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

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Institute for Economic Studies, Keio University
2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan
ies-office@adst.keio.ac.jp
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Abstract

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Daisuke Moriwaki
AI Division, CyberAgent, Inc.
Shibuya Scramble Square 22F 2-24-12 Shibuya Shibuya-Ku, Tokyo
moriwaki_daisuke@cyberagent.co.jp

Soichiro Harada
AI Division, CyberAgent, Inc.
Shibuya Scramble Square 22F 2-24-12 Shibuya Shibuya-Ku, Tokyo
soichiro_harada@cyberagent.co.jp

Jiyan Schneider
Faculty of Economics, Keio University
2-15-45, Mita, Minato-ku, Tokyo
jiyan.schneider@gmail.com

Takahiro Hoshino
Faculty of Economics, Keio University
2-15-45, Mita, Minato-ku, Tokyo
hoshino@econ.keio.ac.jp

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Daisuke Moriwaki[1] , Soichiro Harada[1], Jiyan Schneider[2] , and Takahiro Hoshino[2]*

November 8, 2020

[1]AI Lab, CyberAgent, Inc., Shibuya, Shibuya, Tokyo, Japan.

[2]Faculty of Economics, Keio University, Tokyo, Japan / RIKEN Center for Advanced Intelligence Project, Tokyo, Japan.

Abstract: Voluntary preventive behaviors are essential to slow the spread of the coronavirus disease 2019 (Covid-19), and such behaviors can be promoted by nudge messaging. In this context, this study investigated the effectiveness of nudge-based messages in increasing individuals' engagement in preventive behaviors. We employed a large-scale randomized controlled trial involving 0.3 million mobile device users from Tokyo; these users were sent nudge-based messages through display advertising. This approach enabled us to track the GPS-based geolocation history of these users through various apps, in July 2020, when the second wave of Covid-19 hit Japan. Specifically, our study is the first attempt to measure the effect of the nudge intervention effects on the spatial movement behavior of people, by using smartphone's GPS information. The results revealed that the nudge-based messages increased users' avoidance of closed spaces, crowded spaces, and close contact during the weekends (characterized by heightened leisure activities, and hence spatial movements). The most effective messages emphasized financial loss aversion. The delivery cost of messages was less than $0.1/person, and the people who received the messages reduced outdoor activities by approximately 52 minutes/weekend day. Our follow-up survey suggests that the nudge-based messages cost 2.5–6.5 % of the monetary compensation given for stay-at-home compliance, which achieves the same result. These findings have implications for the development of government marketing strategies and effective nudge-based interventions to overcome the current pandemic.

Keywords: Covid-19; Heterogeneity; Loss aversion; Nudge; Treatment effect

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Introduction

The rapid spread of coronavirus disease 2019 (Covid-19) has endangered the global economy. The International Monetary Fund (IMF) has predicted a 4.9% decline in the world economy owing to the pandemic (*1*). To manage both economic and public health, the governments worldwide have been implementing stringent to lenient measures, from the compulsory shutdown of all the non-essential outlets (e.g., China, several European countries, and the United States of America) to very mild responses (Sweden). The measure taken by the Japanese government also lies between these extremes. Although the government did not shutdown the business activities, the general public was urged to avoid the closed spaces, crowded spaces, and close contact (the 3Cs). The national health authorities; the Ministry of Health, Labor, and Welfare (MHLW); and the local governments call for compliance with preventive behaviors by emphasizing the avoidance of 3Cs (*2*). These voluntary preventive behaviors have been effective in regulating the spread of Covid-19 in Japan; the country has recorded fairly low levels of mortality due to Covid-19 (1.17 deaths/0.1 million population, as on September 16, 2020).

Despite these measures, the government has been facing challenges and excessive costs to drive high level of public engagement in these behaviors. After the declaration of emergency in April 2020, the local governments called for voluntary shutdown of all the non-essential facilities, such as restaurants and bars. Some local governments also provided cooperation benefits to the owners of these small- and medium-sized facilities to enhance their compliance. In the case of Tokyo, the size of this fund has reached JPY 10 billion or $10 million. However, there are concerns that the emergency will lull the people into a sense of complacency, which will keep them from proactively engaging in preventive behavior. Besides these concerns, the Japanese government has been facing severe limitations in regard to the fiscal and legal measures. The former is caused by unsustainably high debt and the latter by the non-existence of an appropriate rule for a complete shutdown by the central government. Given these challenges, cost-effective and efficient measures to enhance preventive behaviors of citizens might contribute significantly toward preventing the expected the third wave of the pandemic.

The insights from the behavioral economics and psychology show nudging as a promising method to influence people’s behavior. Nudge is a broad concept defined as “any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives” (*3*).

It is well-known that nudges have been successfully applied by government ministries in various countries (*4–6*).

Recent studies have also found effective nudge interventions in public health. (*7*) gauged the effectiveness of messages on a poster that encourages handwashing and found that nudge-based messages play a more effective role in achieving compliance. (*8*) showed how the use of digital nudging on news websites increases users' consciousness of fake news when reading online news articles. Meta-analyses indicated the effectiveness of nudges such as healthy eating behavior (*9-10*) and preventive behavior (*11*). Concerning studies related to Covid-19, (*12*) and (*13*) conducted experiments using a survey to investigate how nudge-based messages change people's preventive behaviors against Covid-19.

