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DOCTORS' AND NURSES' SOCIAL MEDIA ADS REDUCED HOLIDAY TRAVEL AND COVID-19 INFECTIONS: A CLUSTER RANDOMIZED CONTROLLED TRIAL

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We thank the health team at Facebook for their in-kind financial support that allowed us to run the campaign, and for their logistical help. Facebook provided the ad credits used to show the ads and connected the research team with AdGlow, the marketing partner. The ad content went through the usual internal policy review at Facebook for compliance with policies. Facebook had no other role in the design or conduct of the trial, and no role in the interpretation of the data or preparation of the manuscript. In particular, we thank Nisha Deolalikar. We also thank advisors Drew Bernard and Sarah Francis. We thank the team at AdGlow, in particular Camille Orellano and Lauren Novak, for running the campaign. We thank Alex Pompe from Facebook Data for Good for helping us to understand the Facebook mobility data. We thank the team at Damage Control, in particular Pradip Saha, for their tireless work in editing the videos. We thank Nikhil Shankar and

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Doctors' and Nurses' Social Media Ads Reduced Holiday Travel and COVID-19 Infections: A Cluster Randomized Controlled Trial

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ABSTRACT

During the COVID-19 epidemic, many health professionals started using mass communication on social media to relay critical information and persuade individuals to adopt preventative health behaviors. Our group of clinicians and nurses developed and recorded short video messages to encourage viewers to stay home for the Thanksgiving and Christmas Holidays. We then conducted a two-stage clustered randomized controlled trial in 820 counties (covering 13 States) in the United States of a large-scale Facebook ad campaign disseminating these messages. In the first level of randomization, we randomly divided the counties into two groups: high intensity and low intensity. In the second level, we randomly assigned zip codes to either treatment or control such that 75% of zip codes in high intensity counties received the treatment, while 25% of zip codes in low intensity counties received the treatment. In each treated zip code, we sent the ad to as many Facebook subscribers as possible (11,954,109 users received at least one ad at Thanksgiving and 23,302,290 users received at least one ad at Christmas). The first primary outcome was aggregate holiday travel, measured using mobile phone location data, available at the county level: we find that average distance travelled in high-intensity counties changed by -0.993 percentage points (95% CI -1.616, -0.371, p-value 0.002) the three days before each holiday. The second primary outcome was COVID-19 infection at the zip-code level: COVID-19 infections recorded in the two-week period starting five days post-holiday declined by 3.5 percent (adjusted 95% CI [-6.2 percent, -0.7 percent], p-value 0.013) in intervention zip codes compared to control zip codes.

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A supplemental appendix is available at: http://www.nber.org/data-appendix/w29021

INTRODUCTION

Nurses and physicians are among the most trusted experts in the United States (1,2,3). Beyond the individual relationship with their patients, can these health professionals influence behavior at scale by spreading public health messages using social media?

During the COVID-19 crisis many healthcare professionals used social media to spread public health messages (3). For example, the Kaiser Family Foundation has sponsored a large project where doctors have recorded video to provide explanation about COVID-19 vaccination and dispel doubts (1). Since individual adoption of preventative behavior, from mask wearing and staying at home to vaccination, is key to the control of this and future pandemics, it is very important to know whether this communication is effective.

In previous work, we have shown, in online experiments, that video messages, recorded by a diverse group of doctors, affect the knowledge and behaviors of individuals and, and that these effects seem to be strong regardless of race, education, or political leanings (4,5). But there is no systematic evaluation of similar messages when distributed as part of large-scale public health campaigns. Furthermore, given the large sample required, it has not been possible so far to test the impact of such public health campaigns on COVID-19 infection, so the clinical significance of those finding was unclear.

In this study, we sought to estimate whether short video messages recorded by nurses and doctors, and sent on a massive scale as part of a social media ad campaign could impact behavior and COVID-19 infections at the zip code (cluster) level.

In November 2020, the number of COVID-19 cases was rapidly increasing in the United States. Due to concerns that holiday travel would lead to a surge in the epidemic, the Centers for Disease Control and Prevention (CDC) recommended that people stay home for the holidays.

In this context, we ran two large clustered randomized controlled trials with Facebook users. Before Thanksgiving and Christmas, physicians and nurses (all co-authors of this project) recorded twenty-second videos on their smart phones to encourage viewers to stay home for the holidays. Facebook subscribers in randomly selected zip codes in 820 counties in 13 states received these videos as sponsored content (ads). Over 11 million people received at least one ad before Thanksgiving (35% of users in the targeted regions), and over 23 million did before Christmas (66% of users in targeted regions).

The purpose of this study was to identify whether these short videos would influence population level holiday travel in the targeted regions, and in turn a decline in COVID-19 cases after the holidays.

METHODS

Trial Oversight

The design was approved by the institutional review board of the Massachusetts Institute of Technology (MIT) with Massachusetts General Hospital (MGH), Yale and Harvard ceding authority to MIT IRB. Messages were produced by the research team and approved to run (without modification) after going through Facebook's internal policy review to ensure compliance with policies.

The IRB protocol and relevant amendments are available on line (along with the data and code). Procedures that apply to this specific project are highlighted. There was no deviation from the original IRB protocol. Further details on the design were registered in a statistical analysis plan and on the clinicaltrials.gov registration. The analysis in this paper only focuses on the primary outcomes registered on ClinicalTrials.gov. There was just one deviation from the pre-registration in clinicaltrials.gov: we initially planned to construct zip code level mobility outcomes from fine-grained data, but, due to privacy concern, that data is not available for this purpose. Since the publicly available mobility data is at the county level, we use only county-level mobility data (which we had always planned to use).

