How did Disaster Victims Migrate after the Great East Japan Earthquake?: Long-Term Recursive Migration Model after Super Disasters

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Abstract

This study focuses on long-term recursive migration after a super disaster and describes the dynamic migration process based on the ever-changing situation and future utility after a disaster. As natural disasters become more severe due to climate change, it is urgent to establish aid schemes for disaster-induced migration. Although various case studies have clarified the relationship between disasters and migration, few studies have focused on the long-term migration process after disasters. We aim to model the long-term migration with a discounted recursive logit model where victims choose their location and relocation timing considering the future utility. As a case study, we adapted the model to the 10-year residential history of the Great East Japan Earthquake victims and confirmed the usability of the model. The time discount rate is estimated to be smaller for the victims in Fukushima Prefecture, who were forced to evacuate from their hometowns due to the nuclear power plant accident and continued to be in an uncertain situation for a long period. The result indicates that it was difficult for them to choose a place to live with an eye on the future due to extreme uncertainty. In addition, it shows that the level of income and life cycle would be essential factors for victims to choose their location and timing of housing recovery. This model helps consider not only the scale of reconstruction projects but also their optimal timing because it can incorporate the progress of projects and environmental changes over time.

INTRODUCTION

In discussing the movement after disasters, it is needed to manage two movements: evacuation and migration. The former is related to studies on dynamic traffic management to maximize evacuation flow per unit time by controlling traffic capacity and information (*1*)(*2*)(*3*), while the latter is the problem of managing migration and resettlement of migrants after disasters. Although these migration choices taken by disaster-affected people until they settle on can be defined as a dynamic decision-making problem (*4*)(*5*), it is difficult to say that there is an established methodology to describe it.

Evacuation is a decision made in a short period, and therefore easy to obtain data to understand the phenomena, leading to a large amount of research accumulated in traffic management. On the other hand, disaster-induced migration could be a long-term movement that takes place over a while, so many things are not understood from a phenomenological point of view. Aggregate analyses of the relationship between disasters and migration are often conducted over decades (*6*)(*7*). However, because of the limited availability of residential trajectory data on individual migration, many works, especially micro-level models, are forced to focus on the initial residential choice or the one at one particular point in time (*8*). Urata et al. (*9*) uses mobile phone traffic data to reveal changes in the Spatio-temporal characteristics of population distribution before and after a disaster for one month. However, such big data might not be suitable for analyzing long-term residential choices over decades. Such partial observations and modeling make it challenging to analyze the behavior of disaster victims who are displaced over the long term and design disaster compensation schemes that respond to differences in disaster conditions.

As for the dynamic effect of migration on transportation demand, in the framework of panel analysis, it has been shown that migrants have different transportation behavioral characteristics from natives, and it takes several years or more to assimilate. Therefore, it is essential to understand the migration trends and their influences on the transport demand in the destination city to improve urban transit demand modeling and long-term investment decisions (*10*)(*11*).

On the other hand, the residential choice itself has often been taken as a static problem, like the model of McFadden (*12*), pioneering work in discrete choice modeling. In recent research on urban traffic demand forecasting, microsimulation, which can simulate the decision-making of each traveler individually and dynamically, is getting more critical compared to the traditional four-step (*13*)(*14*). These models need population synthesis methods for constructing a list of the population as an input, which is put together with comprehensive demographic and socioeconomic attributes (*15*). In this way, to acquire the population as an essential input for the transportation demand forecast, extensive studies are trying to reproduce underlying distribution and statistical properties of the actual population as accurately as possible, using available micro samples and marginals from census data (*16*)(*17*). While these models produce each individual's activity pattern in a typical day as output, when we consider the disaster-induced discontinuous population flows resulting from dynamic migration choices, it is important to explicitly model the dynamic and recursive decision-making. Recursive decision-making here means thinking about the future utility, including the life cycle changes or environmental and policy variables.

