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**The financial incentivization and communication effects of a government's postpandemic measure: The "go-to-travel" campaign and consumer behaviors in Japan**

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# The financial incentivization and communication effects of a government's postpandemic measure: The "go-to-travel" campaign and consumer behaviors in Japan

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## Abstract

This study empirically explores how a government policy seeking to induce consumer demand impacts consumer behavior in the postpandemic context. The COVID-19 pandemic significantly changed global economic, political, and business structures. Financial incentivization is a typical economic intervention to boost consumer demand. This study leverages a quasi-experiment involving the "go-to-travel" campaign, a government intervention designed to induce domestic travel demand in Japan, and empirically assesses the effects of a public policy on postpandemic consumer behavior. However, consumers in a specific area were ineligible to participate. Utilizing this structure, this study conducts difference-in-differences specification with two-way fixed-effect models. The results show no significant effect of eligibility for the go-to-travel campaign. However, additional analyses reveal that even ineligible consumers traveled more

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frequently after campaign implementation when controlling for individual fixed effects, frequency of going out for other purposes, and infection rates. This study implies the importance of the government communication effect in that the policy itself is observable to ineligible consumers, and this observability affects consumer behavior.

**Keywords:** COVID-19, Business recovery, Economic measure, Tourism, Two-way fixed effect

## Introduction

The COVID-19 pandemic significantly changed global economic, political, and business structures. Infection prevention measures and new customs (e.g., social distancing, stay-at-home requests, community lockdowns, and congestion avoidance) halted global traffic and consumption. Thus, many countries designed economic interventions to protect the domestic economy and businesses. This study aims to empirically reveal the effects of a postpandemic demand promoting policy on consumer behavior. Policymakers may focus on financial incentives (e.g., discount rate) when considering effective demand-promoting measures. However, the series of analyses in this study indicate the possibility that public communication changes people's perceptions of the importance of stay-at-home requests and consumption behavior.

Regarding the impacts of these economic measures, studies should understand that the economic shocks from COVID-19 are unequal across industries (Susskind and Vines 2020). For example, Del Rio-Chanona et al. (2020) predicted that both supply and demand shocks harm the tourism industry, whereas other sectors are harmed by demand (e.g., transport) and others by supply (manufacturing) shocks. Furthermore, nonpharmaceutical public health interventions are critical public policy for combating COVID-19 (Yan et al. 2020). Governments need to promote the reduction of infection rates and domestic business recovery simultaneously. Thus, business recovery measures should specify the target business sector and target population (e.g., consumer demographics) to balance economic enhancement and infection risks.

The “go-to-travel” campaign in Japan is a typical example of such targeted interventions. This campaign focuses on the tourism industry and people who live in certain areas and aims to induce domestic travel in Japan. The primary focus of this study is to explore the effects of the go-to-travel campaign on consumer travel. Unlike many Western countries, Japan did not conduct a community lockdown involving legal enforcement. Therefore, although consumers faced infection risks, they could choose whether to go out shopping or travel during the pandemic. This political and social structure makes Japan a unique research object for understanding how demand-promoting policy works in the context of the COVID-19 pandemic. Despite the opportunities for research that Japan’s COVID-19 response represents, empirical studies of business or tourism in this setting are still limited. Therefore, this study aims to identify the impacts of the go-to-travel campaign in the context of the COVID-19 pandemic. The findings of this study provide fundamental knowledge on how an economic intervention affects postpandemic business recovery.

This study conducted a questionnaire survey of general Japanese consumers from June to October 2020 and developed a monthly panel dataset regarding their behavior and perceptions.

During the data collection period, the Japanese government introduced the go-to-travel campaign, which excluded residents of Tokyo prefecture. This study utilizes this structural difference and empirically analyzes the go-to-travel campaign's effects by difference-in-differences with two-way fixed-effect model estimations. This study also conducts several additional analyses and explores the mechanism of how the go-to campaign affects domestic consumer behavior.

## Literature Review: Economic Interventions for Tourism Recovery

The current circumstances of the COVID-19 pandemic require the tourism industry to reform its business and growth model based on inbound demands. The tourism industry's ultimate recovery depends on a medical solution; otherwise, consumers will be reluctant to travel abroad. Further, Fotiadis, Polyzos, and Huan (2021) predict that the drops may continue longer than expected in the early stage of the pandemic (UNWTO 2020). Therefore, it is unrealistic to expect that global tourist arrivals will suddenly and drastically recover, and the tourism industry must find a way to survive under the current circumstances.

In response to this issue, there has been a turn to domestic tourism to trigger industrial recovery (UNWTO 2020), and a study also focuses on domestic tourism (Altuntas and Gok

2021). Governments have promoted domestic travel by proposing different types of campaigns or vouchers (UNWTO 2020). However, governments need to boost domestic travel while preventing coronavirus spread (Fu et al. 2017). Thus, most countries specify a target demographic group for incentivization to balance demand enhancement and infection risks.

A recent study evaluated the COVID-19 pandemic as an unprecedented disaster (Sigala 2020). The economic impact of the COVID-19 pandemic is more significant than that of previous pandemics of the 21st century, such as severe acute respiratory syndrome (SARS) and swine flu (Cooper 2006; Haque and Haque 2018). However, several studies on such prior pandemics imply the effects of public policies on economic recovery. This section introduces several studies on the effects of governments' financial incentives and communication and proposes theoretical research questions.

Regarding the effects of the go-to-travel campaign, there are three possible mechanisms: financial incentives (e.g., discounts or vouchers), effects of the statement or implementation of the campaign, and consumer traits. Studies have reported that the tourism industry is highly vulnerable to disasters and pandemics (Sigala 2020; Zhang et al. 2021). Thus, it is expected that government policies are adequate to boost tourism demands and achieve postpandemic recovery (Zhang et al. 2021; Zheng, Luo, and Ritchie 2021). For instance, under SARS, the Japanese government implemented a campaign (e.g., discounts) to boost tourism demand (Cooper 2006).