The sample, the specific unit of randomization, the randomization methods and planned analyses were pre-registered prior to the Thanksgiving campaign in a publicly available statistical plan (https://doi.org/10.1257/rct.6821-1.0.). We follow the analysis plan for the primary outcomes outlined on November 25 for both the Christmas campaign and the Thanksgiving campaign in the 13 States, with two deviations. First as noted above, we were not able to obtain zip-level mobility outcome from fine-grained data, so we use only county-level data on mobility. Second, we had not specified a functional form for the number of COVID-19 cases. We specify one below.

In this paper we focus on the direct impacts of the intervention in the thirteen original experimental states on the primary outcomes specified in the ClinicalTrials.gov registration. While the statistical analysis plan also discusses indirect spillover effects, an extension of the campaign in 10 new states three days before Thanksgiving, and various supplementary analyses, these are left for follow-on work.

Intervention

Messages encouraging viewers to stay home for the holidays were recorded on smartphones by six physicians before Thanksgiving, and nine physicians and nurses before Christmas who varied in age, gender, race and ethnicity.

For Thanksgiving, the script of the video was:
"This Thanksgiving, the best way to show your love is to stay home. If you do visit, wear a mask at all times. I'm [Title/ NAME] from [INSTITUTION], and I'm urging you: don't risk spreading COVID. Stay safe, stay home."

A similar script was recorded at Christmas. The videos were then disseminated as sponsored content to Facebook users from a page created for the project. The videos and the Facebook page are available on the project website (https://www.povertyactionlab.org/project/covid19psa). In the Supplementary Appendix, we provide details on the campaign and full scripts.

Trial Design, Eligibility, Randomization and Recruitment

Eligibility for the trial and the cluster randomization strategy were determined by data availability and power considerations. Movement range data computed by Facebook is publicly available at the county-level. COVID-19 level data is available at the zip code level in the states where we conduct this experiment. To make sure we would have adequate power for both the mobility and the COVID-19 outcome with publicly available data, we thus randomized both at county and zip code level to have experimental variation for each level. The CONSORT diagram (Figure 1) describes the factorial design and the allocation of clusters to each arm.

Before the Thanksgiving campaign, we selected 13 states where weekly COVID-19 case-counts data were available at the zip code level (see maps in Figure S1a and S1b) and selected counties within these states where this data was available.

The research team randomly allocated counties to be "high-intensity" (H) or "low-intensity" (L) with probability ½ each. In H counties, the research team randomized zip codes into intervention with probability ¾ and control with probability ¼. In L counties, zip codes were randomized into intervention with probability ¼ and control with probability ¾. Randomization was performed with Stata prior to each of the two interventions.

The lists of zip codes for each intervention were then provided to our marketing partner AdGlow, who managed the advertising campaigns on Facebook. Within the treated zip codes, AdGlow ran ads to allocate the sponsored video content to users, aiming to reach the largest number of people given the advertising budget (see Supplement 1, Section A for further details about Facebook ad campaigns). The video messages were pushed directly into users' Facebook feeds (three to five times per user on average), and users were then free to either watch, share, react to, or entirely ignore the content. The intervention was targeted to the cluster. We did not recruit individuals for the study and do not use individual level data. At Thanksgiving, 30,780,409 videos were pushed to 11,954,109 users between November 14 and November 29, and at Christmas, 80,773,006 videos were sent to 23,302,290 users between December 17 and December 31.

AdGlow provided us with overall engagement figures: Each time a user had an opportunity to view a campaign message, 12.3% watched at least 3 seconds of the video at Thanksgiving and 12.9% at Christmas, while 1.7% watched at least 15 seconds at Thanksgiving and 1.4% at Christmas. Our engagement rates of 12-13% (measured as the total of clicks, 3-second views, shares, likes, and comments divided by total impressions) were well above industry standard benchmarks for Facebook ads, 1%-2%, and Facebook video posts, 6% (14, 15).

We determined that a sample of 820 counties would provide 80% power to detect effect sizes of 0.2 standard deviations for county-level outcomes, comparing intervention (H) vs. control (L), using only average county-level data. For outcomes with zip code level data, using intra-class correlations of 0.2 (0.475) assuming clusters of equal size, a sample of 6,998 zip codes would provide 80% power to detect effect sizes of 0.057 (0.072) standard deviations (using zip code level data).

Outcomes

Our primary outcomes are county level mobility and zip code level COVID-19 infections reported to state health authorities, which we regularly retrieved from state websites beginning on November 12, 2020 (a list of the websites is provided in Supplement 1, Section B).

The movement range data are produced by aggregating location information obtained from mobile devices of Facebook users that opted to share their precise information with Facebook, and adding some noise for privacy protection (6,7) (see Supplement 1, Section B for further details). We use mobility data from 14 November 2020 to 31 December 2020.
The *change in movement metric* is the percentage change in distance covered in a day compared to the same day of the week in the benchmark period of February 2-29, 2020. The mobility data describes the behavior throughout the day, for people who were in each county *that morning*. Since the campaign was targeted based on home location, we can only capture its impact on travel *away* from home, not back home. Thus, we define holiday travel as travel during the three days preceding each holiday. The *stay put metric* is the share of people who stay within a small geographical area (a "bing tile" of 600m*600m) in which they started the day. We used it to compute the *leave home* variable as = 1-*stay put* on the day of the holiday (Thanksgiving Day, Christmas Eve, and Christmas Day).

