Supplementary Information for
Nudging Preventive Behaviors in COVID-19 Crisis: A Large Scale RCT using Smartphone Advertising

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Supplementary text.

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For detail, refer to our discussion paper (DP, *S1*).

Experiment Design

Outcomes: measure of prevention behaviors are “Go-out”, which the minutes spent outside of the 1 km radius of the estimated home location (after 5pm for weekdays), “Eat-out”, which is total count of records inside buildings contains bars and restaurants during each period, and “Indoor leisure”, which is total count of records inside pre-specified buildings (see below), during each period. Messages (C05) and (C06) were not assigned in weekends because these messages are for commuters.

Intervention: Interventions are differentiated in the sense of (i) timing (weekdays morning, weekdays noon, weekdays evening, weekends mornings) and (ii) message. Users are assigned to one of four timings in each treatment (message) arm.

Measurement of Eat-out and Indoor leisure

A visit is considered to be a visit if the location log is recorded for more than 10 minutes within a radius of a building that covers a pre-registered point-of-interests (POIs).
The list of POIs for Eat-out consists of the 79392 restaurants covering the following 21 categories: 'burger', 'cafe','sweets', 'izakaya','udon', 'curry', 'ramen', 'kaitenzushi','tenpura', 'gyudon', 'okonomiyaki', 'soba', 'yakiniku', 'famires','gyutan','korean' ,'pizza', 'syabusyabu','fugu','tonkatsu','buffet'.
The list of POIs for Indoor leisure contains 8856 stores from the four categories; 'pachinko', 'karaoke', 'gamecenter'(arcade), 'netcafe','theater'.
For more information, refer to (*S2*).

Messages

Messages are created by the authors based on the government announcement. We add the essence of nudge to enhance the effect to only general messages.
(G01) The number of Covid-19 cases is increasing in urban areas. The thought that “It will not happen to me” might be dangerous because such a mindset can jeopardize the life of the people around you.
(G02) There is approximately a 5% mortality risk in Covid-19. Stay away from crowds to reduce the risk of infection.
(G03) The second wave of Covid-19 could lead to the worst unemployment rate since the World War II. Protect yourself from infection when outdoors.
(G04) Let us get through this together. The percentage of people that continue to self-quarantine account for 70% of the total population
(C05: non-nudge) Staying from crowded trains can reduce your infection risk
(C06: non-nudge) There is a surge in the number of Covid-19 cases downtown.
C05 and C05 were not sent on weekends.

Data

The data are obtained from the servers for online display advertising. The data is grouped by four; (i) users’ characteristics, (ii) outcome variables, (iii) message reception, and (iv) treatment assignment. Users characteristics includes OS and the number of location

history before the experiment period. We also use outcome variables in the pre-experiment period as characteristics variables. Outcome variables used in the experiment are three; go-out at night, go-out, visits to restaurants and bars, and visits to indoor leisure facilities.
For go-out time we measure the minutes spent outside of the 1 km radius of the estimated home location during each period. Due to the errors the location records are sometimes mis-recorded. To get robust result we truncate too long go-out time at 7200 minutes for weekday, and 5760 for weekends.
For visits to restaurant and bars (Eat-out), we count location records inside pre-determined radius of restaurants and bars in all over Japan. Since more than one restaurants and bars are often located in the same building, we conceivably count multiple time for one visit. To deal with this, we truncate the visit count at 5 each day.
The same is done for indoor leisure facilities. Indoor leisure facilities include pachinko parlors (sort of a casino in Japan), karaoke boxes, theaters, arcades, and internet cafes, which are major leisure spots for Japanese people.
Message reception is the count of the impressions of users to our advertising. Our advertising is delivered on smartphone Apps through open ad exchange market. Since the ad exchange market run by auction, not all the users are exposed to our advertising.

Complier Average Causal Effect Estimation (CACE)

To estimate the effect of the exposure to each message on users' behavior, we apply the instrumental variable regression with the assignment of intervention as an instrument. The ratio of users who received the message is roughly 8–16% (refer to DP, *S1*). This incompleteness stems from the mechanism of the RTB. Each opportunity to advertise is sold via the auctions, and only the highest bidder wins the ad slot. As a result, pre-determined users are not always exposed to advertising. We use the CACE using instrumental variable (IV) estimation, which is frequently applied in economics and medical sciences to estimate the impact of treatment on compliers. The validity of the instrument is ensured because the assignment is randomly chosen and there is a strong correlation between the instrument and the reception of the message.

The validity of the instrument is ensured since the assignment is randomly chosen and the correlation between instrument and reception of message is strong. In particular, F statistics in the first stage exceeds 10.

In this paper we use the change defined as $\Delta y_i = y_i - y_i^{pre}$ where y_i^{pre} is the outcome values in the pre-experiment period and y_i is those in experimental period.

The estimation model is

$$\boldsymbol{\Delta y_i = \alpha + \mathrm{x_i}\beta + D_i\gamma + e_i} \tag{1}$$

for changes between period 1 and pre-experiment, where α is a constant term, $\mathbf{x}$ represents a vector of covariates, and D is a binary variable that takes one when the user i received message. Simple OLS is biased for the model because the reception of message is not random. For example, users who are frequently using mobile devices are more likely to see the messages. Such users may or may not change their behavior a lot. While the reception of the message is not random, the assignment of treatment is randomized. Hence, we use the assignment as an instrument variable. As a result, coefficient γ is the effect of the reception of message on the change. Covariates include the number of location readings, and type of operation system of the device which aims at reducing variance.

