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Analysis of optimal timing of tourism demand recovery policies from natural disaster using the contingent behavior method

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HIGHLIGHTS

- The contingent behavior method is useful for analyzing the tourism demand recovery.
- Announcing safety information would be most effective policy.
- Income effects would change from negative to positive during the recovery process.
- Optimal steps include safety, event, and visitor information, and price discounting.

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ABSTRACT

This paper examines the applicability of contingent behavior (hereafter, CB) method for analyzing dynamic processes and efficient policies in tourism demand recovery. The CB questionnaires used for this study used a hypothetical disaster situation of bird flu in Kyoto, Japan. Safety, event, visitor information, and price discounting policies were designed accordingly. Respondents were then asked about their willingness to travel time. The results showed the optimal timing for devising pertinent policies during the year. We found that the first step requires a safety information announcement, within one week, immediately after disaster site decontamination. The second step is the implementation of event information policy within 24th to 36th week after the disaster. The third step constitutes announcing visitor information within the 37th to 52nd week after the second step. The final step is the implementation of price discounting policy, until the 52nd week, immediately after the third step.

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1. Introduction

Natural disasters have occasionally caused physical and economic damage to both tourist and non-tourist sites, leading to loss of tourism opportunities and the collapse of tourism industries (Murphy & Bayley, 1989; Ritchie, 2009). Given the possibility of long-term economic deterioration due to continuing reduction in tourism demand, opportunity losses are a major concern for policymakers and the industry itself (Chew & Jahari, 2014).

The bird flu outbreak in Japan's Miyazaki prefecture in 2010 forced public officers to prohibit visitor entry to disaster areas, followed by the culling of influenza-stricken birds, which caused losses of approximately ¥8.1 billion (Miyazaki Prefecture, 2011). The Great East Japan Earthquake, which occurred at a magnitude of 9.0, and the ensuing tsunami in Tohoku area (Eastside of Japan), in 2011, killed nearly 200,000 people. These disasters led to economic losses of ¥16.9 trillion, which included losses due to a decrement in the number of tourists—from 27.7 million in 2010 to 21.1 million in 2011 (Cabinet Office, Government of Japan, 2011; Kento, 2015). The Great Kumamoto Earthquake, which occurred in Kyushu area (Westside of Japan) in 2016, caused 67 deaths and economic damages worth ¥2.4 million to ¥4.6 trillion to the Kumamoto and Oita prefectures. It further resulted in a decrease of approximately 2.3 million tourists to the Kyushu area between April and June 2016, compared to the same period in 2015 (Cabinet Office, Government of Japan, 2016; Kyushu Economic Research Center, 2016).

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In previous literature, tourism management studies have analyzed frameworks and methods for tourism recovery at disaster sites (Durocher, 1994; Faulkner, 2001; Huanga & Min, 2002; Mazzocchia & Montini, 2001; Wang, 2009). For instance, Ritchie (2009, p. 262) noted that tourism crisis and disaster management models should be developed for decision-making. However, due to lack of tourism demand data with respect to disasters, few studies have examined the quantitative effects of recovery policies.

Owing to insufficient research on this topic, this study examines a valuation method, while simultaneously measuring the quantitative effects and the optimal timing (order) of tourism recovery policies applying the contingent behavior (hereafter CB) method. By showing the optimal policy timing (order), we expect to contribute toward 1) helping policymakers when they may not be able to undertake rescue operations and recover disaster losses due to financial and human resources shortages simultaneously and 2) development of advance planning (the stage 1 of Faulkner, 2001) before potential disasters.

The CB method design requires consideration of the realities and existence of disaster-related solutions. As it is difficulty to design and establish efficient solutions for earthquakes of large magnitudes, tsunamis, and typhoons—which typically cause considerable damage across a wide area—this study employs a bird flu scenario as a hypothetical natural disaster. The World Health Organization (2013) reported that, from 2003 to 2013, bird flu claimed 630 human lives globally. In Asia alone, 65% and 49.5% of all those infected by bird flu died in China and Vietnam, respectively. Brahmbhatt (2005) reported that bird flu decreased Vietnam's gross domestic product (GDP) by 0.4%. Moreover, the alarming possibility of a worldwide bird flu pandemic continues to exist. In such a scenario, approximately 5 million to 150 million people could die (Ministry of Foreign Affairs of Japan, 2007).

The remainder of this paper is structured as follows. Section 2 summarizes the main objectives of this study based on a review of previous studies. Section 3 describes the estimation models and survey questionnaires. Section 4 presents the estimation results. The discussion and conclusions appear in Sections 5 and 6, respectively.

2. Literature review

2.1. Tourism demand recovery management from disasters

Faulkner (2001) and Ritchie (2009) presented the frameworks of tourism demand recovery processes (strategies). Faulkner (2001)'s framework is divided into six stages: 1) the pre-event (pre-disaster) stage (stage 1) to mitigate the effects of disaster through advance planning, 2) the prodromal stage (stage 2), indicating the inevitability of a disaster, 3) the emergency stage (stage 3) to undertake rescue operations in the event of a disaster, 4) the intermediate stage (stage 4) that responds to the short-term needs (e.g., food, medicines) of people and companies in the disaster site, 5) the long-term recovery stage (stage 5), which includes reconstruction of infrastructure and victim counseling, and 6) the resolution stage (stage 6), which requires restoration of routine along with new and improved state establishments. The fifth and sixth stages are post-event stages, and the focus of this study. Thus, the policy effects from pre-event to the post-event stages and the feedback effects from the post-event to the pre-event stages described in Racherla and Hu (2009) are not our focus. Furthermore, the third and fourth stages would constitute the main parts of emergency policies.

As mentioned in Ritchie (2009), the quantitative valuation of recovery process is one of the most important tasks of tourism disaster management. Faulkner (2001), thus, presented various strategies, such as restoration of business and consumer confidence, and repair of damaged infrastructures. The Ministry of Land, Infrastructure, Transport and Tourism of Japan (MLITT, 2009) states that the recovery process has to include management policies for safety information, pricing, visit campaigns, among others. Moreover, Beirman (2009) suggested the importance of media, public relations, and regional cooperation in case studies. Regardless of these suggestions, policymakers might not know which policies are effective, when they should be implemented, and which policy ordering is desirable under the provision of few quantitative valuations.

The method used in this study could lead policymakers to make quick and appropriate decisions that may reduce or prevent damages related to a disaster.

2.2. Policy analyses by tourism demand functions

The Ministry of Land, Infrastructure, Transport and Tourism of Japan (2009) has published a manual (hereafter the MLITT manual) on the management of tourism demand recovery before and after the occurrence of infections, such as the bird flu. Fig. 1 shows the framework of the recovery process as per the MLITT manual in relation to the stages in Faulkner (2001). The vertical axis shows tourism demand (tourists' choice probability) levels. The horizontal axis shows time series, where t_0 refers to the emergence time of the bird flu, t_1 denotes the time when the affected areas/sites are decontaminated, and t_2 denotes the time that the tourism demand recovers to the standard (pre-stage) demand level. Thus, the *optimal* policy (or policies) in this study refers to a policy or a combination of policies that can recover a tourism demand level immediately after t_1 is closest to or over the standard demand level at t_0 (t_2). The tourism demand process was categorized into Periods 1 to 4. Period 1 almost corresponds to stages 1 and 2 of Faulkner (2001); Period 2, to stages 3 and 4; and Periods 3 and 4, to stages 5 and 6, respectively. One of the aims of this study is to examine the recovery process by estimating the demand function after t_1 in Period 3.

Theoretically, tourism demand is determined by travel prices to tourism sites, individual, or household income, and site attributes data, such as nature, safety levels, and leisure amenities (Dann, 1981; Dwyer, Forsyth, & Dwyer, 2010). Tourism policy evaluations, which are based on demand function approaches, measure policy effects from these factor (policy variable) changes (e.g., discounting the prices and improving attributes). While micro (consumer behavior) data are frequently used for the demand analyses (Fleming & Cook, 2008; Phaneuf, Kling, & Herriges, 2000), the difficulty of researching such data from the time series of

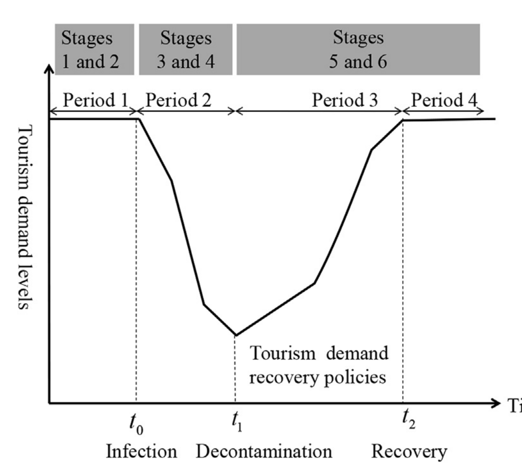

Fig. 1. Process of tourism demand recovery before and after the bird flu outbreak.

independent consumer behaviors sometimes dissuades researchers from analyzing the dynamic processes of demand functions, especially in disaster.

Macro data following the time series are also used for tourism demand analysis (Song & Witt, 2000; Wang, 2009). Using data from the World Health Organization (2013), Kuo, Chen, Tseng, Ju, and Huang (2008, 2009) showed the negative impacts of the Severe Acute Respiratory Syndrome (better known as SARS) and bird flu on tourism activities. Page, Song, and Wu (2012) also showed that the outbreak of bird flu decreased the number of tourists to England. Kuo et al. (2008) and Chang et al.'s (2012) results indicated that analyses based on social statistics may not always be able to estimate the impacts of bird flu on tourism, given the influences of external macro-impact factors, such as economic trends, terrorism, and temperature.

The CB method could overcome these micro and macro data issues, as it analyzes individual behaviors. This method enables researchers to analyze individual behaviors under (researcher -designed) hypothetical situations, and it is used in cases where observable data are limited. For instance, Whitehead, Johnson, Mason, and Walker (2008) used observable data by asking respondents the number of times they visited hockey games depending on game intervals and seat prices. Phaneuf and Earnhart (2011) measured recreational benefits of lakes using trip data under hypothetical trip time and prices. Whitehead, Dumas, Herstine, Hill, and Buerger (2010) valued the benefits of improving the widths of beaches using actual and contingent trip data collected under different accessibility conditions to beaches of various widths. Using the CB method, Whitehead (2005) analyzed hurricane evacuation behaviors by asking respondents about their order of fleeing from their homes depending on the strength of the hurricane.

Overall, few previous studies have incorporated the time series factor into the CB method. This study, on the other hand, examined CB questionnaires from previous studies, such as Phaneuf and Earnhart (2011), and developed a new CB questionnaire with time series factors for analyzing the policy timings and orderings.

2.3. Tourism demand recovery policies of this study

This study mainly examined the effects of information and pricing policies. Three information policies are included in the CB questionnaire. The first is the provision of safety information, by the Japanese government and Kyoto prefectural governments, to ensure safety in traveling to Kyoto prefecture, from the discussions of stage 5 of Faulkner (2001) and the MLITT manual. Note that tourists sometimes may not visit a disaster site without safety information. The second is the provision of event information of the respondents' preferred events that have been performed and/or new tourism facilities that have been established in Kyoto. The third is the provision of visitor information regarding the number of tourists who have already visited Kyoto. The second and third information policies are designed for improving (respondents') destination images referred by Beirman (2003), Chew and Jahari (2014), and Ritchie (2009).

Previous studies suggested that pricing policies, such as decrements of travel, hotel, and food costs, have a positive effect on tourism demand (Garrod & Fyall, 2000; Laarman & Gregersen, 1996). H.I.S. (2016), a major Japanese tourism company, also implemented a tourism campaign (price discounting) in collaboration with the Japanese government to recover tourism demand from Japan to France, following the 2015 terrorist attacks in France. Thus, this study employed price discounting. Thus, tourism demand recovery will be delayed if its effects are not revealed in the recovery process. Thus, this study also examined the pricing policy effect through comparisons with information policies.

3. Estimation models and survey questionnaires

3.1. Estimation model

Previous studies employed the time series analysis (Eilat & Einav, 2004; Gurudeo, 2012; Song, Li, Witt, & Fei, 2010) and the random utility model (Baltas, 2007) in analyzing tourism demands. Here, the CB questionnaires collect "yes/no" response data on individual decisions on travel, and thus, this study used the logit model for the estimations.