Thus, public policies and the incentives play a critical role in the recovery of tourism businesses and organizations (Zhang et al. 2021; Zheng, Luo, and Ritchie 2021). Financial incentives are expected to enhance demand under ordinary conditions, but their effectiveness in the COVID-19 context is still unclear. Despite the presence of financial incentives (e.g., discounts or vouchers), consumers may perceive infection risk and be reluctant to travel. Further, whether the policy enhances traveling exclusively by the target group is also still unknown. Against this backdrop, empirical analyses are critical to understanding the effectiveness of incentivization by the government.

In addition to financial incentives, studies on the marketing-public policy interface reveal that government communication and information delivery are influential factors for economic measures (Okazaki et al. 2015; Scott et al. 2020). If only the financial incentive matters, governments can boost only the target population's demand. However, the implementation of a specific policy or statement by the government can be observed not only by the target but also by ineligible people.

Regarding the pandemic, information on infection rates and severity can be a stigma that leads to fear in populations (Person et al. 2004). Fear-filled messages affect consumer behavioral intentions (Heffner et al. 2021). In terms of the COVID-19 situation, general consumers can collect information from various sources, including online channels (e.g., websites, social media). Information from public sectors or specialists has relatively high reliability (Dadaczynski et al. 2021). The Japanese government organized a specialized epidemiological monitoring group. Based on the discussion within this group, the government reported infection conditions and made various announcements to the population. Therefore, the government's public policy and statements can be considered reliable and influential on consumer psychological responses (e.g., fear, perceived safety), and it is worth studying whether the information or implementation itself has any impact on consumer behavior.

The third factor is the consumer's demographic or psychological traits. For example, consumers' self-efficacy for coping and intention to engage in infection prevention behavior affect their lifestyle and shopping behavior under COVID-19 pandemic circumstances (Laato et al. 2020; Prasetyo et al. 2020). Furthermore, since age or chronic conditions affect the risk of infection and the severity of COVID-19 symptoms, demographic and physical characteristics lead to different reactions to the campaign.

This study focuses on the effects of public policies on postpandemic recovery. Although previous studies are highly suggestive, there is a lack of knowledge on whether a policy boosts tourism demand in the COVID-19 context. In particular, consumer reactions to public policies under the risk of infection are not very easy to quantify. Japan's unique characteristics (e.g., infection risks, no legal compulsion to stay at home, travel promotion campaign) provide us with an opportunity to empirically assess the issues mentioned above. Along with these arguments, this study empirically explores the following research questions (RQs).

RQ1: What are the impacts of eligibility for the go-to-travel campaign (financial incentives)?

RQ2: What are the impacts of the implementation of the go-to-travel campaign (communication effects).

RQ3: What personal traits affect travel in the COVID-19 context?

This study employs different estimation strategies to answer these RQs. For the first question, this study uses the difference-in-differences method with the two-way fixed-effect model. For the second and third questions, this study conducts fixed-effect model estimations that include a post-go-to-travel dummy variable and various consumer characteristics. The results show insignificant effects of eligibility for the go-to-travel campaign. However, additional analyses reveal that even ineligible consumers traveled more frequently after the campaign was implemented when controlling for the individual fixed effect, frequency of going out for other purposes, and infection rates. This study implies a government communication effect in that the policy itself can be observed by ineligible consumers, and this observability affects consumer behavior.

**Background and Dataset**

As of 3 March 2021, Japan had confirmed 434,356 cases of COVID-19, including 7,982 deaths. Japan has a lower infection rate than other countries, even though it has a high population density and many people over 65 years old in the population (Iwasaki and Grubaugh 2020).

Due to the first wave of widespread domestic infection, the Japanese government declared a state of emergency on 7 April 2020 for seven prefectures (Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, Fukuoka). The government expanded this to all prefectures on 16 April. During the emergency state, the government did not conduct community lockdown but requested citizens to stay at home. This request and other measures for COVID-19 mitigation by the Japanese government are not forms of legal enforcement. Therefore, Japanese people could choose whether to stay at home in this circumstance. The government lifted the state of emergency on 25 May for all prefectures.

Regarding tourism measures, the Japanese government initiated the go-to-travel campaign, in which the government covers half of the travel expenses paid by tourists, on 22 July (Anzai and Nishiura, 2021). This campaign offers discounts on hotel expenses and issues vouchers that can be used in local stores. The date of 22 July 2020 was immediately before the four-day holiday from 23 to 26 July, and the Japanese summer holiday (in the middle of August) would be coming soon. The total budget for this project is JPY 1.35 trillion (Kamata 2021).

However, when it was launched, people living in Tokyo were excluded from this campaign because of the infection rates within Tokyo. Thus, the policy did not incentivize people in Tokyo during these holiday periods. The Japanese government later included Tokyo in the go-to travel campaign on 1 October. Therefore, Tokyo residents were not eligible to apply for vouchers from the end of July until October. Figure 1 summarizes the timeline of these political processes.

("Insert Figure 1 about here")

This study conducted monthly questionnaire surveys of general Japanese consumers from June to October (i.e., five questionnaire sessions). The questionnaire asks about respondents' behaviors in the previous month (e.g., behaviors in May were reported on the questionnaire in June). Each questionnaire session collected approximately 3,600 responses, and some respondents were not retained for all five sessions. If some respondents did not answer the questionnaire in a particular month, we replaced them with new individuals. We excluded samples that did not report values for the variables used in this study, and the final dataset included 18,545 individual-month observations from 5,042 individuals.

This study covers information about general consumers' travel from May to September in all Japanese prefectures. Thus, the dataset of this study captures the pre- and post-campaign periods. Furthermore, since this study covers people in all prefectures, it utilizes the structural difference in eligibility for the go-to-travel campaign to identify the effects of a policy that promotes domestic tourism. Questionnaire-based data assessment is a realistic way to collect information that specifies an individual's travel behavior, prefecture of residence, and other critical characteristics, such as income, simultaneously.

In terms of the questions used to assess travel behavior, this study asks the following: "Considering the spread of COVID-19, how has your frequency of going out for travel or sightseeing changed during the month compared to the same month last year?" This study employed the year-on-year comparison to explicitly control for individual travel habits in the restricted number of questions. If we directly assessed the frequency of travel each month in 2020, the low frequency level would not distinguish between people who used to travel a lot and those who rarely traveled. The questionnaire also retrieved respondents' psychological reactions to stay-at-home requests, financial status (e.g., monthly income and year-on-year income change), and demographic information, such as occupation, age, family (cohabitant) structure, and residence prefecture. Furthermore, this study employs frequency of buying daily necessities and nondaily necessities[1] (e.g., alcohol, cigarettes), and frequency of going to social gatherings, including having drinks. For each item, respondents answered the following questions: "Considering the spread of COVID-19, how has your frequency of going out for [buying daily necessities/buying nondaily necessities/social gatherings or having drinks] changed during the month compared to the same month last year?"