This study investigated the effectiveness of various nudge-based messages on people's behavior, using location data from smartphones. Unlike (*12-13*), our study measured the effects of nudge intervention on the spatial movement behavior of people, by using smartphone GPS information. In order to influence people's compliance to preventive behaviors, we send various nudge-based messages in heterogeneous settings to randomly chosen mobile device users through the open online display advertising network. To measure the compliance level, we construct three outcome variables (Go-out/Eat-out/Indoor leisure) and measure them based on the location data of sampled mobile devices.

Data and Experimental Design

Our experiment started on July 7, 2020 (**Figure 1**), and this corresponded with the time when Japan had overcome the first wave. This downward curve of the pandemic led the government to lift the emergency from all 47 prefectures on May 25, 2020. However, on June 28, 2020, the number of new cases increased and exceeded 100 for the first since the emergency lift. To manage this second wave, instead of issuing another emergency declaration, the Japanese government did not issue the state of emergency but only kept alerting and called for the avoidance of the 3Cs.

This study investigates the nudge effect on a sample of 0.3 million mobile device users from the Tokyo area in Japan. We picked devices whose location data were found in a 60 km radius from the center. Subsequently, we delivered nudge-based messages to each device through an open advertisement exchange system called real time bidding (RTB), a marketplace for ad slots in which advertisers bid for each ad slot on apps/websites to deliver an advertisement to the app/website users. We focused on mobile device users whose location data were available and bid for their ad space. 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 time spent outside 1 km radius of users' estimated home. The measurement is based on their location data. 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, 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 Karaoke box, pachinko parler, arcades, and internet caffe, 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.

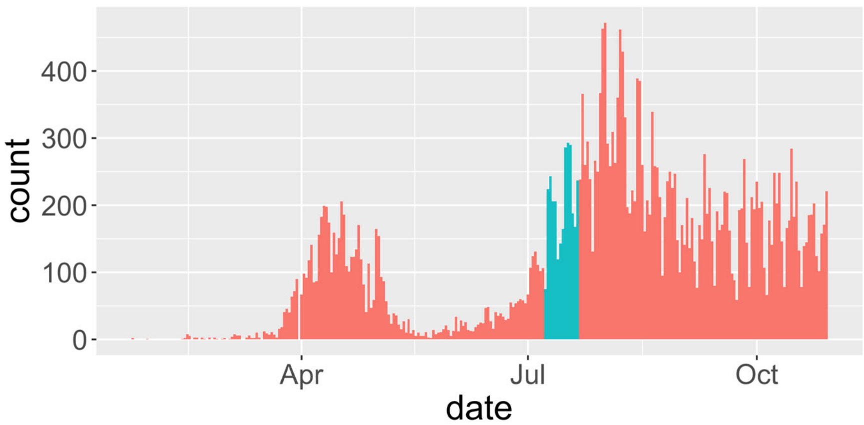

Fig. 1 The number of COVID-19 Cases in Tokyo (Blue bars represent the experiment period)

Table 1 Six messages and types of nudge delivered to mobile apps

	Message	Type of Nudge
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.	Altruism: Avoid physical or close contact with others when facing a medical risk
G02	There is approximately a 5% mortality risk in Covid-19. Stay away from crowds to reduce the risk of infection.	Loss aversion: Personal medical risk
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.	Loss aversion: Financial risk
G04	Let us get through this together. The percentage of people that continue to self-quarantine account for 70% of the total population	Social pressure: Emphasize others' preventive behaviors
C05	Staying from crowded trains can reduce your infection risk	Simple advice (Non-Nudge)
C06	There is a surge in the number of Covid-19 cases downtown.	Simple information (Non-Nudge)

Table 2 Specification of Message.

	Message	Timing
Weekdays	G01, G02, G03, G04, C05, C06	Morning, Noon, Evening
Weekends	G01~G04	Morning

Identification and Estimation

To measure the causal effect, we set a randomly chosen control group. During the experimental period, the user was assigned one type of treatment. The specification of treatment comprised the type of message and timing **(Table 1** and **Table 2**). Among them, G01–04 were nudge-based messages, while C05–06 were non-nudge-based messages. For example, a user might receive the message G01 every morning during weekdays and G03 in the morning on weekends. The complete list of messages is shown in Table 1. These messages intended to remind mobile device users of the need to take prevention behaviors. Messages were delivered through various mobile-based apps in the form of an advertising banner. Since the messages were delivered through an open advertisement exchange platform, the timing and frequency of the exposure varied with users. However, the assignment of the intervention was independent of these factors. This allowed us to deliver the messages to about 48,000 users. To gauge the behavioral changes in the users, we set up three outcome variables (see Table 3) constructed on the basis of mobile GPS-based real-time location data.

We focus on the change from the pre-experiment period, which is called the difference-in-differences period. Specifically, each variable described in **Table 3** was measured during the pre-experiment and during-experiment periods. The during-experiment values subtracted by the pre-experiment values are defined as changes. In other words, concerning the outcome values in the pre-experiment period y_i^{pre} and those in period 1, y_i , the change is defined as $\Delta y_i = y_i - y_i^{pre}$.

