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Conference Paper

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55th Congress of the European Regional Science Association: "World Renaissance: Changing roles for people and places", 25-28 August 2015, Lisbon, Portugal

Provided in Cooperation with:

European Regional Science Association (ERSA)

Suggested Citation: Nohara, Katsuhito; Narukawa, Masaki (2015) : Measuring lost recreational benefits in Fukushima due to harmful rumors using a Poisson-inverse Gaussian regression?, 55th Congress of the European Regional Science Association: "World Renaissance: Changing roles for people and places", 25-28 August 2015, Lisbon, Portugal, European Regional Science Association (ERSA), Louvain-la-Neuve

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Measuring lost recreational benefits in Fukushima due to harmful rumors using a Poisson-inverse Gaussian regression

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Abstract

This paper evaluates the recreational benefits lost due to the economic damage caused by harmful rumors spread over a three-year period from the Great East Japan Earthquake in 2011 to 2014. 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 been made under the hypothetical condition that the radiation accident had not occurred. We consider a Poisson-inverse Gaussian regression model with correction for on-site sampling and expand it into the random effect model framework to propose a random effect Poisson-inverse Gaussian model that estimates the recreational demand function. Our results show that Fukushima Prefecture lost approximately ¥2.85 trillion of recreational benefits over the past three years.

JEL classification: Q26; Q51; C35

Keywords: Harmful rumor; hypothetical travel cost; Poisson-inverse Gaussian regression; random effect model; recreational benefit

1 Introduction

The 2011 Great East Japan Earthquake hereafter, “the Earthquake” and the accident involving radiation leakage at Tokyo Electric Power Company’s Fukushima Nuclear Power Plant No. 1 hereafter, “NPP No. 1” brought fame to Fukushima Prefecture but not in a positive way. If that accident had not occurred, there would have been a higher number of visitors to Fukushima Prefecture from the time of the Earthquake up to the present. On the other hand, it is possible that the extensive media coverage enticed people to take a trip to Fukushima who would not otherwise.

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 have essentially nothing to do with an event or accident” (Kojien sixth edition, 2008). 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 environmental quality at a recreation site); tourists will be detected, and the economy at the site will be negatively affected. However, the degree to which such news coverage and misinformation affect people’s activities is largely dependent on those people’s state of mind. It is impossible to determine the exact number of visits that would have been made to the region in question had there been no such news coverage, no harmful rumors, and no environmental degradation. Thus, after the sensational news coverage about radiation at NPP No. 1, the inclusion of people in the survey sample who had never visited Fukushima Prefecture would have skewed the expected trip numbers and overestimated the monetary loss of tourism.

Therefore, to minimize the effect of bias in response 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. Thus, the analysis is 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). Therefore, using the hypothetical travel cost method (HTCM), which combines the travel cost method (TCM) and contingent behavior (CB) is suitable.

It is fundamentally 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 indices, which 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 index is replaced with an indirect effect on environmental quality, such as the catch rate, it is still difficult to separate the differences in individuals' skills. However, combining RP and SP and asking about travel site selection, trip numbers, and willingness to pay under a hypothetical level of environmental quality makes it possible to measure benefits for different level of environmental quality (Whitehead et al., 2000). Studies using the HTCM date back several decades. In early research, Ribaudo and Epp (1984) estimated the recreational benefit gained from improved water quality in Vermont's St. Albans Bay. More recently, the HTCM has been used not only in research on travel but also in such wide-ranging study 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 the HTCM, and these have been reviewed comprehensively by Whitehead et al. (2008). In addition, 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 RP and SP data (Whitehead et al., 2011). One of the solutions to this problem 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.

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

Next, we summarize the count data models used to analyze trip data gathered through on-site sampling. Count data gathered by on-site sampling are 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 advocated by Shaw (1988), who proposes an estimation method that corrects these problems in the Poisson regression model. However, for count data such as trip number data, the phenomenon of overdispersion, whereby the range of dispersion varies widely from the mean, is known to frequently occur (Sarker and Surry, 2004; Martinez-Espiñeira and Amoako-Tuffour, 2008). Englin and Shonkwiler (1995) propose an estimation method for correcting on-site sampling based on a negative binomial regression model (hereafter, "NB2") that can capture such conditions, and this has become a major method in the TCM using univariate on-site count data (Loomis, 2003; Martinez-Espiñeira and Amoako-Tuffour, 2009). However, as Guo and Trivedi (2002), Sarker and Surry (2004), and Cameron and Trivedi (2013) argue, NB2's capability to capture overdispersion would be limited and inadequate if the data has a distribution with a so-called long (heavy) tail, and therefore a reliable statistical inference cannot be made. Since such strong overdispersion is often observed in trip number data as stated above, it is likely that the existing NB2 approach causes statistical inefficiency in

¹Kaino (2013) statistically analyze whether harmful rumors exist, focusing on the trend of the number of visitors in Fukushima.

the estimates, which implies that NB2 has limitations in the analysis of the trip data.