The survey data were collected from all regions of Japan. Research samples were equally distributed according to gender, age group, and residence prefecture. The selection of the survey sample was undertaken by the marketing research group Macromill. Table 1 presents the demographics of the samples. This study also retrieved the publicly listed monthly infection status (e.g., the number of infected cases) for each prefecture and combined it with our questionnaire panel dataset.

("Insert Table 1 about here")

Table 2 presents the definitions of the variables used in the main and additional analyses in this study. The dependent variable in this study is the self-declared year-on-year monthly travel frequency change. The primary model uses dummy variables representing the treatment conditions of the go-to travel campaign, such as pre- and posttreatment dummies, and a treatment dummy variable that shows whether a respondent is eligible for the campaign (i.e., if a sample lives in Tokyo). Furthermore, this study controls for year-on-year income change because individual fixed effects cannot assess such time-varying individual characteristics.

("Insert Table 2 about here")

In the additional analyses, we utilize variables representing respondents' characteristics, such as gender, marital status, the living with children dummy, income, family size, and a dummy for whether the respondent lives with people over 65 years age. Further, this study employs prefectural infection conditions and respondents' emotional reaction to the stay-at-home request in the additional analyses.

**Empirical Strategy**

This study uses a difference-in-differences (DID) approach to evaluate the impacts of an intervention (i.e., the go-to-travel campaign). The DID approach has been used extensively in the literature to quantify causal effects (De Chaisemartin and D'Haultfoeuille 2020; Fisher, Gallino, and Xu 2019; Song et al. 2020). This approach enables us to compare the relative differences in the outcome of interest (i.e., travel frequency) before and after a policy change between the treated and nontreated groups while controlling for unobservable factors. In this study's setting, the treatment group consisted of respondents who lived in all prefectures except Tokyo, whereas the control group consisted of respondents who lived in Tokyo. The treatment is the application of the go-to-travel campaign from July to the end of September. Thus, this study considers May and June as the pretreatment period and July, August, and September as the posttreatment period.

The DID estimation requires parallel trend assumptions, where the treatment and control groups' outcomes would have changed at a similar rate in the absence of treatment. Figure 2 shows the visual specification of this condition, but it seems that the trends vary across prefectures. Individual characteristics related to consumption, such as income and living expenses, and prefecture-level infected cases may explain the difference.

("Insert Figure 2 about here")

These characteristics may cause different travel trends during the observation period. Therefore, this study estimates the following model to statistically determine if our sample is comparable while controlling for several factors:

$$y_{it} = \delta_0 + \delta_1(Treat_i \times timetrend_t) + \delta_2 Treat_i + \delta_3 Timetrend_t + ConsumerFE_i + Control_{it} + \epsilon_{it}, \quad (1)$$

where $Treat_i$ represents a dummy variable if individual i is eligible for the go-to travel campaign (i.e., the value equals zero when an individual is living in Tokyo). $Timetrend_t$ denotes an ordinal variable of the month since the start of data collection (i.e., May). $ConsumerFE_i$ represents individual *i*'s time-invariant fixed effect, and $Control_{it}$ represents a time varying control variable (year-on-year monthly income change, in this setting).

Furthermore, to verify the reliability, we prepared three different comparison conditions based on the economic background and infection rate of each prefecture. First, we compared responses from all prefectures (n=18,545). Second, we employed thirteen prefectures under special precautions (Hokkaido, Tokyo, Kanagawa, Chiba, Saitama, Ibaraki, Ishikawa, Gifu, Aichi, Osaka, Hyogo, Kyoto, and Fukuoka). On 16 April, the Japanese government specified the thirteen prefectures under special precautions based on the number of infected cases per population. This study utilizes these grouping criteria for sample selection corresponding to the infection situation and estimates the same model using only samples from these thirteen prefectures (n = 5,173). The third comparison group is the three prefectures (n = 1,198) with the highest infection rates per population (Hokkaido, Tokyo, and Osaka). We are interested in the coefficient $\delta_1$, which indicates if the outcome trend differs between the treatment and control groups. Table 3 shows that the results show no significant differences in the outcome trend between the control and treatment groups when the individual fixed effect is controlled. Thus, this study employs the individual fixed effect to satisfy the parallel trend assumptions.

("Insert Table 3 about here")

This study employs the DID specification with a two-way fixed-effect model (i.e., individual and time trend fixed effects) to explicitly assess the impact of government intervention. This approach is widely applied in empirical economics and business studies to assess the causal effect of public or business policies (e.g., De Chaisemartin and D'Haultfoeuille 2020; Fisher, Gallino, and Xu 2019; Song et al. 2020). This study estimates the following model to assess the impacts of the implementation of the go-to-travel campaign on traveling.

$$\begin{aligned} y_{it} &= \alpha_0 + \alpha_1(Treat_i \times Post_t) + \alpha_2 Treat_i + \alpha_3 Post_t \\ &\quad + ConsumerFE_i + MonthFE_t + Control_{it} + \epsilon_{it}, \end{aligned} \tag{2}$$

where $Post_t$ is a dummy variable representing the posttreatment period. In other words, this dummy variable takes the value of one if an observation is in July, August, or September. $MonthFE_t$ represents the time trend fixed effect that controls for the macro time-trend effect, such as national-level infection conditions and short-term economic and political situations. The other variables in equation 2 are consistent with the variables in equation 1. The coefficient $\alpha_1$ of the interaction term $(Treat_i \times Post_t)$, which is our primary coefficient, captures the impact of campaign implementation on the outcome. We emphasize that the independent effects of the treatment condition ($\alpha_2$) and the posttreatment period condition ($\alpha_3$) will be absorbed by the employed fixed effects in the estimation (individual and time trend fixed effects). The estimation also assesses the year-on-year monthly income change and the number of monthly infected cases by prefecture as the control variables. These variables are time-varying and critical for travel under COVID-19. Thus, this study employs this two-way fixed-effect DID specification while assessing the income change and infection cases.