Table 3 Outcome variables, their descriptions, and measurements

Variable	Description	Measurement
Go out at night	Minutes spent outside home after 5 pm through 5 am next day during weekdays	Sum of the minutes spent outside of the 1 km radius of the estimated home location during each period
Go out on weekends	Minutes spent outside home during the day on weekends	Sum of minutes staying outside of the 1 km radius of the estimated home location during each period
Eat-out	Number of visits to bars and restaurants	Total count of records inside buildings contains bars and restaurants during each period
Indoor leisure	Number of visits to indoor leisure locations	Total count of records inside buildings containing pachinko parlors (sort of a casino in Japan), karaoke boxes, theaters, arcades, and internet cafes, during each period

To estimate the effect of the exposure to each message on users' behavior, we apply the instrumental variable regression (*14*) with the assignment of intervention as an instrument. The ratio of users who received the message in the treatment group is roughly 8–16% (refer to Table S1 in Supplementary material). 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 complier average causal effect estimation (CACE) (*15*) 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.

Complier Average Causal Effect Estimation (CACE) using instrumental variable (IV) estimation gives estimates for the impact of treatment on compliers.

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. The estimation model is

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

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.

Results

Main results

Summary Statistics are shown in **Tables 4** and **5**.

Table 4. Descriptive Statistics

Group	Count	iOS(%)	Message Count>0(%)	E(# messages | message > 0)	Mean # of Messages (SD)	Mean # of Records (SD)
Weekend						
G01	65395	0.401	0.080	17.44290	1.401 (9.385)	627.033 (942.568)
G02	65392	0.399	0.082	17.42117	1.425 (8.383)	627.503 (967.341)
G03	65392	0.401	0.081	17.41450	1.411 (8.157)	629.422 (1008.637)
G04	65395	0.397	0.081	16.79955	1.357 (8.019)	631.37 (1057.4)
G99	65398	0.399	0.000	NaN	0 (0)	627.78 (976.17)
Total	326972	0.399	0.065	17.26985	1.119 (7.626)	628.621 (991.21)
Weekday						
C05	46710	0.403	0.162	22.66799	3.662 (18.52)	633.221 (988.944)
C06	46713	0.403	0.163	22.92023	3.733 (20.838)	632.72 (1022.487)
C99	15567	0.399	0.000	1.00000	0 (0.008)	627.238 (946.852)
G01	50304	0.397	0.163	22.86292	3.72 (18.696)	626.398 (952.218)
G02	50302	0.398	0.165	23.01280	3.788 (19.226)	622.56 (941.846)
G03	50309	0.399	0.164	23.25626	3.824 (19.645)	624.559 (949.432)
G04	50301	0.397	0.164	21.81347	3.587 (18.212)	630.526 (1091.74)
G99	16766	0.399	0.000	NaN	0 (0)	637.005 (1013.942)
Total	326972	0.399	0.147	22.75407	3.352 (18.257)	628.621 (991.21)

Note: Due to systemic error, one of C99 user received one message on a weekday. However, this does not hurt the main result.

Table 5. Summary statistics of Metrics with the means for the values Before the experiment, in the experiment and their change for each metric

Metric	Group	Mean Before exp. (SD)	Mean in exp. (SD)	Mean Change (SD)
Weekday				
Eat out	C05	22.961 (17.157)	21.085 (17.692)	-1.876 (9.659)
	C06	22.935 (17.138)	21.145 (17.653)	-1.79 (9.631)
	C99	22.774 (17.194)	20.885 (17.711)	-1.889 (9.665)
	G01	22.583 (17.241)	20.719 (17.743)	-1.864 (9.583)
	G02	22.442 (17.201)	20.633 (17.731)	-1.809 (9.589)
	G03	22.588 (17.252)	20.828 (17.777)	-1.76 (9.648)
	G04	22.511 (17.229)	20.71 (17.735)	-1.801 (9.594)
	G99	22.353 (17.21)	20.674 (17.744)	-1.679 (9.642)
Go-out	C05	1673.572 (1973.841)	1624.804 (2044.877)	-48.768 (1279.167)
	C06	1682.708 (2014.368)	1629.897 (2074.721)	-52.81 (1256.363)
	C99	1676.905 (2014.918)	1630.933 (2089.72)	-45.972 (1270.137)
	G01	1666.308 (2002.263)	1614.75 (2071.123)	-51.558 (1270.449)
	G02	1652.309 (1979.619)	1605.393 (2042.259)	-46.916 (1258.548)
	G03	1654.586 (1998.292)	1603.979 (2059.121)	-50.607 (1276.702)
	G04	1684.028 (2018.627)	1622.822 (2070.366)	-61.206 (1278.91)
	G99	1670.781 (2017.258)	1647.201 (2098.913)	-23.58 (1285.107)
Indoor Leisure	C05	9.672 (11.75)	8.909 (11.753)	-0.763 (6.547)
	C06	9.62 (11.682)	8.851 (11.668)	-0.769 (6.571)
	C99	9.526 (11.727)	8.79 (11.682)	-0.736 (6.542)
	G01	9.508 (11.738)	8.76 (11.712)	-0.748 (6.587)
	G02	9.373 (11.679)	8.669 (11.65)	-0.704 (6.501)
	G03	9.52 (11.728)	8.785 (11.717)	-0.734 (6.568)
	G04	9.477 (11.746)	8.757 (11.728)	-0.72 (6.561)
	G99	9.383 (11.632)	8.677 (11.701)	-0.706 (6.591)
Weekend				
Eat out	G01	7.627 (6.745)	7.155 (6.822)	-0.472 (5.259)
	G02	7.649 (6.744)	7.165 (6.806)	-0.483 (5.269)
	G03	7.604 (6.738)	7.097 (6.81)	-0.507 (5.254)
	G04	7.605 (6.711)	7.116 (6.803)	-0.49 (5.296)
	G99	7.629 (6.732)	7.185 (6.811)	-0.445 (5.214)
Go-out	G01	1523.508 (1702.925)	1512.015 (1800.84)	-11.494 (1350.071)
	G02	1542.554 (1719.385)	1518.258 (1808.461)	-24.297 (1362.149)
	G03	1534.744 (1723.498)	1502.63 (1801.926)	-32.114 (1344.348)
	G04	1531.836 (1716.578)	1519.006 (1811.407)	-12.83 (1364.601)
	G99	1521.028 (1680.856)	1504.779 (1784.583)	-16.249 (1338.485)
Indoor Leisure	G01	3.133 (4.401)	2.892 (4.338)	-0.241 (3.522)
	G02	3.137 (4.412)	2.87 (4.325)	-0.266 (3.547)
	G03	3.145 (4.446)	2.862 (4.334)	-0.283 (3.539)
	G04	3.126 (4.407)	2.858 (4.328)	-0.268 (3.542)
	G99	3.123 (4.4)	2.891 (4.328)	-0.232 (3.492)