When extreme events such as disasters and wars occur, people who lose their original lives begin to travel to new cities, as depicted in Exodus. After a disaster, people temporarily leave the city, and the affected area's population rapidly decreases. While some people may return to the city after reconstruction, others may not because of the time it takes or because gentrification has progressed. In considering the post-disaster population movement, the control of the insurance fitting to the life stage, residential rent support systems, and the timing of infrastructure reconstruction will be significant policy variables (*18*)(*19*)(*20*). It is difficult to say that a methodology has been established to examine policies to maintain the population in disaster-affected areas or optimize the scale of reconstruction projects in light of a declining population. As the first step, it is necessary to understand how the affected people ultimately reached their final decision under various constraints to protect their families and keep the community.

From these perspectives, this study tries to model the long-term recursive migration choices after super disasters theoretically. First, we summarize the existing studies on migration and dynamic decision-making models. Next, the recursive migration model framework is presented and formulated, and then the results of a case study of the Great East Japan Earthquake are presented. Finally, the last chapter concludes and summarizes directions for future development.

LITERATURE REVIEW

Disaster and Migration

The increasing number of disasters caused by climate change and extreme weather events worldwide lead to significant loss of life and property and forced displacement. Since migration could be the only adaptation response in developing countries with high disaster risk and low adaptive capacity, it is necessary to prepare a humanitarian aid framework for the migration of vulnerable people affected by disasters or long-term environmental change (*21*)(*22*). Case studies have revealed various factors in the destination choices for disaster migrants, such as proximity, income, level of education, location of social capital. Based on these factors, it is essential to establish the adaptive capacity of host communities to receive disaster migrants (*23*). In this context, it is necessary to understand the decision-making mechanism of disaster migration to build a support system for reactive post-disaster migration.

Although disaster-induced migration has become an increasingly important issue due to frequent and devastating disasters, few studies have adopted quantitative micro-level models of the relationship between disasters and migration. In order to forecast disaster-induced migration as a household decision-making process, a micro-level approach is necessary (*24*). Do Yun and Waldorf (*24*) indicates whether households migrate or not is affected by the severity of the damage and their resilience, and disaster-affected people are classified into three types, voluntary movers, stayers, and forced movers, based on their income changes after the disaster. Endogenous Switching Regression Results and treatment analysis point out that forced movers suffer from the double burden of damage caused by the disaster and lower income in the destination city. In order to understand the determinants of migration in disaster-prone areas of Mexico, a regression analysis of aggregate data from 1990 to 2000 was conducted, and it is found that lower-income, frequency of disasters, and education level were significant factors determining migration (*7*). In this way, many case studies have been carried out to reveal determinants of disaster migration and its effects, but they often focus on one particular point in time. So the decision-making process of each household/individual over time until reconstruction projects are complete is not well understood.

The reasons why many location choice models are forced to focus on one particular choice over time are lack of residence trajectory data (*8*), and lack of the modeling approaches for representing life course dynamics (*5*). Despite this difficulty, some researches on migration focusing on the time axis have been conducted. Åslund (*8*) tries to challenge this problem by comparing the results of destination choice logit models using two data collected in different periods and finds the difference in factors affecting destination choice between the first and second migration. However, it does not treat the residential trajectories of the same household. On the other hand, Maslova and King (*25*) attempts to clarify the characteristics of domestic housing trajectories of Italians and Russians in London through semi-structured qualitative interviews. Bhat et al. (*11*) shows that it takes a long time for immigrants to be assimilated with the residential preferences and travel behavior of natives by a joint choice model of residence and auto ownership of immigrants in the U.S., which takes into account immigration status and length of stay as an explanatory variable. Loebach (*26*) shows that households with migration experience are more likely to migrate after a disaster to improve their livelihood by discrete-time event history analysis using migration history data from 1996 to 2001, including the year 1998 when Hurricane Mitch happened. A study of rural-urban migration in developing countries shows it is meaningful to take into account not only the income growth expectation but also the discount factor based on the time required to obtain a job and the risk of unemployment in urban areas (*27*).

In this way, some studies consider migration as behavior that occurs over a while with a certain length, while most of the quantitative analyses are static. So the effects of dynamic environmental changes over time and a life plan of each decision-maker on households' residential decision-making are not apparent. From a long-term perspective, the understanding of long-term migration trajectories would be necessary for reconstruction projects to be planed on an appropriate scale, especially in small towns under depopulation trends.

