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Economic Valuation of the Damage to Tourism Benefits by Eastern Japan Great Earthquake Disaster

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Measuring lost recreational benefits in Fukushima caused by spreading harmful rumors

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Abstract: This paper measures the recreational benefits lost due to the economic damage caused by harmful rumors spread over the three-year period from the Great East Japan Earthquake (the Earthquake) until the present. The study analyzed revealed preference (RP) data on the number of actual visits to Fukushima Prefecture and stated preference (SP) data on the number of visits that would have occurred under the hypothetical condition that the radiation accident had not occurred. We consider a Poisson-Inverse-Gaussian regression model that incorporates on-site sampling corrections and expand it into the random effect model framework to propose a random effect Poisson-Inverse-Gaussian model that estimates the demand function. Our results show that Fukushima Prefecture lost approximately ¥374.5 billion of recreational benefits over the past three years, which corresponds to approximately 41% of Fukushima Prefecture's tourism consumption in the year preceding the Earthquake.

1. Introduction

The Great East Japan Earthquake (hereinafter, the Earthquake) and the accident involving radiation leakage at Tokyo Electric Power Company's Fukushima No. 1 Nuclear Power Plant (hereinafter, Fukushima No. 1 Nuclear Plant) brought fame to Fukushima Prefecture but not in a positive way. In general, economic damage caused by misinformation is defined as "damage caused by groundless rumors, in particular, economic damage suffered by people or groups caused by improper news coverage, even though they essentially nothing to do with an event or accident." Regarding tourism, this means that tourism in a given area will be affected by news coverage and misinformation that differ from the facts (for example, degradation in the environmental quality of a tourist attraction), thereby deterring tourists. However, the degree to which such news coverage and misinformation affect people's activities is largely dependent on those people's states of mind. It is impossible to know the exact number of how many visits would have been made to the region in question if there had been no such news coverage, no harmful rumors, and no environmental degradation. Thus, after the sensational news coverage about radiation at Fukushima No. 1 Nuclear Plant, the inclusion of people in the survey sample who had never visited Fukushima Prefecture would have skewed expected trip numbers and overestimated the monetary loss of tourism.

Therefore, to minimize the effect of bias in responses to hypothetical questions, survey subjects were limited to people who had visited Fukushima as that experience becomes the benchmark for considering actions in a hypothetical question. The analysis is thus a combination of the number of visits made to Fukushima Prefecture (revealed preference (RP) data) and the number of visits to Fukushima Prefecture that would have been made under hypothetical conditions (stated preference (SP) data). This necessitates a consideration of the correlation between the observed data and the data generated by the scenario.

Count data gathered by on-site sampling is often used when conducting an empirical analysis using the travel cost method (TCM). Statistical analysis of such on-site count data should account for truncation and endogenous stratification, as indicated by Shaw (1988). Shaw (1988) proposes an estimation method that corrects these problems in the Poisson regression model. However, in the trip number data that are the subject of this paper, this phenomenon of

overdispersion, whereby the range of dispersion varies widely from the mean, is known to frequently occur (Sarker & Surry, 2004; Martinez-Espiñeira & Amoako-Tuffour, 2008). Englin and Shonkwiler (1995) propose an estimation method for correcting on-site sampling based on a negative binomial regression model that can capture such conditions, and this has become a major method in the travel cost method using univariate on-site count data (Loomis, 2003; Martinez-Espiñeira & Amoako-Tuffour, 2009; Nohara, 2011). However, as Guo and Trivedi (2002), Sarker and Surry (2004), and Cameron and Trivedi (2013) argue, because the limits to overdispersion are captured in negative binomial regression models, a distribution with a so-called long (heavy) tail from trip number data is inadequate and therefore a reliable statistical estimate cannot be made.

Nevertheless, this paper aims to estimate, using a negative binomial regression model, the extent of recreational benefits that were lost by economic damage caused by harmful rumors by only asking people who had actually traveled to Fukushima Prefecture during the past three years how many times they had visited Fukushima during the past three years and how many times they hypothetically would have visited Fukushima if the accident had not occurred. Chapter 2 discusses previous research on the hypothetical travel cost method (HTCM), which is a combination of TCM and contingent behavior (CB). Chapter 3 proposes a methodology using a Poisson-Inverse-Gaussian (PIG) regression model instead of a negative binomial regression model for on-site count data. Chapter 4 analyzes the data output and estimates the lost recreational benefit. Finally, Chapter 5 sets forth our conclusions and topics for future research.