## Results

Table 4 presents a summary of the two-way fixed-effect model results for three group specifications. The results show that the primary variable ($Treat_i \times Post_t$) does not significantly impact travel. Regarding the reliability check, this study also ran an alternative model with equation 2. The only difference is that the alternative version employs prefecture-level fixed effects instead of individual consumer fixed effects. However, the insignificant results are consistent across all estimation patterns. Thus, these results indicate that the effect of the go-to-travel campaign on *Travel* does not significantly differ from zero. Furthermore, prefecture-level fixed effect estimations reveal that income change positively impacts travel. The results imply that consumers tend to travel more when year-on-year monthly income increases.

("Insert Table 4 about here")

Regarding the reliability of the two-way fixed-effect estimation, De Chaisemartin and D'Haultfoeuille (2020) show that the negative weights of average treatment effects cause problematic DID estimation results, especially when the constant treatment effect assumption is implausible. In our setting, for example, the impact of the go-to-travel campaign may change over time. When the average treatment effects are heterogeneous across groups or periods, the negative weights cause an issue in that the regression coefficient may be negative while the treatment effects are positive (De Chaisemartin and D'Haultfoeuille 2020).

To tackle this problem, De Chaisemartin and D'Haultfoeuille (2020) recommend that applied researchers calculate the weights of the regression coefficients and run modified DID estimation when the negative weights matter. Thus, this study estimates the weights attached to the coefficients and the modified DID estimators using STATA packages such as *twowayfeweights* and *did_multiplegt* (e.g., De Chaisemartin and D'Haultfoeuille 2020). The results revealed that 70 percent are strictly positive, 30 percent are strictly negative, and the sum of the weights is almost one (i.e., a positive value). Further, the modified DID estimation results are consistent (i.e., insignificant effect; coefficient = -0.041, standard error = 0.043) with our primary results. The modified DID estimator relies on a common trend assumption. Thus, this study estimates a "placebo estimator" that compares the mean outcome change from the *t-2* period to the *t-1* period. The placebo estimator is small and insignificant (coefficient = 0.018, standard error = 0.025), meaning that prefectures where the degree of travel changed (i.e., increased/decreased) between *t-1* and *t* did not have significantly different trends from *t-2* to *t-1* than prefectures in which the degree was stable. Overall, the results of our two-way fixed-effect estimation established reliability.

In sum, the two-way fixed-effect DID specifications identified that the go-to-travel campaign does not improve consumers' year-on-year travel frequency change. Although this result provides empirical evidence on the relationship between public policy and travel, it does not explain why the campaign seems ineffective.

Our results did not reveal a significant effect of the go-to-travel campaign. Was the campaign meaningless, then? The insignificant effect implies two possible mechanisms: (1) the treatment group's outcome does not change or (2) the control group's outcome changes. In the ordinary randomized assignments such as clinical examination, (2) does not occur, but our primary treatment is a public policy, and ineligible consumers can observe the implementation of the go-to-travel campaign and the government's statements. This observability might affect consumer behavior. To explore the implications behind the DID results, this study estimates one-way fixed-effect models. More specifically, we estimate the individual and the prefecture fixed-effect models for each grouping criterion (i.e., full sample, 13 prefectures, 3 prefectures). Furthermore, in this section, we analyze fixed-effect models with only samples who live in Tokyo. Since Tokyo is the capital and produces approximately 19% of the GDP of Japan (Tokyo Metropolitan Government 2019), lifestyles and consumption behavior in Tokyo may be different from those in other prefectures. This specification enables us to infer how the campaign affected Tokyo residents' behavior.

The additional analyses aim to identify individual characteristics that increase/diminish travel under COVID-19 and how Tokyo residents reacted to the go-to-travel campaign's implementation (i.e., to answer RQ2 and RQ3). The announcement and commencement of the go-to-travel campaign may have triggered going out for travel. Ruan, Kang, and Song (2020) show that government actions can contribute to consumer perceived safety and tourism recovery under individual health threats. This finding implies that the go-to-travel campaign implementation may have led consumers to perceive the circumstances as less severe, making them more likely to travel. If there is a communication effect, people in Tokyo will increase their frequency of travel in the posttreatment period even if they are not financially incentivized.

Furthermore, Laato et al. (2020) show that self-efficacy and protective motivations are critical aspects that affect infection prevention behavior, such as the decision whether to stay at home. Thus, this study asked respondents about their "sympathy with the opinion that people should stay at home" and their agreement with the statement that "staying at home can be achieved from individual efforts" (seven-point Likert scale). In sum, we employ a posttreatment dummy, consumer characteristics, and prefectural infection conditions as dependent variables in the additional analyses. The model for the additional analyses is as follows:

$$y_{it} = \gamma_0 + \gamma_1 Post_t + X\gamma + ConsumerFE + \epsilon_{it}, \qquad (3)$$

where $X\gamma$ refers to a vector of the consumer characteristic variables that are listed in Table 2 (e.g., year-on-year income changes, year-on-year monthly frequency changes in going out to buy daily necessities, year-on-year monthly frequency changes in going out to buy nondaily necessities, year-on-year monthly frequency changes in going out for drinks or social gatherings, sympathy with the "stay at home" request, self-efficacy for "staying at home", gender, marital status, whether a child exists, annual income, whether living with a person older than 65, family size). Furthermore, this study estimates an alternative model that uses prefecture fixed effects instead of individual consumer fixed effects in equation 3. Thus, the additional analyses aim to assess whether *Travel* is higher in the posttreatment period (i.e., whether $\gamma_1$ = 0) while controlling for the variables mentioned above and the fixed effect.

The primary reason for adding these variables is to control for the general trend of consumers tending not to stay at home. Since the state of emergency was declared in April and lifted in May, consumers might have perceived it as less important to stay at home as time passed. Thus, the model assesses the posttreatment effect while controlling for the frequency of going out for other purposes. If the general behavioral change (e.g., consumers generally stayed at home less as time passed) can explain the posttreatment effect on *Travel*, those control variables absorb $\gamma_1$. Thus, $\gamma_1$ compares travel in the pre- and posttreatment periods while controlling for the frequency of going out to shop or eat out.

