enrolled in SNAP. 95% confidence intervals are provided.

Appendix Figure D.9: Event Study: Reason for Disenrollment

(a) Withdrew from SNAP



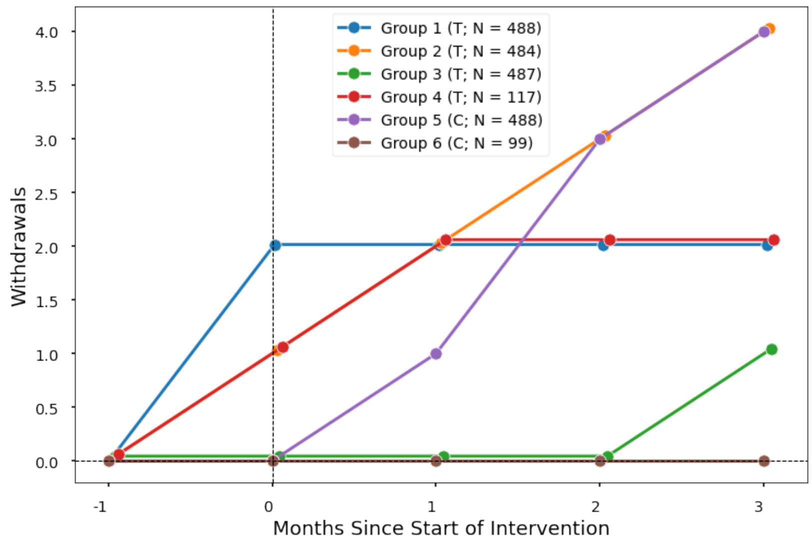
(b) Lapse Followed by Re-Enrollment



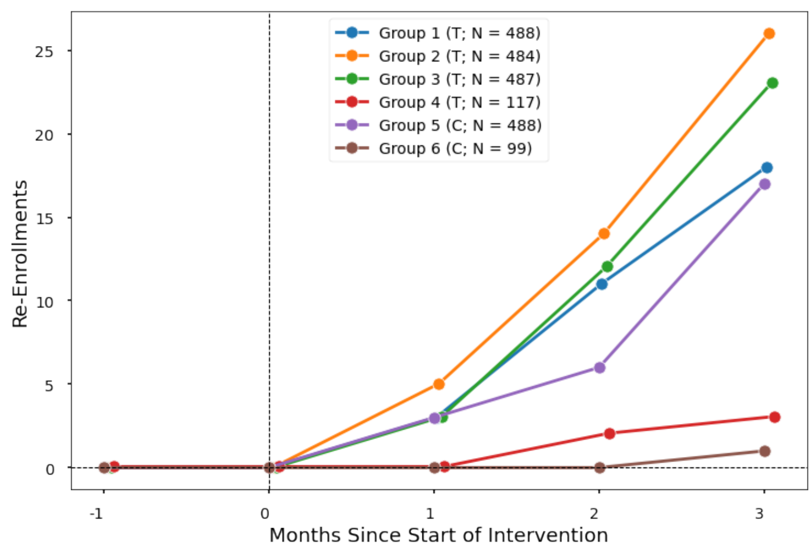
Note: The figure presents the coefficients obtained from estimating Equation 2 for the withdrawal and re-enrollment outcomes among prior enrollees, separately for the pooled and Spanish groups. It illustrates the temporal evolution of these outcomes by prior enrollment status of the pooled sample and Groups 1–4 (see Figure 1), separately, relative to control groups, with a reference period at $t = -1$. Panel (a) presents the event-study estimates for changes in the likelihood of SNAP withdrawal among prior enrollees (in the given intervention month), while panel (b) presents estimates for the likelihood of re-enrollment among individuals who were previously enrolled in SNAP. 95% confidence intervals are provided.

Appendix Figure D.10: Raw Trends: Withdrawals and Re-Enrollments by Treatment Group Among Prior Non-Enrollees

(a) Withdrawals



(b) Re-Enrollments



Note: The figure separately plots the raw number of individuals withdrawing and re-enrolling among prior SNAP enrollees by treatment groups across the study period. Groups 1–4 are the treatment groups, and groups 5 and 6 are the controls. The reported value of "N" represents the number of unique prior enrollees in each treatment group rather than the number of individual–month observations. The letters "T" and "C" indicate whether the groups are treatment or controls. Enrollee status is determined in the month prior to the start of the intervention.