2. Review of previous research

Fundamentally, it has been difficult to estimate changes in consumers' surplus (CS) from changes in the environmental quality of a site using the traditional TCM. This is because the environmental quality enjoyed by visitors at a particular site (for example, such scientific measures as air pollution and water pollution) is the same for all individuals, but environmental metrics that vary among individuals cannot be measured unless they have an indirect effect on individuals' activities (such as the effect of water pollution on catch rates). Even if an environmental metric is substituted by an indirect effect on environmental quality, such as the catch rate, it is still difficult to separate the differences in individuals' skills. Combining RP and SP and asking about travel site selection, trip numbers, and amounts willing to spend under a hypothetical environmental quality thus makes it possible to measure benefits for different environmental qualities (Whitehead et al., 2000).

The HTCM is classified as a frequency data model. For example, as Layman et al. (1996) have shown, studies that have employed various HTCMs use pooled RP and SP data. However, this approach is problematic because it does not consider the correlation between these two types of data (Whitehead et al., 2011). One way to address this is to regard the combined RP and SP data as pseudo panel data and apply them in panel data analysis. Whitehead et al. (2008) and Beaumais and Appéré (2010) use this approach in their analysis.

Studies using HTCM date back many years. In early research, Ribaud and Epp (1984) estimated the recreational benefit gained from improvement in water quality in Vermont's St. Albans Bay. More recently, HTCM has been used not only in research on travel but also in such

wide-ranging areas as household trash, agricultural technology, consumption of marine products, and food safety technology (Nestor, 1998; Hubbell et al., 2000; Huang et al., 2004; Morgan et al., 2013). Various other studies have also applied HTCM, and these have been reviewed comprehensively by Whitehead et al. (2008).

As shown above, considerable research on HTCM already exists, and research subjects have not been limited to the natural environment but have branched out to areas such as trash collection and agriculture. However, to the best of the authors' knowledge, no literature exists that investigates the economic damage caused by harmful rumors in the wake of the accident at Fukushima's No. 1 Nuclear Plant and its impact on Fukushima Prefecture's recreational benefits over the past three years.¹

Next, we summarize count data models used to analyze trip data gathered through on-site sampling. As stated above, overdispersion is often observed in trip number data. Therefore, we believe that there is a limit to performing more precise estimates when a strong overdispersion is present in existing Poisson regression models and negative binomial regression models. However, Willmot (1987) and Dean et al. (1989) consider the PIG regression model to be a more easily usable parametric model because, in an analysis of insurance data, it depicts more heavy-tailed count data than the negative binomial regression model, even with the same number of parameters. Guo and Trivedi (2002) apply the PIG regression model to an analysis of patent data. Because this paper uses trip number data from an on-site survey, we base our estimation method on the PIG regression model, adding the on-site sampling correction of Shaw (1988). Moreover, to conduct a combined analysis of RP and SP data, this paper expands to a random effect model that can use pseudo panel data, as in Beaumais and Appéré (2010).

3. Model estimation methods

3.1 Poisson-Inverse-Gaussian regression model

First, we introduce a PIG model for cases in which the count data are univariate. The following formula expresses parameter λ_i as the average, whereby y_i is the number of trips by individual i , $\mathbf{x}_i = (x_{i1}, \dots, x_{ik})'$ is the k -dimensional explanatory variable vector including a constant, and β is the corresponding coefficient (parameter) vector:

$$\lambda_i = E(y_i | \mathbf{x}_i) = \exp(\mathbf{x}_i' \boldsymbol{\beta}), \quad i = 1, \dots, N. \quad (1)$$

However, because of unobserved heterogeneity in data on individual questionnaires, we introduce v_i to Equation (1) to express this heterogeneity as follows:

$$\mu_i = \lambda_i v_i, \quad i = 1, \dots, N.$$

Here, $E(v_i) = 1$ and y_i are independent of each other, and the density function is expressed as $g(v_i)$. Further, $E(\mu_i | \lambda_i) = \lambda_i$ is obtained by definition. Therefore, by multiplicatively adding unobserved