Table 5 summarizes the series of additional analyses. Some coefficients for consumer characteristics (e.g., marital status) were estimated in the consumer fixed-effect model estimation. These characteristics rarely change in a short time period, and the consumer fixed effect absorbs the impacts. Thus, for example, the model (1) in Tokyo estimation could not provide coefficients for male, marital status, child, and income, but these become calculable after collecting more comprehensive samples (i.e., model (1) in the full-sample estimation).

("Insert Table 5 about here")

The results in Table 5 show that consumers are more likely to go out for travel in the posttreatment period. This trend is consistent even in the Tokyo samples when controlling for the individual or the prefecture fixed effect. Thus, we can conclude that the year-on-year travel frequency change is higher after the go-to-travel campaign is implemented when the time-invariant individual or prefectural fixed effects and other consumer characteristics are controlled. Only the three-prefecture model with prefecture fixed effects yields an insignificant impact. The effects of Hokkaido may explain this result. Hokkaido had the most severe infection rate before the first wave in Japan, and the prefectural government declared a state of emergency at the end of February. Therefore, Hokkaido residents may have different values. Similar to the Tokyo-specific estimation in Table 5, we separately ran the same regression with Hokkaido samples. The coefficient of *Post* was not significant (coefficient = 0.117, standard error = 0.166, p-value > 0.05). The separate estimation with Osaka samples showed a positive and significant effect (coefficient = 0.398, standard error = 0.155, p-value < 0.05), consistent with Tokyo's result. Therefore, we can predict that the results from Hokkaido influenced the three-prefecture model results.

Furthermore, *Sympathy* has a negative impact on *Travel*. Thus, if consumers believe that they should stay at home during the current circumstances, they are less likely to travel. Since individual values affect such evaluation, the coefficients of sympathy in individual consumer fixed effects are not significant except for the full-sample estimation.

Regarding other consumer characteristics, the results show that males have a higher level of *Travel* than females. In addition, people who have a partner or are married and households with a child (or children) have a lower *Travel* level. These results can be interpreted as indicating that people or families with such characteristics tend to be risk averse and less likely to travel under current circumstances.

Table 6 shows the results of another set of additional analyses. The models in Table 6 employ *Sympathy* as the dependent variable. The results reveal that consumers perceive staying at home to be less important after the go-to-travel campaign is implemented. This result is consistent when controlling for individual consumer fixed effects. Thus, even when we control for time-invariant personal traits and monthly infection cases, consumers are less likely to think that they should stay at home. Furthermore, consumers with higher self-efficacy are more likely to consider that people should stay at home under the current circumstances.

("Insert Table 6 about here")

## Conclusion

Due to the significant damages by COVID-19 (Qiu et al. 2020; Sigala 2020), Governments implemented health and economic measures (e.g., community lockdown, stay-at-home requests, vouchers for tourism) to overcome this crisis. Unlike many Western countries, Japan did not conduct community lockdowns involving legal enforcement. Therefore, consumers could choose whether to go out shopping or travel, and Japan is therefore a unique case for how government interventions impact consumer behavior in the context of the COVID-19 pandemic.

With this in mind, this study empirically examined the effects of the go-to-travel campaign in Japan. The empirical results of the DID specification with a two-way fixed-effects model revealed the insignificant impact of the campaign. The results of additional analyses indicated that the travel frequency was higher after the go-to-travel campaign was implemented when controlling for the perceived importance of staying at home, the frequency of going out to shop or eat out, and the (consumer or prefecture) fixed effects. These results can be interpreted as indicating that the implementation of the policy itself may have a communication effect, because the government's communication and information delivery are influential factors for economic measures (Okazaki et al. 2015; Scott et al. 2020).

This study outlines opportunities for future studies. The results show that consumers have higher travel frequency in the posttreatment period when controlling for consumer fixed effects, perceived importance of staying at home, and number of infection cases. However, this study employed self-report measurements. This method is a reasonable way to collect relevant information in the current circumstances, but as broader and more detailed information becomes available, replication studies that use actual behavioral observations are required. Second, this study focuses on the consumer perspective, but research from the firm's perspective (e.g., Kamata 2021) provides a more comprehensive understanding of business recovery under COVID-19. Third, the status of international tourism recovery remains unknown. Since it is not realistic to analyze international tourism recovery as of March 2021, international tourism in the postpandemic context is another further research opportunity. Fourth, the results of additional analyses do not explicitly assess the causal effect of the go-to-travel campaign. Even though the additional analyses provide informative results, further research that complements the current study is required.

Policymakers may focus on financial incentives (e.g., discount rate) when considering effective demand-promoting measures. However, the current study indicates the possibility that public communication changes people's perceptions of the importance of stay-at-home requests and travel behavior. This implication highlights the potential of recovery from the current state once things settle down and consumers perceive safety.

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## Footnotes

[1]The questionnaire uses the term “Shikohin” for nondaily necessities in Japanese. “Shikohin” is a widely used term that indicates a category of products consumed for taste or pleasure rather than sustenance, such as alcohol, coffee, tea, and cigarettes.

**Tables**

**Table 1.** Demographic characteristics of the samples

| Variable | Percent |
|---|---|
| Age group | |
| ≧19 | 0.64 |
| 20~24 | 2.92 |
| 25~29 | 5.69 |
| 30~34 | 9.51 |
| 35~39 | 11.22 |
| 40~44 | 11.83 |
| 45~49 | 13.23 |
| 50~54 | 12.25 |
| 55~59 | 11.11 |
| 60≦ | 21.61 |
| Familysize | |
| One | 13.34 |
| Two | 29.7 |
| Three | 26.58 |
| Four | 20.36 |
| Five | 6.58 |
| More than six | 3.44 |
| Income group | |
| Less than 200million yen | 38.05 |
| 200～ less than 400million yen | 26.59 |
| 400～less than 600million yen | 16.1 |
| 600～less than 800million yen | 7.24 |
| 800～less than 1000million yen | 3.27 |
| 1000～ess than 1200million yen | 1.25 |
| 1200～less than 1500million yen | 0.58 |
| 1500～less than 2000million yen | 0.39 |

| | |
|---|---|
| More than 1500million yen | 0.29 |
| NA | 6.24 |
| Marital status | |
| No | 34.08 |
| Yes | 65.92 |
| Living with people over 65 | |
| Yes | 27.56 |
| No | 72.44 |
| Gender | |
| Male | 49.71 |
| Female | 50.29 |

