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A Bayesian quantile regression analysis of the determinants for supporting nuclear power generation in Japan

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Abstract

Using internet survey data from 6,500 individuals, this study examines the determinants for supporting the restart of nuclear power plants operation in Japan. As in previous studies, the variable of interest is a categorical and ordered variable that measures the level of support, for which ordered logit or ordered probit is commonly estimated. This study departs from the literature by using Bayesian ordinal quantile regression recently proposed by Rahman (2015). This approach allowed us to explore whether covariates have differential effects at various conditional quantiles of the latent response variable, which can be interpreted as the willingness to support the restart. The results show that for most of the covariates we examined, including concerns about meltdowns and the storage of nuclear material and concerns about global warming, the effects differ across conditional quantiles. In other words, the covariate effects depend on individuals' unobserved preferences for the restart (conditional on observables). The results also show that for some covariates, the effects differ considerably across gender.

Keywords: Energy; Nuclear power; Public attitude; Ordinal data; Quantile regression
JEL Code: Q40, C20

1. Introduction

The damage from nuclear accidents can be enormous. Since the nuclear accident at Fukushima triggered by the Tohoku earthquake occurred in March 2011, evacuees have been estimated to be over fifty thousand people (The Reconstruction Agency of Japan, 2014). Agriculture, fishery and tourism in the affected regions suffer not only from radioactive substances and the nuclear fallout but also from harmful rumors spread after the accident (Consumer Affairs Agency, 2015; Kainou, 2013). A large share of the Japanese population has been feeling insecure about the health effects of radioactivity. The situation worsens even today, as there is no concrete strategy to handle the radioactive waste generated by the accident. After the accident, all nuclear power plants were shut down. The government, meanwhile, has ordered the Nuclear Regulation Authority to revise safety regulations. This means that with the new regulations providing guidelines for safely and securely managing nuclear power generation, any reactors can be restarted as long as they satisfy the regulations. For example, the Sendai plant in the Kagoshima prefecture, owned by Kyushu Electric Power Co., has met the amended standards and it is now loading fuels into its reactors.

The restart of nuclear plants is motivated by several factors. First, the country faced a serious electricity supply shortage while all the plants were being closed. The demand rose significantly due to a record-setting heat wave and heavy snow. Electricity bills were increasing along with rising fossil fuel prices. While renewable energy has been promoted via policy measures, the cost of switching from nuclear to renewable energy is known to be expensive. According to the estimation by the Energy and Environment Council (2012), the average household's electricity would increase by 1.5 to 2 times per month if nuclear power's contribution to electricity becomes 0%

in 2030.[1] With the benefits of nuclear energy taken into consideration – its low external costs, reliable energy supply and potential to help mitigate greenhouse gas (GHG) emissions – restarting the existing plants became an option worthy to consider.[2] Following the Sendai plants, other plants in Japan are currently undergoing safety reviews in preparation for restart (Nuclear Energy Institute, 2015).

Given the benefits and potential of nuclear energy, do individuals support the restart of nuclear power plants? Or, despite the benefits, do they oppose the restart because they are more concerned about nuclear risks? More broadly, what determines individuals' attitudes (i.e., the level of support and opposition) with regard to resuming plants' operation in Japan? The objective of this study is to provide insights into these questions by using online survey data from 6,500 respondents and modeling the level of support for the restart.

A number of studies have examined questions similar to ours and identified possible factors that are associated with public acceptance of nuclear power generation. For example, previous studies found that an increase in perceived risks of nuclear power predicts negative attitudes toward nuclear power (Greenberg and Truelove, 2011; Huang et al., 2013; Siegrist et al., 2014; Tanaka, 2004; Visschers et al., 2011; Visschers and Siegrist, 2013; Whitfield et al., 2009). Stoutenborough et al. (2013) provided further evidence regarding the perceived risks of nuclear power. Specifically, when concerned about the risk of nuclear meltdowns, the storage of nuclear waste or the transportation of nuclear waste, individuals are less likely to support a policy

[1]In 2010, immediately before the Fukushima accident, nuclear energy provided 28.6% of the country's electricity, 29.3% by LNG, 25% by coal, 8.5% by hydroelectric, 7.5% by oil and 1.1% by renewables. The cost of promoting renewable energy is passed onto households, as seen in the case of Germany where the increase in electricity bill per household was 5.277ct/kWh in 2013 with the introduction of a feed-in tariff.

[2]See IAEA (2014) for a comprehensive review of merits and risks of nuclear power generation.

promoting nuclear energy.

In contrast to risk perception, an increase in perceived benefits is associated with positive attitudes toward nuclear power (Huang et al., 2013; Siegrist et al., 2014; Tanaka, 2004; Visschers et al., 2011; Visschers and Siegrist, 2013). Concerns about global warming may also be an important factor for acceptance. Using survey data of U.K. residents, Pidgeon et al. (2008) found that individuals reluctantly accept nuclear power if they believe it contributes to climate change mitigation. Corner et al. (2011) also examined individuals in the U.K and argued that concerns about climate change will increase the acceptance of nuclear power, particularly when other options have been exhausted.

Further, trust in the government and nuclear-governance institutions was examined as a possible determinant for the acceptance of nuclear power. (Huang et al., 2013; Greenberg and Truelove, 2011; Stoutenborough et al., 2013; Tanaka, 2004; Visschers et al., 2011; Visschers and Siegrist, 2013; Whitfield et al., 2009). The majority of previous studies provided evidence in favor of the role of trust in the government and institutions. A somewhat broader concept, social trust, was examined in a study by Visschers et al. (2011). Their results show that social trust may indirectly influence acceptance through benefit and risk perception.

The Fukushima accident may be another factor that influences individuals' attitudes. Using surveys from before and after the accident, previous studies examined whether individuals' attitudes toward nuclear power has changed (Huang et al., 2013; Poortinga et al., 2013; Siegrist et al., 2014; Visschers and Siegrist 2013). In most studies, the accident is found to have a negative influence on the acceptance of nuclear power.

Despite providing much evidence, however, the previous studies focused exclusively on the central tendency, specifically, how the average individual (conditional on covariates) responds to a change in a determinant. This is due to the fact that almost all, if not all, previous studies relied on standard methods that examined the central tendency, such as analysis of variance (e.g., Eiser et al., 1989; Siegrist and Visschers, 2013), linear regression (e.g., Corner et al., 2011; Greenberg, 2009; Siegrist et al., 2014; Tanaka, 2004), binary logit (e.g., Greenberg and Truelove, 2011), ordered logit or probit (e.g., Stoutenborough et al, 2013; Arikawa et al., 2014) and structural equation modeling (e.g., Huang et al., 2013; Visschers et al., 2011; Visschers and Siegrist, 2013; Whitfield et al., 2009). As a result, the previous studies have not addressed whether the covariate effects may differ across different segments of a population.