The effect size of each message is shown in **Figure 2**. The effect size was calculated by comparing the control groups (G99 and C99) with the treatment groups (G01–04 and C05–06).

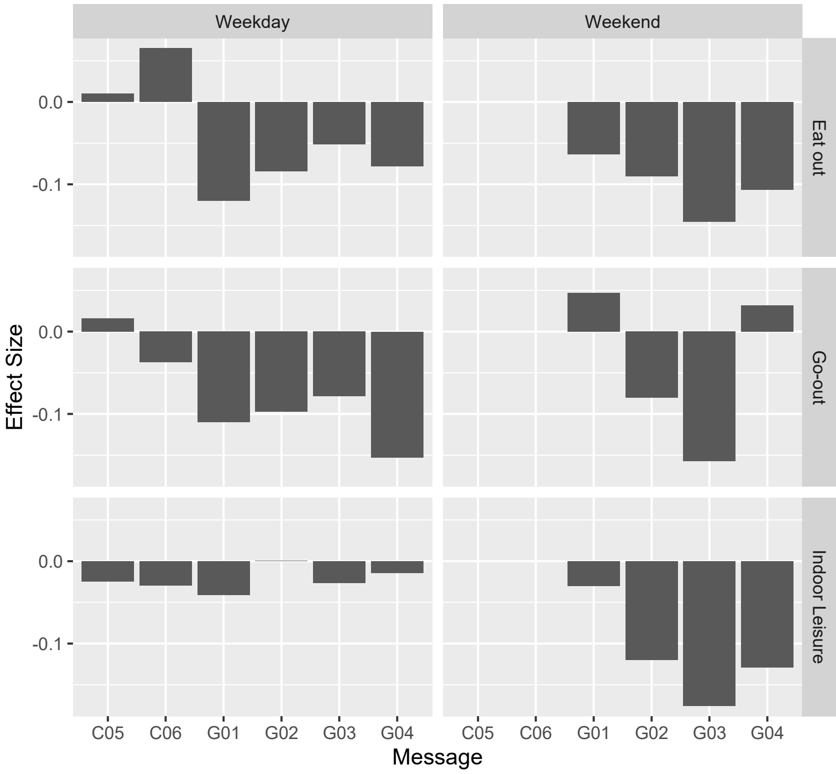

Fig. 2 Effect Size of Each Message

Note: Effect size is calculated as the ratio of CACE coefficient to standard deviation of the treatment and control groups.

Figure 3 shows the effect of one or more messages on each stay-at-home action. For the go-out from home variable, messages G01 and G04 had a statistically significant effect on weekdays, while G03 had a statistically significant effect on weekends. The messages reduced by as much as 3 hours in 10 days on weekdays and 4 hours, on an average, only on four weekend days. However, both C05 and C06 had no significant effect. This can be attributed to the fact that the messages were not nudge-based.

For the Eat-out variable, only the G01 message had a statistically significant effect on weekdays, but G03 was statistically significant on weekends. Finally, for the indoor leisure variable, none of the messages were effective on weekdays. Conversely, all the messages, except for G01, were statistically significant on weekends. Precisely, effective messages reduced the visits to restaurants, bars, and indoor leisure facilities by approximately 0.7 times on the four weekend days.

For the weekday intervention, we split each message group into three categories and varied the timing of the message delivery: morning (6:00–11:00 am), noon (11:00 am–16:00 pm), and evening (16:00–21:00 pm). In other words, we have 6 × 3 = 18 small groups. **Figure 4** shows the separately estimated results for each timing. The figure highlights that the message exerted the maximum effect during the noon period. The message delivered in the morning was probably forgotten by the users, while those delivered in the evening could not effect a change in the same day owing to the short duration between the message delivery timing and the end of the calendar day. Hence, the messages were delivered at noon to change the behavior.