¹ Kaino (2013) conducted a statistical analysis of rumor-based economic damage by examining past trends in data on incoming tourist numbers to Fukushima Prefecture.

heterogeneity and assuming that y_i follows the Poisson distribution of the mean parameter μ_i , because the conditional probability density function is given as

$$f(y | \mathbf{x}, \nu) = \frac{\exp(-\mu)\mu^y}{y!},$$

the conditional probability density function y_i is introduced as a Poisson mixed distribution, as shown in Equation (2) below. (The subscript i denoting an individual has been eliminated for purposes of simplification.)

$$h(y | \mathbf{x}) = \int_0^\infty \frac{\exp(-\lambda \nu)(\lambda \nu)^y}{y!} g(\nu) d\nu. \quad (2)$$

Although a model constructed in this way is usually referred to as a Poisson mixture model, a Poisson mixture model in which $g(\nu)$ is assumed to have a gamma distribution becomes a negative binomial regression model.

This paper considers estimates using the PIG regression model of Dean et al. (1989), in which ν followed an inverse distribution. The density function of an inverse distribution that normalizes $E(\nu) = 1$ is given as

$$g(\nu) = \sqrt{\frac{1}{2\pi\tau\nu^3}} \exp\left(-\frac{(\nu-1)^2}{2\tau\nu}\right),$$

in which $Var(\nu) = \tau$ and $\tau > 0$ is the parameter determining the shape (Tweedie, 1957; Folks & Chhikara, 1978, and others for details on inverse distribution). From the explicit expression of the probability of a Poisson inverse Gaussian distribution as shown by Willmot (1987), the conditional probability density function (probability function) of the PIG regression model can be obtained from Equations (3) and (4) below. If $y > 0$,

$$h(y | \mathbf{x}) = p(0) \frac{\lambda^y}{\Gamma(y+1)} \sum_{k=0}^{y-1} \frac{\Gamma(y+k)}{\Gamma(y-k)\Gamma(k+1)} \left(\frac{\tau}{2}\right)^k (1+2\tau\lambda)^{-\frac{y+k}{2}}, \quad (3)$$

but if $y = 0$,

$$p(0) = \exp\left(\tau^{-1} \left(1 - \sqrt{1 + 2\tau\lambda}\right)\right) \quad (4)$$

However, when $\tau \rightarrow 0$, the PIG regression model becomes similar to an ordinary Poisson regression model, and τ becomes the parameter determining overdispersion.

In the PIG regression model obtained by the above method, we insert some corrections proposed by Shaw (1988) in order to perform some estimates using on-site count data. There are some problems in on-site sampling, such as using 0 as the cut-off point for count data (truncation) when survey subjects are only those individuals who made a trip and relying on the frequency of individual trips in the sample (endogenous stratification). Shaw (1988) proposes the following method for correcting the conditional probability density function to resolve such problems involved in sampling:

$$h^S(y | \mathbf{x}) = h(y | \mathbf{x})w(y, \lambda), \quad w(y, \lambda) = \frac{y}{E(y | \mathbf{x})} \quad (5)$$

By adding the corrections used in Equation (5), we can construct a log-likelihood function, such as that shown in Equation (6), based on the PIG regression model using on-site sampling data:

$$\begin{aligned} \log L_N(\boldsymbol{\beta}, \tau) &= \sum_{i=1}^N \log h^S(y_i | \mathbf{x}_i) = \sum_{i=1}^N \log \left(\frac{y_i}{\lambda_i} p(y_i) \right) \\ &= \sum_{i=1}^N \left\{ \log \frac{\lambda_i^{y_i-1}}{\Gamma(y_i)} + \tau^{-1} (1 - \sqrt{1 + 2\tau\lambda_i}) + \log \left(\sum_{k=0}^{y_i-1} \frac{\Gamma(y_i + k)}{\Gamma(y_i - k)\Gamma(k+1)} \left(\frac{\tau}{2} \right)^k (1 + 2\tau\lambda_i)^{-\frac{y_i+k}{2}} \right) \right\}. \end{aligned} \quad (6)$$