The second primary outcome we study is the number of new COVID-19 cases per fortnight, calculated from the cumulative case counts we manually retrieved from county or state webpages, one or twice a week and cleaned. Our primary outcome is the number of new

COVID-19 cases detected in each zip code during fortnight that starts five days after each holiday: given the incubation period of five days, this is the one two-week period where we should see an impact. We use COVID-19 infection data collected from November 13 to February 11.

Statistical Analysis

The analysis was performed by original assigned group (intention to treat), following equations 1 and 2 in the statistical plan.

- Effect on Mobility (County-level)

At the county level, the analysis compares the "high-intensity" counties to the "low-intensity" counties. Because, on average, only 75% of the zip codes in high-intensity counties received the intervention, and 25% in low-intensity counties received the intervention, this is "an intention to treat" specification which is a lower bound of the effect of treatment.

For any day or set of days, the coefficient of interest is β_1 in the OLS regression:

$$y_{it} = \beta_0 + \beta_1 High_i + \beta_2 y_{i0} + \boldsymbol{X_i}\beta_3 + \varepsilon it \ (1)$$

where y_{it} is the outcome of interest on day t, and y_{i0} its baseline value. This regression is estimated for both campaigns together, and for each separately. Standard errors are adjusted for heteroskedasticity, and clustering at zip code levels when both campaigns are pooled (we also provide randomization inference p-values) (8). As pre-specified in the analysis plan, in the supplementary appendix, we present a regression controlling for state fixed effects and a set of county level outcomes chosen via machine learning (9) as well as quantile regressions.

- Effect on Number of COVID-19 Cases (Zip Code-level)

To measure the effect on COVID-19 cases reported in each zip code, we run the regression:

$\text{Asinh}(fortnightly\ COVID_{it}) = \beta_0 + \beta_1 Treated_i + \beta_2 \log(cumulative\ COVID_{i0}) + \boldsymbol{\beta_3^T stratum_i} + \varepsilon it$ (2),

Where $fortnightly\ COVID_{it}$ is the number of new cases of COVID-19 detected in the fortnight beginning five days after each holiday (for primary outcome results), $Treated_i$ is a dummy that indicates that zip code *i* was a treated zip code. The hyperbolic sine transformation is appropriate when the data is approximately lognormal for higher values, but a small number of observations have zero cases (10,11) (also see Supplement 1, Section C). The coefficient of "Treated" can be interpreted as a proportional change. In the supplementary appendix we explore robustness to other commonly used ways to handle zeros. We also investigate robustness by estimating the same regression for other fortnights.

Regression (2) is estimated for both campaigns pooled, and for the Thanksgiving campaign and the Christmas campaign separately, with county fixed effects (the randomization strata). Standard errors adjust for heteroskedasticity and clustering and we compute p-values with randomization inference. We estimate the impact of treatment overall, and separately in the two strata (high- and low-intensity counties).

In supplementary material, we also explore heterogeneity of effects by prior COVID-19 circulation and demographic variables, and present quantile regressions. Analyses were performed using R, version 4.0.3, including the following packages (versions): *stats* (4.0.3), *tidyverse* (1.3.0), *estimatr* (0.28.0), *readr* (1.4.0), *dplyr* (1.0.5), *lubridate* (1.7.10), *hdm* (0.3.1), *car* (3.0.10), *MASS* (7.3.53), sandwich (3.0.0), foreign (0.8.80), readstata13 (0.9.2), readxl (1.3.1), quantreg (5.75). The data and all the statistical codes will be made available upon publication.

Role of the Funding Source

Facebook provided the ad credits used to show the ads and connected the research team with AdGlow, the marketing partner. The ad content went through the usual internal policy review at Facebook for compliance with policies. Facebook had no other role in the design or conduct of the trial, and no role in the interpretation of the data or preparation of the manuscript.

RESULTS

Trial Population

Of the 8,671 potentially eligible zip codes in the 13 states in the studies, 1,554 were removed before the Thanksgiving campaign because of missing COVID-19 infection data, and 119 were removed because they could not be matched to county-level census data, yielding a sample of 6998 zip codes in 820 counties. Prior to the Christmas campaign, 60 fully rural counties in the top tercile of votes for Donald Trump in the 2020 election were removed from the study. This was done out of caution and to avoid adverse effects. The research team was concerned that the messaging campaign might have adverse unintended effects in very rural, heavily Republican-leaning counties given the growing polarization in December. The remaining sample had 767 counties. We included in the campaign all zip codes in the intervention in the selected counties (even if they could not be matched to COVID-19 infection data). For the COVID-19 outcomes, we have a final sample of 6716 zip codes. The realized sample size of 820 counties at Thanksgiving and 767 counties at Christmas was close enough to the original sample size to not lead to significant loss in power.

Summary statistics on the sample that was randomized are shown in Table 1 (Figures S1a and S1b in the supplementary appendix shows their localization on the map). Counties had on average 36% Democrats, 62% Republicans (based on election share in 2020) and 46% of zip codes were classified as urban. On November 13, 2020, distance travelled was 8.73% lower than during the benchmark month of February 2020; In the Christmas sample, it was 8.89% lower. In both samples, 82.4% of people left home on November 13, 2020.

Effects of the Campaign on the Mobility of Facebook users

Figure 2 shows day-by-day regressions estimates of equation (1). Distance travelled away from the morning location declined a few days before each holiday in high-intensity counties, relative to low-intensity counties.

Table 2 shows that, pooling both campaigns together, distance travelled three days before each holiday was 4.384 percent lower than in February 2020 in high-intensity counties, and 3.597 percent lower in low-intensity counties. The adjusted difference was 0.993 percentage points (95% CI -1.616, -0.371, p. value 0.002). The effects were very similar at Thanksgiving (adjusted difference: -0.924 percentage point, 95% CI (-1.785, -0.063, p. value 0.035) and Christmas (adjusted difference: -1.041 percentage point 95% CI -1.847, -0.235, p value 0.011).