We also investigated the weak low effects of the weekday-treatment on the restaurant and indoor-leisure metrics; we split the sample into subgroups according to their pre-study value and, subsequently, performed the same CACE on each subgroup. We merged the lower two quartiles into one 0–50% quantile because their intervals overlapped on weekdays. The results are shown in **Figure 5.**

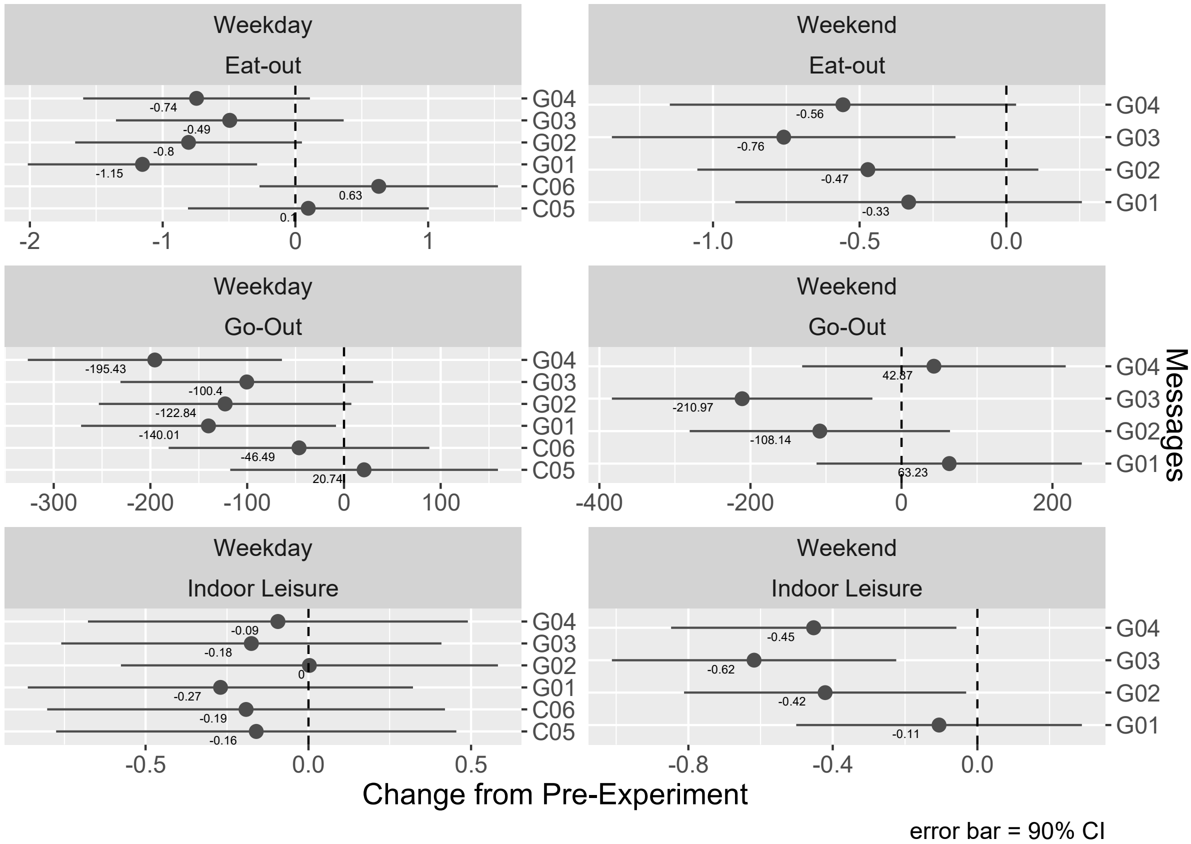

Fig. 3 The CACE results of message reception on the three outcome variables.
The effect is estimated separately for (i) weekends, (ii) weekdays and each message.