This study departs from the literature by using a quantile regression approach. Quantile regression (Koenker and Bassett, 1978; Koenker, 2005) can shed light on possibly differential effects at various conditional quantiles. Therefore, it can be used to supplement standard methods, providing a more complete picture of the underlying relationship. In our context, the quantile approach can explore, for example, whether three otherwise identical individuals, the first with an average unobserved preference for the restart, the second with a low unobserved preference, and the third with a high unobserved preference, respond similarly or differently to a change in a covariate. The econometric challenge faced by this study is the fact that the dependent variable in our analysis is ordered and categorical, taking a value of 1 (I do not support the restart at all) to 5 (I strongly support the restart). Linear regression is inappropriate for ordinal data; so is the standard quantile regression since it is to model a continuous variable.

This study therefore uses quantile regression designed specifically for ordered and categorical data (Rahman, 2015).

This study also differs from many previous studies (e.g., Greenberg and Truelove, 2011; Huang et al., 2013; Stoutenborough et al., 2013; Siegrist et al., 2014; Tanaka, 2004; Visschers et al., 2011; Visschers and Siegrist, 2013; Whitfield et al., 2009) in that it analyzes males and females separately. We do this because gender is likely to play a key role in shaping one's attitude toward the restart. Tindall et al. (2003), for instance, showed that females with higher environmental concerns are more involved with environmentally friendly behavior, while the level of environmental concern does not significantly influence environmentally friendly behavior among males.

Gender differences are also reported with regard to the level of environmental concern and risk perception. Females are found to have greater environmental concern (Davidson and Freudenburg, 1996) and greater risk perception (Flynn et al., 1994) toward nuclear power compared to males. These and other differences are likely to influence individuals' attitudes toward the restart.

In what follows, we first explain the characteristics of the data and then variables used for analysis along with their descriptive statistics. In Section 3, we explain the empirical approach that this study adopts, specifically, Bayesian quantile regression recently developed by Rahman (2015). In Section 4, estimation results for females are explained, followed by those for males. Section 5 concludes the study.

2. Data

The data for this study are derived from a survey conducted online in February 2014 titled, "Survey on household energy-saving awareness." Dividing the country into six broad regions, we collected the data in such a way that the distributions of gender and age (those between twenty and seventy years old) in each region correspond to those in the Population Census of Japan. We focus on individuals who were aged from 20 to 69 residing in Japan.

To examine whether the distributions differ between our data and the census at the prefecture level, we conducted the Wilcoxon matched-pairs signed-ranks test. The null hypothesis that their distributions are identical cannot be rejected at the 10% level. This suggests that our data reflects the gender and age distributions across regions of Japan.

We also tested for the sample representativeness by comparing our data with the census in terms of the percentage of unmarried population (older than 15 years old) and educational attainment. With regards to unmarried population, our sample was found to be reasonably close to that in the census: 39.4 (31.9) % of males and 24.1 (23.3) % of females are unmarried in our study (the census). Regarding educational attainment, the percentage of those holding a bachelor's degree or higher are compared. 56.7 (26.7) % of males and 29.2 (11.9) % of females have a bachelor's degree or higher in our study (the census), indicating that those with a higher education level are overrepresented in our study and our results must be interpreted accordingly.

3. Variables and descriptive statistics

In this section, we explain how we construct the variables used in this study. The dependent variable is first explained, followed by a set of independent variables. Table 3 presents the descriptive statistics of the variables for all respondents, those for males, and those for females.

3.1. Dependent variable

The dependent variable in our analysis is the degree of support for the restart. In the survey, we first reminded the respondents that the current government was planning to restart power plants and then asked them the extent to which they supported this policy. The respondents were asked to choose a scale of 1 (I do not support it at all) to 5 (I strongly support it). The mean of this variable is found to be 2.68, somewhat leaning toward support. It should be noted, however, that this result is driven by males who are more supportive than females (2.86 for males and 2.50 for females). The distributions of support levels for females and males are presented in Figures 1 and 2, respectively.

3.2. Independent variables

A number of factors can potentially influence the willingness to support the restart. We choose independent variables based mainly on the previous studies mentioned in the introduction. We consider, among others, perceived risks and benefits of nuclear power, concerns about global warming and trust in the government. We also consider individuals' experience with the Fukushima accident as well as socio-demographic factors.

To measure how the respondents perceived risks of nuclear power, we borrow the idea of Stoutenborough et al. (2013) by asking the respondents about their overall perception of nuclear power and how much they are concerned about risks pertaining to nuclear power. The respondents were first asked whether they thought nuclear power is a safe technology. They were given three alternatives: 1 if yes, 2 if no, and 3 if they do not know. Two-thirds of the respondents do not think of nuclear power as a safe technology, revealing high concerns about technical safety. It should be also noted that there is a considerable gender difference in the proportion of those who think of nuclear as a safe technology; it is far lower for females than for males (0.08 for females and 0.21 for males). For estimation, we create a set of dummy variables and take the second category as a base category.

The respondents were then asked to give their answers on a scale of 1 (not concerned at all) to 5 (extremely concerned) with regard to the possibilities of meltdowns, accidents while transporting radioactive wastes, and accidents resulting from the storage of nuclear waste. The average value of their answers for each type of the risks is found to be almost 4, revealing that the respondents are highly concerned about the risks. The results also show that females are more concerned than males. For example, the means regarding meltdowns are 3.98 and 3.65 for females and for males, respectively. Similar patterns are observed for the other types of risks.

To examine whether the respondents were aware of the economic benefit of nuclear energy, we asked in the survey, "Do you know whether electricity provided by renewable energy leads to an increase in electricity bills?" This question may be interpreted as indirectly asking about the relative cost advantage of nuclear energy to renewable energy. The fact that 60% of the respondents answered "yes" suggests that the majority are aware of the benefit. We also find that males are more aware than females (65% of the males and 51% of the females answered "yes").

The respondents were then asked about their concerns regarding global warming, electricity supply shortage and fossil fuel depletion in the future. On global warming, they were asked to answer on a scale of 1 (I am not concerned at all) to 5 (I am extremely concerned). Concerning electricity supply shortage (fossil fuel depletion), the survey asked, “Do you think that we will likely be faced with a serious electricity supply shortage (a serious shortage in fossil fuel) in the next ten (thirty) years?” They were asked to choose from a five-point scale where a larger number corresponds to a higher likelihood. The mean for each of these questions is above three, suggesting that individuals are concerned to some extent. For each, females are found to have a relatively higher degree of concerns than males.

Following a number of studies, we also examine trust in the government as a possible determinant for the acceptance of nuclear power. Trust in the government is measured based on the question, “How much do you trust the government?” with a five-point scale ranging from 1 (I do not trust it at all) to 5 (I trust it very much). The mean is found to be about 2.5, revealing that, on average, individuals in Japan neither trust nor distrust the government. It is also found that males have a slightly higher level of trust (2.53) than females (2.46).