The intervention had no impact on the share of people leaving home on the day of the holiday (Table 2 and supplementary appendix Figure S2). On average, 72.33% of people left their home tile on the day of the holiday in high-intensity counties, and 72.39% in low-intensity counties (adjusted difference 0.030 95% CI (-0.361, 0.420), p. value 0.881).

Table S4 in the supplement shows that these results are robust to adding control variables chosen by machine learning from a large set of county-level covariates (12). Table S5 show that effects are found at all quantile of the mobility distribution, and are not driven by tail events.

Effect of the Campaign on COVID-19 Cases

Table 3 shows that the campaigns were followed by a drop in COVID-19 cases in treated zip codes, relative to control zip codes, for the two-week period beginning five days after the holiday. The adjusted difference in asinh (covid) was 0.035 (adjusted 95% CI [-0.062, -0.007], p. value 0.013), which can be interpreted as a 3.5% reduction in COVID-19 cases. The effects were slightly smaller in magnitude at Thanksgiving (adjusted difference: -0.027 (adjusted 95% CI [–0.059, +0.005], p. value 0.097) than at Christmas (adjusted difference, -0.042 95% CI [-0.073, -0.012] p. value 0.007). These results are robust to alternative ways to treat zero (Tables S6a, S6b, and S6c in the supplement). The quantile regressions in table S5 shows that the effect are found at all level of the distribution, and are not driven by tail levels (since there are relatively few zeros, only lowest quantiles are affected by the way zero are handled).

To provide evidence that these differences are indeed due to the campaign, and not to any pre-existing difference, Figure 3 show the results of estimating equation (2) for a number 2-weeks periods (omitting the five days following Christmas). There is no significant difference in intervention and comparison zip codes in any period other than the period where we expected an impact. This makes it very unlikely that the difference in COVID-19 cases is due to random chance.

Treatment Effect Heterogeneity

We test for several pre-specified (in the statistical analysis plan) dimensions of heterogeneity of the effect of the campaign on mobility and COVID-19 infection in Tables S2a-b and S3a-g in the supplementary appendix: baseline COVID-19 infection, urban versus rural counties, and majority Republican versus majority Democratic counties.

We found no significant difference in the impact of the campaign either on mobility or COVID-19 cases between Republican and Democratic counties, or between rural and urban counties. We also did not find that the interaction between political leaning and urban designation is significant (Tables S3e and S3f in the supplement). The effects on COVID-19 infections are lower in counties with high infection at baseline.

DISCUSSION

There was widespread concern before the Thanksgiving and Christmas holidays that heavy travel and mixing households would lead to an increase in COVID-19 patients. Indeed, households did travel more around the holidays, though even then mobility remained lower than its February 2020 level.

In counties where a larger proportion of zip codes were randomly assigned to a high-coverage Facebook ad campaigns in which clinicians encouraged people to stay home before the Thanksgiving and Christmas holidays, Facebook users reduced the distance they travelled in the three days before the holidays. They were no more likely to stay put on the day of the holiday. However, the clinical importance of this second finding is unclear, since they could either have been spending time outside or visiting other households.

A potential concern before the campaign was that in a polarized environment, a campaign such as this one could be effective in some communities and backfire in others (this is why we excluded a few counties in the Christmas campaign). But the effects did not seem to depend on county characteristics, including political leanings. These findings accord with previous research that found that individuals are responsive to physician delivered messages, regardless of political affiliation (5).

We found a significant impact on new COVID-19 infections reported by health authorities 5 to 19 days later. These effects might be under-estimated, because the treatment and control zip codes are very close to each other, and the reductions in infection in treatment zip codes might also have led to a decrease in infection in neighboring places.

There are several limitations of the study. First, it is was conducted with Facebook subscribers and mobility is collected for Facebook users. Although Facebook has a remarkable reach, this remains just one type of media. Second, it was an ad campaign. The messages might have been more or less effective if they had been relayed by celebrities or locally known figures, as we have tested in other work (12,13). Third, we tested one kind of message, recorded by clinicians on smartphones. The results could be different changing message content, identity of the messenger, length of message, production value of the videos, or name recognition of the originating organization.