3.2 Expansion to the random effect model

In this section, we expand to the random effect model as one way to handle multivariate count data. Estimating the benefits of combined RP and SP data, which is the aim of this study, is a matter of obtaining various trip number data from each individual. Moreover, it is not desirable to analyze each response from a given individual as univariate count data. The most natural expansion is to analyze it as multivariate count data, as done by Egan and Herriges (2006). However, the calculation required to perform the estimate is difficult as the likelihood function is usually complex. As an alternative methodology, their paper proposes an estimation method that uses the seemingly unrelated negative binomial (SUNB) regression model of Winkelmann (2000), because it is easy to use even though the correlation structure becomes restrictive. On the other hand, Beaumais and App  r   (2010) view multivariate data as pseudo panel data and propose a methodology that applies the random effect Poisson gamma model to panel count data, as constructed by Hausman et al. (1984). We can view this as a simple expansion of the negative binomial regression model to panel data. Based on Hausman's thinking, we take the PIG regression model on which on-site sampling correction has been performed, as discussed in Section 3.1, and expand it into the random effect model.

Assuming that individual i takes y_{ij} trips in scenario j , parameter λ_{ij} , which expresses the mean, can be formulated as the following equation:

$$\mu_{ij} = \exp(\mathbf{x}'_{ij}\boldsymbol{\beta})v_i = \lambda_{ij}v_i, \quad i = 1, \dots, N, \quad j = 1, \dots, J,$$

In this equation, $\mathbf{x}_{ij} = (x_{1ij}, \dots, x_{kij})'$ is the k -dimensional explanatory variable vector including a constant in scenario j , and $\boldsymbol{\beta}$ is the coefficient (parameter) vector to which this applies. The distinguishing characteristic when handling this as panel data is that v_{ij} , which denotes heterogeneity of individuals in response to a scenario, is taken as a random effect that is not dependent on scenario j , so that $v_{ij} = v_i$. In this way, although the random effect is denoted by a probability variable that follows a common inverse distribution, it should be pointed out that this restricts the correlation structure. Because each individual's trip number now becomes multivariate count data, if $\mathbf{y}_i = (y_{i1}, \dots, y_{iJ})'$, $\tilde{\mathbf{x}}_i = (\mathbf{x}_{i1}, \dots, \mathbf{x}_{iJ})'$, then the conditional probability density function of the PIG random effect model expands Equation (2) in Section 3.1 to

$$h(\mathbf{y} | \tilde{\mathbf{x}}) = \int_0^\infty \prod_{j=1}^J \frac{\exp(-\mu_j) \mu_j^{y_j}}{y_j!} g(v) dv = \prod_{j=1}^J \frac{\lambda_j^{y_j}}{y_j!} \int_0^\infty \exp\left(-v \sum_{j=1}^J \lambda_j\right) v^{\sum_{j=1}^J y_j} g(v) dv \quad (7)$$

and the subscript i denoting an individual has been omitted for simplification). Because $g(v)$ is the density function of the inverse distribution, we can draw a conclusion following Section 3.1 and express the density function of Equation (7) as follows:

$$h(\mathbf{y} | \tilde{\mathbf{x}}) = \prod_{j=1}^J \frac{\lambda_j^{y_j}}{y_j!} \cdot \frac{y_j^*!}{\lambda_j^{*y_j^*}} \cdot p(y_j^*), \quad y_j^* = \sum_{j=1}^J y_j, \quad \lambda_j^* = \sum_{j=1}^J \lambda_j,$$

$$p(y_j^*) = \exp\left(\tau^{-1} \left(1 - \sqrt{1 + 2\tau\lambda_j^*}\right)\right) \frac{\lambda_j^{*y_j^*}}{\Gamma(y_j^* + 1)} \sum_{k=0}^{y_j^*-1} \frac{\Gamma(y_j^* + k)}{\Gamma(y_j^* - k) \Gamma(k + 1)} \left(\frac{\tau}{2}\right)^k \left(1 + 2\tau\lambda_j^*\right)^{-\frac{y_j^* + k}{2}}.$$

In sum, we obtain the following results.