Attitudes toward the restart may be associated with where individuals live. For example, Greenberg (2009) showed that individuals residing near nuclear facilities favor increasing use of nuclear power more than in the national sample. To examine this issue, we create a dummy variable that takes a value of one if the individual lives in prefectures with nuclear power plants. We also examine whether individuals who suffered from the Tohoku accident have different attitudes toward nuclear power generation. For this purpose, we construct a dummy variable that takes one if the individual suffered from the earthquake physically, mentally or monetarily. Finally, we account for standard socio-demographic factors: age, education (a dummy variable that takes one if the individual has a bachelor’s degree or higher) and marital status (a dummy variable that takes one if the individual is not married).

3. Econometric Framework

3.1. Standard approach

The dependent variable in our analysis is an ordered categorical variable that represents the degree of support for the restart (*sp*); it takes a scale of 1 (I do not support it at all) to 5 (I strongly support it). This type of ordered categorical variable has been examined in previous studies. For example, Arikawa et al. (2014) examined the dependent variable that takes one, two and three, if the respondent is opposed to, neutral to, or supportive of nuclear power use for the prevention of global warming, respectively.

A standard approach to modeling an ordered categorical variable is to use ordered logit or probit that can be motivated by a latent variable framework. In our context, the willingness of the individual i to support the restart (wts_i) is assumed to be a continuous latent variable and depend on a set of independent variables ($\mathbf{x}_i$) explained in the previous section:

$$wts_i = \mathbf{x}_i \boldsymbol{\beta} + u_i$$

where $\mathbf{x}_i$ is a $(1 \times k)$ vector that includes one for the constant term, $\boldsymbol{\beta}$ is a $(k \times 1)$ vector of unknown parameters, and u_i is a continuous random disturbance term with distribution function $F(u_i \mid \mathbf{x}_i) = F(u_i)$. The latent response variable (wts_i) is associated with the observed response variable (sp_i) in the following manner:

$$\begin{aligned} sp_i &= 1 \quad \text{iff} \quad wts_i \le \mu_1 \\ &= 2 \quad \text{iff} \quad \mu_1 < wts_i \le \mu_2 \\ &= 3 \quad \text{iff} \quad \mu_2 < wts_i \le \mu_3 \\ &= 4 \quad \text{iff} \quad \mu_3 < wts_i \le \mu_4 \\ &= 5 \quad \text{iff} \quad \mu_4 < wts_i \end{aligned}$$

where μ_1 is set to 0 for normalization and (μ_2, μ_3, μ_4) are unknown threshold parameters to be estimated. The model specification is completed by the assumption of the disturbance term. In particular, if it is assumed to follow a standardized logistic distribution (a standard normal distribution), then the model becomes the ordered logit (the ordered probit). The parameters for the ordered logit and probit can be easily estimated by maximum likelihood.

3.2. Quantile regression with ordinal data

Quantile regression for ordered categorical data is a relatively new technique. Hong and He (2010) developed the transformed regression quantile estimator, a semiparametric single-index model for ordered categorical data, which was subsequently extended by Hong and Zhou (2013) to a multi-index model. The estimators are proved to be consistent and found to be useful for prediction; however, the asymptotic distribution is not provided for each estimator. We therefore decided to adopt the Bayesian method proposed by Rahman (2015), which allows us to perform parameter inference.

We first review quantile regression (Koenker and Bassett, 1978; Koenker, 2005) and then explain Bayesian quantile regression (Yu and Moyeed, 2001; Kozumi and Kobayashi, 2011), a basis of the quantile regression for ordered categorical data (Rahman, 2015). Assume that for the pth ($0 < p < 1$) quantile, y_i is generated according to the model

$$y_i = x_i\beta_p + u_{pi}, \tag{1}$$

where β_p are the quantile-specific parameters and the pth quantile of u_{pi} conditional on

$\boldsymbol{x}_i$ equals zero. Then, the pth quantile of y_i conditional on x_i is $x_i\beta_p$. In other words, y_i conditional on $\boldsymbol{x}_i$ is less than or equal to $x_i\beta_p$ with probability p.

The pth quantile regression estimator for β_p minimizes

$$\sum_{i=1}^{n} \rho_p(y_i - x_i\beta_p), \tag{2}$$

where $\rho_p(u) = u(p - I(u < 0))$ is the loss function and $I(\cdot)$ is the indicator function. Because the objective function is not differentiable, linear programming methods are often used to solve the problem. Standard errors for the estimator are obtained by using asymptotic theory or bootstrapping.

Bayesian estimation of quantile regression (Yu and Moyeed, 2001) is based on the fact that the above problem can be formulated as a maximum likelihood problem where y_i follows an asymmetric Laplace distribution (*ALD*). A random variable y_i is said to have a skewed *ALD*, denoted as $AL(\mu, \sigma, p)$, if its probability density function is

$$f(y_i \mid \mu, \sigma, p) = [p(1-p)/\sigma]\exp[(-\rho_p((y_i - \mu)/\sigma)], \tag{3}$$

where

$$\rho_p(u) = u(p - I(u < 0)), \tag{4}$$

and μ, σ, and p are the location, scale, and skewness parameters, respectively. Assuming that y_i follows $AL(x_i\beta_p, \sigma, p)$, or alternatively, the conditional distribution of u_{pi} in equation (1) is $AL(0, \sigma, p)$, the likelihood function is

$$L(\beta_p, \sigma; y, p) \propto (1/\sigma^n)\exp\left[-\sum_{i=1}^{n} \rho_p((y_i - x_i\beta_p)/\sigma)\right], \tag{5}$$

for independent observations $y = (y_1,\ldots,y_n)$. If we consider σ a nuisance parameter, maximization of equation (5) is equivalent to minimization of equation (2) because equation (4) is identical to the loss function in the quantile objective function (2) (Yu and Moyeed, 2001). This property of the *ALD* is exploited by the Bayesian approach to quantile regression. Specifically, Bayesian inference for quantile regression proceeds by constructing a likelihood based on the *ALD* irrespective of the original distribution of the data, specifying the quantile to be examined, p, and then placing priors on the parameters β_p and σ. Although fully parametric, this method is found to perform reasonably well even when the original distribution is not the *ALD* (Kozumi and Kobayashi, 2011; Luo, et al., 2012; Sriram et al., 2013).

We now explain Bayesian quantile regression for ordered categorical data proposed by Rahman (2015), which is an extension of Bayesian binary quantile regression developed by Benoit and Van den Poel (2012). The model setup is essentially the same as Bayesian quantile regression, except the left-hand side variable; now it is an unobserved latent response variable. Assume that for the pth ($0 < p < 1$) quantile, a continuous latent response variable z_i is generated by

$$z_i = x_i\beta_p + u_{pi}, \tag{6}$$

where u_{pi} conditional on x_i follows $AL(0, 1, p)$. The scale parameter is set to one for normalization. The latent response variable (z_i) is associated with the observed response variable (y_i) in the same manner as ordered logit or probit via threshold parameters; for $j = 1,\ldots,J$,

$$y_i \quad = \quad j \quad \text{iff} \quad \mu_{p,j-1} \le z_i < \mu_{p,j} \tag{7}$$

where $\mu_{p,0} = -\infty$, $\mu_{p,J} = \infty$, and $\mu_{p,1}$ is set to 0 to ensure identifiability. In our context, y

is the observed level of support for the restart (*sp*), z is the unobserved willingness to support the restart (*wts*), and $J = 5$.