Some studies share this research objective of describing the dynamics in the residential choices. Yu et al. (*5*) develops a dynamic residential choice model over the life course by explicitly expressing the time-constant and time-varying preference influenced by the past life events and the future expectations. In addition, by introducing discount factors to the past, present, and future utility, each contribution to the location choice at the time can be understood. While this model is sophisticated in accommodating inter-temporal dependencies to describe the very long-term decision-making process over the life course, it cannot describe when to move or the decision to stay at the same place. Our model could be another modeling approach to capture the dynamics in the residential location choices because it can describe when to and where to relocate simultaneously as a sequential residential history after disasters, incorporating the future utility (Figure 1).

From these perspectives, we focus on the sequence of residential location choices over time, accounting for the discount factor, which indicates how the disaster-affected households anticipate the future utilities defined by the speed of reconstruction, housing recovery support, or their life events.

Dynamic decision making model

Based on these insights about disaster-induced migration and difficulties in studying residential trajectories, this study proposes a long-term recursive migration choice model for disaster-affected households. In this section, we review some of the dynamic decision-making models that have been developed in the transportation field.

In this study, we apply the Recursive Logit Model (RL model) as a sequential route choice model proposed by Fosgerau et al. (*28*) to model a dynamic and recursive migration choice under post-disaster uncertainty. The RL model by Fosgerau et al. (*28*) corresponds to dynamic discrete choice models (*29*) and describes the route choice problem as the result of a series of link choices. Here, sequential path choice is performed at each node to maximize the sum of instantaneous utility and expected downstream utility to the destination. Then the Discounted Recursive Logit

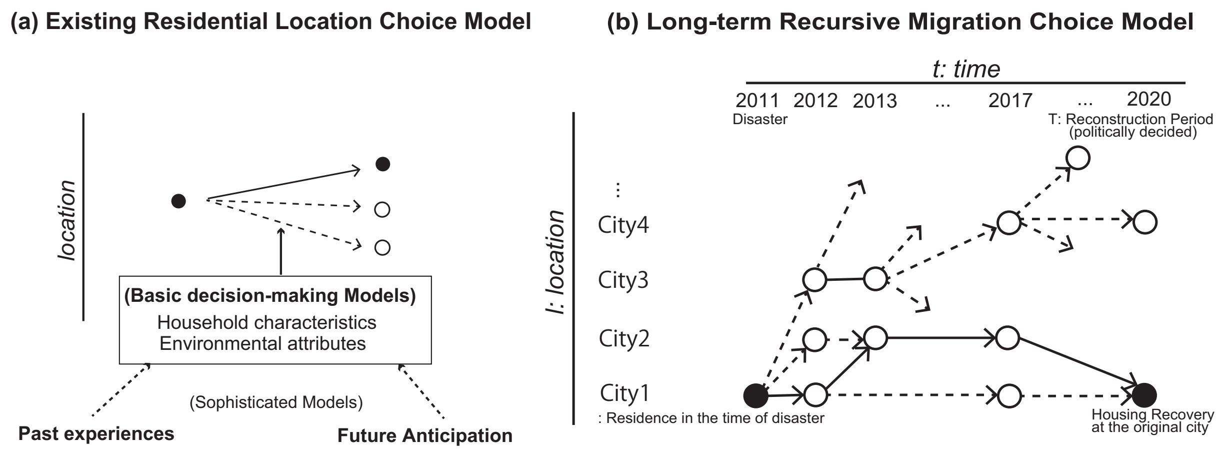


FIGURE 1 Residential choices on the time-space network after large-scale disasters

Model (DRL model) was proposed (*30*), where the expected future maximum utility is discounted by the discount factor β, considering that uncertainty exists in the future for the decision-maker. Moreover, the nested recursive logit model (*31*) and the recursive cross-nested model (*32*) have been proposed to relax the independence from irrelevant alternatives (IIA). In addition, a mixed RL model has been applied to the activity-travel scheduling decisions model in a time-space network where activity, location, time, and traffic mode are defined as state nodes (*33*).