$$h(\mathbf{y} | \tilde{\mathbf{x}}) = \prod_{j=1}^J \frac{\lambda_j^{y_j}}{y_j!} \cdot q(y_j^*), \quad (8)$$

$$q(y_j^*) = q(0) \sum_{k=0}^{y_j^*-1} \frac{\Gamma(y_j^* + k)}{\Gamma(y_j^* - k) \Gamma(k + 1)} \left(\frac{\tau}{2}\right)^k \left(1 + 2\tau\lambda_j^*\right)^{-\frac{y_j^* + k}{2}}, \quad q(0) = \exp\left(\tau^{-1} \left(1 - \sqrt{1 + 2\tau\lambda_j^*}\right)\right).$$

Furthermore, in $\mathbf{y}_i = (y_{i1}, \dots, y_{iJ})'$, the RP data become the count data from the on-site sampling. Because this is normally limited to one, we set it at y_{i1} , so that when on-site sampling correction is taken into consideration, the conditional probability density function of Equation (8) becomes

$$h^S(\mathbf{y} | \tilde{\mathbf{x}}) = \frac{\lambda_1^{y_1-1}}{(y_1-1)!} \prod_{j=2}^J \frac{\lambda_j^{y_j}}{y_j!} \cdot q(y_j^*).$$

As a result, we can construct a log-likelihood function in the same way as in Equation (6) in Section 3.1 to make estimates based on the on-site sampling of the PIG random effect model. However, in the same way as for the SUNB model and the random effect Poisson gamma model, it must be noted that the correlation structure among the multivariate count data in the model used in this paper is limited to positive correlations, so that one parameter is almost the sole determinant of the outcome.

4. Empirical analysis

4.1 Radiation levels in Fukushima Prefecture and the tourism situation

According to the Japanese Radiation Research Society, the total amount of radiation in 2011 after the earthquake in Fukushima City was five millisieverts (mSv), which is not large enough to cause serious health damage. Moreover, although the International Commission on Radiological Protection (ICRP) states 1-20 mSv as acceptable and safe for the general population; in fact, the effect of radiation on people's health has not been adequately clarified

from a scientific perspective. The extent to which radiation of up to 100 mSv causes cancer remains unknown. However, the current radiation amount accumulated over one year in areas of Fukushima Prefecture outside the emergency evacuation zone does not exceed the range of the ICRP recommendations. Furthermore, for visits to the area lasting only a few days, as in the case of sightseeing, the dose of radiation would not be problematic. Nevertheless, rumor-driven economic damage caused by mistaken perceptions about radiation and the dissemination of harmful rumors and overreactions to the situation has not yet been rectified.

In April 2013, the Reconstruction Agency released its “Package of Countermeasures to Deal with Rumor-Driven Economic Damage and Other Effects of the Nuclear Disaster,” which was followed by a supplemental version in November. These documents state that urgent steps are necessary because agriculture, forestry, fisheries, tourism, and other regional industries are still being affected by the “harmful rumors” associated with the image of “an area affected by a nuclear disaster.” However, according to the Reconstruction Agency’s FY2014 provisional budget outline, the amount allocated for dealing with rumor-driven economic damage was reduced to ¥900 million, down from an initial budget of ¥1.3 billion in FY2013. It should be noted that measures being taken in regard to economic damage from misinformation concern not only tourism-related industries but also agricultural products. The countermeasures being taken regarding rumor-driven economic damage consist primarily of helping tourism-related businesses and responding to the economic damage caused by misinformation through public relations (PR). Here, the aim is to promote a proper understanding of Fukushima Prefecture’s agricultural and other products and to restore Fukushima’s brand image.

Various efforts are underway in Fukushima Prefecture to rectify the economic damage caused by misinformation. For example, as the prefectural government could not continue allocating large portions of its budget only for helping those affected by rumor-driven economic damage, they came up with a way of motivating ordinary citizens to help by offering the Fukurum Card, a loyalty points card that also functions as a credit card. Card members can exchange accumulated points for local Fukushima products, gift certificates, tickets to Fukushima tourism facilities, and other things. Simultaneously, 0.1% of all purchases made with the card are donated to the Fukurum Card Promotion Council. The Council then channels these funds toward helping those suffering from rumor-driven economic damage.