**Table 2.** Variable definitions

| | Variable name | Notation | Description |
|---|---|---|---|
| Outcome | Travel | *y* | Year-on-year monthly travel frequency changes<br>1. Decreased,…4. Unchanged,…, 7. Increased |
| DID measurement | Treatment | *Treat* | Whether a sample is eligible to participate in the go-to-travel campaign.<br>Dichotomous variable |
| | Posttreatment period | *Post* | Whether the observation is in the posttreatment period.<br>Dichotomous variable |
| | Time trend | *Timetrend* | Months from May. |
| Individual characteristics | Income changes | *Service* | Year-on-year monthly income change<br>1. More than 50% reduction,…, 4. Unchanged,…, 7. More than 50% increase |
| | Shopping for daily necessities | *Necessity* | Year-on-year monthly frequency changes in going out to buy daily necessities<br>1. Decreased,…4. Unchanged,…, 7. Increased |
| | Shopping for nondaily necessities | *Nonnecessity* | Year-on-year monthly frequency changes in going out to buy nondaily necessities<br>1. Decreased,…4. Unchanged,…, 7. Increased |
| | Social gathering or having drinks | *Social gathering* | Year-on-year monthly frequency changes in going out for drinks or social gatherings<br>1. Decreased,…4. Unchanged,…, 7. Increased |
| | Sympathy with "stay at home" request | *Symp* | "Considering the request to stay at home, I sympathize with the opinion that we should stay at home."<br>1. Strongly disagree, …, 7.Strongly agree |
| | Self-efficacy for "staying at home" | *Efficacy* | "Considering the request to stay at home, I think that staying at home can be achieved through individual effort."<br>1. Strongly disagree, …, 7.Strongly agree |
| | Gender | *Male* | Whether the sample is male.<br>Dichotomous variable |
| | Marital status | *Marital status* | Whether the sample is married or has a partner.<br>Dichotomous variable |
| | Existence of a child | *Child* | Whether the sample has a child in a household.<br>Dichotomous variable |

| | | | |
|---|---|---|---|
| | Annual income | *Income* | 9-point interval scale |
| | Living with people over 65 | *Over 65* | Whether the sample lives with a person older than 65 years of age. |
| | Family size | *Family size* | The number of people within a household |
| Prefectural characteristics | The number of infected cases | *Infection* | The number of monthly infected cases for each prefecture. (Sourced from public data) |

**Table 3.** Trend check

| DV: Travel | Full sample | 13 prefectures | 3 prefectures |
|---|---|---|---|
| Treat×Timetrend | -0.028 | 0.014 | 0.038 |
| | (0.028) | (0.032) | (0.044) |
| Income change | 0.016* | 0.008 | 0.018 |
| | (0.008) | (0.016) | (0.034) |
| Intercept | 1.752** | 1.467** | 1.444** |
| | (0.171) | (0.191) | (0.240) |
| Consumer fixed effect | Yes | Yes | Yes |

Significance at the 5% level; **significance at the 1% level

Values in parentheses show standard errors.

**Table 4.** Two-way fixed-effect DID estimation

| DV: Travel | Full sample | | 13 prefectures | | 3 prefectures | |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (1) | (2) | (1) | (2) |
| Treat × Post | 0.061 | -0.046 | 0.038 | 0.005 | 0.480 | -0.015 |
| | (0.175) | (0.164) | (0.144) | (0.148) | (0.184) | (0.185) |
| Income change | 0.011 | 0.080** | 0.023 | 0.092* | -0.012 | 0.090* |
| | (0.010) | (0.010) | (0.011) | (0.016) | (0.032) | (0.017) |
| Infection | 5.E-05 | 4.E-05 | 4.E-06 | -2.E-05 | -1.E-04 | -8.E-05 |
| | (5.8E-05) | (6.E-05) | (5E-05) | (6.E-05) | (8.E-05) | (7.E-05) |
| Intercept | 1.768** | 1.474** | 1.705** | 1.444** | 2.062** | 1.580** |
| | (0.165) | (0.137) | (0.138) | (0.134) | (0.261) | (0.186) |
| Time trend fixed effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Consumer fixed effect | Yes | No | Yes | No | Yes | No |
| Prefecture fixed effect | No | Yes | No | Yes | No | Yes |

Significance at the 5% level; **Significance at the 1% level

Values in parentheses show standard errors.