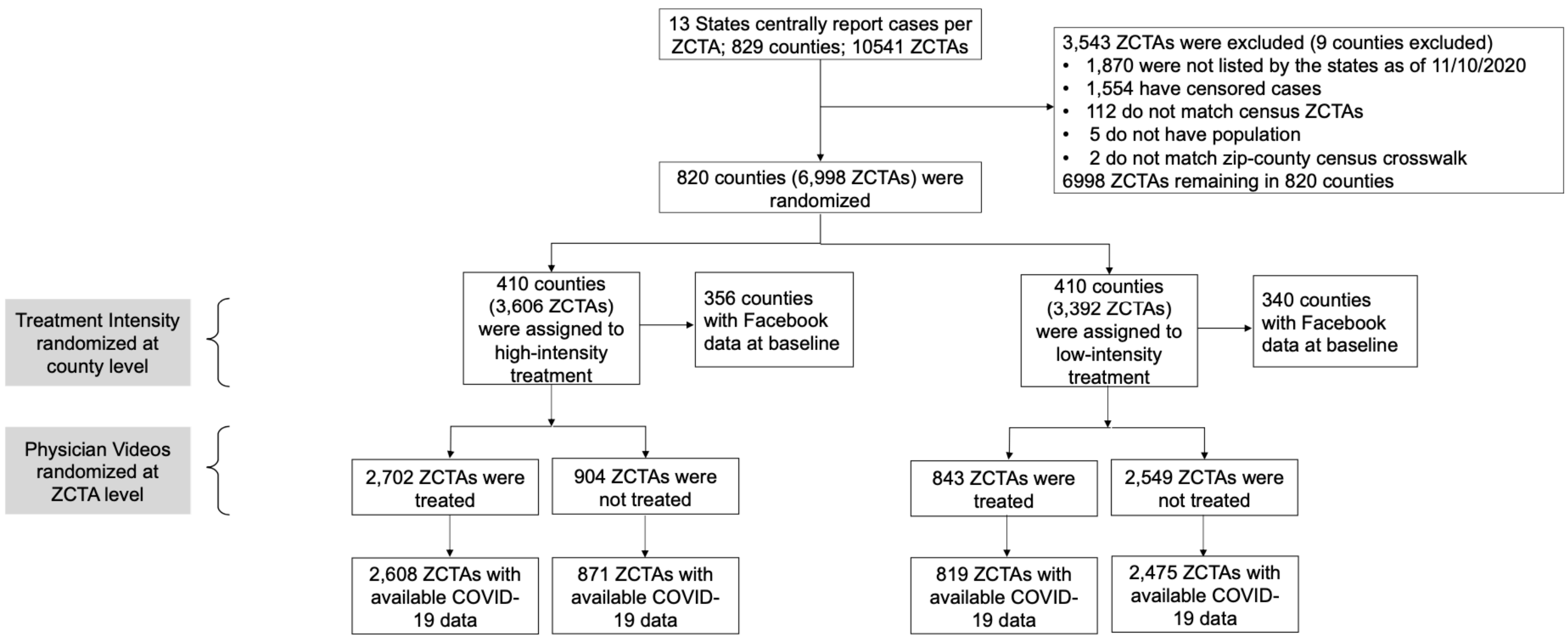
Despite these limitations, the findings provide evidence that clinicians can be an effective channel to communicate life-saving information at scale, through social media. This a new role that physicians and nurses embraced during the COVID-19 crisis, and we demonstrate that this is another way in which they can prevent illness and save lives.

These findings also demonstrate, in a clustered randomized control trial, the impact of a travel reduction, a key non-clinical intervention whose impact had not been evaluated in a randomized controlled trial before.

The findings suggest directions for future work. In particular, would similar messages be effective in encouraging COVID-19 vaccine uptake?