Therefore, although the Reconstruction Agency’s budget allocation for countermeasures in response to rumor-driven economic damage is declining, Fukushima Prefecture, local municipalities, and local tourism-related businesses are joining together to grapple with rumor-driven economic damages. Perhaps for this reason, tourists are gradually returning, although they have still not reached pre-Earthquake levels (Nohara(2013)).

4.2 Data compilation

This study is based on a questionnaire survey limited to people who actually visited Fukushima Prefecture during the three-year period from when the Earthquake occurred to the present (the survey was conducted in March 2014). We hired Rakuten Research, Inc. to conduct an internet survey, which took place over a three-day period from March 12 to March 14, 2014.

Of 388,480 people initially contacted, a sample of 797 who met the condition of having visited Fukushima Prefecture over the past five years was obtained. Moreover, the gender breakdown of the contact list mirrored that of the 2010 national census.

Three types of people took recreational trips to Fukushima Prefecture over the past five years. Taking the Earthquake as the starting point, the first type consisted of those who made trips during the two-year period prior to the Earthquake (72.8%); the second type consisted of those who made trips during the three-year period from the Earthquake to the present (65.7%); and the third type consisted of those who made trips during both periods (38.5%). However, in accordance with this study's previously mentioned objective of selecting only those who took trips during the three years from the Earthquake until the present, the final survey sample was reduced to 507.

The survey divided transportation costs into increments of ¥2,000, starting at ¥1,000 or less and ending at ¥100,000 and above (respondents who spent more than ¥100,000 were asked to write in the amount). Transportation costs included such items as the cost of gasoline, train fares, plane fares, and car rental charges traveling to and from the destination while in the area. From this data, we derived the median value. We then calculated the opportunity cost of time by taking one-third of the value of the hourly wage based on median income and multiplied this with the round-trip access time between home and Fukushima Prefecture. We then added this to the transportation cost to determine the trip cost.

Variables used in the analysis other than transportation costs included number of children; experience participating in volunteer activities in Fukushima Prefecture both before and after the Earthquake; donations before and after the Earthquake; past residency in Fukushima Prefecture or past/present relatives' residency in Fukushima; age; and income.

4.3 Estimation results

Here, we estimate the trip demand function with an estimation model (RE-PIG) that uses the random effect PIG model constructed in Chapter 3. The estimated demand function is as follows.

$$\begin{aligned} \lambda_{ij} = \exp(&\beta_0 + \beta_1 SP_{ij} + \beta_2 TC_{ij} + \beta_3 Income_{ij} + \beta_4 SP * Income_{ij} \\ &+ \beta_5 Age_{ij} + \beta_6 Child_{ij} + \beta_7 Volunt_bef_{ij} + \beta_8 Volunt_aft_{ij} \\ &+ \beta_9 Donat_bef_{ij} + \beta_{10} Donat_aft_{ij} + \beta_{11} Fate_fukushima_{ij}) \quad i = 1, \dots, N, \quad j = 1, 2 \end{aligned}$$

The SP dummy variable is 0 in cases of observed data and 1 in cases of data under hypothetical situations. TC is the trip cost. Income is the respondent's income, while SP*Income is a dummy variable for income. Age is the respondent's age; Child is the number of children; and Volunt_bef and Volunt_aft are dummy variables expressing experience or lack of experience participating in volunteer activities in Fukushima Prefecture before and after the Earthquake, respectively. Donat_bef and Donat_aft are dummy variables expressing experience or lack of experience making donations before and after the Earthquake, respectively. Fate_fukushima is the dummy variable for past residency in Fukushima Prefecture or of having relatives living there now or in the past. In addition, for comparative purposes, we performed estimates using the