Let $\mathbf{X}$ be a vector of variables and $\boldsymbol{\beta}'$ be a transported vector of parameters. *pr*, defined by equation (1), is the probability of obtaining a negative response ("no") from the *i*th respondent. Equation (2) shows the log-likelihood function. The estimations were performed using the glm function in R ver 3.01.

$$pr = \frac{\exp(\mathbf{X}\boldsymbol{\beta}')}{1 + \exp(\mathbf{X}\boldsymbol{\beta}')} \tag{1}$$

$$LL = \log\left\{\sum\nolimits_{i=1}^{N} pr_i^{I_i} \times \left(1 - pr_i^{1-I_i}\right)\right\} \tag{2}$$

3.2. Survey questionnaires

3.2.1. Site selection and description

The following hypothetical site conditions were considered for the CB questionnaires: i) short distance from all respondents' homes to reduce the number of rejected responses typical with long distance travel, ii) actual bird flu experiences to add reality to the hypothetical situation described in the CB questionnaires, and iii) use of a famous site to avoid wrong answers resulting from respondents' unawareness. The questionnaires were in Japanese.

This study selected Kyoto prefecture, one of Japan's most famous tourism sites, as the site for the hypothetical case. Fig. 2 shows the location of Kyoto prefecture with the hypothetical bird flu outbreak. Kyoto prefecture is located in the central part of Japan (E135° 45′, N35° 01′), satisfying condition (i). Its area is 4613.21 km^2, and the Japan Sea lies towards its north, while Nara Prefecture lies to its south and Mie prefecture is located towards its east. The population in 2014 was 2.6 million (Kyoto Prefectural Government, 2016), and, in 2014, approximately 55,636 thousand Japanese and foreign tourists visited Kyoto (Kyoto City Government, 2014).

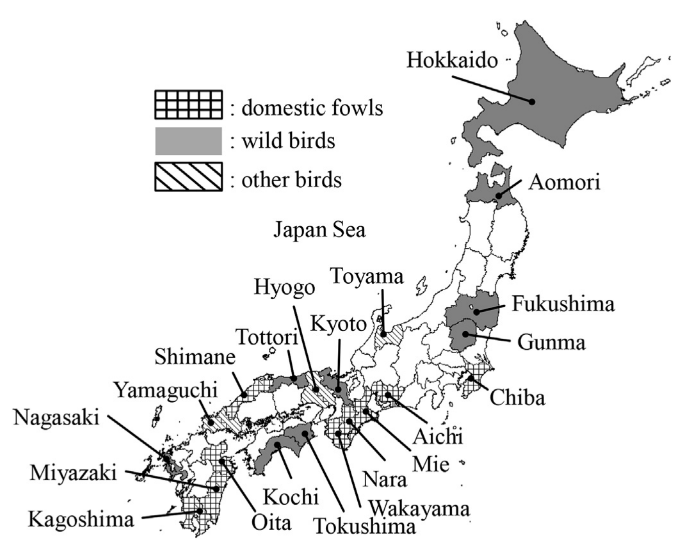

Fig. 2. Locations of Kyoto prefecture and the areas affected by bird flu in Japan.

Kyoto was the capital of Japan nearly 1100 years from the eighth century onwards. Many historical temples and shrines that were built during the period still exist. Seventeen historic sites, such as Kiyomizu-dera Temple and Nijo Castle, are recognized as World Heritage Sites. Kyoto has three major festivals, which attract tourists: the Aoi-matsuri Festival in early summer, the Gion-matsuri Festival in mid-summer, and the Jidai-matsuri Festival in fall. These events are hugely popular with both Japanese and foreign travelers.

The bird flu outbreaks (Fig. 2) in this study are categorized as domestic bird flu, wild bird flu, and other bird flu (Ministry of Agriculture, Forestry, and Fisheries, 2011). Kyoto prefecture is hypothesized to have a case of wild bird flu, satisfying condition (ii).

Condition (iii) was confirmed by the survey questionnaires—respondents were asked whether they had heard of and ever been to Kyoto. All respondents answered "yes" to the former question, while 92.6% of them answered "yes" to the latter question, thus satisfying condition (iii).

The CB questionnaire was implemented in four steps, as shown in Appendix 1. The first step (Appendix 1-A) was to research respondents' credible information source to avoid respondents' distrust in an information source, described in Appendix 1-D. Specifying respondents' credible information sources reduces the rate of rejection responses in the CB questionnaires. The second step was to provide explanations on bird flu (Appendix 1-B); the third, to present a hypothetical bird flu outbreak (Appendix 1-C); and the fourth, to implement the CB questionnaire (Appendix 1-D).

Alternatives and results of respondents' credible information sources are shown in Table 1 and Appendix 1-A. The most credible information source is public information (35.48%). The contents of explanations on bird flu are almost same as those in the introduction. Fig. A1 in Appendix 1-B shows the actual and hypothetical areas with bird flu outbreak to the left and right, respectively. In the explanation, respondents were also explained that the bird flu outbreak in Kyoto had not resulted in any damages to humans and food items. As shown in the right panel of the figure, designating all of Kyoto prefecture as a hypothetical area with bird flu outbreak would avoid misunderstandings among the respondents (and hence, any wrong answers). Otherwise, some respondents might respond that they visited areas affected by the bird flu outbreak against their will. In addition, the fact that the flu outbreak in Kyoto prefecture was attributed to wild birds might have made the hypothetical situation more realistic.

3.2.2. Information policies

Announcements made after disasters play an important role in tourism demand recovery. Safety information would particularly alleviate tourists' anxiety and assure them that any danger from the situation has passed. This study designed three hypothetical information policies (see Appendix 1-D): safety information (Information 1), event information (Information 2), and visitor information (Information 3), as mentioned in section 2.3.

Combinations of the policies were presented to the respondents via the CB questionnaires. The combinations were mainly categorized as Type A and B, based on the inclusion or exclusion of safety information, respectively. IP denotes the dummy variables for both Types, respectively: 1 for yes, 0 for others. The subscript *safe* (e.g., IP_{safe}) means safety information (Type A) is provided, while *nosafe* (e.g., IP_{nosafe}) indicates none is provided. Thus, the IP_{nosafe} variable is used to explore the natural recovery process of tourism demand over time. The superscripts *event* and *visitor* (e.g., IP^{event} and $IP^{visitor}$) mean event and visitor information are provided, respectively. Thus, IP^{event}_{safe} and $IP^{visitor}_{safe}$ indicate mixed (simultaneous) policies of event and visitor information with safety information, respectively. IP^{event}_{nosafe} and $IP^{visitor}_{nosafe}$ indicate single policies of event and visitor information without safety information, respectively. For example, $IP^{event}_{safe} = 1$ means the respondents selected a WTT value to a CB questionnaire when event and safety information are simultaneously provided; $IP^{event}_{nosafe} = 1$ means the respondents selected a WTT value when only event information is provided.

3.2.3. Price discounting policy

Estimating the travel cost variables (hereafter *TC*) allowed the analysis of the effects of price discounting policies on increasing tourism demand. Firstly, a hypothetical tourism design is considered. Two-day and one-night travel times were assumed as the hypothetical travel times. The Japan Tourism Agency (2013) reported that the average total overnight stay days in trips per year and average number of trips per year by the Japanese in 2011 were 2.08 and 1.3, respectively. Thus, the average overnight trip days per trip is 2.08/1.3 = 1.6 in 2011, 2.09/1.32 = 1.58 in 2010, and 2.38/1.46 = 1.63 in 2009. The average values of overnight trip days per trip indicate that almost half of the Japanese do not (or would not like to) travel for over 1.6 days. Two-day and one-night travel times were also assumed to avoid reject responses due to longer travel times and expensive cost.

The website of JTB (a Japanese major travel company, http://www.jtb.co.jp/) showed that the maximum travel cost in January 2012 was ¥40,000 per trip. A sum of ¥20,000 (half the maximum value) was employed to help respondents understand the price difference. As a hypothetical campaign for price discounting, a sum of ¥1000 was presented as the lowest price level (such as a positive follow up campaign in Ritchie, 2009, p. 187). In examining the survey, it is expected that some respondents might consider ¥1000 too expensive for a travel trip to Kyoto. For example, respondents living in Takatsuki city in Osaka prefecture could travel to and from Kyoto within ¥780 in March 2017 (West Japan railway company, http://www.westjr.co.jp/global/en/; in English). The influence of low price design on tourism demand was confirmed through simulation—a larger price discounting would lead to larger tourism demand recovery compared to information policies.

3.2.4. Willingness-to-travel time

Respondents were asked about their willingness-to-travel time (hereafter WTT) after the bird flu outbreak was resolved under the

Table 1
The alternatives and basic statistics on information source.

Alternatives	Means	S.D.
Public information from governments or related organizations	0.3548	0.4786
Private information from blogs and social network services, etc.	0.1076	0.3100
Private information from family, relatives, and/or friends	0.1259	0.3319
Private information from media such as television, newspapers, etc.	0.3116	0.4632
Private information from tourism companies	0.0808	0.2726
Others	0.0193	0.1375

Note: S.D.: standard deviation; N = 2128; respondents selected one of the alternatives; 1 if respondents selected an alternative, and 0 otherwise.

hypothetical situation, given information policies and travel costs. The minimum WTT was designed as “a (1) week” to ensure sufficient planning time for respondents. Depending on respondents' annual income, the maximum WTT was “a year (52 weeks).” For periods exceeding a year, respondents' different budget constraints would have resulted in varied consumption schemes. Thus, the other alternatives were “a month (4 weeks),” “three months (12 weeks),” “six months (24 weeks),” “nine months (36 weeks),” and “Never (0 weeks).” The values within the parentheses denote the value of the *WTT* variable.

Appendix 1-D shows an example of the CB questionnaire. The matrix-type answer format was used in the questions (Broberg & Brännlund, 2008; Evans, Flores, & Boyle, 2003; Wang & Heb, 2011). Each respondent was assigned to either group A or B (with or without safety information), after which they answered three questionnaires (one for each of the price levels). To avoid order effects, respondents were randomly assigned to either Type A or B, and then asked to answer another Type questionnaire (Bateman & Langford, 1997; Halvorsen, 1996). A dummy variable, *ODR*, was used to examine the order effect, where *ODR* took 1 for the first questionnaire (Type A or B), and 0 for the other.

Respondents who selected “Never” in Type A (including safety information) with *TC* of ¥1000 (the lowest travel cost) were asked about their reasons for rejection using a free response format. The questionnaire showed four reasons for rejection: “Anxiety about being infected by the bird flu (*RANXIETY*),” “Distrust safety information provided by central and local governments (*RDTRUST*),” “Not willing to travel to Kyoto (*RNWILL*),” and “Others (*ROTHER*).”

Finally, “yes/no” response data for the logit model were constructed from the WTT data (Bishop & Heberlein, 1979; Habb & McConell, 2002). Let WTT_{ji} $(WTT_j \in \{1, 4, 12, 24, 36, 52\})$ denote the time that respondent i is willing to travel, given the hypothetical situation. Respondent i's positive (“yes”) response to WTT_{ji} conduces positive (“yes”) responses for the periods $WTT_{ki} \geq WTT_{ji}$ $(k \neq j)$; otherwise, it conduces negative (“no”) if responses or the periods $WTT_{hi} < WTT_{ji}$ $(h \neq j)$. The “yes/no” response data for *WTT* were constructed accordingly, and the pooling data were employed for the estimations.

3.2.5. Individual characteristics

Table 2 shows the questionnaires for the individual characteristics. As observed in previous studies, respondents' gender, age, income, jobs, and educational status were analyzed. Respondents' travel experience (*EXKYOTO*), interest to tour Kyoto (*INTKYOTO*), and anxiety about the bird flu (*AXBF*) were also studied as impact factors for the tourism demand recovery process. Note that questions on *EXKYOTO*, *INTKYOTO*, and *AXBF* are asked to respondents before the questionnaire on the credible information in Appendix 1-A; questions on other variables are asked after the CB questionnaire.

3.3. Specifying models

3.3.1. Logit model formulations

This study estimated the following three models. Model 1 was used to estimate the parameters of the main variables (*WTT*, information policies from IP_{safe} to $IP^{visitor}_{nosafe}$, *TC*, and *ICM*) and reasons for rejection. Model 2 included the main reasons for rejection and individual characteristic variables to conduct statistical evaluations for all parameters. Here, Model 2 also confirmed the signs and statistical evaluations of parameters by *WTT* periods; the pooling data of a period were used. Thus, the *WTT* variable was not included. A part of the result is examined in the result and discussion section, and Appendix 2 shows all the results. Model 3 was formulated by eliminating the statistically insignificant variables from Model 2. Thus, Model 3 provided the final estimation results, and was used for the simulations. The robustness of the signs and statistical evaluations of the parameters were checked using the estimation models. Impacts of individual characteristics on decisions were revealed by the results of Model 3.