However, Willmot (1987) and Dean et al. (1989) consider the Poisson-inverse Gaussian (PIG) regression model to be a more easily usable parametric model because, in an analysis of insurance data, it reflects more heavy-tailed count data than the NB2, 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, our estimation method is based on the PIG regression model and add Shaw's (1988) correction for on-site sampling. 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). Another alternative is, for example, the semiparametric method of Gurmu et al. (1999) for example, which makes it possible to flexibly analyze count data with overdispersion. Narukawa and Nohara (2011) modify their method to deal with the data collected through on-site sampling. However, in view of the expansion to panel data or multivariate models, this method would be impractical because of cumbersome calculations to obtain the estimates even in a univariate case.

This paper thus aims to estimate, using the PIG approach, the extent of the recreational benefits lost due to economic damage caused by harmful rumors by only asking people who had actually traveled to Fukushima Prefecture during a three-year period from the Earthquake to March 2014 how many times they had visited Fukushima during the three-years and how many times they hypothetically would have visited Fukushima if the accident had not occurred. Section 2 proposes a methodology based on the PIG regression model for on-site count data. In Section 3 we describe the data and the model specification for our empirical analysis. In Section 4 we provide the estimation results and estimate the lost recreational benefit. Finally, Section 5 sets forth our conclusions and topics for future research.

2 A Poisson-inverse Gaussian regression with on-site correction

In this section, we first introduce the PIG model for univariate count data developed by Dean et al. (1989) and Willmot (1987) and then extend it to include the random effect model to estimate the recreational benefits by combining RP and SP data.

2.1 A univariate model

Let y_i and $\mathbf{x}_i = (x_{1i}, \dots, x_{ki})'$ denote the number of trips by individual i and the k -dimensional explanatory variable vector including a constant, respectively. Then it follows from the exponential mean specification (see, e.g. Cameron and Trivedi, 2013, p. 71) that the conditional mean of y_i , denoted by λ_i , is defined as

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

If y_i is independently Poisson distributed with the above mean parameter λ_i , Equation (1) is the well-known standard Poisson regression model. However, this specification has the so-called equidispersion property which means that the conditional variance equals its mean. To relax this restrictive property, we introduce v_i , which expresses the unobserved heterogeneity of individuals to Equation (1) as follows:

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

where v_i is independent of y_i , and thus $E(\mu_i | \lambda_i) = \lambda_i$, $i = 1, \dots, N$ because we can assume that $E(v_i) = 1$ without loss of generality. Thus, unobserved heterogeneity is multiplicatively incorporated into the exponential conditional mean. Now, assuming that y_i follows the Poisson distribution of the mean parameter μ_i , the conditional probability density function is shown as

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

where the subscript i for an individual is omitted for notational simplicity. It is easily seen from the above density that letting $g(\nu)$ denote the probability density function of ν , the marginal probability density function of y_i is given by

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

which is called a mixed Poisson distribution. This expression is a generalization of the standard Poisson regression model, although specifying $g(\nu)$ is necessary to obtain the explicit form of the density. The most popular example is to assume that ν follows a gamma distribution – that is, that the mixed Poisson distribution (2) is the Poisson-gamma mixture, which leads to the well-known negative binomial regression model.

This paper considers the PIG regression model of Dean et al. (1989), in which ν follows an inverse Gaussian distribution. Because $E(\nu) = 1$, the probability density function of an inverse Gaussian distribution is given by

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

where $\text{Var}(\nu) = \tau$, $\tau > 0$ is a shape parameter and unknown. For further details on the inverse Gaussian distribution, see Tweedie (1957) and Folks and Chhikara (1978), among others. Thus, we have a Poisson inverse Gaussian mixture as the mixed Poisson distribution (2). From the explicit expression of a PIG distribution shown by Willmot (1987), the conditional probability mass function for the PIG regression model can be obtained from Equations (3) and (4) below. If $y > 0$

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

whereas if $y = 0$,

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

Note that as the shape parameter $\tau \rightarrow 0$, the PIG regression model becomes similar to the standard Poisson regression model, and thus τ is the parameter describing overdispersion.