**Table 5.** Summary of additional analyses 1

| DV: Travel | Full sample | | 13 Prefectures | | 3 Prefectures | | Tokyo | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Post | 0.153*** | 0.148*** | 0.153*** | 0.148*** | 0.246*** | 0.254*** | 0.453** | 0.401* |
| | (0.036) | (0.035) | (0.036) | (0.035) | (0.086) | (0.081) | (0.178) | (0.222) |
| Age | 0.0166 | -0.00224 | 0.0166 | -0.00224 | 0.0732 | -4.97E-05 | -0.115 | -0.0162 |
| | (0.057) | (0.002) | (0.057) | (0.002) | (0.118) | (0.005) | (0.121) | (0.011) |
| Sympathy | -0.0579** | -0.122*** | -0.0579** | -0.122*** | -0.0443 | -0.160*** | -0.189* | -0.311*** |
| | (0.029) | (0.025) | (0.029) | (0.025) | (0.066) | (0.054) | (0.102) | (0.090) |
| Self-efficacy | 0.00662 | 0.000834 | 0.00662 | 0.000834 | -0.0759 | -0.0259 | -0.109 | -0.0127 |
| | (0.024) | (0.022) | (0.024) | (0.022) | (0.050) | (0.045) | (0.108) | (0.099) |
| Income changes | 0.0328* | 0.0345** | 0.0328* | 0.0345** | 0.0353 | 0.0213 | 0.0549 | 0.0114 |
| | (0.017) | (0.015) | (0.017) | (0.015) | (0.044) | (0.033) | (0.069) | (0.061) |
| Nonnecessities | 0.0167 | 0.0251* | 0.0167 | 0.0251* | -0.00837 | -0.00361 | -0.0371 | 0.071 |
| | (0.016) | (0.015) | (0.016) | (0.015) | (0.037) | (0.033) | (0.054) | (0.066) |
| Necessities | 0.0332* | 0.0419** | 0.0332* | 0.0419** | 0.0318 | 0.0466 | 0.110* | -0.0397 |
| | (0.020) | (0.017) | (0.020) | (0.017) | (0.045) | (0.040) | (0.064) | (0.068) |
| Drinking or social gathering | 0.501*** | 0.560*** | 0.501*** | 0.560*** | 0.424*** | 0.538*** | 0.133 | 0.416*** |
| | (0.031) | (0.022) | (0.031) | (0.022) | (0.072) | (0.050) | (0.083) | (0.088) |
| Male | NA | 0.254*** | NA | 0.254*** | NA | 0.289** | NA | 0.442** |
| | NA | (0.055) | NA | (0.055) | NA | (0.118) | NA | (0.199) |
| Marital status | 0.274 | -0.0145 | 0.274 | -0.0145 | 0.732*** | 0.0401 | NA | 0.026 |
| | (0.407) | (0.069) | (0.407) | (0.069) | (0.179) | (0.168) | NA | (0.287) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Child | NA | -0.214*** | NA | -0.214*** | NA | -0.223 | NA | 0.00196 |
| | NA | (0.072) | NA | (0.072) | NA | (0.145) | NA | (0.246) |
| Income | 0.0302 | -0.00533 | 0.0302 | -0.00533 | NA | -0.00429 | NA | 0.0128 |
| | (0.044) | (0.010) | (0.044) | (0.010) | NA | (0.020) | NA | (0.037) |
| Family size | -0.0413 | -0.0172 | -0.0413 | -0.0172 | -0.131 | -0.0815 | -0.161 | -0.235 |
| | (0.066) | (0.026) | (0.066) | (0.026) | (0.146) | (0.061) | (0.205) | (0.145) |
| Over 65 | 0.0723 | -0.029 | 0.0723 | -0.029 | -0.0965 | 0.00924 | -0.0388 | -0.261 |
| | (0.127) | (0.059) | (0.127) | (0.059) | (0.199) | (0.131) | (0.129) | (0.238) |
| Infection | -1.74E-05 | -2.79E-05 | -1.74E-05 | -2.79E-05 | -6.47e-05* | -8.09e-05** | -0.000124* | -0.00013 |
| | (2.800E-05) | (2.930E-05) | (2.800E-05) | (2.930E-05) | (3.620E-05) | (3.870E-05) | (7.130E-05) | (8.230E-05) |
| Intercept | -0.721 | 1.216*** | -0.721 | 1.216*** | -3.325 | 1.535*** | 8.316 | 3.680*** |
| | (2.848) | (0.240) | (2.848) | (0.240) | (5.986) | (0.503) | (5.849) | (0.867) |
| Consumer fixed effect | Yes | No | Yes | No | Yes | No | Yes | No |
| Prefecture fixed effect | No | Yes | No | Yes | No | Yes | No | Yes |

* Significance at the 5% level; **Significance at the 1% level

Values in parentheses show standard errors.

(1) and (2) represent the individual consumer fixed-effect model and prefecture fixed-effect model, respectively.

**Table 6.** Summary of additional analyses 2

| DV: Sympathy | Full sample | | 13 Prefectures | | 3 Prefectures | | Tokyo | |
|---|---|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Post | -0.195** | -0.197** | -0.246** | -0.266** | -0.296** | -0.293* | -0.386** | -0.408** |
| | (0.012) | (0.014) | (0.025) | (0.030) | (0.060) | (0.052) | (0.103) | (0.095) |
| Age | -0.036 | 0.004** | -0.049 | 0.007** | -0.010 | 0.007 | -0.083 | 0.005 |
| | (0.021) | (0.001) | (0.041) | (0.001) | (0.071) | (0.003) | (0.152) | (0.007) |
| Efficacy | 0.306** | 0.432** | 0.279** | 0.418** | 0.267** | 0.419** | 0.253** | 0.331** |
| | (0.008) | (0.007) | (0.014) | (0.013) | (0.050) | (0.028) | (0.049) | (0.043) |
| Income change | 0.006 | 0.001 | 0.008 | 0.008 | -0.022 | 0.003 | -0.025 | -0.042 |
| | (0.012) | (0.005) | (0.012) | (0.009) | (0.021) | (0.027) | (0.045) | (0.037) |
| Male | NA | -0.177** | NA | -0.182** | NA | -0.175 | NA | -0.415** |
| | NA | (0.014) | NA | (0.028) | NA | (0.078) | NA | (0.152) |
| Marital status | -0.484 | 0.034 | 0.142 | 0.059 | -0.418** | -0.010 | NA | -0.221 |
| | (0.249) | (0.018) | (0.383) | (0.036) | (0.156) | (0.150) | NA | (0.190) |
| Child | 1.059 | -0.029 | NA | -0.010 | NA | 0.071 | NA | 0.227 |
| | (0.540) | (0.019) | NA | (0.037) | NA | (0.090) | NA | (0.216) |
| Income | -0.033 | -0.006* | 0.801 | -0.002 | NA | 0.005 | NA | -0.017 |
| | (0.046) | (0.003) | (0.481) | (0.005) | NA | (0.030) | NA | (0.030) |
| Family size | 0.012 | 0.011 | 0.022 | 0.001 | 0.101 | 0.156 | -0.090 | 0.199* |
| | (0.022) | (0.007) | (0.052) | (0.014) | (0.096) | (0.043) | (0.330) | (0.099) |
| Over 65 | 0.003 | -0.058** | -0.013 | -0.121 | -0.081 | -0.259 | 0.001 | -0.209 |
| | (0.037) | (0.017) | (0.068) | (0.034) | (0.135) | (0.106) | (0.311) | (0.174) |
| Infection | 1.61E-05 | 2.35E-05 | 1.99E-05 | 3.35E-05 | 7.39E-06 | 8.56E-08 | 1.61E-05 | 2.13E-05 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (2.12E-05) | (2.76E-05) | (2.40E-05) | (3.17E-05) | (2.80E-05) | (2.28E-06) | (3.94E-05) | (3.89E-05) |
| Intercept | 3.605 | 2.217** | 2.599 | 2.180** | 4.085 | 2.037 | 7.391 | 2.827** |
| | (1.300) | (0.062) | (2.665) | (0.116) | (3.703) | (0.481) | (7.495) | (0.525) |
| Consumer fixed effect | Yes | No | Yes | No | Yes | No | Yes | No |
| Prefecture fixed effect | No | Yes | No | Yes | No | Yes | No | No |

*Significance at the 5% level; **Significance at the 1% level

Values in parentheses show standard errors.