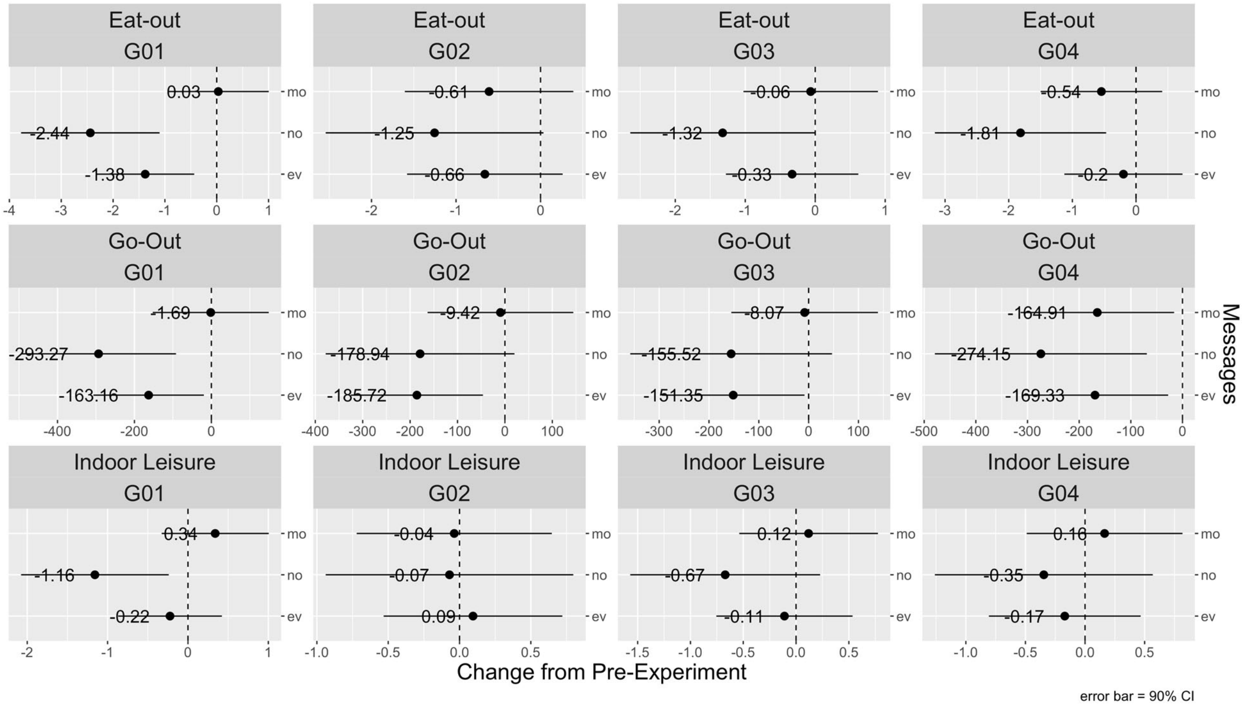

Fig. 4 Timing of the Message Delivery

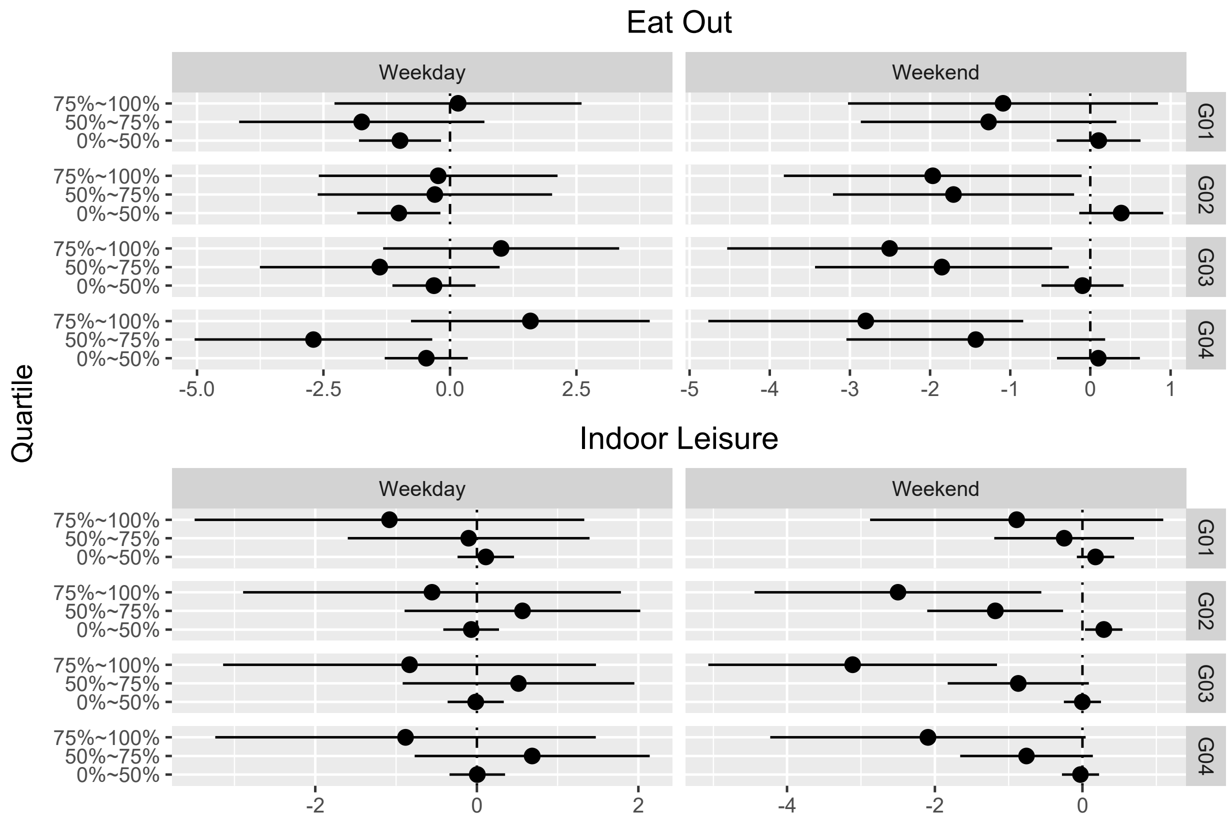

Fig. 5 Estimates for different Quantiles of the sample for the "Indoor leisure" and "Eat out" metrics

We found that the effects of the two 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.