If count data are collected by on-site sampling, there are two problems: truncation and endogenous stratification, as stated above. This is because non-visitors are excluded, which means that the sample is truncated at zero, and visitors who make frequent trips to the site are oversampling. The endogenous stratification problem is one of the particular forms of so-called choice-based sampling and will cause biased and inconsistent estimators of parameters, which may lead to serious mistakes in statistical inference. Following Shaw (1988), we derive a probability mass function of the PIG regression model that allows for on-site sampling. Shaw (1988) proposes the following correction for the conditional probability density function to control the effects involved in on-site 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 applying the key result given by Equation (5), we can construct a log-likelihood function suitable for the on-site sampling data based on the PIG regression model, as shown in Equation (6):

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

Here $\boldsymbol{\theta} = (\boldsymbol{\beta}', \tau)'$ is the unknown parameters, and thus we obtain the maximum likelihood estimators based on the PIG model under on-site sampling.

2.2 Expansion to the random effect model

In order to measure the recreational benefits, which is the aim of this paper, it is necessary to analyze the combined RP and SP data. This involves multivariate data for the number of trips from each individual. Thus, it is not desirable to analyze each response from a given individual as univariate count data because ignoring multivariate dependence will cause efficiency loss of the estimators and may also affect their consistency. The most natural expansion is to handle it as multivariate count data, as in Egan and Herriges (2006). However, it is not easy to obtain the estimates because the likelihood function is usually complicated and its computational burden may be heavy. As an alternative estimation method, their paper proposes using the seemingly unrelated negative binomial (SUNB) regression model of Winkelmann (2000) because it avoids computational complexity even though the correlation structure is restrictive. On the other hand, Beaumais and Appéré (2010) view multivariate data as pseudo panel data, which implies that the time index of the standard panel data model is regarded as the number of scenarios that accompany with SP data, and propose an estimation method invoking the so-called gamma distributed Poisson random effect model of Hausman et al. (1984), in which each of the random effects is independently and identically distributed as gamma. It seems from the definition that this model is considered a simple expansion of the standard Poisson regression model to a panel data model with overdispersion of the negative binomial form. Following Beaumais and Appéré (2010), we first propose the PIG random effect model, which is the expansion of the univariate PIG regression model introduced in Section 2.1; then, to analyze RP and SP data simultaneously, we control the effects of on-site sampling caused by the RP data in a similar way to that given in Section 2.1.

Let y_{ij} be the number of trips in scenario j for individual i , and let $\mathbf{x}_{ij} = (x_{1ij}, \dots, x_{kij})'$ denote the k -dimensional explanatory variable vector including a constant in scenario j . In a similar manner to Section 2.1, we assume that the conditional mean, which is denoted by λ_{ij} and satisfies $E(\mu_{ij} | \lambda_{ij}) = \lambda_{ij}$, can be described as follows:

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

where $\boldsymbol{\beta}$ is the parameter vector. The characteristic feature of this specification is that ν_{ij} , which denotes the heterogeneity of individuals in a scenario, is taken as a random effect that is not dependent on scenario j so that $\nu_{ij} = \nu_i$. In this way, although the random effect is denoted by a random variable that follows a common inverse Gaussian distribution, it should be noted that it restricts the correlation structure. The number of trips for each individual is now multivariate count data, so we introduce some new notations: $\mathbf{y}_i = (y_{i1}, \dots, y_{iJ})'$ and $\tilde{\mathbf{x}}_i = (\mathbf{x}_{i1}, \dots, \mathbf{x}_{iJ})'$. Then, by expanding Equation (2) in Section 2.1 to the present context, the conditional probability density function of the PIG random effect model is given by

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

where the subscript i denoting an individual is omitted for notational simplification. Since $g(\nu)$ is the density function of the inverse Gaussian distribution, it follows from the same argument as in Section 2.1 that after some calculation, we obtain the conditional probability mass function for the PIG random effect model as follows:

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

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

It is easily seen from the definition that this is expressed as the following simple form:

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

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

Next, it is necessary to allow for the fact that the RP data included in $\mathbf{y}_i = (y_{i1}, \dots, y_{iJ})'$, are assumed to be collected via on-site sampling. Because there is typically one variable with on-site sampling in \mathbf{y}_i , which we set it at y_{i1} – that is, $j = 1$ (scenario 1) means the RP data for the number of trips – it is sufficient to control the effects of on-site sampling only for variable y_1 . Thus, taking this point into consideration, the conditional probability mass function with on-site correction is written as

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

As a result, we can construct a log-likelihood function in the same way as in Equation (6) in Section 2.1 and obtain the maximum likelihood estimators of parameters, which are given by

$$\max_{\boldsymbol{\theta}} \sum_{i=1}^N \log h^S(\mathbf{y}_i | \tilde{\mathbf{x}}_i, \boldsymbol{\theta}),$$

$$\log h^S(\mathbf{y}_i | \tilde{\mathbf{x}}_i; \boldsymbol{\theta}) := (y_{i1} - 1) \log \lambda_{i1} - \log \Gamma(y_{i1}) + \sum_{j=2}^J (y_{ij} \log \lambda_{ij} - \log \Gamma(y_{ij} + 1)) + (J - 1) \log q(y_j^*),$$

where $\boldsymbol{\theta} = (\boldsymbol{\beta}', \tau)'$ is the unknown parameters. It should be noted that the proposed estimation approach has a similar correlation structure to the SUNB model and the gamma-distributed Poisson random effect model, and thus the correlation structure among the multivariate count data (that is, over scenarios) is restricted to be positive and is mainly determined by only one parameter. For further details, see, for example, Egan and Herriges (2006) and Beaumais and Appéré (2010).

3 Data and model specification

We describe the trend of radiation levels in Fukushima from the Earthquake to March 2014 and explain the data used in our study after reviewing the countermeasures to harmful rumors by a reconstruction agency and Fukushima Prefecture.

3.1 Radiation levels in Fukushima Prefecture and the tourism circumstances

Fukushima Prefecture is divided by mountain ranges into three regions: Hamadori, Nakadori and Aizu from east to west, as depicted in Figure 1. Figure 2 indicates the measured value of environmental radiation (Sv/h) in each region after the earthquake and the annual average value without the accident.² The value of radiation level at each region was high just after the earthquake, but has since declined and now only slightly exceeds the annual average value, as shown in Figure 2.

According to the Japanese Radiation Research Society, the total amount of radiation in 2011 after the Earthquake was five millisieverts (mSv), which is not sufficient to cause serious health damage.³

²Figure 2 is drawn from the data available at the Fukushima Prefecture's website (<http://www.pref.fukushima.lg.jp/sec/16025d/h22-24-7houbu.html>).

³For details, see the Japanese Radiation Research Society's website (<http://jrrs.kenkyukai.jp/special/?id=5548>).

Moreover, although the International Commission on Radiological Protection (ICRP) states that up to 20 mSv is acceptable and safe for the general population: the effect of radiation on people’s health has not been adequately clarified from a scientific perspective.⁴ 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 has not exceeded 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 have 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 that 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.” One of the Reconstruction Agency’s emphases through this plan is to rehabilitate the image of and provide support for the tourism industry in the disaster area to increase the number of domestic and foreign visitors by boosting demand in the Tohoku region. However, according to the Reconstruction Agency’s FY2014 provisional budget outline, the amount allocated to address rumor-driven economic damage was reduced to ¥900 million from an initial budget of ¥1.3 billion in FY2013. It should be noted that the 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). Concerning agriculture, 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