Model 1: Using main variables only ($\mathbf{X}\boldsymbol{\beta}'$)

$$\begin{aligned}\mathbf{X}\boldsymbol{\beta}' = CONT + \beta_{WTT}WTT + \beta_{safe}IP_{safe} + \beta^{event}_{safe}IP^{event}_{safe} + \beta^{visitor}_{safe}IP^{visitor}_{safe} + \beta^{event}_{nosafe}IP^{event}_{nosafe} + \beta^{visitor}_{nosafe}IP^{visitor}_{nosafe}\\ +\beta_{TC}TC + \beta_{ICM}ICM + \beta_{RANXIETY}RANXIETY + \beta_{RDTRUST}RDTRUST + \beta_{RNWILL}RNWILL + \beta_{ROTHER}ROTHER\end{aligned}$$

Model 2: Adding individual characteristic variables ($\tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}'$) to $\mathbf{X}\boldsymbol{\beta}'$ in Model 1

$$\begin{aligned}\tilde{\mathbf{X}}\tilde{\boldsymbol{\beta}}' = {} & \beta_{GND}GND + \beta_{AGE}AGE + \beta_{MAR}MAR + \beta_{JBTS}JBTS + \beta_{JBPTJ}JBPTJ + \beta_{JBSOB}JBSOB + \beta_{JBFP}JBFP + \beta_{JBHM}JBHM + \beta_{JBST}JBST + \beta_{JBNM}JBNM\\ & + \beta_{EDHS}EDHS + \beta_{EDVC}EDVC + \beta_{EDJC}EDJC + \beta_{EDTC}EDTC + \beta_{EDUV}EDUV + \beta_{EXKYOTO}EXKYOTO + \beta_{INTKYOTO}INTKYOTO + \beta_{AXBF}AXBF\\ & + \beta_{ODR}ODR\end{aligned}$$

Model 3: Eliminating statistically insignificant variables from Model 2.

To do so, this study employed the criterion as less than 1% of the *p*-value.

CONT denotes a constant. In all models, the expected parameters were negative for $\beta_{RANXIETY}$, $\beta_{RDTRUST}$, β_{RNWILL}, β_{ROTHER}, and β_{TC} because of negative motivations for traveling; otherwise, they were positive for β_{WTT}, β_{safe}, β^{event}_{safe}, $\beta^{visitor}_{safe}$, β^{event}_{nosafe}, and $\beta^{visitor}_{nosafe}$. The sign of β_{ICM} would also be positive if tourism during disasters is a normal good. The signs of the other parameters were confirmed though the estimations.

Table 2
Individual characteristics (variables and explanations).

Research items	Variables	Explanations (units)
Gender	*GND*	Respondent's gender: 1 for male, 0 for female
Age	*AGE*	Respondent's actual age (years)
Married or not	*MAR*	Dummy variable: 1 for married, 0 otherwise
Household income	*ICM*	Respondent's household income (10,000 yen per year)
Job status - Temporary staff	*JBTS*	Respondent's job status: 1 for temporary staff, 0 otherwise
Job status - Part time job	*JBPTJ*	Respondent's job status: 1 for part-time job, 0 otherwise
Job status - Self-owned business	*JBSOB*	Respondent's job status: 1 for self-owned business, 0 otherwise
Job status - Freelancer	*JBFP*	Respondent's job status: 1 for freelancer, 0 otherwise
Job status - Home maker	*JBHM*	Respondent's job status: 1 for home-maker, 0 otherwise
Job status - Student	*JBST*	Respondent's job status: 1 for student, 0 otherwise
Job status - Unemployed	*JBNM*	Respondent's job status: 1 for unemployed, 0 otherwise
Educational status - High school	*EDHS*	Respondent's final educational status: 1 for high school, 0 otherwise
Educational status - Vocational college	*EDVC*	Respondent's final educational status: 1 for vocational college, 0 otherwise
Educational status - Junior college	*EDJC*	Respondent's final educational status: 1 for junior college, 0 otherwise
Educational status - Technical college	*EDTC*	Respondent's final educational status: 1 for technical college, 0 otherwise
Educational status - University	*EDUV*	Respondent's final educational status: 1 for university, 0 otherwise
Tourism experience in Kyoto	*EXKYOTO*	1 if the respondent has traveled to Kyoto per year, 0 for no response
Respondent's interest in traveling to Kyoto	*INTKYOTO*	1 if the respondent is interested in traveling to Kyoto, 0 for no response
Respondent's anxiety about the bird flu	*AXBF*	1 if the respondent feels anxiety about the bird flu, 0 otherwise.

The applicability of the CB method was examined using the expected signs of the parameters. $\beta_{visitor}$ and β_{event} were used to check whether preference ordering on information policies would be preserved. For example, $\beta^{visitor}_{safe} > \beta^{event}_{safe}$ if $\beta^{visitor}_{nosafe} > \beta^{event}_{nosafe}$.

3.3.2. Information policy simulations

Estimation results were used to simulate policy effects into the tourism demand recovery process. Determining a pre-disaster demand level could help to understand the policy effects through simulation analyses. This study designed the standard level as 92.6% following *INTKYOYO*, in Table 2, because actual behavior data (*EXKYOTO*) would be inadequate for the stated preference-based simulations due to differences between revealed and stated behaviors (Whitehead, 2005). Moreover, it was assumed that $ODR = 0$ eliminated the order effects in all simulations.

The probabilities for a "yes" response from a week to a year were simulated by applying the estimated parameters ($\widehat{\boldsymbol{\beta}}$) in Model 3 and the mean values ($\overline{\mathbf{X}}$) in Tables 2, 5 and 6 to equation (1), that is

$$pr = \exp\left(\overline{\mathbf{X}}\widehat{\boldsymbol{\beta}}'\right) \Big/ 1 + \exp\left(\overline{\mathbf{X}}\widehat{\boldsymbol{\beta}}'\right) \tag{3}$$

Tourism demand recovery processes by Model 3 were simulated under the following simulation conditions (*SCs*). Here, the interpretations for the superscripts and subscripts of *SCs* are same as *IPA* and *IPB* variables, as mentioned earlier. A policy variable that equals 1 (e.g., $IP_{safe} = 1$) refers to an implementation of the policy, and 0 (e.g., $IP_{safe} = 0$) refers to no implementation. For simplicity, the policy effect was assumed to sustain from the starting point (1st week) to the terminal point (52nd week). For example, the effect of safety information beginning at the 1st week continues until the 52nd week.

Ten *SC*s are examined. The SC_{nosafe} showed a natural recovery process, indicating an increase in the number of tourists without policies (all information variables equal to zero). Next, the single effect of safety information (IP_{safe}) is observed for the process under SC_{safe}—only $IP_{safe} = 1$. The demand recovery processes by the mixed effects of the safety and event information (IP^{event}_{safe}), and of safety and visitor information ($IP^{visitor}_{safe}$), appear under SC^{event}_{safe} and $SC^{visitor}_{safe}$, respectively.

$$SC_{nosafe} : IP_{safe} = IP^{event}_{safe} = IP^{visitor}_{safe} = IP^{event}_{nosafe} = IP^{visitor}_{nosafe} = 0$$

$$SC_{safe} : IP_{safe} = 1,\ \ IP^{event}_{safe} = IP^{visitor}_{safe} = IP^{event}_{nosafe} = IP^{visitor}_{nosafe} = 0$$

$$SC^{event}_{safe} : IP^{event}_{safe} = 1,\ \ IP_{safe} = IP^{visitor}_{safe} = IP^{event}_{nosafe} = IP^{visitor}_{nosafe} = 0$$

$$SC^{visitor}_{safe} : IP^{visitor}_{safe} = 1,\ \ IP_{safe} = IP^{event}_{safe} = IP^{event}_{nosafe} = IP^{visitor}_{nosafe} = 0$$

Similarly, the following conditions from SC^{event}_{nosafe} to SC_{full} were designed to reveal the effects of the Type B group without safety information: event information (IP^{event}_{nosafe}) under SC^{event}_{nosafe} and visitor information ($IP^{visitor}_{nosafe}$) under $SC^{visitor}_{nosafe}$. Finally, the effects of implementing all policies (*full*) were simulated under SC_{full}. Here, IP^{event}_{safe} and $IP^{visitor}_{safe}$ were designed as zero, owing to the overlapping effects of safety information (IP_{safe}).

$$SC^{event}_{nosafe} : IP^{event}_{nosafe} = 1,\ \ IP_{safe} = IP^{event}_{safe} = IP^{visitor}_{safe} = IP^{visitor}_{nosafe} = 0$$

$$SC^{visitor}_{nosafe} : IP^{visitor}_{nosafe} = 1,\ \ IP_{safe} = IP^{event}_{safe} = IP^{visitor}_{safe} = IP^{event}_{nosafe} = 0$$

$$SC_{full} : IP_{safe} = IP^{event}_{nosafe} = IP^{visitor}_{nosafe} = 1,\ \ IP^{event}_{safe} = IP^{visitor}_{safe} = 0$$

The conditions under SC_{nosafe} to SC_{full} might be insufficient to allow tourism demand recovery to the pre-disaster demand level. Hypothetical policies that overcome the reasons for rejection were designed from SC^{ranx}_{full} to SC^{allrr}_{full}, based on SC_{full}. SC^{ranx}_{full} is a policy to overcome anxiety about getting infected with bird flu (the superscript notation, *ranx*) under SC_{full}, $SC^{ranx\&rdtrust}_{full}$ is a policy to overcome both anxiety and distrust toward government information (the superscript notation, *ranx&rdtrust*) under SC_{full}, and SC^{allrr}_{full} is a policy to overcome all reasons for rejection (the superscript notation, *allrr*) under SC_{full}.

$$SC^{ranx}_{full} = SCfull\ \&\ RANXIETY := 0$$

$$SC^{ranx\&rdtrust}_{full} :\ \ SCfull\&RANXIETY = RDTRUST = 0$$

$$SC^{allrr}_{full} : SCfull\ \&RANXIETY = RDTRUST = RNWILL = ROTHER = 0$$

3.3.3. Price discounting policy simulations

Simulating the travel cost (price) discount due to the simulated tourism demand from SC_{safe} to SC^{allrr}_{full} would help compare effects of price discounting under different information policies. Simulated tourism demands were calculated based on the 52nd week probability levels from SC_{safe} to SC^{allrr}_{full}. Let STD_{52} be a simulated "yes"-response (tourism demand) probability for 52 weeks calculated from SC_{safe} to SC^{allrr}_{full}, and let $\overline{TC}$ be the mean value presented to respondents in Table 5 below. Then, the simulated discounting costs (*SDC*) were calculated by equation (4). The simulated "pure" price discounts for overcoming *RANXIETY*, *RANXIETY*, and *RDTRUST*, and all reasons for rejection, were calculated as the *SDC* values from SC^{ranx}_{full}, $SC^{ranx\&rdtrust}_{full}$, and SC^{ranx}_{full}, minus the *SDC* value from SC_{full}. Here, $\overline{\mathbf{X}}\widehat{\boldsymbol{\beta}}'$ is an inner product of the vectors of the mean values and the parameters of the other variables.

$$\min\left\{SDC\middle|STD_{52} - \exp\left(\overline{\mathbf{X}}\widehat{\boldsymbol{\beta}}' + \beta_{TC}\left(\overline{TC} - SDC\right)\right)\Big/\left(1 + \exp\left(\overline{\mathbf{X}}\widehat{\boldsymbol{\beta}}' + \beta_{TC}\left(\overline{TC} - SDC\right)\right)\right) \equiv 0\right\} \tag{4}$$

4. Results

4.1. Survey

The survey was conducted by an internet research company for 20- to 69-year-old residents living in 18 major cities of Japan, in February 2012. The respondents' average age and rates of numbers in the cities were designed to be as consistent as possible with the national survey data for 2010 (Statistics Bureau, 2011). The company paid online reward points (available for shopping in registered stores) to respondents for motivating them to participate. The questionnaires were sent by e-mail to 17,277 respondents who had registered with the company. Overall, 2128 of 17,277 respondents satisfied the above conditions. However, the exact response rate was unknown due to the lack of information collected by the company on the number of non-participants. Data were collected from 2128 respondents.

4.2. Individual characteristics

Table 3 presents the individual characteristics of the respondents. The proportion of male respondents was 63.53%, with an average age of 42.45 years. The corresponding national survey of Japan indicated that these values were 50.17% and 41.98 years, respectively, in 2011. The average household income was approximately ¥6.57 million, while the national survey recorded a value of

Table 3
Individual characteristics (variables, means, and S.D.).