Figure 1. Consort Diagram

PANEL A: Thanksgiving Campaign



PANEL B: Christmas Campaign

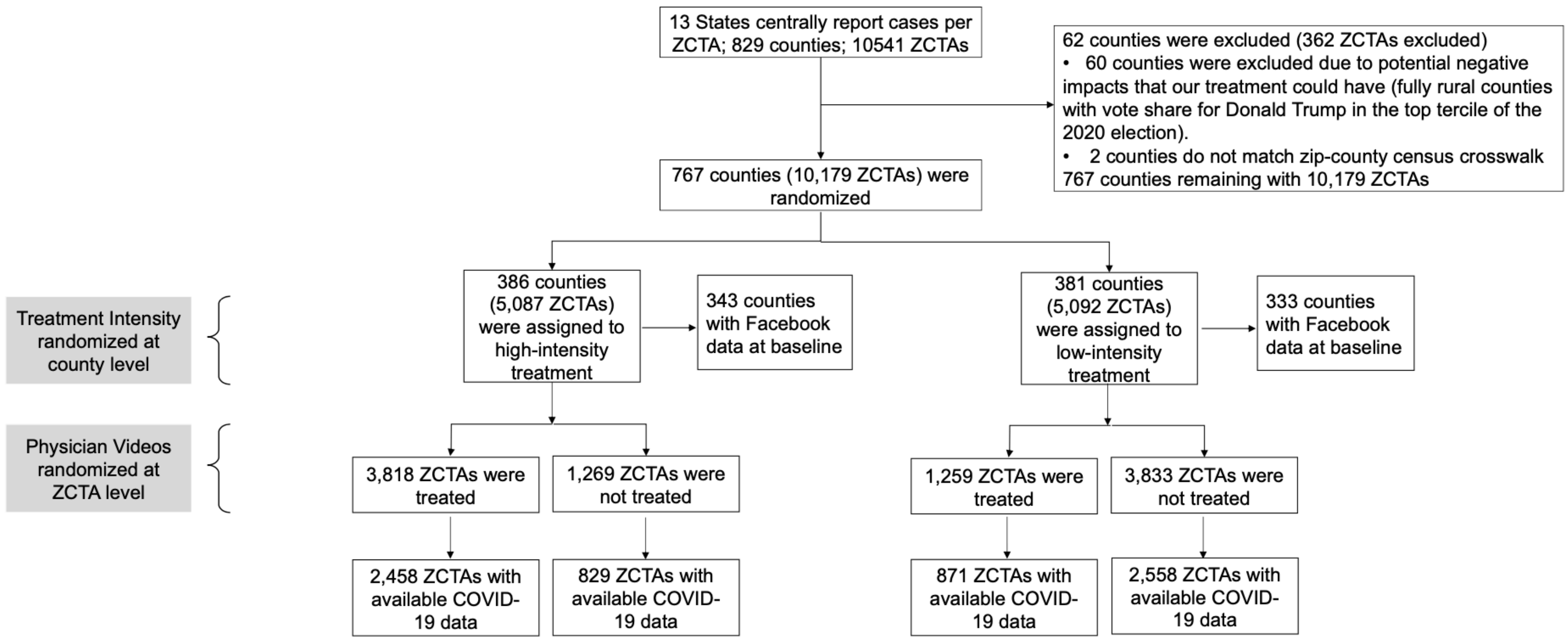
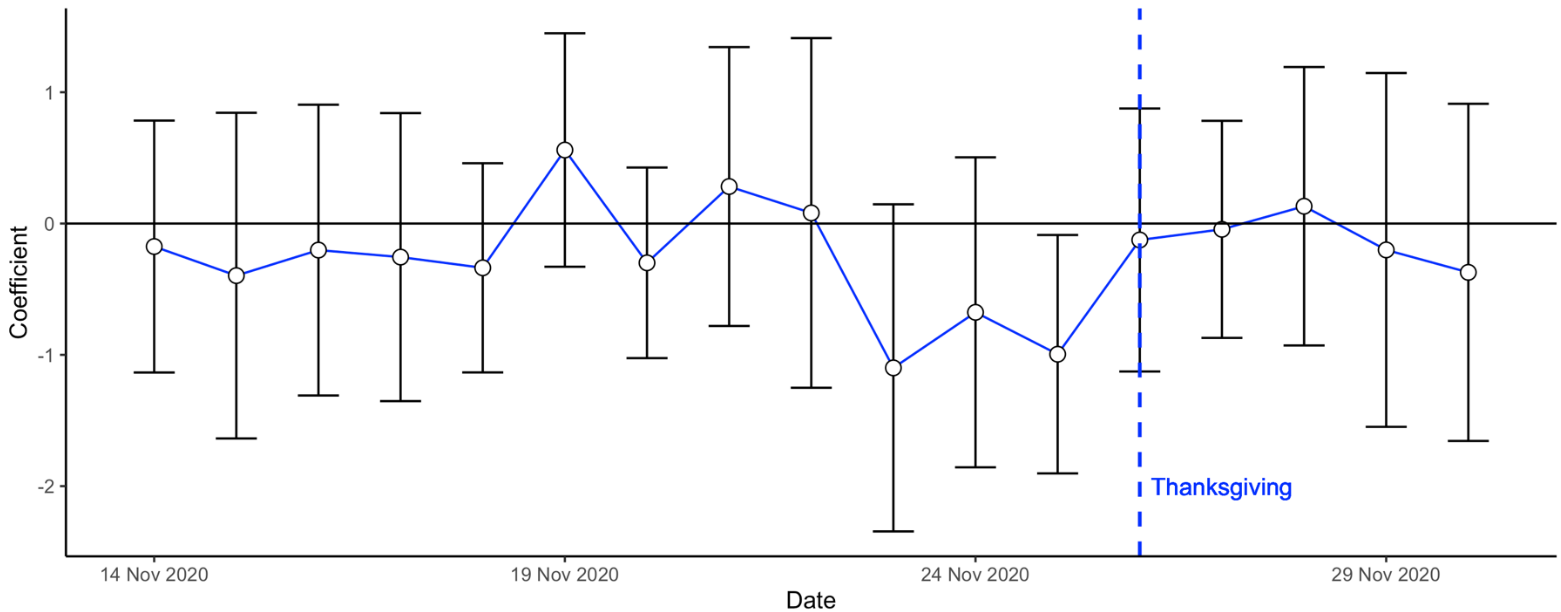
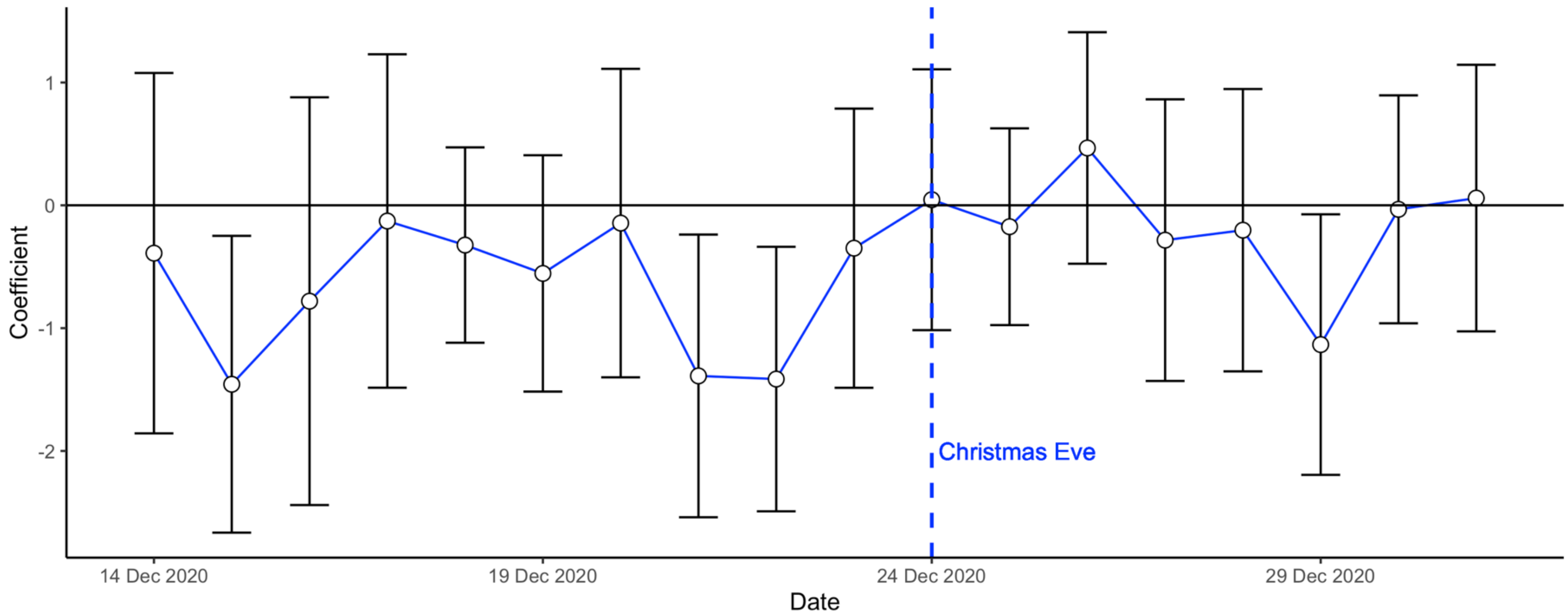