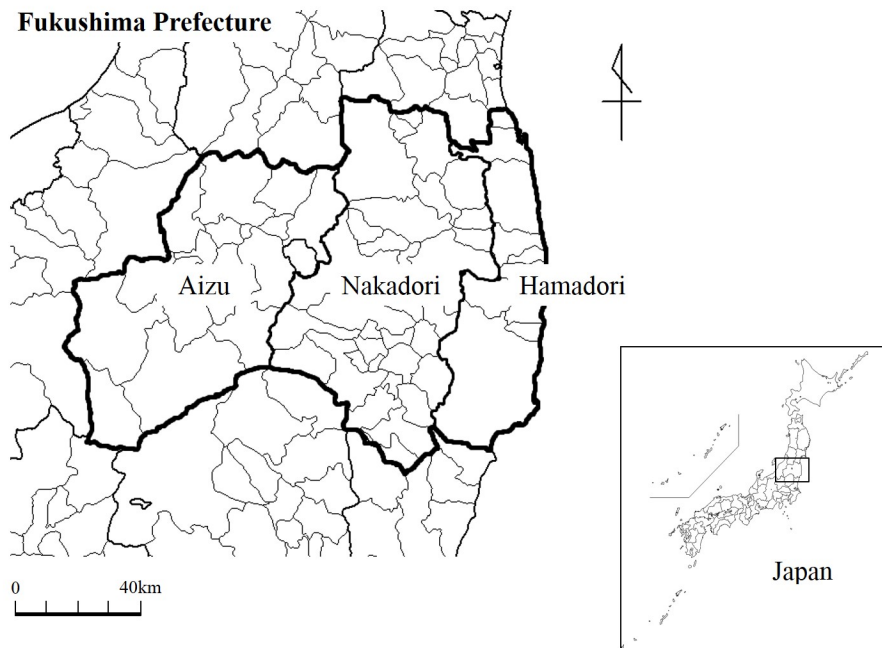


Figure 1: The three regions in Fukushima Prefecture

⁴For details, see the International Commission on Radiological Protection’s website (<http://www.icrp.org/>).