Then, the likelihood function for independent observations $y = (y_1,\ldots,y_n)$ is expressed as

$$\begin{aligned} L(y \mid \beta_p, \mu_p) &= \prod_{i=1}^{n}\prod_{j=1}^{J} \Pr(y_i = j \mid \beta_p, \mu_p)^{I(y_i=j)} \\ &= \prod_{i=1}^{n}\prod_{j=1}^{J}\left[F_{AL}(\mu_{p,j} - x_i\beta_p) - F_{AL}(\mu_{p,j-1} - x_i\beta_p)\right]^{I(y_i=j)}, \end{aligned}$$

where $\mu_p = (\mu_{p,2}, \ldots, \mu_{p,J\text{-}1})$ and $F_{AL}(\cdot)$ is the distribution function of the random variable that follows $AL(0, 1, p)$. See a study by Yu and Zhang (2005) for the shape of the distribution function.

For estimation purposes, Rahman (2015) reparameterized the likelihood function by using a logarithmic transformation to the thresholds parameters; specifically, for $2 \leq j < J - 1$,

$$\delta_{p,j} = \ln(\mu_{p,j} - \mu_{p,j-1}). \tag{8}$$

μ_p can then be obtained by using a one-to-one mapping between μ_p and $\delta_p = (\delta_{p,2},\ldots,\delta_{p,J\text{-}1})$. This reparametrization can ensure that μ_p always satisfies the ordering constraints, i.e., $\mu_{p,1} < \mu_{p,2} < \cdots < \delta_{p,J\text{-}1}$.

To proceed with a Bayesian analysis, Rahman (2015) assumed the following independent normal priors for β_p and δ_p:

$$\begin{aligned} \beta_p &\sim N(\beta_{p0}, B_{p0}), \\ \delta_p &\sim N(\delta_{p0}, D_{p0}). \end{aligned}$$

Bayesian inference concerning the parameters is based on the posterior distribution, which can be obtained by Bayes' theorem:

$$\pi(\beta_p, \delta_p \mid y) \propto L(y \mid \beta_p, \delta_p)\pi(\beta_p)\pi(\delta_p).$$

As is often the case, the posterior distribution is analytically intractable because it does not have a closed form. To estimate the posterior distribution, Rahman (2015) therefore relied on a Markov Chain Monte Carlo (MCMC) method and developed a Gibbs sampling algorithm. For that purpose, Rahman (2015) exploited the fact that the *ALD* can be represented as a mixture of normal-exponential distribution (Kotz et al, 2001). Specifically, if u_{pi} follows $AL(0, 1, p)$, then it can be expressed as

$$u_{pi} = \theta v_i + \tau \sqrt{v_i} w_i,$$

where $\theta = (1 - 2p)/p(1 - p)$, $\tau^2 = 2/p(1 - p)$, $v_i \sim EXP(v_i \mid 1)$ and $w_i \sim N(0,1)$ are mutually independent, and $EXP(\cdot|\varphi)$ denotes an exponential distribution with mean φ. Equation (6) can therefore be rewritten as

$$z_i = x_i \beta_p + \theta v_i + \tau \sqrt{v_i} w_i. \tag{9}$$

This representation was originally used by Kozumi and Kobayashi (2011) who developed an efficient Gibbs sampling algorithm examined for Bayesian quantile regression where z_i is observed. Rahman (2015) recognized that even when z_i is not observed, their idea can be applied by using data augmentation of z_i (Albert and Chib, 1993; Tanner and Wong, 1987).

The joint posterior distribution of the unobservables, z, β_p, δ_p, and v can be derived as

$$\pi(z,\beta_p,\delta_p,v \mid y_i) \propto$$
$$\left\{\prod_{i=1}^{n}\prod_{j=1}^{J} I(\mu_{p,j-1} \le z_i < \mu_{p,j}) N(z_i \mid x_i\beta_p + \theta v_i, \tau^2 v_i) EXP(v_i \mid 1)\right\} \times N(\beta_{p0}, B_{p0}) N(\delta_{p0}, D_{p0})$$

where z = ($z_1,\ldots,z_n$) and v = ($v_1,\ldots,v_n$). The Gibbs sampling algorithm then can be implemented in the following manner. We first choose initial values $\Theta_{p,(0)}$ = ($z_{(0)}$, $v_{(0)}$, $\beta_{p,(0)}$, $\delta_{p,(0)}$) where $z_{(0)} = \{z_{1,(0)},\ldots, z_{n,(0)}\}$ and $v_{(0)} = \{v_{1,(0)},\ldots, v_{n,(0)}\}$. Set $m = 0$. Then we proceed with the following steps:

Step 1. Generate $\Theta_{p,(m+1)}$ as follows: (1) Generate $\beta_{p,(m+1)}$ from the conditional distribution $\pi(\beta_p \mid z_{(m)}, v_{(m)})$. (2) Generate $v_{i,(m+1)}$ from the conditional distribution $\pi(v_i \mid \beta_{p,(m+1)}, z_{i,(m)})$ for $i = 1,\ldots n$. (3) Generate $\delta_{p,(m+1)}$ from the conditional distribution $\pi(\delta_p \mid \beta_{p,(m+1)}, y)$. (4) Generate $z_{i,(m+1)}$ from the conditional distribution $\pi(z_i \mid \beta_{p,(m+1)}, \mu_{p,(m+1)}, v_{(m+1)}, y_i)$ for $i = 1,\ldots n$.

Step 2. Set $m = m + 1$ and go to Step 1.

The conditional distribution of β_p is normal, from which it is straightforward to draw. The conditional distribution of v_i follows a Generalized Inverse Gaussian (*GIG*) distribution, for which efficient random variate generators are available (Dagpunar, 1988, 1989, 2007; Hörmann and Leydold, 2014). The conditional distribution of z_i is a truncated normal distribution, where the region of truncation is determined based on equation (7) along with δ_p. See a study by Robert (1995) for simulation of truncated normal random variables. In contrast to other parameters, δ_p does not have a known conditional distribution. Rahman (2015) therefore proposed to use the Metropolis-Hastings algorithm for δ_p. See Rahman (2015) for the conditional distributions as well as calculation details.

4. Estimation Results

For estimation, we set priors reasonably vague to minimize their influence on the posterior distributions: $\beta_p \sim N(0, 10I)$ and $\delta_p \sim N(0, 10I)$ where I is an identity matrix. To draw δ_p from the full conditional distribution, we use a random-walk Metropolis-Hastings algorithm by following Rahman (2015). The proposal distribution is chosen to be normal and centered at the current state of the chain. The variance of the proposal distribution is tuned so that the acceptance rate is in the range [0.25, 0.35].