The CACE estimates, standard errors are as follows:

Metric	Group	Est. Coefficient	S.E.	t-statistic	p
Weekday					
Indoor Leisure	G01	-0.270	0.361	-0.749	0.2270
	G02	0.003	0.353	0.009	0.4965
	G03	-0.175	0.356	-0.492	0.3115
	G04	-0.094	0.356	-0.263	0.3960
	C05	-0.160	0.375	-0.428	0.3345
	C06	-0.191	0.373	-0.513	0.3040
Eat out	G01	-1.151	0.526	-2.188	0.0145
	G02	-0.804	0.520	-1.545	0.0610
	G03	-0.494	0.523	-0.944	0.1725
	G04	-0.745	0.521	-1.429	0.0765
	C05	0.098	0.553	0.177	0.4300
	C06	0.628	0.548	1.147	0.1255
Go-out	G01	-140.013	80.276	-1.744	0.0405
	G02	-122.837	79.507	-1.545	0.0610
	G03	-100.401	79.619	-1.261	0.1035
	G04	-195.432	80.020	-2.442	0.0075
	C05	20.737	84.376	0.246	0.4030
	C06	-46.489	82.113	-0.566	0.2855
Weekend					
Indoor Leisure	G01	-0.106	0.241	-0.439	0.3305
	G02	-0.421	0.238	-1.770	0.0385
	G03	-0.618	0.240	-2.576	0.0050
	G04	-0.453	0.241	-1.880	0.0300
Eat out	G01	-0.333	0.360	-0.925	0.1775
	G02	-0.472	0.354	-1.332	0.0915
	G03	-0.759	0.357	-2.124	0.0170
	G04	-0.557	0.360	-1.548	0.0610
Go-out	G01	63.232	107.125	0.590	0.2775
	G02	-108.143	105.000	-1.030	0.1515
	G03	-210.967	105.144	-2.006	0.0225
	G04	42.866	106.387	0.403	0.3435

Note that the unit of the estimate for “Go-out” is minutes, and that for “Eat-out” and “Indoor Leisure” is count.

Robustness Check

To check the validity of our CACE results, we conducted a robustness check in various estimation frameworks. The CACE results were consistent with the intent-to-treat (ITT) and CACE estimation, excluding the low frequency message receivers. First, we conduct Intent-To-Treat (ITT) Estimation. ITT is estimated by a simple OLS model, $\Delta y = \alpha + \mathbf{x\beta} + \zeta W + e$, where W represents the assignment of message instead of actual message receipt. The estimate of ζ is the effect of assigning treatment. In other word, the estimate is theoretically equivalent to the mean difference of treatment group and control group while the variance is reduced.

As another robustness check, we eliminate users with 1-4 message receipt and re-run CACE analysis. The effect of message is increasing with the number of impressions. Apparently, the magnitude of the effects of messages are increased. (*S1*) shows very similar to the results shown, which validates the results here.

Subsample Analysis

We also split the sample into subgroups according to their pre-study value and, subsequently, performed the same CACE on each subgroup (see *S1*). We found that the effects of the “Eat-out” and “Indoor Leisure” metrics showed a similar pattern on weekends and weekdays. On weekends, the messages seemed to mostly influence the users who had high activity during the pre-study period; this may show a ceiling effect in which individuals who care about the risk of infection would stay at home on weekends. On weekdays, however, we did not find any effect on individuals with a high pre-study measure. This may be attributed to the inability of the individuals to self-quarantine owing to work or other obligations, which requires most individuals to leave the home on weekdays.

Survey on Willing-To-Accept and Equivalent Monetary Compensation

We conducted a Willing-To-Accept survey for a part of our experiment samples. The questions are shown in Table S3. The survey respondents are sampled from the sample population of the experiment. The respondents are asked to answer the questions online. The summary statistics are shown in (*S1*). We calculate equivalent monetary compensation as follows.
Let X(A) be the coefficient of message receipt in CACE for action A, Y(A) be the averaged minimum monetary compensation for the same action. Then the equivalent monetary compensation for the same impact by nudging M(A) is ;
M(A) = X(A) Y(A)

For example, the impact of G03 on go-out weekend is 52.7minutes per day and the average monetary compensation for giving up going out weekend is 6112 yen. The average minutes for going out in weekends is 395 minutes. Then the equivalent monetary compensation is 52.7/395 * 6112 = 814.3yen.

SI References

S1. D. Moriwaki, S. Harada, J. Schneider, T. Hoshino. Nudging Preventive Behaviors in COVID-19 Crisis: A Large Scale RCT using Smartphone Advertising, *Keio-IES Discussion Paper Series DP2020-021, Institute for Economic Studies, Keio University* (2020).

S2. Kawanaka, T. and Moriwaki, D. "Uplift modelling for Location-Based Advertising", LocalRec '19: Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Location-based Recommendations, Geosocial Networks and GeoadvertisingNovember 2019 Article No.: 10 Pages 1–4.