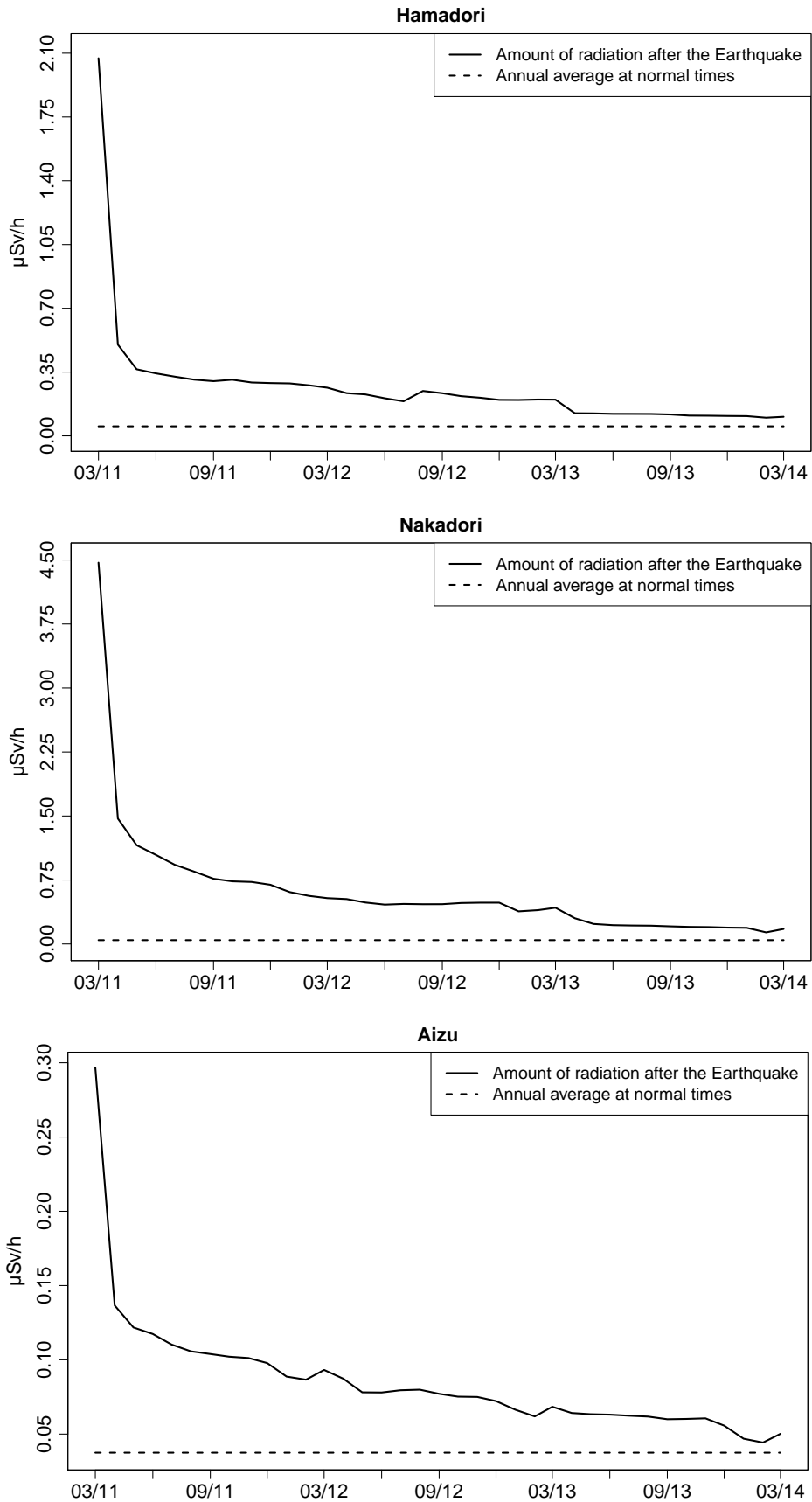


Figure 2: Environmental radiation in Fukushima Prefecture from Mar. 2011 to Mar. 2014.

misinformation. For example, as the prefectural government could not continue to allocate large portions of its budget to alleviate rumor-driven economic damage, they developed a method to motivate 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 items. 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. Another example is Tsuchiyu Spring located at the intermountain area of Fukushima City, where binary electrical generator uses the low boiling point coolant to lower the spring temperature to the extent that people can bathe. Other example of regional revitalization include the sake of generalized electricity through a feed-in tariff and the introduction of other sources of renewable energy, such as solar power and hydroelectric power.

Thus, although the Reconstruction Agency's budget allocation for countermeasures to rumor-driven economic damage has decreased, Fukushima Prefecture, local municipalities, and local tourism-related businesses have joined together to mitigate this damage. Perhaps for this reason, tourists are gradually returning, although they have still not reached pre-Earthquake levels.

3.2 Modeling recreational demand

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 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 the 388,480 people initially contacted, a sample of 797 who met the condition of having visited Fukushima Prefecture in 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 had taken recreational trips to Fukushima Prefecture in 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 2014 (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-year period from the Earthquake to 2014, 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 incurred traveling to and from the destination while in the area. From these 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 the median income and multiplied this by the round-trip access time between home and Fukushima Prefecture. We then added this to the transportation cost to determine the travel cost. Variables used in the analysis other than transportation costs included the number of children, participation 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.

In view of the above survey, the demand function for the recreational trips is now described as follows:

$$\lambda_{ij} = \exp(\beta_0 + \beta_1 S P_{ij} + \beta_2 TC_{ij} + \beta_3 Income_{ij} + \beta_4 (S P \times Income)_{ij} + \beta_5 Age_{ij} + \beta_6 Child_{ij} + \beta_7 VB_{ij} + \beta_8 VA_{ij} + \beta_9 DB_{ij} + \beta_{10} DA_{ij} + \beta_{11} RF_{ij}), \quad i = 1, \dots, N, \quad j = 1, 2.$$

The SP dummy variable is 0 in cases of observed data and 1 in cases of data under hypothetical situations. TC is the travel cost, Income is the respondent's income, Age is the respondent's age, Child is the

Table 1: Variable descriptions and summary statistics

Variable	Description	Mean	SD
y_1	Number of actual trips	2.004	5.960
y_2	Number of stated trips	3.105	2.079
TC	Travel cost to Fukushima (in ten thousand yen)	3.922	3.588
Income	Income of respondent (in million yen)	6.535	4.160
Age	Age of respondent	48.773	15.940
Child	Number of children	0.225	0.622
VB	Dummy for volunteer before the Earthquake	0.041	0.199
VA	Dummy for volunteer after the Earthquake	0.081	0.273
DB	Dummy for donations before the Earthquake	0.462	0.499
DA	Dummy for donations after the Earthquake	0.817	0.387
RF	Dummy for residency or relatives in Fukushima	0.225	0.418

number of children, and VB and VA are dummy variables expressing participation or lack of experience participation in volunteer activities in Fukushima Prefecture before and after the Earthquake, respectively. DB and DA are dummy variables expressing donations or lack of donations before and after the Earthquake, respectively. RF is the dummy variable for prior residency in Fukushima Prefecture or of having relatives living there now or in the past. Table 1 presents the summary statistics of each variable. First, most respondents are elderly and comparatively well-off, as the mean Age is almost 50 and the mean Income is ¥6.5 million. Second, most respondents do not have children, as the mean Child is substantially less than 1. Furthermore, the means of the specific variables in this study, VB and VA, are less than 1 and have very low values. In a particularly characteristic point in this study, on the other hand, more than 80% of respondents donated after the Earthquake. This result corresponds with the fact that large donations were gathered throughout Japan after the Earthquake.