Appendix Table D.1: Static Effect of Treatment on SNAP Participation Outcomes

Outcome	Estimate	Standard Error	N
A: Overall Effect			
(i) Take-Up	-0.0024	0.0026	99060
(ii) Take-Up (Prior Non-Enroll.)	-0.0003	0.002	86082
(iii) Disenrollment (Prior Enroll.)	0.0170	0.0140	12978
(iv) Withdrawal (Prior Enroll.)	0.0012	0.0026	12978
(v) Re-Enroll (Prior Enroll.)	0.0066+	0.0039	12978
B: Effect on English Speakers			
(ii) Take-Up	-0.0028	0.0029	85320
(ii) Take-Up (Prior Non-Enroll.)	-0.0012	0.0023	73638
(iii) Disenrollment (Prior Enroll.)	0.0134	0.0148	11682
(iv) Withdrawal (Prior Enroll.)	0.0007	0.0021	11682
(v) Re-Enroll (Prior Enroll.)	0.0064	0.0044	11682
C: Effect on Spanish Speakers			
(i) Take-Up	-0.0006	0.0070	13740
(ii) Take-Up (Prior Non-Enroll.)	0.0036	0.0060	12444
(iii) Disenrollment (Prior Enroll.)	0.0422	0.0420	1296
(iv) Withdrawal (Prior Enroll.)	0.0149	0.0106	1296
(v) Re-Enroll (Prior Enroll.)	0.0082	0.0068	1296

Note: The table show the estimates of Equation 1 for various SNAP enrollment outcomes. Panels A, B, and C show results for the full sample, the English-speaking groups, and the Spanish-speaking group, respectively. Rows (i)–(v) report the estimates for take-up, take-up among the previously unenrolled, disenrollment among the previously enrolled (the inverse of take-up), enrollee-initiated withdrawals (a subset of disenrollment), and re-enrollments among the previously enrolled. The sample size includes multiple snapshots for the same individual across sequential data waves, explaining the difference in sample sizes between this table and Table 1. A plus sign (+) indicates statistical significance at the 0.10 level.

Appendix Table D.2: Reasons for SNAP Disenrollment by Experimental Group

Group	Reason Category	Count
1	Documentation, Verification, and Recertification Non-Compliance	30
1	Eligibility Criteria	9
1	Enrollee-Initiated Withdrawals	2
1	None Provided	1
2	Documentation, Verification, and Recertification Non-Compliance	41
2	Eligibility Criteria	8
2	Other	2
2	Enrollee-Initiated Withdrawals	2
3	Documentation, Verification, and Recertification Non-Compliance	32
3	Eligibility Criteria	7
3	None Provided	3
3	Other	1
4	Documentation, Verification, and Recertification Non-Compliance	7
4	Eligibility Criteria	2
4	Other	2
4	Enrollee-Initiated Withdrawals	2
4	None Provided	1
5	Documentation, Verification, and Recertification Non-Compliance	30
5	Eligibility Criteria	5
5	Other	1
5	Enrollee-Initiated Withdrawals	1
6	Documentation, Verification, and Recertification Non-Compliance	2
6	Eligibility Criteria	1

Note: The table lists the reasons for disenrollment by experimental group, including only those that occurred after the first intervention month ($t = 1$). Groups 1–3 represent the English-speaking treatment groups, Group 4 represents the Spanish-speaking treatment group, Group 5 the English-speaking control group, and Group 6 the Spanish-speaking control group. Disenrollment due to missing or incomplete documentation—such as the Semi-Annual Report (SAR 7), SAR 22 Form, CalWORKs Redetermination, or failure to provide required verification (e.g., age, income, identity, property)—–is categorized under "Documentation, Verification, and Recertification Non-Compliance." "Eligibility Criteria" covers cases such as exceeding income/resource limits, residency issues, college student ineligibility, inter-county transfers, or failure to complete employment services. "Enrollee-Initiated Withdrawals" includes any voluntary exits from the program, either verbal or written. All other reasons fall under "Other." Notably, all disenrollment reasons are due to actions taken by enrollees, not the county.