Figure 2. Day-by-day Difference between High and Low Intensity Counties on Distance Traveled relative to February 2020*

PANEL A: Thanksgiving Campaign

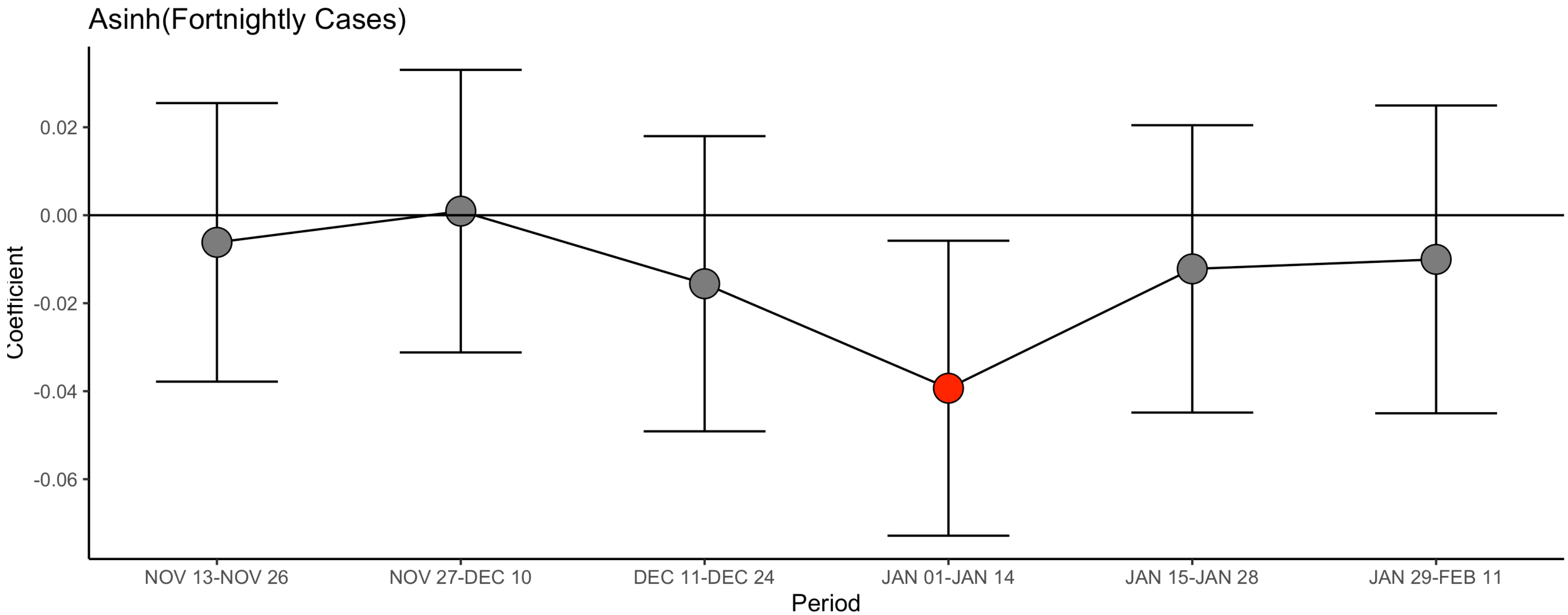


PANEL B: Christmas Campaign



*These figures display a day by day estimation of the regression equation (1). The outcome is the distance traveled relative to February 2020.

Figure 3. Difference between treated and control zip codes (Christmas intervention), for various periods*



*Each dot represents the point estimate of estimating equation (2) for the given period. The whiskers are the 95% confidence intervals

Table 1. Summary Statistics*

PANEL A: Thanksgiving Campaign

	Thanksgiving sample		
	Sample	**High Intensity counties**	**Low Intensity counties**
Number of counties	820	410	410
Movement, mean (sd)			
Baseline Movement Metric	-8.73 (6.77)	-8.58 (7.10)	-8.88 (6.42)
Baseline Leave Home	82.41 (2.47)	82.33 (2.42)	82.49 (2.53)
Missing Baseline Facebook outcomes	0.15 (0.36)	0.13 (0.34)	0.17 (0.38)
Covid-19, mean (sd)			
Baseline Fortnightly Cases	590.30 (2297.94)	683.90 (3032.94)	496.70 (1165.17)
Baseline Fortnightly Deaths	5.07 (17.63)	5.51 (22.35)	4.64 (11.08)
Demographic, mean (sd)			
Share Urban	0.46 (0.34)	0.47 (0.34)	0.44 (0.34)
Share Democrats	0.36 (0.15)	0.36 (0.15)	0.35 (0.15)
Share Republicans	0.62 (0.15)	0.62 (0.16)	0.63 (0.15)
Population in 2019	112654 (317672)	122491 (349501)	102818 (282369)