4 Estimation results

4.1 Parameter estimates

Table 2 shows the estimation results of the trip demand function using the PIG random effect (PIG-RE) model constructed in Section 3 and the gamma- distributed Poisson random effect (GMP-RE) model. The result for GMP-RE, which was introduced by Beaumais and Appéré (2010) as a pseudo panel approach combining RP and SP data, is provided for comparative purposes. This model is regarded as the simple expansion of the univariate NB2 to panel data. All the computations in this study are conducted with Ox (Doornik, 2009).

In both cases, the sign of the coefficient TC, which designates trip cost, is negative. This negative correlation between trip numbers and prices conforms to economic theory, satisfies the sign conditions, and is significant at the 5% level. Furthermore, the parameters SP, which denotes the dummy constant and SP×Income, which denotes the dummy coefficient for income are both significant at the 1% level. Therefore, we find statistically significant differences in RP and SP. In the PIG-RE model, only Age is significant at the 15% level, while the other parameters are all significant at levels of 10% or less. LR, which denotes the likelihood ratio statistic, rejects the null hypothesis that all coefficients except the constant are set at 0 at the 1% level in both cases. We find from the significance of both α and τ at the 1%

Table 2: Estimation results using GMP-RE and PIG-RE

GMP-RE			PIG-RE		
Variable	Coeff.	SE	Variable	Coeff.	SE
SP	1.3937***	0.0930	SP	1.3930***	0.0929
TC	-0.0177***	0.0082	TC	-0.0174**	0.0088
Income	0.0163***	0.0037	Income	0.0161***	0.0038
SP × Income	-0.0121***	0.0035	SP × Income	-0.0120***	0.0035
Age	0.0038*	0.0029	Age	0.0033 ^Δ	0.0022
Child	0.1109**	0.0530	Child	0.0991*	0.0528
VB	0.4824***	0.1602	VB	0.4894***	0.1617
VA	0.4307***	0.1255	VA	0.3803***	0.1274
DB	0.1724**	0.0687	DB	0.1530**	0.0703
DA	-0.2043**	0.0867	DA	-0.1784**	0.0883
RF	0.2734***	0.0780	RF	0.2828***	0.0797
Constant	-0.8853***	0.1590	Constant	-0.8233***	0.1582
α	0.3918***	0.0583	τ	0.3315***	0.0411
Log-likelihood	-1704.82		Log-likelihood	-1690.01	
LR	670.92***		LR	659.35***	
AIC	3435.65		AIC	3406.01	
Sample	1014 (507 respondents)				

Note: ***, **, *, and Δ indicate significance at the 1%, 5%, 10%, and 15% levels, respectively.

level that the trip number data have clearly overdispersion. Since Akaike's information criterion (AIC), which evaluates the goodness of fit of the model, is lower for PIG-RE than for GMP-RE, it seems that the PIG approach is more appropriate and thus the trip number data indicate a long-tailed distribution. Note that although the dummy variable parameters for volunteer activities in Fukushima Prefecture both before and after the Earthquake are positive, the dummy variable parameter for donations made positive before the Earthquake, but the parameter for donations made after it is negative. Although large donations were collected nationwide after the Earthquake, many people in Fukushima Prefecture said that they preferred direct visits to making donations. In other words, people who helped Fukushima Prefecture's recovery by visiting for tourism purposes tended not to make 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 with a connection to Fukushima Prefecture had at least some effect in inducing people to visit the area. As RF is positive and significant at the 1% level, people who had lived in the past in Fukushima Prefecture or who had relatives living there now or in the past are less influenced by harmful rumors and tend to visit more frequently. This may support the idea that the extent to which harmful rumors affect people's activities is largely dependent on people's state of mind.