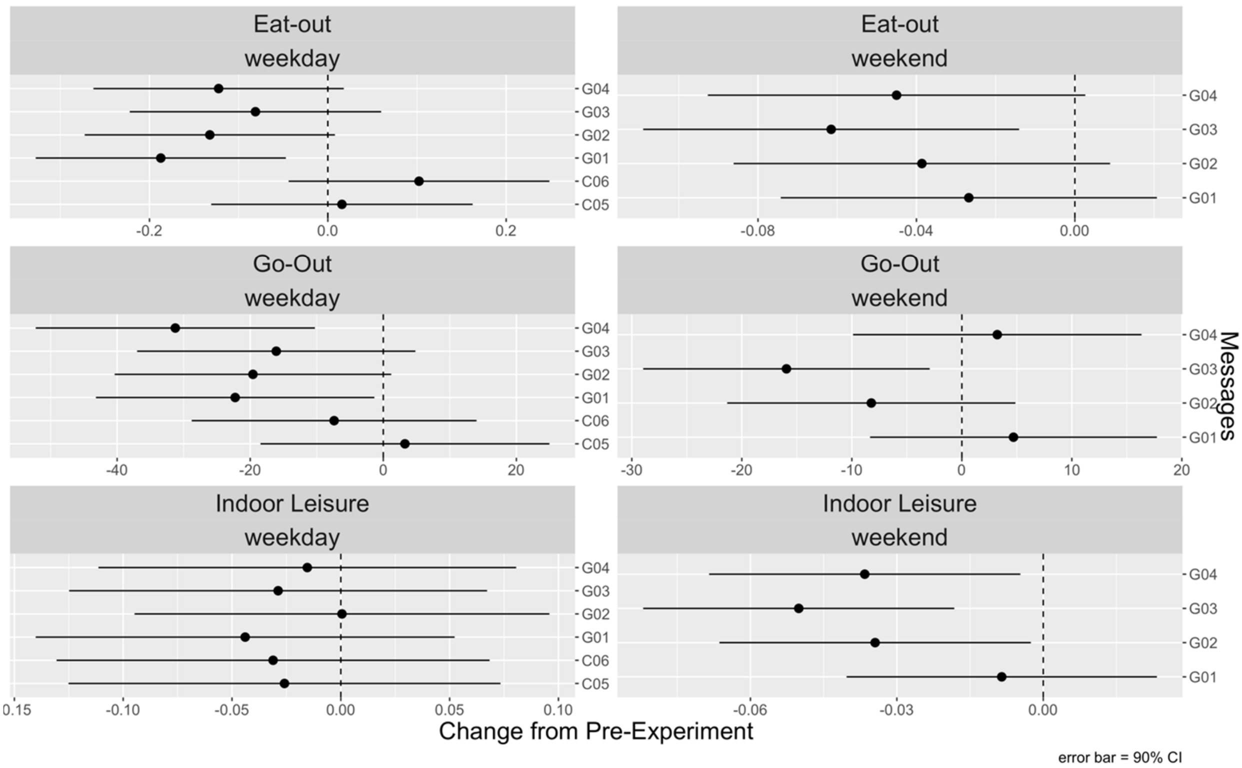

Fig 6. ITT estimation results

Robustness Check

To check the validity of our CACE results, we conducted a robustness check in three estimation frameworks. The CACE results were consistent with the intent-to-treat (ITT) and CACE estimation, excluding the low frequency message receivers.

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. **Figure 6** shows very similar to the results shown in and validate the results.

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 (**Figure 7**). Apparently, the magnitude of the effects of messages are increased.