Table 1 Estimation results using RE-PGM and RE-PIG

RE-PGM				RE-PIG			
Variable	Coeff.	SE	p-value	Variable	Coeff.	SE	p-value
SP	1.3937***	0.0930	0.000	SP	1.3930***	0.0929	0.000
TC	-0.0177**	0.0082	0.031	TC	-0.0174**	0.0088	0.048
Income	0.0163***	0.0037	0.000	Income	0.0161***	0.0038	0.000
SP*Income	-0.0121***	0.0035	0.000	SP*Income	-0.0120***	0.0035	0.000
Age	0.0038*	0.0029	0.082	Age	0.0033	0.0022	0.135
Child	0.1109**	0.0530	0.036	Child	0.0991*	0.0528	0.061
Volunt_bef	0.4824***	0.1602	0.003	Volunt_bef	0.4894***	0.1617	0.002
Volunt_aft	0.4307***	0.1255	0.001	Volunt_aft	0.3803***	0.1274	0.003
Donat_bef	0.1724**	0.0687	0.012	Donat_bef	0.1530**	0.0703	0.029
Donat_aft	-0.2043**	0.0867	0.018	Donat_aft	-0.1784**	0.0883	0.043
Fate_fukushima	0.2734***	0.0780	0.000	Fate_fukushima	0.2828***	0.0797	0.000
Const	-0.8853***	0.1590	0.000	Const	-0.8233***	0.1582	0.000
α	0.3918***	0.0583	0.000	τ	0.3315***	0.0411	0.000
LR	670.92***		0.000	LR	659.351***		0.000
Log-likelihood	-1704.82			Log-likelihood	-1690.01		
AIC	3435.65			AIC	3406.01		
Sample size	507 (1014)			Sample size	507 (1014)		

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

estimation model (referred to as RE-PGM) of Beaumais and Appéré (2010), which is based on the random effect Poisson gamma model that takes the expansion of the negative binomial regression model into univariate panel data into account. Table 1 shows the estimation output. The p-value in Table 1 expresses P in relation to t. The study used Ox (Doomik (2009)) for numerical computation.

In both cases, the sign of the coefficient TC, which designates trip cost, is negative. Since this indicates a negative correlation between trip numbers and prices, this conforms to economic theory, fulfills the sign conditions, and is significant at the 5% level. Furthermore, the parameters SP (denoting the dummy constant) and SP*Income (denoting the dummy coefficient for income) are both significant at the 1% level. Therefore, we see significant differences in RP and SP. In the RE-PIG model, only Age was not significant, while other parameters were all significant at levels of 10% or less. LR, which shows the likelihood ratio test of the null hypothesis set at 0 for

Table 2 Estimation results for consumer surplus

	RE-PGM	RE-PIG
ΔCS	85.390	90.527
ΔCS (Three year aggregate)	353,311,300	374,567,500

Unit: ¥10,000

all coefficients except the constant, is significant at the 1% level in both cases. Both α and τ are significant at the 1% level. This shows the clear presence of overdispersion. However, because Akaike's information criterion (AIC), which assesses model suitability, is lower for RE-PIG than for RE-PGM, we believe the approach that uses the PIG model is more appropriate for analyzing trip number data. Of particular note is that although both dummy variable parameters for volunteer activities in Fukushima Prefecture before and after the Earthquake are positive, the dummy variable parameters for donations made before and after the Earthquake are positive before the Earthquake, but negative after the Earthquake. Although large donations were collected nationwide after the Earthquake, many people in Fukushima Prefecture said they preferred direct visits over donations. In other words, people helping Fukushima Prefecture's recovery by visiting for tourism purposes would have a tendency to refrain from making post-Earthquake donations. Donating and volunteering usually have a complementary relationship, but the survey results show that the preference for direct visits voiced by people in Fukushima Prefecture had at least some effect in inducing people to visit the area.

4.4 Estimation of lost recreational benefits

This study selected people who visited Fukushima Prefecture during the three-year period since the Earthquake to estimate various demand coefficients using actual number of trips and how many trips people would have hypothetically taken if the radiation leakage accident had not occurred. The estimated demand coefficients were then used to compute the extent of lost recreational benefits from the Earthquake until the present. The equation for estimating CS used in the computation and the change in CS in the event that there is no change in the marginal effect of trip costs in response to changes in environmental quality can be expressed as follows (Haab and McConnell (2002)).

$$CS_j = -\frac{\lambda_j}{\beta_2}, \quad \Delta CS = CS_2 - CS_1 = \frac{\lambda_1 - \lambda_2}{\beta_2}$$