Figure 3 presents the time series plots of the draws for each marginal distribution when $p = 0.1$. Other quantiles look similar, revealing that the MCMC chain converges quickly (usually within 200-300 iterations). To ensure convergence, however, we adopt a burn-in of 3,000 iterations. All results are based on a sample of 10,000 draws obtained after the burn-in period.

4.1 Results for Females

Results for females are presented in Table 2. Column (1) shows the results for a standard ordered probit model for comparison purposes. Columns (2), (3), (4), (5) and (6) present the results for the 0.1th, 0.3th, 0.5th, 0.7th, and 0.9th conditional quantiles, respectively. For each parameter, we provide the posterior mean (Mean) and the standard deviation (SD).

From Table 2, we observe that for almost all parameters there are considerable variations across conditional quantiles in the posterior means. Estimates particularly in the tails of the conditional distribution tend to differ considerably from that for the 0.5th quantile as well as that obtained by ordered probit. These results suggest that almost all covariates exert heterogeneous effects across various conditional quantiles of the latent variable, i.e., the willingness to support the restart. Our quantile regression analysis therefore seems to be able to uncover relationships previously unnoticed in the published research.

We find that across all quantiles females who think of nuclear power as a safe technology support the restart more than those who do not (see row 1). The posterior mean of the parameter decreases until the 0.5th quantile and then increases thereafter. The largest and smallest values are observed at the 0.1th and 0.5th quantiles, respectively. This suggests that willingness to support the restart increases the most (the least) for those who have a low (moderate) unobserved preference for the restart conditional on observables, when the perception about nuclear power changes from "not a safe technology" to "a safe technology." A similar pattern is also observed for the variable that measures the level of trust in the government; the extent to which females support the restart is most (least) associated with the level of trust most for those who have a low (moderate) unobserved preference for the restart conditional on observables (see row 10).

Across all quantiles, females seem to support the restart more when they are unsure about whether nuclear power is a safe technology than when they do not think it is (see row 2). Put differently, upon changing her perception from "unsure" to "not a safe technology," willingness to support the restart decreases across all conditional quantiles. The posterior mean of the parameter is found to decrease monotonically as the quantile increases unlike before, though the largest value is observed at the 0.1th quantile like before.

These results have an implication for the role of the government in promoting willingness for females to support the restart. Females with low unobserved preferences for the restart may drastically change their attitudes toward the restart if they are convinced that the government is trustable and that nuclear power is a safe technology. This does not seem to be the case for those with moderate unobserved preferences, however; even if they are convinced, the extent to which they change their attitudes may be small.

We also find that the degree of willingness to support the restart is associated with the types of nuclear risks. In terms of concerns about meltdowns, the posterior mean of the parameter is estimated to be negative across all conditional quantiles. In other words, when females become more concerned about meltdowns, they become less favorable to the restart. The posterior mean of the parameter increases until the 0.5th quantile and then decreases thereafter (see row 3). The effect of this concern is the largest for the 0.9th quantile (i.e., for those who have high unobserved preferences conditional on observables).

A somewhat different pattern is observed for concerns about the storage of nuclear materials in that the posterior mean of the parameter increases until the 0.7th quantile and then decreases thereafter (see row 5). In addition, the covariate effect is found to be the largest for the 0.1th quantile (i.e., for those who have low unobserved preferences), which is in sharp contrast to that of the meltdown concerns.

Concerns about nuclear waste transportation exhibit a totally different pattern. It is only for the 0.1th conditional quantile that this concern seems to influence individuals' attitudes (see row 4). Put differently, females with moderate or high unobserved preferences may not respond to the risks associated with transporting nuclear waste. Interestingly, the opposite pattern is found for concerns about the shortage of fossil fuel; only for females with high unobserved preferences (i.e., for the 0.9th conditional quantile), this concern is associated with willingness to support the restart (see row 8). The results also show that if a female individual becomes more concerned about the shortage of electricity supply, the willingness to support the restart will increase for all conditional quantiles (see row 7). The degree to which it increases, however, depends crucially on conditional quantiles; it is found to be the largest for the 0.1 quantile, while the smallest for the 0.5 quantile.

With regards to concerns about global warming, for the 0.1-0.5th conditional quantiles, global warming does not seem to affect willingness to support the restart (see row 9). For high conditional quantiles (i.e., the 0.7th and 0.9th quantiles), the posterior mean of the parameter has a negative sign. That is, if females with high unobserved preferences become more concerned about the global warming problem, then they will favor the restart less than before. This suggests that if the government emphasizes the global warming problem to increase support for the restart, it may actually work the opposite from what the government expects.

The result is somewhat odd because nuclear power is supposed to contribute to mitigating global warming. A possible reason is that those individuals incorrectly perceive nuclear power as accelerating global warming. This argument is in line with evidence provided by Fukae (2006). Conducting a survey on the effect of nuclear energy on global warming, the author examined responses from 1421 individuals older than twenty years old residing in Western Japan. A greater number of females than males were found to have the misperception that nuclear energy accelerates global warming and thus they negatively conceive of nuclear energy.

It is also found that for the 0.1th, 0.3th, and 0.5th quantiles, willingness to support the restart is not influenced by knowing the economic benefit of nuclear energy (i.e., the use of renewable energy results in an increase in electricity price). In other words, the economic benefit influences females only when they have high unobserved preferences for the restart. While almost half of the females are unaware of the benefit as shown in the summary statistics, informing them about the relative cost advantage of nuclear energy may not influence public opinions as much as the government hopes.

The results for the other variables are briefly summarized as follows. Across all quantiles, those who are married (see row 11) and younger (see row 12) tend to favor the restart. The willingness to support the restart does not seem to be associated with whether the individual has a bachelor's degree or higher (see row 13) or whether the individual lives in a prefecture with a nuclear power plant (see row 14). Likewise, whether the individual has suffered from the Tohoku earthquake is apparently not linked with the level of support (see row 15).

4.2 Results for Males

Table 3 provides the results for males. The results show that while some variables have the same or similar patterns observed for females, other variables do not. In what follows, we explain the variables that exhibit different patterns than those of females. First, when males become more concerned about the transportation of nuclear waste, they will support less across all quantiles. This pattern was not observed for females. Females respond to this concern only when they have low unobserved preferences for the restart (i.e., the 0.1th quantile).

Second, across all quantiles, males become more supportive of the restart if they know that renewable energy leads to an increase in electricity price than if they do not. An implication from this result is that the provision of information on the relative cost advantage of nuclear energy may work effectively for males to the extent that it is not recognized by about half of the males. This implication is in sharp contrast to that for females where the effect of information provision seems to be rather limited, as discussed earlier.