4.2 Estimation of lost recreational benefits

This study selected people who visited Fukushima Prefecture during the three-year period following the Earthquake to estimate various demand coefficients using the actual number of trips taken 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 to 2014. The equation for estimating the 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 (Whitehead et al., 2000):

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

Here, λ_2 indicates the expected value of the trip numbers forecast in the hypothetical scenario and λ_1 is the expected value of the actual trip numbers, while β_2 is the parameter for trip costs. As stated above, the PIG-RE method is more suitable from the standpoint of AIC. Table 3 shows the results of computing the per capita recreational benefit lost over the three years using the forecast value of λ_1 and the estimated value of β_2 , which are both taken from the estimation results in Table 2. As can be seen, the amount in the case of GMP-RE is approximately ¥830,000, while that in the case of PIG-RE is approximately ¥880,000. Using 19,512,000 as the number of visitors to Fukushima over the three years (4,968,000 in 2011, 7,272,000 in 2012, and using the 2012 figure for 2013 in the absence of official numbers)⁵ and regarding the mean number of actual trips in the three years 2.004 (see Table 1) as the mean number of visits by each respondent, we calculate that the real number of visits per year is 3,245,510. This comes to lost recreational benefits of approximately ¥2.680 trillion and ¥2.853 trillion for the GMP-RE and PIG-RE cases, respectively. The estimate using PIG-RE was approximately ¥170 billion higher over the three years than that using GMP-RE, so it is highly probable that the GMP-RE result is an underestimation. In terms of the annual amount, the loss in the case of PIG-RE is approximately ¥0.951 trillion. As no studies have estimated the benefits lost due to the Earthquake using the HTCM, it seems impossible to compare our estimation with similar studies. However, considering that the estimated capital stock damage which does not include other damage caused by the NPP No. 1 accident was approximately ¥3.130 trillion as of April 2011 according to Development Bank of Japan⁶ and the amount of compensation payouts over the three years to disaster victims by Tokyo Electric Power Company was approximately ¥11 trillion, our result is not unrealistically high value. However, since most people overreact to radioactivity, our result may be an overestimation.

Table 3: Estimation results for consumer surplus

	GMP-RE	PIG-RE
ΔCS (Per capita)	82.587	87.901
ΔCS (Three year aggregate)	268,036,850	285,283,485

Unit: ¥10,000.

5 Conclusion

This paper estimated the recreational benefits lost in Fukushima Prefecture due to rumor-driven economic damage from the NPP No. 1 radiation leakage accident in March 2011 to March 2014. Considering the hypothetical scenario in which a radiation leakage accident did not occur in Fukushima, we asked

⁵The data are available at Japan Tourism Agency's website (<http://www.mlit.go.jp/kankocho/siryou/toukei/irikomi.html>).

⁶DBJ News Release (in Japanese) (http://www.dbj.jp/ja/topics/dbj_news/2011/files/0000006633_file1.pdf).

survey respondents how many times they would have visited the prefecture in this scenario and analyzed the responses using the HTCMM. 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 will improve the standard Poisson regression model in the analysis of count data with strong overdispersion, into a random effect model. In addition, to deal with the data collected through on-site sampling, we applied Shaw's correction to the PIG random effect model and used it to estimate the demand function for the recreational trip. The estimation results showed that Fukushima Prefecture's lost recreational benefits due to rumor-driven economic damage totaled approximately ¥2.85 trillion over the three years from the radiation leakage accident to March 2014.

Three years after the Earthquake, Fukushima Prefecture had 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 aid and policy measures (in particular, by the Reconstruction Agency) and indemnification payments from the Tokyo Electric Power Company. As mentioned above, the Reconstruction Agency's fiscal 2014 provisional budget outline has a decreased allocation for rumor-driven economic damage from the 2013 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 2014 budget. Since rumor-driven damage is a reflection of people's state of mind, not only should the government and the Tokyo Electric Power Company pay compensation and indemnification for the actual amounts lost, steps should also be taken to disseminate accurate knowledge and information regarding radiation and policies should 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 not been a radiation leakage accident, regardless of whether they had previously taken a trip to Fukushima. As stated in Section 1, in the strict sense, this could lead to an underestimation of the recreational benefits lost as a result of rumor-driven damage. It is difficult for those who have never gone to Fukushima to have an accurate mental image of the prefecture. The nuclear accident has produced a negative legacy, and 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 lead to a substantial 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.

Acknowledgments

This research was supported by Japan Society for the Promotion of Science (JSPS) Grant-in-Aid for Young Scientists (B) (80584854).

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