# Figures

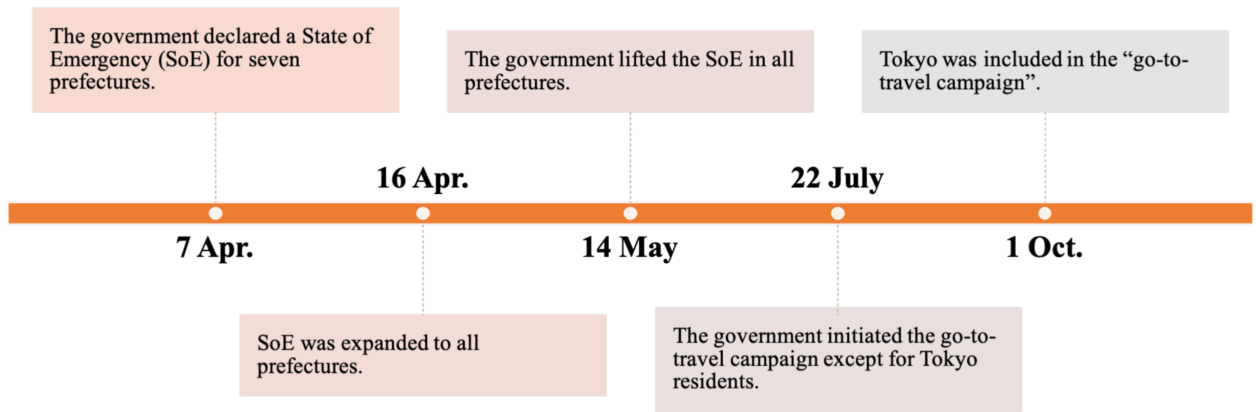


**Figure 1.** Timeline of political reactions in Japan

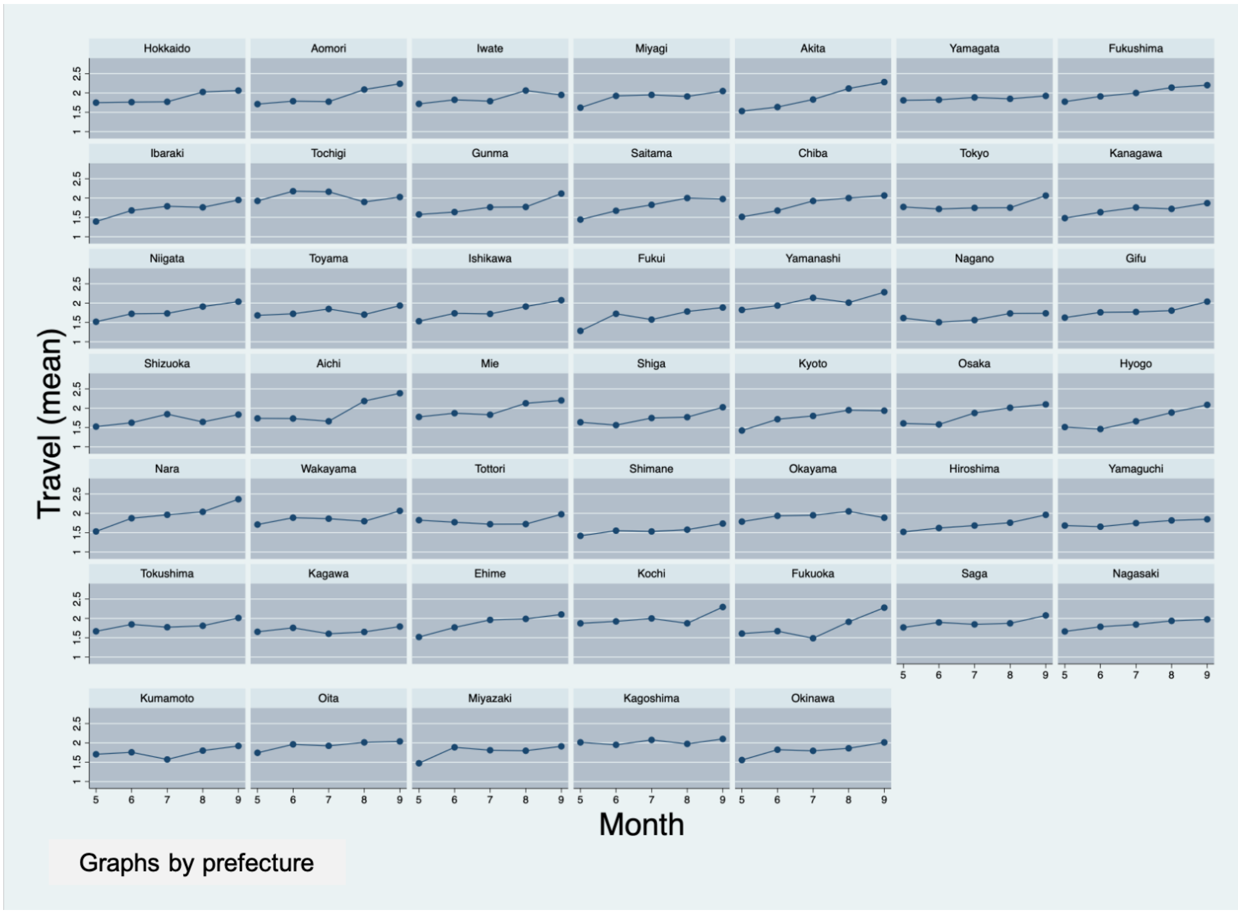


**Figure 2.** Time trend of the outcome variable by prefecture