Third, concerns about the shortage of fossil fuel are associated with the level of support except for the 0.9th quantile. The pattern is totally opposite to that of females; it is only for the 0.9th quantile where this concern plays a role in shaping attitudes toward the restart.

Finally, an interesting difference is found for the dummy variable that takes one if the individual lives in a prefecture with nuclear power plants. While not associated with the level of support for females across all quantiles, this variable is found to be important for high quantiles (0.7^{th} and 0.9^{th}) for males. This may be partly because some of the males may be employed at nuclear power plants or may be engaged in business related to the nuclear industry.

5. Conclusion

Using internet survey data, this study examined the determinants of individuals' perception about resuming plants operation in Japan. While drawing on insights from the previous literature, the study departed from the literature by using Bayesian ordinal quantile regression. This approach allowed us to explore whether covariates have differential effects at various conditional quantiles of the latent response variable, which can be interpreted in our context as the willingness to support the restart.

It was found that gender does play a key role in shaping one's attitude toward the restart. Our results suggest that females who have higher concern about global warming are more likely to oppose the restart. This tendency is not found among males. The result points out the possibility that the benefit of nuclear power (i.e., potential contribution to mitigating global warming) is not thoroughly perceived by females.

It was also found that males tend to support the restart due to economic and monetary reasons. We found that, for example, males who reside in regions with nuclear power plants tend to support the restart. The result may suggest that males put more importance on employment opportunities provided by the nuclear industry than females. Another tendency we found among males is that knowing the economic benefit of nuclear energy positively and strongly influences their attitudes toward the restart. For males, the low cost of nuclear energy also counts as a reason to support the restart. These results contrast with Arikawa et al. (2014) which concluded that the costs and benefits of nuclear energy does not have an influence on one's attitude toward the restart. By considering males and females separately, we may have been able to identify the gender-specific tendency.

The differing tendencies between males and females found in this study provide important policy implications. If the government aims to foster support for the restart, the provision of information should be done while considering the gender differences. According to our results, an effective approach to promoting support among males is, for example, to highlight the economic and monetary benefits of nuclear energy. Whether the information provision instantly leads to changing one's perception is another empirical question, however. Likewise, it is not certain if the change in perception soon results in supporting the restart. It is also worthy of consideration what forms of media are most effective and efficient in reaching target social groups. These inquiries need to be explored along with the continuing discussion on resuming plants' operation.

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Table 1. Descriptive Statistic

	All (N = 6,500)		Female (N = 3,240)		Male (N = 3,260)	
	Mean	SD	Mean	SD	Mean	SD
Support the restart of nuclear power plants (1-5)	2.679	1.238	2.500	1.091	2.857	1.345
Think Nuclear power is safe technology (0/1)	0.147	0.354	0.080	0.272	0.213	0.409
Don't think nuclear power is a safe technology (0/1)	0.642	0.480	0.671	0.470	0.613	0.487
Don't know whether nuclear power is a safe technology (0/1)	0.212	0.408	0.249	0.433	0.174	0.379
Concerned about melt down (1-5)	3.826	1.051	3.983	0.956	3.670	1.116
Concerned about the transportation of nuclear waste (1-5)	3.802	1.030	3.960	0.927	3.646	1.101
Concerned about the storage of nuclear (1-5)	3.916	1.010	4.051	0.916	3.783	1.079
Know renewable energy leads to an increase in electricity bills (0/1)	0.581	0.493	0.507	0.500	0.654	0.476
Concerned about the shortage of electricity supply (1-5)	3.269	1.000	3.400	0.921	3.140	1.057
Concerned about the shortage of fossil fuel (1-5)	3.458	0.985	3.566	0.890	3.349	1.060
Concerned about global warming (1-5)	3.574	1.029	3.756	0.931	3.393	1.089
Trust government (1-5)	2.495	0.964	2.463	0.905	2.527	1.018
Male (0/1)	0.502	0.500	0.000	0.000	1.000	0.000
Not married (0/1)	0.318	0.466	0.241	0.428	0.394	0.489
ln(age) (continuous)	3.770	0.322	3.770	0.322	3.770	0.323
Bachelor's degree or higher (0/1)	0.430	0.495	0.292	0.455	0.566	0.496
Live in a prefecture where a nuclear power plant is located (0/1)	0.198	0.398	0.195	0.397	0.200	0.400
Have suffered from the Tohoku earthquake (0/1)	0.132	0.339	0.131	0.338	0.133	0.340

Table 2. Estimation results (Female)

	(1)		(2)		(3)		(4)		(5)		(6)	
	Ordered Probit		0.1Q		0.3Q		0.5Q		0.7Q		0.9Q	
	Coeff	SE	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
(1) Think Nuclear power is safe technology	1.057***	0.083	6.261	0.634	3.798	0.294	3.149	0.243	3.223	0.252	4.428	0.444
(2) Don't know whether nuclear power is a safe technology	0.454***	0.050	3.011	0.277	1.493	0.151	1.308	0.132	1.109	0.146	1.077	0.218
(3) Concerned about melt down	-0.359***	0.038	-1.616	0.205	-0.920	0.110	-0.873	0.096	-1.098	0.114	-1.792	0.186
(4) Concerned about the transportation of nuclear waste	-0.057	0.043	-0.708	0.231	-0.221	0.124	-0.189	0.103	-0.078	0.125	0.275	0.210
(5) Concerned about the storage of nuclear	-0.173***	0.044	-1.365	0.253	-0.737	0.129	-0.444	0.109	-0.423	0.124	-0.557	0.201
(6) Know renewable energy increases electricity price	0.101**	0.041	0.393	0.241	0.204	0.114	0.158	0.095	0.280	0.109	0.879	0.201
(7) Concerned about the shortage of electricity supply	0.274***	0.028	1.901	0.187	0.846	0.087	0.657	0.069	0.771	0.080	1.211	0.149
(8) Concerned about the shortage of fossil fuel	0.013	0.029	-0.309	0.188	-0.127	0.087	-0.027	0.071	0.146	0.081	0.654	0.142
(9) Concerned about global warming	-0.038	0.026	0.058	0.149	0.070	0.074	-0.021	0.063	-0.154	0.074	-0.494	0.131
(10) Trust government	0.341***	0.024	2.320	0.160	1.081	0.074	0.866	0.063	0.893	0.073	1.119	0.118
(11) Not married	-0.209***	0.052	-0.372	0.292	-0.541	0.143	-0.554	0.120	-0.635	0.137	-0.438	0.255
(12) ln(age)	-0.433***	0.072	-0.648	0.402	-1.016	0.194	-1.040	0.166	-1.166	0.194	-1.102	0.324
(13) Bachelor's degree or higher	-0.056	0.044	-0.370	0.268	-0.075	0.123	-0.070	0.101	-0.065	0.122	-0.287	0.214
(14) Live in a prefecture with a nuclear power plant	-0.040	0.050	-0.082	0.307	-0.052	0.141	-0.075	0.121	-0.037	0.134	-0.284	0.249
(15) Have suffered from the Tohoku earthquake	0.036	0.059	0.067	0.377	0.181	0.165	0.102	0.137	0.079	0.159	0.169	0.295
(16) Constant	3.117***	0.304	4.232	1.587	6.883	0.821	7.615	0.716	9.495	0.858	16.359	1.417
μ_2	0.801***	0.024	4.232	1.587	2.267	0.083	1.930	0.071	2.323	0.089	5.682	0.233
μ_3	2.404***	0.033	18.871	0.442	7.943	0.189	6.144	0.150	6.529	0.166	12.846	0.314
μ_4	3.342***	0.050	31.790	0.879	12.393	0.318	9.165	0.221	9.185	0.232	16.150	0.377

Note: For the ordered probit model, maximum likelihood estimates are presented where ***, ** and * denote significance at the 1, 5, and 10 percent levels, respectively. Mean and SD denote posterior mean and posterior standard deviation, respectively.