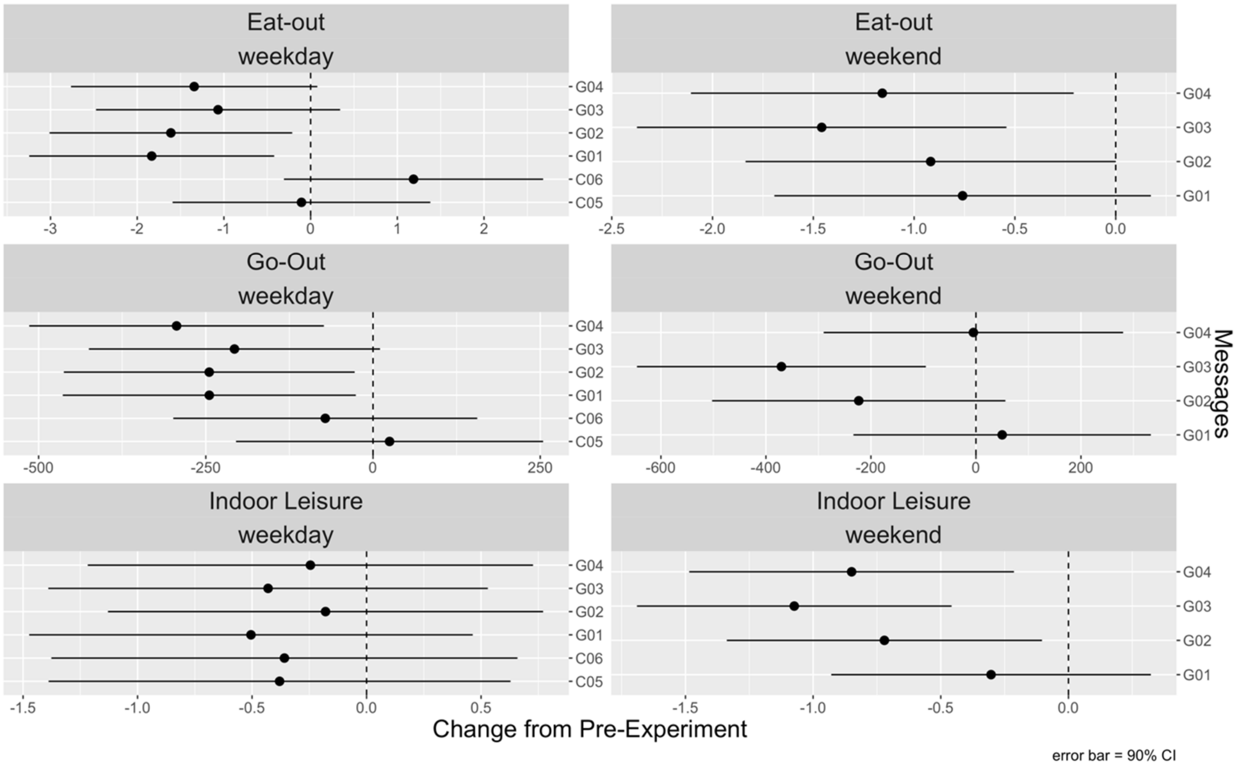

Fig. 7 CACE estimation results excluding 1-4 impressions

Cost-Effectiveness

We also compared the cost-effectiveness of the nudge-based interventions with that of the traditional monetary incentives. We conducted a follow-up survey on the minimum monetary compensation for stay-at-home compliance. More concretely, we conducted a Willing-To-Accept survey for a part of our experiment samples. The questions are shown in **Table 6**. The survey respondents are sampled from the sample population of the experiment. The respondents are asked to answer the questions online. Approximately, 1,000 respondents were sampled from the main group. We asked about the minimum compensation they received for each stay-at-home action. The summary statistics are shown in **Table 7**.

Table 6. WTA Survey Questions

Q1. What is the minimum compensation per day for giving up going out after 5 pm weekdays? Q2. What is the minimum compensation per day for giving up going out weekends? Q3. What is the minimum compensation per day for giving up dinner at restaurants and bars during? Please answer for weekend and weekday separately. Q4. What is the minimum compensation per day for giving up lunch at restaurants and bars during? Please answer for weekend and weekday separately. Q5. What is the minimum compensation per day for giving up going to indoor leisure such as karaoke box, internet caffe, and pachinko during weekends? Please answer for weekend and weekday separately.

Table 7. WTA for Giving Up various Activities

	N	Mean in Yen	S.D.
Go-out weekday	1034	4431.75	3475.55
Go out weekend	1034	6112.25	3508.77
Lunch weekdays	1034	3181.36	3137.38
Lunch weekends	1034	4087.48	3365.72
Dinner weekdays	1034	3584.88	3184.27
Dinner weekends	1034	4435.74	3414.61
Indoor leisure Weekdays	1034	3204.70	3299.56
Indoor leisure Weekend	1034	3893.63	3491.36

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

We compared the impact of the best nudge-based message on each outcome variable with the equivalent monetary compensation (**Table 8**). Since the cost of messaging is JPY 6.8/person and JPY 4.9/per person on weekdays and weekends, respectively (the latter groups received at least one additional message), the cost is approximately 2.5–6.5 % of the monetary compensation.

Table 8. The Impact of Nudge-based Message and Equivalent Compensation

outcome	Impact by the best nudge-based message	Equivalent Compensation (Yen)
goout weekday (minutes/day)	19.54	511.80
goout weekend (minutes/day)	52.74	814.35
leisure weekday (times/day)	0.03 ≤	86.58
leisure weekend (times/day)	0.15	601.78
lunch weekday (times/day)	0.12	366.33
lunch weekend (times/day)	0.12	412.80
dinner weekday (times/day)	0.19	775.67
dinner weekend (times/day)	0.19	841.76

Conclusion and Discussion

To summarize the results, users were more responsive to the intervention on weekends. This is reasonable because, on weekdays, employees and students are usually not allowed to freely determine their work location. According to a survey conducted by the Japanese government, less than 20% of the employees are eligible to work from home (*16*).

Among the four messages for the general group, G03 was consistently statistically effective for the three outcome variables. The nudge theory emphasizes the importance of *loss aversion*, which is reported to have a significant effect on preventive behavior (11). Both own mortality risk and economic impact are considered as losses by the message recipients. However, in this study, the use of financial loss aversion (G03) was stronger than that that of a medical risk aversion (G02). This may be attributed to the fact that older people who have a high pandemic anxiety stayed at home during the pre-study period, which is consistent with the result in Figure 5.

We also noted the effectiveness of the message “Others continue to self-quarantine.” This message exerted a *social pressure* or triggered the “do what others do” intention among the users. This message reduced the number of visits to indoor leisure facilities and the going-out-at-night habit, respectively, on the weekends and weekdays. The message may have influenced those who are not concerned about their health or financial risk but care for others’ behavior.

We conducted a large-scale nudging experiment to enhance users’ engagement in preventive behaviors during the Covid-19 crisis. We found that people alter their behaviors in response to messages that emphasize loss and social pressure. The effect varies with the content and the geographic target market.

Since this study is the first attempt to evaluate the effectiveness of nudge in driving people to stay at home, based on the GPS location information, we used a simple randomization strategy. Based on these results and the demographic information obtained from the follow-up surveys, the personalized assignment (17) of nudges is expected to provide a more effective intervention to the society at large to overcome the current pandemic.

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