Research items	Variables	Means	S.D.
Gender	*GND*	0.6353	0.4814
Age	*AGE*	42.4525	12.1896
Married or not	*MAR*	0.5883	0.4922
Household income	*ICM*	6.5728	4.6793
Job status: Temporary staff	*JBTS*	0.0221	0.1470
Job status: Part-time job	*JBPTJ*	0.0634	0.2438
Job status: Self-owned business	*JBSOB*	0.0451	0.2076
Job status: Freelancer	*JBFP*	0.0221	0.1470
Job status: Home maker	*JBHM*	0.1100	0.3129
Job status: Student	*JBST*	0.0385	0.1925
Job status: Unemployed	*JBNM*	0.0526	0.2233
Educational status: High school	*EDHS*	0.1631	0.3695
Educational status: Vocational college	*EDVC*	0.0846	0.2783
Educational status: Junior college	*EDJC*	0.0705	0.2560
Educational status: Technical college	*EDTC*	0.0080	0.0890
Educational status: University	*EDUV*	0.5587	0.4967
Tourism experience in Kyoto	*EXKYOTO*	0.1762	0.3811
Respondent's interest in traveling to Kyoto	*INTKYOTO*	0.9258	0.2622
Respondent's anxiety about the bird flu	*AXBF*	0.2307	0.4214
Reason for not traveling: Anxiety about being infected by the bird flu	*RANXIETY*	0.0846	0.2783
Reason for not traveling: Distrust safety information provided by the central and local governments	*RDTRUST*	0.0592	0.2360
Reason for not traveling: Not willing to travel to Kyoto	*RNWILL*	0.0174	0.1307
Reason for not traveling: Others	*ROTHER*	0.0385	0.1925

Note: N = 2128. S.D.: Standard deviation.

Table 4
Results for the periods (in weeks) selected by the respondents.

Variables	IP_{safe}	IP_{safe}^{event}	$IP_{safe}^{visitor}$	IP_{nosafe}	IP_{nosafe}^{event}	$IP_{nosafe}^{visitor}$
Information	Information 1	Information 1 & 2	Information 1 & 3	Without Information 1	Information 2	Information 3
¥1000	21.5877	18.9270	18.6354	24.4051	21.4784	21.3618
	(20.1271)	(18.9140)	(19.5293)	(20.6724)	(19.3300)	(19.8750)
	[428]	[333]	[296]	[585]	[483]	[442]
¥20,000	23.9039	20.9972	20.7218	26.1573	23.6779	23.6221
	(20.2449)	(19.1666)	(19.6347)	(20.3688)	(19.5088)	(20.0241)
	[453]	[363]	[338]	[710]	[588]	[559]
¥40,000	25.8879	23.5276	23.2987	28.1957	25.7279	25.4054
	(20.6074)	(19.9442)	(20.4555)	(20.5766)	(20.0356)	(20.3987)
	[710]	[623]	[615]	[932]	[838]	[823]

Note: N = 2128. Standard errors are in parentheses. Number of respondents who answered "Never" appears in brackets.

Table 5
Analysis of "yes" responses under different policies.

Variables	Explanations	Means	S.D.
WTT	Respondents' willingness-to-travel time (WTT; in weeks) to Kyoto before the bird flu outbreak	21.5000	18.0901
IP_{safe}	1 for a "yes" response to WTT under Policy 1, 0 otherwise	0.1667	0.3727
IP_{safe}^{event}	1 for a "yes" response to a WTT under Policy 1 and Policy 2, 0 otherwise	0.1667	0.3727
$IP_{safe}^{visitor}$	1 for a "yes" response to a WTT under Policy 1 and Policy 3, 0 otherwise	0.1667	0.3727
IP_{nosafe}^{event}	1 for a "yes" response to a WTT under Policy 2, 0 otherwise	0.1667	0.3727
$IP_{nosafe}^{visitor}$	1 for a "yes" response to a WTT under Policy 3, 0 otherwise	0.1667	0.3727
TC	Travel costs (thousands, yen) shown in the questionnaires	20.3333	15.9237

Note: a: Policy 1 — Announcements of safety information by the central and local governments, b: Policy 2 — Announcements of events and/or new tourism facilities, c: Policy 3 — Announcements of information regarding how many tourists have already visited Kyoto.

Table 6
Analysis of reasons not to visit.

Reasons	Variables	Numbers
Anxiety about being infected by the bird flu	*RANXIETY*	163
Distrust safety information provided by the central and local governments	*RDTRUST*	131
Not willing to travel to Kyoto	*RNWILL*	62
Others	*ROTHER*	107

Note: N = 463.

¥5.482 million in 2011 (Ministry of Health, Labour and Welfare, 2013). The data indicated that the values corresponding to the male respondents and households in this survey would be slightly higher. However, the average age was almost the same.

The highest "yes" response rates for jobs and educational statuses were about 0.11% for homemakers (*JBHM*) and 55.87% for undergraduate university students (*EDUV*). Tourism experience at Kyoto (*EXKYOTO*) was 17.62%, but 92.6% respondents were interested in visiting Kyoto (*INTKYOTO*). Finally, 23.07% respondents felt anxious about the bird flu outbreak (*AXBF*).

4.3. Willingness-to-travel time

Table 4 shows the results of the CB questionnaires, including IP_{safe} and IP_{nosafe}^{event}. The second row shows the results for combinations of policies. The third, fourth, and fifth rows show the means, standard deviations, and number of respondents who answered "Never," respectively, for ¥1000 to ¥40,000. The mean value and standard deviation were 22.9222 weeks (about five months) and 20.0821, respectively. The minimum and maximum WTT values were 18.6354 weeks for IP_{safe}^{event} and 24.4051 weeks for IP_{nosafe} for ¥1,000, 20.7218 weeks for IP_{safe}^{event} and 26.1573 weeks for IP_{nosafe} for ¥20,000, and 23.2987 weeks for IP_{safe}^{event} and 28.1957 weeks for IP_{nosafe} for ¥40,000, respectively. The minimum and maximum numbers for the respondents who replied "Never" were 296 (the third row for IP_{safe}^{event}) and 932 (the fifth row for the IP_{nosafe}), respectively. Finally, Table 5 shows the pooling data for the logistic simulations.

Table 6 shows the reasons for rejection for 463 respondents. One hundred and sixty-three respondents answered "Anxiety about being infected by the bird flu." The second and third reasons for rejection were "Distrust safety information provided by central and local governments" and "Other," respectively.

4.4. Estimation results

The estimation results in Table 7 showed that the parameters of all the models had the same signs, indicating the low probability of multi-collinearity. The obtained parameter signs satisfied expectations: negative for $\beta_{RANXIETY}$, $\beta_{RDTRUST}$, β_{RNWILL}, β_{ROTHER}, and β_{TC}, while positive for β_{WTT}, β_{safe}, β_{safe}^{event}, β_{safe}^{visit}, β_{nosafe}^{event}, β_{nosafe}^{visit}, and β_{ICM}. Thus, the CB questionnaires in this study proved to be appropriate for studying individual preferences.

The results of Model 2 showed that income (*ICM*), part-time job (*JBPTJ*), high school education (*EDHS*), vocational college education (*EDVC*), and anxiety about being infected by the bird flu (*AXBF*) were not statistically significant. The results of Model 3 showed that the parameter signs of *GND*, *AGE*, *JBTS*, *JBFP*, *JBST*, *EDJC*, *EDUV*, *EXKYOTO*, and *INTKYOTO* were positive, while those of *MAR*, *JBSOM*, *JBHM*, and *EDTC* were negative. Finally, the statistically significant and positive sign of β_{ODR} indicated that the probability of attaining a "yes" response was influenced by the order effect.

The results of main variables by *WTT* periods from Model 2 are shown in Table 8. The complete details of all results are shown in

Table 7
Estimation results.

Variables	Model 1		Model 2		Model 3	
	Estimates	S.E.	Estimates	S.E.	Estimates	S.E.
CONT	−1.4254[a]	0.0172	−2.1684 [a]	0.0377	−2.1656 [a]	0.0344
WTT	0.0584 [a]	0.0003	0.0589 [a]	0.0003	0.0589 [a]	0.0003
IP_{safe}	0.4677 [a]	0.0177	0.4713 [a]	0.0178	0.4713 [a]	0.0178
IP_{safe}^{event}	0.7673 [a]	0.0176	0.7734 [a]	0.0177	0.7733 [a]	0.0177
$IP_{safe}^{visitor}$	0.8482 [a]	0.0177	0.8549 [a]	0.0177	0.8549 [a]	0.0177
IP_{nosafe}^{event}	0.2947 [a]	0.0178	0.2970 [a]	0.0179	0.2970 [a]	0.0179
$IP_{nosafe}^{visitor}$	0.3657 [a]	0.0177	0.3685 [a]	0.0178	0.3685 [a]	0.0178
TC	−0.0198 [a]	0.0003	−0.0200 [a]	0.0003	−0.0200 [a]	0.0003
ICM	0.0055 [a]	0.0011	0.0009	0.0012		
RANXIETY	−2.3876 [a]	0.0249	−2.3588 [a]	0.0250	−2.3594 [a]	0.0250
RDTRUST	−2.0828 [a]	0.0271	−2.0644 [a]	0.0273	−2.0626 [a]	0.0273
RNWILL	−3.2541 [a]	0.0702	−3.0716 [a]	0.0709	−3.0707 [a]	0.0709
ROTHER	−2.5988 [a]	0.0384	−2.5298 [a]	0.0387	−2.5287 [a]	0.0386
GND			0.1506 [a]	0.0136	0.1577 [a]	0.0129
AGE			0.0073 [a]	0.0005	0.0072 [a]	0.0005
MAR			−0.1483 [a]	0.0128	−0.1475 [a]	0.0125
JBTS			0.2033 [a]	0.0353	0.2137 [a]	0.0349
JBPTJ			−0.0437 [c]	0.0229		
JBSOB			−0.1047 [a]	0.0250	−0.1011 [a]	0.0249
JBFP			0.1103 [a]	0.0339	0.1126 [a]	0.0338
JBHM			−0.2298 [a]	0.0216	−0.2230 [a]	0.0206
JBST			0.0943 [a]	0.0280	0.0913 [a]	0.0277
JBNM			−0.1591 [a]	0.0251	−0.1587 [a]	0.0245
EDHS			0.0040 [d]	0.0204		
EDVC			0.0369 [d]	0.0237		
EDJC			0.1472 [a]	0.0263	0.1376 [a]	0.0222
EDTC			−0.2298 [a]	0.0598	−0.2364 [a]	0.0584
EDUV			0.1273 [a]	0.0164	0.1205 [a]	0.0109
EXKYOTO			0.1651 [a]	0.0132	0.1659 [a]	0.0132
INTKYOTO			0.3409 [a]	0.0220	0.3404 [a]	0.0220
AXBF			−0.0266 [b]	0.0121		
ODR			0.0753 [a]	0.0102	0.0756 [a]	0.0101
Max.LL	−118619.9288		−117817.2182		−117823.5415	
AIC	237265.8575		235698.4364		235701.0830	
R^2	0.2360		0.2412		0.2411	

Note: a: *p*-values are less than 1%, b: *p*-values are less than 5%, c: *p*-values are less than 10%, d: *p*-values are over 10%; S.E: standard errors, Max. LL: maximum value of log likelihood, AIC: Akaike information criterion, R^2: McFadden's pseudo *r*-squared; N = 229,824.

Appendix 2. The estimated parameters of main variables (from β_{safe} to β_{TC}) without income parameters (β_{ICM}) are statistically significant in all periods, while the β_{ICM} are statistically significant in first week and 52 week, though not in other periods. The parameter signs from β_{safe} to β_{TC} are same in Models 1 to 3. Furthermore, the signs of β_{ICM} are negative from the 1st week to the 12th week, and positive from the 24th week to the 52nd week.

4.5. Simulation results

Table 9 shows the simulation results for SC_{nosafe} to SC_{full}. The minimum and maximum values were 0.0934 and 0.2431 for the 1st week, 0.1095 and 0.2770 for the 4th week, 0.1646 and 0.3804 for the 12th week, 0.2855 and 0.5546 for the 24th week, 0.4476 and 0.7164 for the 36th week, and 0.6753 and 0.8664 for the 52nd week, respectively.