Table 3. Estimation results (Male)

	(1)		(2)		(3)		(4)		(5)		(6)	
	Ordered Probit		0.1Q		0.3Q		0.5Q		0.7Q		0.9Q	
	Coeff	SE	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
(1) Think Nuclear power is safe technology	0.927***	0.060	5.320	0.396	2.957	0.205	2.559	0.158	2.668	0.175	4.752	0.363
(2) Don't know whether nuclear power is a safe technology	0.195***	0.055	2.289	0.315	0.880	0.158	0.478	0.125	0.254	0.140	0.049	0.261
(3) Concerned about melt down	-0.352***	0.034	-2.127	0.212	-1.050	0.100	-0.954	0.087	-1.035	0.095	-1.550	0.183
(4) Concerned about the transportation of nuclear waste	-0.135***	0.036	-0.803	0.207	-0.346	0.103	-0.281	0.087	-0.366	0.097	-0.775	0.200
(5) Concerned about the storage of nuclear	-0.142***	0.037	-0.739	0.217	-0.501	0.113	-0.386	0.088	-0.408	0.097	-0.624	0.188
(6) Know renewable energy increases electricity price	0.268***	0.042	1.263	0.267	0.719	0.122	0.614	0.098	0.777	0.112	1.618	0.220
(7) Concerned about the shortage of electricity supply	0.254***	0.023	1.572	0.160	0.698	0.068	0.577	0.058	0.691	0.065	1.468	0.132
(8) Concerned about the shortage of fossil fuel	0.053**	0.024	0.796	0.152	0.272	0.070	0.135	0.059	0.123	0.063	0.091	0.120
(9) Concerned about global warming	-0.005	0.022	0.031	0.149	0.011	0.066	0.010	0.053	-0.005	0.059	-0.047	0.110
(10) Trust government	0.373***	0.022	3.218	0.151	1.268	0.075	0.961	0.058	0.951	0.064	1.354	0.121
(11) Not married	0.005	0.049	0.487	0.274	0.173	0.136	0.054	0.113	0.015	0.132	0.105	0.274
(12) ln(age)	-0.385***	0.076	-1.429	0.395	-0.733	0.210	-0.783	0.169	-1.010	0.198	-1.573	0.404
(13) Bachelor's degree or higher	-0.032	0.040	-0.100	0.243	-0.134	0.110	-0.057	0.089	-0.050	0.107	-0.199	0.219
(14) Live in a prefecture with a nuclear power plant	0.088*	0.050	0.161	0.293	0.115	0.145	0.176	0.117	0.307	0.139	0.670	0.275
(15) Have suffered from the Tohoku earthquake	0.060	0.059	0.456	0.348	0.113	0.170	0.069	0.134	0.038	0.157	0.525	0.353
(16) Constant	2.648***	0.320	1.269	1.549	4.362	0.916	6.110	0.737	8.891	0.863	19.48	1.636
μ_2	0.740***	0.024	4.428	0.195	2.191	0.092	1.859	0.079	2.125	0.087	4.917	0.217
μ_3	1.854***	0.027	12.29	0.328	5.739	0.155	4.689	0.125	5.133	0.134	10.54	0.285
μ_4	2.874***	0.038	21.59	0.514	9.525	0.229	7.536	0.173	7.902	0.182	14.96	0.343

Note: For the ordered probit model, maximum likelihood estimates are presented where ***, ** and * denote significance at the 1, 5, and 10 percent levels, respectively. Mean and SD denote posterior mean and posterior standard deviation, respectively.

Figure 1. The Distribution of Support Levels (Females)

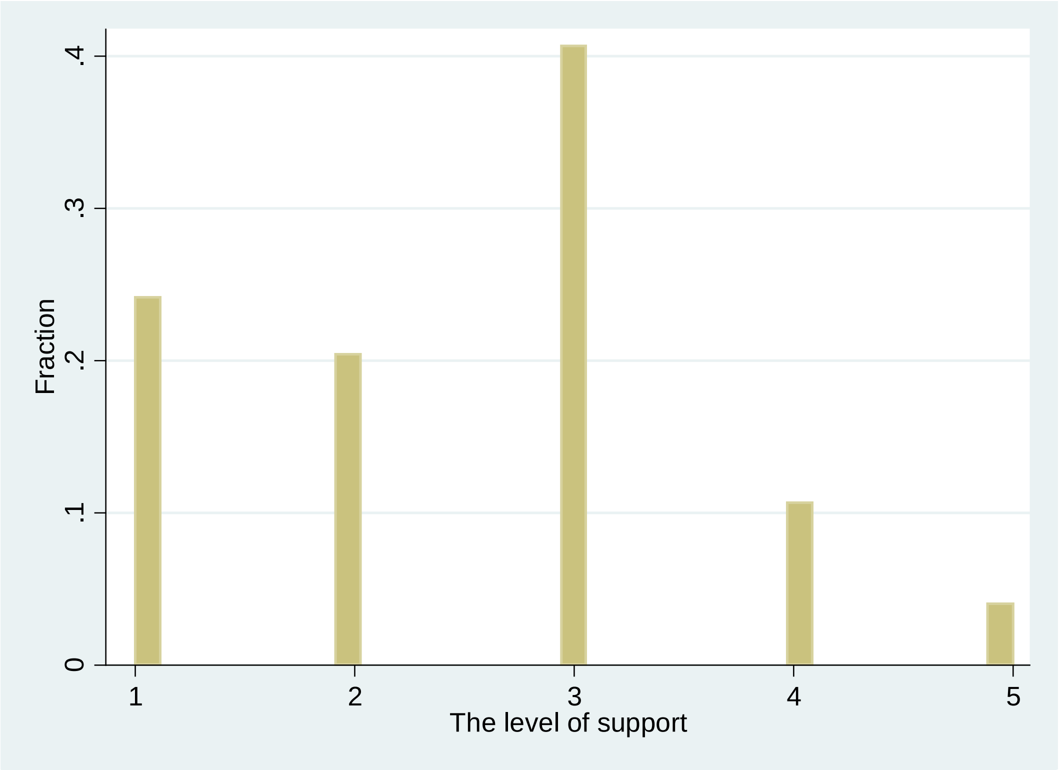

Figure 2. The Distribution of Support Levels (Males)