Here, λ_2 stands for the expected value of trip numbers forecast in the hypothetical scenario and λ_1 is the expected value of actual trip numbers, while β_2 is the parameter for trip costs. As stated in Section 4.3, the RE-PIG method is more suitable from the standpoint of AIC. Table 2 shows the

results of computing the per capita lost recreational benefit over three years using the forecast value of λ_1 and the estimated value of β_2 , both taken from the estimation results in Table 1. As can be seen, the amount in the case of RE-PGM is approximately ¥850,000, while that in the case of RE-PIG is approximately ¥900,000. Using 12,412,900 as the number of visitors to Fukushima over the three years (3,521,100 in 2011, 4,445,900 in 2012, and using the 2012 figure for 2013 in the absence of official numbers), this comes to lost recreational benefits of approximately ¥3.533 trillion and ¥3.745 trillion for the two cases, respectively. The estimate using RE-PIG was approximately ¥200 billion higher over the three years than that using RE-PGM, so it is highly probable that the RE-PGM result is an underestimation. In terms of annual amount, the loss in the case of RE-PIG is approximately ¥1.25 trillion. As there are no studies which estimate the lost benefits by earthquake using HTCM, it is impossible to compare our estimation with some similar studies. However, considering that the earthquake and tsunami damage in the disaster were estimated to have totaled approximately ¥951.2 billion in 2012 and the amount of compensation payouts for three years by Tokyo Electric Power Co to disaster victim was approximately ¥11 trillion, our result would not unrealistically high value. Needless to say, as almost all people overreact to radioactivity, our result may include the possibility of overestimation.

5. Conclusion

This study estimated the lost recreational benefits in Fukushima Prefecture caused by rumor-driven economic damage from the time of the Fukushima No. 1 Nuclear Plant radiation leakage accident in March 2011 until the present. Considering the hypothetical scenario in which a radiation leakage accident did not occur in Fukushima, we asked survey respondents how many times they would have visited the prefecture in this scenario and analyzed the responses using the HTCM. In addition, since the survey participants were people who had actually visited the prefecture, we considered our data as pseudo on-site sampling. We thus expanded the PIG regression model, which improves Poisson regression in the analysis of count data collected through on-site sampling, into a random effect model and used this model to estimate the demand coefficient. The results showed that Fukushima Prefecture's lost recreational benefits due to rumor-driven economic damage totaled approximately ¥3.745 trillion over the three years from the radiation leakage accident until the present.

Even now, three years after the Earthquake, Fukushima Prefecture has not regained its pre-Earthquake levels in terms of either its hard or soft aspects. Although tourist numbers seem to be on an upward trend, they have still not returned to their previous levels. This fact is not unrelated to the insufficient progress made in advancing government (in particular, the Reconstruction Agency) aid and policy measures and indemnification payments from the Tokyo Electric Power Company. As mentioned above, the Reconstruction Agency's fiscal 2014 provisional budget outline shows a decline in the allocation for rumor-driven economic damage from last year's budget, even though only 0.04% of the agency's total budget is being allocated to this area. As our study shows, a large gap exists between the amount of economic benefit lost as a result of the rumor-driven damage and the amount allocated to this area in the current year's budget. Since

rumor-driven damage is a reflection of people's state of mind, not only should the government and Tokyo Electric Power pay compensation and indemnification on actual amounts lost, but it is also urgent that steps be taken to disseminate accurate knowledge and information regarding radiation and that policies be put in place to stimulate tourism demand in Fukushima Prefecture.

Finally, we set forth some topics for future studies. This study was limited to people who had actually visited Fukushima Prefecture and excluded those who had not visited Fukushima. In other words, it excluded people who might have visited Fukushima if there had hypothetically not been a radiation leakage accident, regardless of whether they had previously taken a trip to Fukushima. As stated in Chapter 1, in the strict sense, this could lead to an underestimation of recreational benefits lost as a result of rumor-driven damage. It is difficult for those who have never gone to Fukushima to have an image of the prefecture. In fact, the nuclear accident has produced a negative legacy, so it is possible that demand that would otherwise never have existed could be induced in the hypothetical scenario. Therefore, collecting samples that do not factor in prior visits to Fukushima Prefecture could very well lead to a broad overestimation of lost benefits. However, a more precise measurement of the benefits lost due to rumor-driven damage should include people who have not visited Fukushima. Such an exercise would necessitate an examination of the suitability of the hypothetical questions and a reconsideration of the sampling methodology and estimation methods.

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