Table 10 shows the results for SC_{full}^{ranx} to SC_{full}^{allrr}. The minimum and maximum values were 0.2816 and 0.3400 for the 1st week, 0.3187 and 0.3807 for the 4th week, 0.4284 and 0.4962 for the 12th week, 0.6032 and 0.6664 for the 24th week, 0.7551 and 0.8020 for the 36th week, and 0.8878 and 0.9123 for the 52nd week, respectively. The order of the simulation values from SC_{nosafe} to SC_{full}^{allrr} was as follows: $SC_{nosafe} < SC_{nosafe}^{event} < SC_{nosafe}^{visitor} < SC_{safe} < SC_{safe}^{event} < SC_{safe}^{visitor} < SC_{full} < SC_{full}^{ranx} < SC_{full}^{ranx\&rdtrust} < SC_{full}^{allrr}$.

Table 8
The estimated parameters of information policies by WTT periods.

Parameters	1st week	4th week	12th week	24th week	36th week	52nd week
β_{safe}	0.3972 [a]	0.4216 [a]	0.4127 [a]	0.4572 [a]	0.4760 [a]	0.7098 [a]
β_{safe}^{event}	0.5773 [a]	0.6514 [a]	0.7224 [a]	0.7915 [a]	0.8827 [a]	1.0794 [a]
$\beta_{safe}^{visitor}$	0.7604 [a]	0.8046 [a]	0.7971 [a]	0.8632 [a]	0.8541 [a]	1.1833 [a]
β_{nosafe}^{event}	0.1619 [a]	0.1825 [a]	0.2795 [a]	0.3322 [a]	0.3949 [a]	0.3330 [a]
$\beta_{nosafe}^{visitor}$	0.3275 [a]	0.3183 [a]	0.3411 [a]	0.3972 [a]	0.3851 [a]	0.4288 [a]
β_{TC}	−0.0166 [a]	−0.0179 [a]	−0.0178 [a]	−0.0206 [a]	−0.0203 [a]	−0.0311 [a]
β_{ICM}	−0.0122 [a]	−0.0049 [d]	−0.0040 [d]	0.0049 [d]	0.0023 [d]	0.0173 [a]

Note: a: *p*-values are less than 1%, d: *p*-values are over 10%.

Table 9
Simulations of demand levels for recovering the standard demand level.

WTT ($weeks$)	SC_{nosafe}	SC_{safe}	SC^{event}_{safe}	$SC^{visitor}_{safe}$	SC^{event}_{nosafe}	$SC^{visitor}_{nosafe}$	SC_{full}
1st	0.0934	0.1417	0.1825	0.1950	0.1218	0.1296	0.2431
4th	0.1095	0.1646	0.2104	0.2242	0.1420	0.1509	0.2770
12th	0.1646	0.2399	0.2992	0.3165	0.2096	0.2217	0.3804
24th	0.2855	0.3903	0.4640	0.4844	0.3497	0.3661	0.5546
36th	0.4476	0.5648	0.6371	0.6557	0.5217	0.5395	0.7164
52nd	0.6753	0.7692	0.8184	0.8302	0.7368	0.7504	0.8664

Note: the standard demand level in pre-disaster (a positive response rate to Interest to Visit Kyoto) is assumed as 92.6%.

Table 10
Simulations of overcoming reasons for rejection for recovering the standard demand level.

WTT ($weeks$)	SC^{ranx}_{full}	$SC^{ranx\&rdtrust}_{full}$	SC^{allrr}_{full}
1	0.2816	0.3070	0.3400
4	0.3187	0.3458	0.3807
12	0.4284	0.4586	0.4962
24	0.6032	0.6321	0.6664
36	0.7551	0.7770	0.8020
52	0.8878	0.8994	0.9123

Note: the standard demand level in pre-disaster (a positive response rate to Interest to Visit Kyoto) is assumed as 92.6%.

Table 11 shows the results of the price discounting (prices after the discount) policy simulations. The minimum and maximum values were ¥9984 for SC^{ranx}_{full} and ¥56,867 for SC_{full}, respectively.

5. Discussion and policy implications

5.1. Estimation results

The applicability of the CB method and information policy effects were evident from the results of Model 3 in Table 7. First, the signs of the parameters were as expected. Second, the results $\beta^{visitor}_{safe} > \beta^{event}_{safe}$ and $\beta^{visitor}_{nosafe} > \beta^{event}_{nosafe}$ indicated that the preference orderings were preserved. Thus, the CB method can be used to analyze tourism demand recovery from disasters. The orderings indicated that providing visitor information could be more effective than event information.

Next, the ordering $\beta_{safe} > \beta^{visitor}_{nosafe} > \beta^{event}_{nosafe}$ indicated that safety information could have the highest effect among all information policies. Most tourists were not willing to travel to disaster sites without safety information. The ordering $\beta^{visitor}_{safe} > \beta^{event}_{safe} > \beta_{safe}$ indicated that mixed policies could have a greater recovery effect over single policies. These results also supported the applicability of the CB method for estimating preferences. The findings confirmed the mixed effects of safety and other information. A pure effect of event information was that $\beta^{event}_{safe} - \beta_{safe} = 0.3020 > \beta^{event}_{nosafe}$. Furthermore, according to the visitor information, $\beta^{visitor}_{safe} - \beta_{safe} = 0.3836 > \beta^{visitor}_{nosafe}$. These results indicated that mixed policies could generate synergetic effects. Moreover, the fact that the value of β_{safe} was larger than the pure effect values indicated that providing safety information could have the highest effect.

Table 8 indicates that the parameters of information policies totally tend to increase in spending periods (although there are cases of increment and decrement by periods). For example, the estimated parameters of IP_{safe} (β_{safe}) are 0.3972 in the 1st week and 0.7098 in the 52nd week, respectively. The estimated parameters of $IP^{visitor}_{safe}$ ($\beta^{visitor}_{safe}$) are 0.7604 in the 1st week and 1.1833 in the 52nd week, respectively. The reason could be that the respondents' anxiety toward the bird flu outbreak decreased as time passed; respondents might come to think the bird flu outbreak would not occur. Thus, the travel cost parameters (β_{TC}) decrease from −0.0166 in the 1st week to −0.0311 in the 52nd week. This indicates that the price effects are enhanced over time due to an increase in the number of willing-to-travel respondents by reducing (overcoming) their anxiety.

Table 8 also shows that the signs of ICM parameters (β_{ICM}) turned negative from the 1st week to the 12th week to positive from the 24th week to the 52nd week β_{ICM} was statistically significant for the 1st week and 52nd week, and insignificant from the 4th week to the 36th week. The results indicated that tourism at disaster sites was an inferior good (that decreases corresponding to increments of ICM) in the period just after its occurrence, but changed to a normal good (that increases corresponding to increments of ICM) as time passed. This can be attributed to the fact that a tourism site in disaster would be considered a low-quality good that was not be preferred to other non-disaster tourism sites (Loomis & Walsh, 1997, p. 91).

Finally, the results for the individual characteristics indicated that the following persons were willing to travel provided information announcements were made: male respondents (because of their tolerance level, they typically suffer less anxiety about being infected by the bird flu compared to women); the elderly, temporary staff, freelance professionals, and university students (because they have ample free time to plan and travel); and those interested in traveling to Kyoto. Information policies could be effective at attracting these persons to travel. Otherwise, persons who were married, operating self-owned businesses, homemakers, and those educated at technical colleges were not swayed by information policies, possibly because of the fear of catching the infection themselves and/or infecting their children (the negative influence of tourists' perceived risks for tourism sites described in Law, 2006 and Rittichainuwat & Chakraborty, 2009). Furthermore, they could also possibly have little time to travel because of their jobs or study commitments (the substitution between work and leisure time described in Weiermair, 2006).

5.2. Effects of information policies

Table 9 shows that information policies cannot help post-disaster tourism demand levels (the maximum was approximately 86.6% for SC_{full}) recovery to reach the pre-disaster demand level (92.6%). Overcoming the reasons for the rejection in Table 10 makes it possible for the post-disaster demand level to come close to the pre-disaster demand level (91.2% for SC^{allrr}_{full}). Thus, an issue in recovering tourism demand is how to compensate for demand losses by the reasons for rejection.

Table 11
Discount levels for improving tourism demand in 52 weeks.

STD_{52}	SC_{safe}	SC^{event}_{safe}	$SC^{visitor}_{safe}$	SC^{event}_{nosafe}	$SC^{visitor}_{nosafe}$	SC_{full}	SC^{ranx*}_{full}	$SC^{ranx\&rdtrust*}_{full}$	SC^{allrr*}_{full}
SDC (yen)	23,577	38,685	42,764	14,857	18,433	56,867	9984	16,094	23,639

Note: the superscript * means that these values were calculated by the SDC value of X minus the value of SC_{full}; here, X = {$SC^{ranx}_{full} SC^{ranx\&rdtrust}_{full}$, SC^{allrr}_{full}}; these price discounting values do not correspond to the 80% discount level discussed below.

Table 12
The starting points and adjusted willingness-to-travel time.

$AWTT_i$	*WTT values*					
	1st week	4th week	12th week	24th week	36th week	52nd week
$AWTT_1$	1	4	12	24	36	52
$AWTT_4$	0	1	9	21	33	49
$AWTT_{12}$	0	0	1	13	25	41
$AWTT_{24}$	0	0	0	1	13	29

Note: the super script a means the starting points of ATT_js.

5.3. Effects of price discounting policies

The results of price discounting policies (prices after the discount) in Table 11 showed that the *SDT* values for SC_{safe}, SC_{safe}^{event}, $SC_{safe}^{visitor}$, SC_{full}, and SC_{full}^{allrr} exceed the average travel cost per trip (¥20,333 in Table 5). This indicated that the tourism demand recovery, to levels of information policy by price discounting, would not be feasible due to the high discounting rates. Here, it might be feasible to discount ¥16,094 (a discount rate of about 80%) of $SC_{full}^{ranx\&rdtrust}$ that corresponds to overcome *RANXIETY* (the anxiety for the bird flu) and *RDTRUST* (the distrust toward the safety information from governments). For example, The Japanese government has implemented a maximum rate of 70% as a price discount for travel to Kyushu area in order to encourage economic recovery after the Kumamoto Earthquake of 2016 (Kumamoto Prefecture Tourist Federation, 2016). Thus, the 80% price discounting could be feasible as a policy for tourism demand recovery.

$$\mathbf{X\beta}' = CONT + \beta_{WTT}WTT + \beta_{safe}IP_{safe} + \beta_{safe}^{event}IP_{safe}^{event} + \beta_{safe}^{visitor}IP_{safe}^{visitor} + \beta_{nosafe}^{event}IP_{nosafe}^{event} + \beta_{nosafe}^{visitor}IP_{nosafe}^{visitor}$$
$$+\beta_{TC}TC + ICM \times (\gamma_{ICM1}D_1 + \gamma_{ICM52}D_{52}) + WTTC + \widehat{\mathbf{X}}\widehat{\boldsymbol{\beta}}' \quad (5)$$

model. In equation (5), D_1 and D_{52} are dummy variables; $D_1 = 1$ for $WTT = 1$ (0 if others) and $D_{52} = 1$ for $WTT = 52$ (0 if others); the γ_{ICM1} and γ_{ICM52} are parameters of the interaction term variables of *ICM* with D_1 and D_{52}, respectively. Similarly, different policy effects can be observed by taking the interaction term with WTT variable. The notations from γ_{safe} to γ_{TC} in equation (6) are parameters of the interaction term variables of *WTT* with information and travel cost variables. The superscripts and subscripts mean the same with β. The other variables ($\widehat{\mathbf{X}}\widehat{\boldsymbol{\beta}}'$) are same as in Model 3. The expected signs are positive for γ_{safe}, γ_{safe}^{event}, $\gamma_{safe}^{visitor}\gamma_{nosafe}^{event}$, $\gamma_{nosafe}^{visitor}$, and γ_{ICM52}, and negative for γ_{TC} and γ_{ICM1} from results in Tables 7 and 8.

$$WTTC \equiv WTT \times \Big(\gamma_{safe}IP_{safe} + \gamma_{safe}^{event}IP_{safe}^{event} + \gamma_{safe}^{visitor}IP_{safe}^{visitor}$$
$$+ \gamma_{nosafe}^{event}IP_{nosafe}^{event} + \gamma_{nosafe}^{visitor}IP_{nosafe}^{visitor} + \gamma_{TC}TC\Big) \quad (6)$$

5.4. Tourism demand recovery process

5.4.1. Reexamination of estimation and simulation models

Early implementation of tourism demand recovery policies after decontaminating the disaster site could shorten recovery periods. However, sometimes, lack of information in planning may act as an obstacle to implement the policies before the disaster. This section reexamines the estimation and simulation models based on the above findings in order to consider an optimal timing of tourism demand recovery policies. The estimation and simulation results were used for determining the optimal policy orderings.