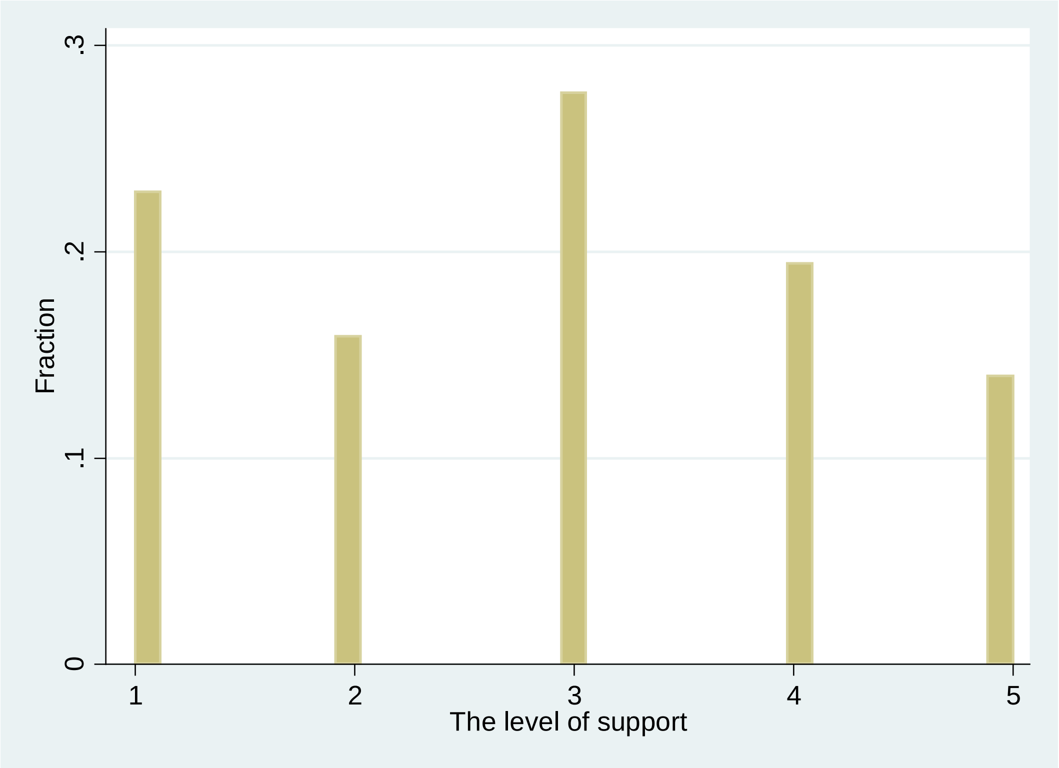

Figure 3. The Time Series Plot of the Draws for a Selected Set of Parameters

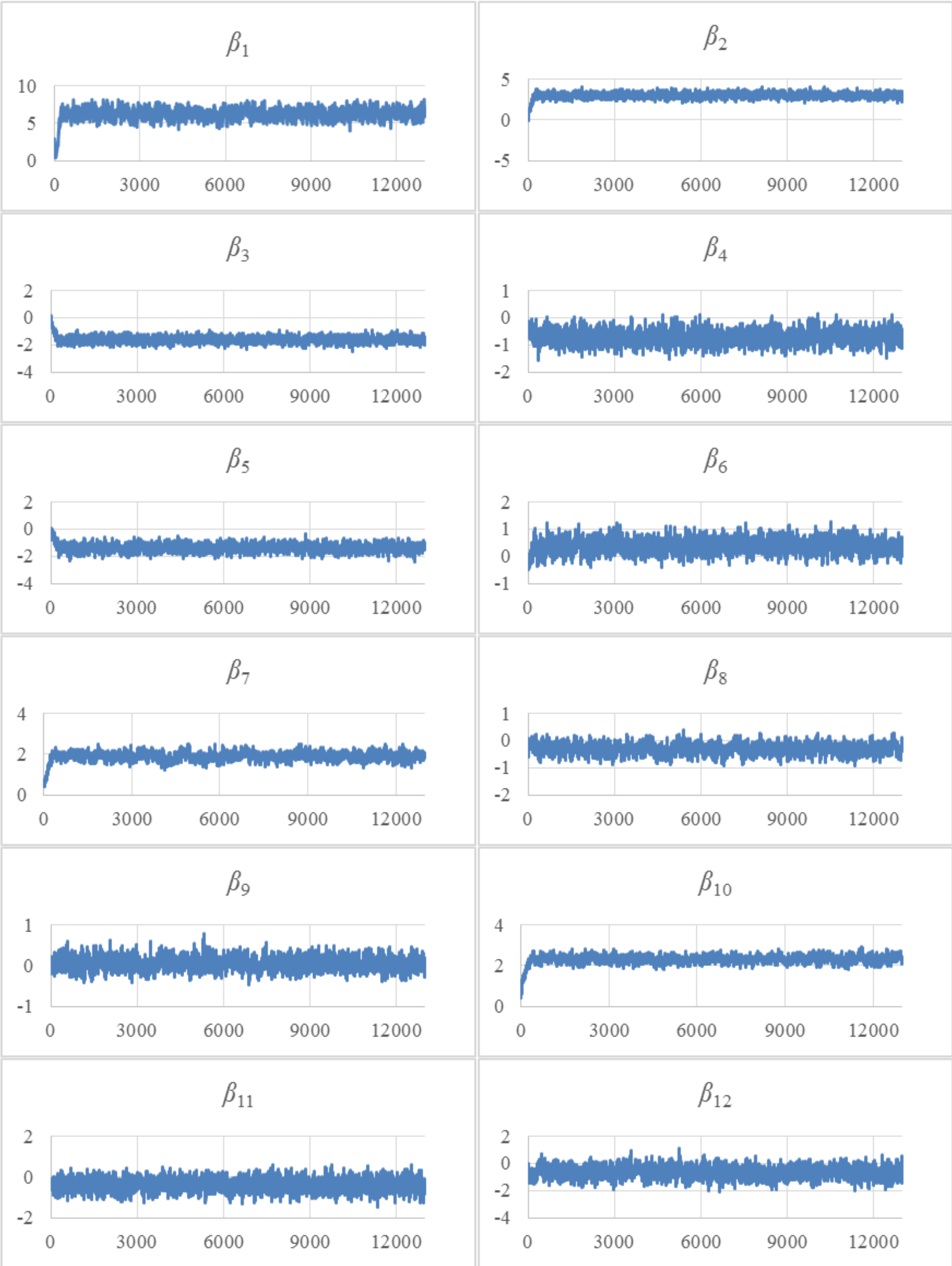

Figure 3 (Continued)