PANEL B: Christmas Campaign

	Christmas sample		
	Sample	**High Intensity counties**	**Low Intensity counties**
Number of counties	767	386	381
Movement, mean (sd)			
Baseline Movement Metric	-8.89 (6.72)	-8.69 (6.88)	-9.09 (6.56)
Baseline Leave Home	82.42 (2.41)	82.40 (2.43)	82.44 (2.40)
Missing Baseline Facebook outcomes	0.12 (0.32)	0.11 (0.32)	0.13 (0.33)
Covid-19, mean (sd)			
Baseline Fortnightly Cases	626.84 (2371.71)	654.77 (3067.53)	598.54 (1343.02)
Baseline Fortnightly Deaths	5.38 (18.19)	5.70 (23.07)	5.07 (11.29)
Demographic, mean (sd)			
Share Urban	0.49 (0.33)	0.48 (0.33)	0.50 (0.33)
Share Democrats	0.37 (0.15)	0.37 (0.15)	0.37 (0.15)
Share Republicans	0.61 (0.15)	0.61 (0.15)	0.61 (0.15)
Population in 2019	119811 (327266)	116787 (344511)	122875 (309239)

*These tables present summary statistics on baseline variables, for both Thanksgiving and Christmas samples. Baseline = Nov 13.

Table 2. Effect of Treatment on Movement Outcomes*

			Mean (95% CI)		OLS model			Number of days*counties
Campaign	**Outcome**	**Period**	**High county**	**Low county**	**High county (95% CI)**	**p-value**	**RI p-value**	
Both	**Distance Traveled**	**from d-3 to d-1**	-4.384 (-4.973,-3.796)	-3.603 (-4.254,-2.952)	-0.993 (-1.616,-0.371)	0.002	0.002	4059
	Share Ever Left Home	**Thanksgiving (Nov 26) or Christmas (Dec 24-25)**	72.326 (72.012,72.639)	72.381 (72.092,72.670)	0.030 (-0.361,0.420)	0.881	0.879	2017
Thanksgiving	**Distance Traveled**	**from d-3 to d-1**	-6.082 (-6.822,-5.341)	-5.320 (-6.113,-4.527)	-0.924 (-1.785,-0.063)	0.035	0.030	2072
	Share Ever Left Home	**Thanksgiving (Nov 26)**	71.308 (70.885,71.731)	71.468 (71.071,71.866)	0.012 (-0.438,0.461)	0.959	0.966	689
Christmas	**Distance Traveled**	**from d-3 to d-1**	-2.603 (-3.279,-1.927)	-1.823 (-2.588,-1.057)	-1.041 (-1.847,-0.235)	0.011	0.012	1987
	Share Ever Left Home	**Christmas (Dec 24-25)**	72.859 (72.507,73.210)	72.852 (72.520,73.185)	0.095 (-0.289,0.479)	0.629	0.661	1328

*This table provides the control and treatment means at the county level and different periods, in addition to the estimate of the treatment coefficient in equation (1). Standard errors are clustered at the county level. 95% CI are reported in parentheses. P-values based on a 2-sided test. RI p values are computed using randomization inference, accounting for the two-stage design.

Table 3. Treatment Effect on COVID-19 Cases at Zip Code Level*

				Mean (CI 95%)		OLS model			Number of zip codes
Campaign	**Outcome**	**Period**	**County treatment**	**Treatment**	**Control**	**Treatment (CI 95%)**	**p-value**	**RI p-value**	
Both	**Asinh(Fortnightly Cases)**	**Dec/Jan 1-14**	**All**	4.350 (4.302,4.398)	4.370 (4.323,4.417)	-0.035 (-0.062,-0.007)	0.013	0.009	13489
			Low Intensity	4.359 (4.273,4.445)	4.358 (4.305,4.411)	-0.032 (-0.067,0.004)	0.080	0.097	6723
			High Intensity	4.347 (4.295,4.399)	4.407 (4.325,4.489)	-0.039 (-0.075,-0.003)	0.033	0.038	6766
Thanksgiving	**Asinh(Fortnightly Cases)**	**Dec 1-14**	**All**	4.333 (4.278,4.388)	4.298 (4.243,4.353)	-0.027 (-0.059,0.005)	0.097	0.108	6773
			Low Intensity	4.284 (4.170,4.399)	4.256 (4.192,4.320)	-0.015 (-0.063,0.033)	0.535	0.498	3294
			High Intensity	4.348 (4.285,4.411)	4.418 (4.313,4.523)	-0.039 (-0.082,0.004)	0.078	0.096	3479
Christmas	**Asinh(Fortnightly Cases)**	**Jan 1-14**	**All**	4.368 (4.310,4.425)	4.442 (4.385,4.499)	-0.042 (-0.073,-0.012)	0.007	0.010	6716
			Low Intensity	4.429 (4.312,4.547)	4.456 (4.391,4.522)	-0.048 (-0.091,-0.006)	0.025	0.043	3429
			High Intensity	4.346 (4.280,4.412)	4.396 (4.281,4.510)	-0.036 (-0.080,0.008)	0.108	0.111	3287

*This table provides the control and treatment means at the zip code level, in addition to the estimate of the treatment coefficient in equation (2). The outcome is the inverse hyperbolic sine of the fortnightly cases, during a period which starts five to seven days after the event (Thanksgiving or Christmas). 95% CI are reported in parentheses. Standard errors are clustered at the zip level. P-values based on a two-sided test. RI p-values are computed by randomization inference, accounting for the two-stage design.

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