First, the estimation model is reexamined. The estimation results of Table 8 indicate that the main variables would be influenced by *WTT* periods. Thus, Model 4 is designed based on Model 3 as equations (5) and (6). Here, including the ICM variable with information of the 1st week and the 52nd week could help confirm different parameter signs by one week and 52 weeks, as shown in Appendix 2, and to improve estimation accuracy of the estimation

Next, the simulation procedure was examined. First, it is assumed that only a single policy can be implemented in a period; policymakers cannot implement multiple policies simultaneously. For example, event information could not be announced in one week if safety information was announced at that time. In this case, the safety information (IP_{safe}) must necessarily be the first policy in order to permit visiting the site after solving the disaster. Thus, an efficient ordering of event information, visitor information, and price discounting were examined. The IP_{safe}^{event} and $IP_{safe}^{visitor}$ variables are used as event and visitor information due to the synergetic effects with the safety information, as discussed in section 5.1. Thus, the IP_{nosafe}^{event} and $IP_{nosafe}^{visitor}$ variables are designed as zero in all simulations. The price discounting policy is designed as an 80% discount of the mean value of TC ($\overline{TC} \times 0.2$) from the result in section 5.3. The 40% discount cases ($\overline{TC} \times 0.6$; arbitrarily decided) are also simulated for comparisons. Note that $ODR = 0$ for all simulations.

The terminal point is also the 52nd week. A policy effect is assumed to sustain from the starting point at *j* weeks ($j \in \{1, 4, 12, 24\}$ due to four recovery policies) to the terminal point. For

Table 13
Simulations for analyzing effective policy ordering.

Policies	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11
Safety information	–	$AWTT_1$	–	–	–	$AWTT_1$	$AWTT_1$	$AWTT_1$	$AWTT_1$	$AWTT_1$	$AWTT_1$
Event information	–	–	$AWTT_1$	–	–	$AWTT_4$	$AWTT_4$	$AWTT_{12}$	$AWTT_{24}$	$AWTT_{12}$	$AWTT_{24}$
Visitor information	–	–	–	$AWTT_1$	–	$AWTT_{12}$	$AWTT_{24}$	$AWTT_4$	$AWTT_4$	$AWTT_{24}$	$AWTT_{12}$
Price discounting	–	–	–	–	$AWTT_1$	$AWTT_{24}$	$AWTT_{12}$	$AWTT_{24}$	$AWTT_{12}$	$AWTT_4$	$AWTT_4$

simplicity, the 36th and 52nd weeks are not selected. Even if the 36th and 52nd weeks are considered as a starting point, the orderings of recovery levels of tourism demand and the optimal policy ordering would be same due to the linearity of *WTT* variable in the interaction terms. Thus, the recovery levels of tourism demand would differ.

$j = 1$ is determined to implement the safety information policy as mentioned above. Thus, $j' \in \{4, 12, 24\}$ are the main points for analyzing the optimal ordering. An issue in simulation is how to treat the time delay. For example, the effect of event information policy with *WTT* variable ($WTT \times \gamma^{event}_{safe} \times IP^{event}_{safe}$ in equation (6)) beginning at the 4th week ($WTT = 4$) is calculated as $4 \times \widehat{\gamma}^{event}_{safe} \times 1$, even though the beginning time is $j = 4$; the exact calculation is $1 \times \widehat{\gamma}^{event}_{safe} \times 1$. Thus, values of the adjusted *WTT* at *jth* week ($AWTT_j$) for a policy shown in Table 12 are used by replacing the *WTT* value in the interaction terms (e.g., $AWTT^{event}_4 \times \gamma^{event}_{safe} \times IP^{event}_{safe}$; the superscripts of $AWTT_i$ indicate the policy name). For example, $AWTT^{event}_4$ means the event information policy begins from the 4th week, and the $AWTT_4$ value at that time is 1 (thus, $1 \times \widehat{\gamma}^{event}_{safe} \times 1$ is calculated). In the next (12th) week, 9 is assigned as the $AWTT_4$ value (i.e., $9 \times \widehat{\gamma}^{event}_{safe} \times 1$).

The estimated parameters $\widehat{\beta}^{event}_{safe}$, $\widehat{\beta}^{visitor}_{safe}$, $\widehat{\gamma}^{event}_{safe}$, and $\widehat{\gamma}^{visitor}_{safe}$ in equations (5) and (6) were adjusted as $\widehat{\beta}'^{event}_{safe} = \widehat{\beta}^{event}_{safe} - \widehat{\beta}_{safe}$, $\widehat{\beta}'^{visitor}_{safe} = \widehat{\beta}^{visitor}_{safe} - \widehat{\beta}_{safe}$, $\widehat{\gamma}'^{event}_{safe} = \widehat{\gamma}^{event}_{safe} - \widehat{\gamma}_{safe}$, and $\widehat{\gamma}'^{visitor}_{safe} = \widehat{\gamma}^{visitor}_{safe} - \widehat{\gamma}_{safe}$ in order to eliminate the safety information effect. Thus, the simulation model was redesigned as equation (5)′and (6)′. Here, k, l, and $m \in \{4, 12, 24\}$ and $k \neq l \neq m$. The mean values in Table 3 and estimated parameters by Model 4 are used for $\widehat{\mathbf{X}\boldsymbol{\beta}}'$.

$$\mathbf{X}\boldsymbol{\beta}' = CONT + \widehat{\beta}_{WTT}WTT + \widehat{\beta}_{safe}IP_{safe} + \widehat{\beta}'^{event}_{safe} IP^{event}_{safe} + \widehat{\beta}'^{visitor}_{safe} IP^{visitor}_{safe} + \widehat{\beta}^{event}_{nosafe} \times 0 + \widehat{\beta}^{visitor}_{nosafe} \times 0 + \widehat{\beta}_{TC}\overline{TC} + \overline{ICM} \times \left(\widehat{\gamma}_{ICM1}D_1 + \widehat{\gamma}_{ICM52}D_{52}\right) + WTTC + \mathbf{X}\widehat{\boldsymbol{\beta}}' \tag{5'}$$

$$WTTC \equiv \widehat{\gamma}_{safe}IP_{safe} \times AWTT^{safty}_1 + \widehat{\gamma}'^{event}_{safe} IP^{event}_{safe} \times AWTT^{event}_k + \widehat{\gamma}'^{visitor}_{safe} IP^{visitor}_{safe} \times AWTT^{visitor}_l + \widehat{\gamma}_{TC}TC \times AWTT^{TC}_m \tag{6'}$$

Finally, the 11 patterns of policy orderings listed in Table 13 are examined. Case 1 corresponds to SC_{nosafe} (natural recovery) in Table 9. Cases 2 to 4 show the single effects of information policies as time passes by. Case 2 corresponds to SC_{safe} in Table 9, whereas Cases 3 and 4 do not correspond to SC^{event}_{safe} and $SC^{visitor}_{safe}$ due to the synergetic effects that overestimate tourism demand recovery levels than those calculated by a single policy. Case 5 corresponds to the price discounting policy. Here, the 80% price discounting policy (that compensates for the demand losses from the reasons for rejections, *RANXIETY* and *RDTRUST*) was assumed from discussions in section 5.3. Cases 6–11 were designed to simulate the optimal policy order. For example, Case 6 shows that the safety information policy begins from the 1st week (ATT_1), the event information policy from the 4th week (ATT_4), the visitor information policy from the 12th week (ATT_{12}), and the price discounting policy from the 24th week (ATT_{24}).

5.4.2. Result and discussion

The estimation results in Table 14 showed that only $\gamma^{visitor}_{nosafe}$ is not statistically significant. The signs of estimated parameters are same as Model 3. The ordering of degree of information policy parameters was also same as that of Model 3—$\beta^{visitor}_{safe} > \beta^{event}_{safe} > \beta_{safe} > \beta^{visitor}_{nosafe} > \beta^{event}_{nosafe}$. Otherwise, the results of interaction term variables showed that $\gamma^{event}_{safe} > \gamma^{visitor}_{safe} > \gamma_{safe} > \gamma^{event}_{nosafe} > \gamma^{visitor}_{nosafe}$; the visitor information parameters were smaller than the event information parameters. Similarly, the ordering of pure effects of event and visitor information is $\widehat{\beta}'^{visitor}_{safe} = 0.3715 > \widehat{\beta}'^{event}_{safe} = 0.2364$ and $\widehat{\gamma}'^{event}_{safe} = 0.0034 > \widehat{\gamma}'^{visitor}_{safe} = 0.0008$.

The estimation results indicated that safety information would have the highest effect on demand recovery. The ordering of event and visitor information are reversed with and without the time series factor. The reason could be that the visitor information based on the actual behavior might give respondents a sense of trust regarding the safety of a disaster site regardless of the periods. Deutsch and Gerard (1955) showed that an individual's behavior is sometimes influenced by the information obtained from another as evidence about reality. Furthermore, McFerran, Dahl, Fitzsimons, & Morales. (2010) showed that a part of the purchase behavior was determined by other consumers' purchase quantities. The parameters of visitor information show little changes as time passes by (also see Table 11).

Second, combinations of these information policies would generate synergetic effects on tourism demand recovery with and without the time series factor.

Third, the parameters of $ICM \times D_1$ and $ICM \times D_{52}$ in Table 14 showed that tourism at disaster sites would be an inferior good in the period immediately after the disaster, and thereafter, changing to a normal good with time. The third result and the negative sign of price parameter might also indicate that researchers would be allowed to analyze the cost-benefit ratio using the consumer surplus for reconstructing infrastructures in tourism sites in a year after the disaster (Johansson, 1987).

Finally, the AIC and R2 values of Model 4 indicate that it is more suitable for simulations due to the lower and higher values than the ones of Models 1 to 3, respectively.

Table 15 shows the simulation results from Cases 1–5. As references, values in brackets show SC_{nosafe} and SC_{safe} values in Table 9 for Cases 1 and 2, respectively. The values of Cases 2–5 in the "1st week" column showed the recovery amounts by policies immediately after disaster site decontamination—the first is safety information, followed by visitor information, price discounting, and event information (Policy effect order 1; PEO1). The "52nd week" column showed that the order changes to safety information followed by visitor information, event information, and finally price discounting (PEO2). Thus, implementing safety information as the first step is valid.

The result indicates the following: First, planning requires dynamic policy effect analyses because of the possibility of changing policies with time, in contrast to static analyses, due to lack of information. Moreover, it would be necessary to consider applicable tourism management frameworks, in disaster, corresponding to

Table 14
Estimation results of Model 4.

Variables	Estimates	S.E.
CONT	−1.9808 [a]	0.0394
WTT	0.0523 [a]	0.0009
IP_{safe}	0.3711 [a]	0.0301
IP^{event}_{safe}	0.6075 [a]	0.0296
$IP^{visitor}_{safe}$	0.7426 [a]	0.0294
IP^{event}_{nosafe}	0.2161 [a]	0.0305
$IP^{visitor}_{nosafe}$	0.3245 [a]	0.0302
TC	−0.0158 [a]	0.0005
$ICM \times D_1$	−0.0904 [a]	0.0026
$ICM \times D_{52}$	0.0004 [a]	$4.3177e^{-5}$
RANXIETY	−2.3696 [a]	0.0252
RDTRUST	−2.0740 [a]	0.0275
RNWILL	−3.0978 [a]	0.0715
ROTHER	−2.5309 [a]	0.0387
GND	0.1634 [a]	0.0129
AGE	0.0075 [a]	0.0005
MAR	−0.1363 [a]	0.0126
JBTS	0.2057 [a]	0.0348
JBSOB	−0.1067 [a]	0.0250
JBFP	0.1147 [a]	0.0340
JBHM	−0.2308 [a]	0.0206
JBST	0.0748 [a]	0.0276
JBNM	−0.1838 [a]	0.0244
EDJC	0.1347 [a]	0.0222
EDTC	−0.2365 [a]	0.0583
EDUV	0.1281 [a]	0.0109
EXKYOTO	0.1714 [a]	0.0133
INTKYOTO	0.3435 [a]	0.0221
ODR	0.0740 [a]	0.0102
$WTT \times IP_{safe}$	0.0042 [a]	0.0010
$WTT \times IP^{event}_{safe}$	0.0075 [a]	0.0010
$WTT \times IP^{visitor}_{safe}$	0.0050 [a]	0.0010
$WTT \times IP^{event}_{nosafe}$	0.0033 [a]	0.0010
$WTT \times IP^{visitor}_{nosafe}$	0.0017 [d]	0.0010
$WTT \times TC$	−0.0002 [a]	$1.8924e^{-5}$
Max. LL	−116,941.9246	
AIC	233,953.8491	
R^2	0.2468	

Note: a: *p*-values are less than 1%, d: *p*-values are over 10%; $e^{-x} = 10^{-x}$;S.E: standard errors, Max. LL: maximum value of log likelihood, AIC: Akaike information criterion, R^2: McFadden's pseudo *r*-squared; N = 229,824.

policy effect changes with time. Second, the pricing policy after solving a disaster will not have a significant effect, in contrast to previous studies, possibly due to respondents' anxiety matching income effects. Table 8 also shows that the β_{TC} decreases from −0.0203 in week 36 to −0.0311 in week 52. This result indicates that rapid and broad announcements of information polices could be more important. The simulation results of price discounting also indicated that the low price design in the CB questionnaire might not cause bias due to the small difference—0.7238 and 0.7057 in 52 weeks for 80% and 40% price discounting in Table 15, respectively.

The simulation results from Cases 6–11 are shown in Table 16. In the 80% price discounting case, the minimum and maximum values in 52 weeks are 90.83% in Case 11 and 91.50% in Case 6. Thus, the ordering of Case 6 could recover tourism demand in 52 weeks to near the standard demand level (92.6%). The result showed that the optimal policy ordering is Case 6, which implements safety information as the first step, followed by event information, visitor information, and price discounting, in contrast to the results of policy effect orderings in Table 15—Case 9 for PEO 1 and Case 8 for PEO 2. The results indicated that the policy orderings based on the effects would not be optimal, that is, they may not achieve the highest recovery of tourism demand due to the time delay (in Table 13) and the policy effect changes by period.

The optimal policy ordering would be valid. After announcing safety information, policymakers and/or companies could encourage tourists to visit the site by events. Then, informing the situation, the price discounting could enhance the increment of the number of tourists. The validity of designing the price discounting in the final step is also supported from another viewpoint. Canina, Enz, and Lomanno (2006) stated that price discounting helps increase tourism supply (e.g., hotel rooms), but this comes at a cost to revenues. To elaborate, (extreme) price discounting might have a positive effect on tourism demand recovery, whereas it might deteriorate the finances of the government and/or the tourism company. The measurement of price discount rate without deterioration of finances of other stakeholders should be considered in future research.

Finally, the optimal timing of implementing the policies is discussed based on Table 17 and drawn from Table 8. Table 17 shows the changes of synergetic effects of mixed policies ($\beta^{event}_{safe} - \beta_{safe}$ and $\beta^{visitor}_{safe} - \beta_{safe}$) and β_{TC} by *WTT* periods. Here, we assume two conditions: i) the policy ordering of Case 6 is employed and ii) the policies were implemented one by one.

Announcing safety information in the first step as soon as possible—within week 1, immediately after decontaminating the disaster—would result in faster tourism demand recovery at such sites. Since the $\beta^{event}_{safe} - \beta_{safe}$ values decrease from the 36th to the 52nd week, it is preferable to time the second step (event information) within 24th to 36th weeks after the disaster. The increment of $\beta^{visitor}_{safe} - \beta_{safe}$ values from the 36th to the 52nd week and condition (ii) indicated that it would be timed until the 52nd week after the 37th week for the third step timing (visitor information). Thus, it would be appropriate to implement the fourth step (price discounting) immediately after the third step due to the decrement of β_{TC} values from the 36th to the 52nd week.

Table 15
Simulation results of from Cases 1–5: Policy effect ordering.

WTTs	1st week	4th week	12th week	24th week	36th week	52nd week
Case1: natural recovery	0.0703	0.1381	0.1958	0.3132	0.4608	0.6644
	(−)	(−)	(−)	(−)	(−)	(−)
	[0.0934]	[0.1095]	[0.1646]	[0.2855]	[0.4476]	[0.6753]
Case2: safety information	0.0991	0.1910	0.2706	0.4223	0.5902	0.7810
	(−)	(−)	(−)	(−)	(−)	(−)
	[0.1417]	[0.1646]	[0.2399]	[0.3903]	[0.5648]	[0.7692]
Case3: event information	0.0876	0.1706	0.2430	0.3851	0.5499	0.7491
	(−)	(−)	(−)	(−)	(−)	(−)
Case4: visitor information	0.0988	0.1890	0.2628	0.4029	0.5608	0.7498
	(−)	(−)	(−)	(−)	(−)	(−)
Case5: price discounting	0.0943	0.1805	0.2496	0.3817	0.5339	0.7238
	(0.0937)	(0.1786)	(0.2449)	(0.3713)	(0.5182)	(0.7057)

Note: the values of 40% price discounting cases are in parentheses; (−) means the 40% price discounting case was not simulated; values in the standard demand level in 52 weeks is assumed as 92.6%.

Table 16
Simulation results from Case 6 to Case 11: Optimal policy ordering using price discounts.

	1st week	4th week	12th week	24th week	36th week	52nd week
Case 6	0.0991	0.2308	0.4127	0.6674	0.8046	0.9150
	(−)	(−)	(−)	(0.6656)	(0.8003)	(0.9109)
Case 7	0.0991	0.2308	0.4003	0.6631	0.8015	0.9135
	(−)	(−)	(0.3984)	(0.6570)	(0.7941)	(0.9077)
Case 8	0.0991	0.2551	0.4078	0.6629	0.8014	0.9134
	(−)	(−)	(−)	(0.6611)	(0.7971)	(0.9092)
Case 9	0.0991	0.2551	0.4275	0.6517	0.7934	0.9094
	(−)	(−)	(0.4256)	(0.6456)	(0.7857)	(0.9034)
Case 10	0.0991	0.2455	0.3924	0.6556	0.7962	0.9108
	(−)	(0.2440)	(0.3875)	(0.6466)	(0.7865)	(0.9038)
Case 11	0.0991	0.2455	0.4244	0.6487	0.7912	0.9083
	(−)	(0.2440)	(0.4194)	(0.6397)	(0.7814)	(0.9011)

Note: the values of 40% price discounting cases are in parentheses; (−) means the 40% price discounting case was not simulated due to nontarget of simulations; the standard demand level is assumed as 92.6% in 52 weeks; the value of $SC_{full}^{ranx\&rdtrust}$ in 52 weeks is 0.8994 in Table 10.

Table 17
Parameters of event and visitor information without synergetic effect and travel cost by periods.

Weeks	1st week	4th week	12th week	24th week	36th week	52nd week
$\beta_{safe}^{event} - \beta_{safe}$	0.1801	0.2298	0.3097	0.3343	0.4067	0.3696
$\beta_{safe}^{visitor} - \beta_{safe}$	0.3632	0.3830	0.3844	0.406	0.3781	0.4735
β_{TC}	−0.0166	−0.0179	−0.0178	−0.0206	−0.0203	−0.0311

In summary, it is preferable to implement announcing the safety information (the first step) within one week, the event information (the second step) within 24th to 36th week after the first step, visitor information (the third step) within 37th to 52nd week after the second step (e.g., 40th week), and the price discounting until the 52nd week immediately after the third step (e.g., 41th week).

Note that the timing relies on the framework of this study. More proper policy timing analyses are needed for the (optimal) recovery process of restructuring infrastructures of tourism sites as described in Faulkner (2001).

6. Concluding remarks

Disasters in tourism sites urge policymakers to implement effective tourism demand recovery policies through optimal timing. However, the difficulty of micro data collection in disasters and external factors in macro data make it difficult for policymakers and researchers to analyze policy effects. This study examined the CB method with the time series factor as an appreciable method for analyzing the policy effects and timing (orderings) after solving the disaster.

A bird flu emergency in Kyoto prefecture, Japan, acts as the hypothetical disaster in the CB questionnaire. The respondents were asked about their WTT under this hypothetical situation, assuming combinations of three information policies (safety, event, and visitor information) and three travel costs (¥1,000, ¥20,000, and ¥40,000). The alternatives for WTT were designed to range from week 1 to week 52.

The estimation results indicated the following. First, safety information has the highest effect on demand recovery. The second is event information, if it relates to the time series factor (the willingness to travel time variable), and visitor information, if not. Event information would be more important in considering the optimal timing due to its relation with the time series factor. Second, combinations of these information policies could generate synergetic effects on tourism demand recovery. Third, tourism at disaster sites would be an inferior good in the period immediately after the disaster, changing to a normal good with time.

The simulation results indicate the following. First, the necessity to analyze the dynamic policy effect due to changes with time would require researchers to examine applicable management frameworks corresponding to the effect changes (e.g., announcing music festivals in a tourism site until the 4th week or informing the visitors' looks of enjoying the festivals to other non-visited tourists through the media until the 12th week). Second, the pricing policy, after solving a disaster, would not have a significant effect due to tourists' anxiety. Third, the optimal policy ordering and timings are determined as follows: the provision of safety information within a week, event information within 24th to 36th week after the disaster, visitor information within the 37th week to the 52nd week, and price discounting until the 52nd week immediately after the third step (e.g., 41th week). Here, the optimal policy ordering results indicated that the policy orderings based on the effects would not be optimal due to the time delay and the policy effect changes.

The results conclude that the method of this study could be useful for analyzing dynamic tourism demand processes by recovery policies. The method aims to show policymakers the policy effects and the optimal policy ordering for recovery from disaster damages, especially through advance planning.

Moreover, the method of this study could be applicable to other disasters, such as earthquakes, hurricane, crimes, and terrorism, by modifying the contents of policies in the CB questionnaire (the solutions for the issues are necessary as well). For example, the policy contents for recovering demands from terrorism would include the announcement of arresting terrorists, establishment of security cameras to monitor terrorism, and police deployment.

Finally, this study has certain limitations. The first is the difficulty in reducing the number of CB questionnaires when the number of policies or periods increase—the order effect might occur by the answer format of this study. For example, the choice experiments, which could possibly implement the same analysis in this study, were not employed owing to its difficulty. The second limitation is how to design and estimate the policy effects from the pre-event to the post-event stages, and the feedback effects from the post-event to the pre-event stages, for improving disaster planning, training and education, among others. The third is to research more realistic trip information (e.g., the type and quality of accommodation, food and beverage, and distances from respondents' homes to the tourist site) in order to estimate more realistic price effects, especially in low-price level situations (¥1000 in hypothetical prices). The simulation results could be improved by collecting these details, and thus further studies could take up these challenges. Additionally, new research could also involve adjusting the difference between real and hypothetical behaviors, and applying the proposed method to varied disaster events, such as earthquakes and tsunamis.

Conflict of interest

No other relationships, conditions, and circumstances present a potential conflict of interest.

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Appendix 1. Explanations and Questionnaires on contingent behavior (original sentences were written in Japanese)

1-A) Questionnaire and basic statistics on credible information source and interest to visit Kyoto

Q. Please select an alternative on your most credible information source.

Q. Have you visited Kyoto? 1. Yes 2. No.

Q. Would you be interested in visiting Kyoto if you have the time to travel?

1. I would like to visit 2. I would not like to visit.

Q. Dou you feel anxiety about dasmaging your health if the bird flu occurs in your neighborhood?

1. No problem 2. I feel anxiety* 3. I cannot imagine.

*respondents who select alternative 2 were assigned for 1; 0 for others.

1-B) Explanation on the bird flu

In general, the bird flu influenza virus infects many birds living in nature—mainly water birds, such as ducks (*Anas*). Bird flu does not frequently infect humans, but it rarely does so when a person touches or is in close contact with an infected bird. In recent years, cases of H5N1 type bird flu influenza virus infection on humans has been reported and developed. The observed bird flu influenza type in Japan is H5N1. In Asian countries, it has also been reported that symptoms of seriously ill patients infected by the H5N1 type are pneumonia, multiple organ dysfunction, among others, while the main symptom of mildly ill patients infected by H7N7 type observed in the Kingdom of the Netherlands is conjunctivitis. The WHO reported that 568 persons were infected, of whom 334 persons were dead from 2003 to November 2011. Another reason that public organizations pay serious attention to the bird flu is the *influenza pandemic* caused by various bird flu influenza viruses through infections from birds to humans. Hence, the pandemic might rapidly expand across the world. Currently, the Japanese government prevents the bird flu outbreak by euthanizing infected (or probably infected) birds. Note that the bird flu shot (vaccination) has not been implemented in Japan.

1-C) Explanations on a hypothetical bird flu outbreak

Please read the explanation below and answer the next questionnaire.

In Kyoto prefecture, a wild bird infected by the bird flu was observed and decontaminated (see the left panel in Fig. A1). However, the spread of infections to humans and food items was not confirmed. It is expected to be difficult in future to undertake protective measures for whole infection cases of the bird flu due to wide action ranges of wild birds.

Here, the bird flu is assumed to be observed in the entire area of Kyoto prefecture (see the right panel in Fig. A1) in the next questionnaire. This bird flu outbreak is called an influenza pandemic, as described above. Here, the outbreak is assumed to expand only to birds, and not to humans and food items, among others. Note that the area of the outbreak is assumed as only the Kyoto prefecture.

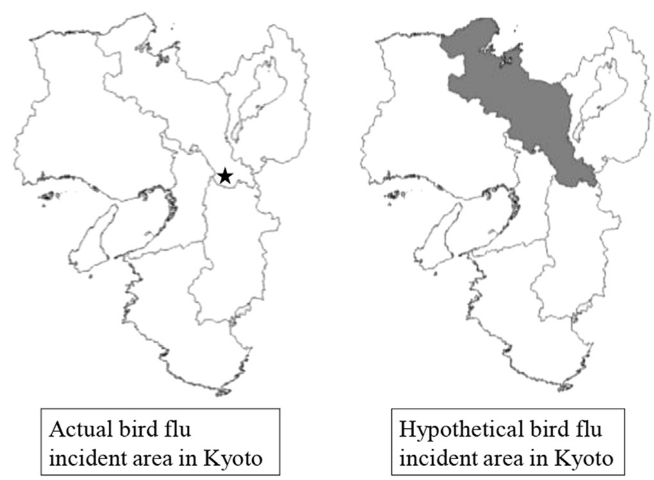

Fig. A1. Actual and hypothetical areas hit by the bird flu.

1-D) Questionnaire on contingent behaviors

This questionnaire requests you to provide your assumed travel behavior under the hypothetical situations described below. Please read the information carefully. Note that the travel costs (¥1,000, ¥20,000, and ¥40,000) differ by the questions presented to you.

[Hypothetical situation: Travel to Kyoto prefecture].

Imagine that you plan to travel to Kyoto prefecture alone. During your planning, you realize that a bird flu emergency has occurred throughout Kyoto prefecture (see the Table below). You are also aware that the Japanese local governments could decontaminate the bird flu-affected areas without causing human and physical damages. Then, you are provided each of following three pieces of information by a credible information source.

Table A1
Information policies in Type A and B questionnaires

	Type A questionnaire	Type B questionnaire
Information 1	Safety information from central and local governments	No safety information
Information 2	Safety information from central and local governments + Details about events and/or new tourism facilities that you prefer, which are performed/have been established in Kyoto	Details about events and/or new tourism facilities that you prefer, which are performed/have been established in Kyoto
Information 3	Safety information from central and local governments + Information about the number of tourists who have already visited the area	Information about the number of tourists who have already visited the area

Please answer what would be the earliest period you would be willing to travel to Kyoto prefecture, depending on the information provided to you. (Please provide this answer even if you live in Kyoto in the present time). Your travel period is assumed to be two days and one night, with the assumed travel cost being ¥X [b] (including accommodation and the travel fee). Assume that there are no factors (job, homework, etc.) impeding your travel in each period.

Periods	Information 1	Information 2	Information 3
After a year (52 weeks)			
After nine months (36 weeks)			
After six months (24 weeks)			
After three months (12 weeks)			
After a month (4 weeks)			
After a week			
Never			

a: Only the descriptions provided in the brackets were shown for the Type B group.
b: X, yen = {1000 (special price for campaign), 20,000, 40,000}.

Q. Please answer your main reason for selecting "Never" from Information 1 to 3. Please write box here [ ].

Appendix 2. Estimation results by periods.

Weeks	1st Estimates	4th Estimates	12th Estimates	24th Estimates	36th Estimates	52nd Estimates
CONT	−2.1703 [a]	−1.6572 [a]	−1.0713 [a]	−0.6171 [a]	−0.3133 [a]	0.5713 [a]
	(0.1229)	(0.0957)	(0.0841)	(0.0808)	(0.0812)	(0.0965)
WTT	–	–	–	–	–	–
IPA_{safe}	0.3972 [a]	0.4216 [a]	0.4127 [a]	0.4572 [a]	0.4760 [a]	0.7098 [a]
	(0.0602)	(0.0465)	(0.0406)	(0.0387)	(0.0389)	(0.0478)
IPA^{event}_{safe}	0.5773 [a]	0.6514 [a]	0.7224 [a]	0.7915 [a]	0.8827 [a]	1.0794 [a]
	(0.0587)	(0.0456)	(0.0401)	(0.0391)	(0.0397)	(0.0501)
$IPA^{visitor}_{safe}$	0.7604 [a]	0.8046 [a]	0.7971 [a]	0.8632 [a]	0.8541 [a]	1.1833 [a]
	(0.0574)	(0.0451)	(0.0401)	(0.0392)	(0.0397)	(0.0508)
IPB^{event}_{nosafe}	0.1619 [a]	0.1825 [a]	0.2795 [a]	0.3322 [a]	0.3949 [a]	0.3330 [a]
	(0.0626)	(0.0478)	(0.0409)	(0.0387)	(0.0388)	(0.0459)
$IPB^{visitor}_{nosafe}$	0.3275 [a]	0.3183 [a]	0.3411 [a]	0.3972 [a]	0.3851 [a]	0.4288 [a]
	(0.0609)	(0.0470)	(0.0407)	(0.0387)	(0.0388)	(0.0463)
RANXIETY	−1.5979 [a]	−1.7225 [a]	−2.0234 [a]	−2.1841 [a]	−2.3231 [a]	−3.0412 [a]
	(0.1031)	(0.0753)	(0.0644)	(0.0534)	(0.0522)	(0.0470)
RDTRUST	−1.7005 [a]	−1.7001 [a]	−1.6994 [a]	−1.9115 [a]	−2.0221 [a]	−2.6884 [a]
	(0.1277)	(0.0881)	(0.0672)	(0.0582)	(0.0564)	(0.0514)
RNWILL	−3.9104 [a]	−4.3229 [a]	−3.6578 [a]	−2.7372 [a]	−2.8041 [a]	−3.3021 [a]
	(0.7094)	(0.5787)	(0.3054)	(0.1513)	(0.1438)	(0.1094)
ROTHER	−1.5527 [a]	−1.7763 [a]	−2.0021 [a]	−2.4826 [a]	−2.5899 [a]	−3.1335 [a]
	(0.1461)	(0.1138)	(0.0948)	(0.0887)	(0.0851)	(0.0693)
TC	−0.0166 [a]	−0.0179 [a]	−0.0178 [a]	−0.0206 [a]	−0.0203 [a]	−0.0311 [a]
	(0.0010)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0009)
ICM	−0.0122 [a]	−0.0049 [d]	−0.0040 [d]	0.0049 [d]	0.0023 [d]	0.0173 [a]
	(0.0040)	(0.0030)	(0.0027)	(0.0027)	(0.0027)	(0.0035)
GND	0.2811 [a]	0.2307 [a]	0.2552 [a]	0.1218 [a]	0.0918 [a]	−0.0485 [d]
	(0.0437)	(0.0346)	(0.0308)	(0.0301)	(0.0305)	(0.0388)
AGE	0.0064 [a]	0.0098 [a]	0.0076 [a]	0.0084 [a]	0.0060 [a]	0.0060 [a]
	(0.0017)	(0.0014)	(0.0012)	(0.0012)	(0.0012)	(0.0015)
MAR	−0.2914 [a]	−0.2341 [a]	−0.1222 [a]	−0.1394 [a]	−0.1405 [a]	−0.0061 [d]
	(0.0400)	(0.0320)	(0.0287)	(0.0284)	(0.0288)	(0.0367)
JBTS	0.3457 [a]	0.5493 [a]	0.2645 [a]	0.1832 [b]	0.0410 [d]	−0.1974 [b]
	(0.1037)	(0.0831)	(0.0791)	(0.0794)	(0.0802)	(0.0985)
JBPTJ	−0.0332 [d]	0.0047 [d]	−0.0160 [d]	−0.0495	−0.1282 [b]	−0.0470
	(0.0746)	(0.0587)	(0.0521)	(0.0503)	(0.0508)	(0.0636)
JBSOB	0.0266 [d]	−0.0004 [d]	−0.1506 [a]	−0.1511 [a]	−0.1101 [c]	−0.2275 [a]
	(0.077)	(0.0619)	(0.0565)	(0.0555)	(0.0564)	(0.0710)
JBFP	0.2551 [a]	0.0699 [d]	0.0849 [d]	0.1842 [b]	0.0345	0.1514 [d]
	(0.0983)	(0.0836)	(0.0759)	(0.0769)	(0.0777)	(0.1098)
JBHM	−0.3547 [a]	−0.1436 [b]	−0.1724 [a]	−0.2084 [a]	−0.2520 [a]	−0.4593 [a]
	(0.0795)	(0.0574)	(0.0496)	(0.0473)	(0.0476)	(0.0584)
JBST	0.1851 [b]	0.3305 [a]	0.1769 [a]	0.0891 [d]	0.0450 [d]	−0.2935 [a]
	(0.0837)	(0.0677)	(0.0627)	(0.0622)	(0.0632)	(0.0753)
JBNM	−0.1993 [b]	−0.0249 [d]	−0.2155 [a]	−0.1535 [a]	−0.1385 [b]	−0.2805 [a]
	(0.0817)	(0.0624)	(0.0574)	(0.0555)	(0.0562)	(0.0677)
EDHS	0.0269 [d]	−0.0127 [d]	−0.1509 [a]	0.0200 [d]	−0.0022 [d]	0.2405 [a]
	(0.0629)	(0.0507)	(0.0460)	(0.0450)	(0.0454)	(0.0578)
EDVC	−0.0910 [d]	−0.0858 [d]	−0.0456	0.0973 [c]	0.0676 [d]	0.2900 [a]
	(0.0754)	(0.0599)	(0.0534)	(0.0522)	(0.0527)	(0.0665)

(*continued*)

Weeks	1st Estimates	4th Estimates	12th Estimates	24th Estimates	36th Estimates	52nd Estimates
EDJC	−0.0197 [d]	−0.0304 [d]	0.1896 [a]	0.2380 [a]	0.1992 [a]	0.2177 [a]
	(0.0864)	(0.0675)	(0.0592)	(0.0580)	(0.0585)	(0.0721)
EDTC	−1.5018 [a]	−0.7306 [a]	−0.2762 [b]	0.2504 [c]	0.0842 [d]	−0.3106 [b]
	(0.3272)	(0.1765)	(0.1365)	(0.1304)	(0.1311)	(0.1513)
EDUV	−0.0517 [d]	−0.0199 [d]	0.0593 [d]	0.2194 [a]	0.2722 [a]	0.2143 [a]
	(0.0504)	(0.0406)	(0.0366)	(0.0362)	(0.0367)	(0.0464)
EXKYOTO	0.1379 [a]	0.2325 [a]	0.1816 [a]	0.1903 [a]	0.1917 [a]	0.0286 [d]
	(0.0413)	(0.0325)	(0.0296)	(0.0297)	(0.0303)	(0.0385)
INTKYOTO	0.1502 [b]	0.1331 [b]	0.2007 [a]	0.3371 [a]	0.3265 [a]	0.7931 [a]
	(0.0756)	(0.0583)	(0.0508)	(0.0480)	(0.0478)	(0.0517)
AXBF	−0.2163 [a]	−0.0888 [a]	−0.0309 [d]	−0.0484 [c]	0.0188 [d]	0.1595 [a]
	(0.0403)	(0.0308)	(0.0272)	(0.0267)	(0.0271)	(0.0346)
ODR	0.0144 [d]	0.0719 [a]	0.0708 [a]	0.0227 [d]	0.0504 [b]	0.2706 [a]
	(0.0325)	(0.0257)	(0.0229)	(0.0225)	(0.0229)	(0.0288)
Max.LL	−13062.6938	−18736.7791	−22281.2353	−23002.3179	−22552.82456	−15858.9221
AIC	26187.3876	37535.5582	44624.4706	46066.6357	45167.64911	31779.8443
R^2	0.0659	0.0810	0.1000	0.1330	0.14876	0.2829

Note: a: p-values are less than 1%, b: p-values are less than 5%, c: p-values are less than 10%, d: p-values are over 10%; S.E: standard errors, Max. LL: maximum value of log likelihood, AIC: Akaike information criterion, R2: McFadden's pseudo r-squared; N = 38,304.

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