In this study, we try to model the decision-making process of disaster victims who have to choose their residence under the ever-changing post-disaster uncertainty. We suppose they anticipate the future utility to some extent and capture it using the DRL model with discount factor. This study is characterized by applying a dynamic decision-making model to analyzing the long-term migration after a super disaster.

MODELING FRAMEWORK

In this chapter, we formulate the long-term recursive migration choice model for post-disaster victims, based on the DRL model proposed by Oyama and Hato (*30*).

Time-Space Network

First, the residential trajectories of disaster victims are represented on a time-space network with a time axis after a disaster and a spatial axis representing a vast urban area, as shown in Figure 1 (b).

Consider the time-space network $G = (S, A)$. S is a state node representing the residential place at time t, and A is a set of links representing the Spatio-temporal transition behavior of the residence. In order to describe a city that changes in the process of post-disaster reconstruction, S has different residential nodes $s = (t, l), (t \in T, l \in L)$ for each time point t. T is the reconstruction period, and L is the set of cities considered alternatives in residential location choice.

The dynamic migration history of the disaster victims from the onset of the disaster to the period T is represented as a series of links where they chose their housing location s at each time point t, $\sigma = [s_1, ...s_T](s_T = d = (T, l))$. In the following, the residential state node at time t is denoted as s_t to express the state node's time step explicitly.

Since the state node is defined by time and space, the residential choice path does not include a cyclic path. Therefore, we can depict various residential trajectories such as a path where a person moves out of the region and then returns, a path where a person stays in the same city continuously, and paths where households stay in the same city for different periods.

Formulation

In the time-space network mentioned above, the residence in the next time step is chosen sequentially. A disaster victim in the residential state s_τ at a certain point in time τ chooses the residential state $s_{\tau+1}$ (whether to stay in the same city or migrate and if migration chosen, to which city) at the next time step from the set of possible residential states $S(s_\tau)$ at the next point in time. Here, the victim n chooses the residence state $s_{\tau+1}$ at the next time point $\tau+1$ so as to maximize the sum of the instantaneous utility $u(s_{\tau+1} \mid s_\tau)$ obtained from the residential state $s_{\tau+1}$ and the expected maximum utility $V^d(s_{\tau+1})$ from the residential state $s_{\tau+1}$ to the residence state $s_T = d = (T, l)$. The instantaneous utility $u(s_{\tau+1} \mid s_\tau)$ is expressed in Equation (1). For the sake of simplification, the subscript n indicating the affected household is omitted in the following.

$$u(s_{\tau+1} \mid s_\tau) = v(s_{\tau+1} \mid s_\tau; \theta) + \mu\varepsilon(s_{\tau+1}) \tag{1}$$

$v(s_{\tau+1} \mid s_\tau; \theta) = v(x_{s_{\tau+1}|s_\tau}; \theta)$ is the deterministic utility component of instantaneous utility, $x_{s_{\tau+1}|s_\tau}$is a vector of observed characteristics of the connected states $(s_\tau, s_{\tau+1})$, and θ is an unknown parameter vector to be estimated. $\varepsilon(s_{\tau+1})$ is a random term of the instantaneous utility and follows an i.i.d extreme value I with scale parameter μ. The expected maximum utility $V^d(s_\tau)$ to the residence state d at T is formulated by the Bellman equation (*34*), described recursively as Equation (2). In the notation below, the unknown parameter θ is omitted for simplification.

$$\begin{aligned} &V^d(s_\tau) \\ &= \max_{s_{\tau+1} \in S(s_\tau)} E\left[\sum_{t=\tau}^{T} \beta^{t-\tau} u(s_{\tau+1} \mid s_\tau)\right] \\ &= E\left[\max_{s_{\tau+1} \in S(s_\tau)} \{v(s_{\tau+1} \mid s_\tau) + \beta V^d(s_{\tau+1}) + \mu\varepsilon(s_{\tau+1})\}\right] \end{aligned} \tag{2}$$

$S(s_\tau)$ is a set of residential states available after the state s_τ. β is a discount factor satisfying $0 \leq \beta \leq 1$. The closer to one the value of β is, the more highly valued the future expected utility in the decision-making. In contrast, the closer to 0 the value of β is, the more myopic decision-making takes place, which highly values the instantaneous utility. The discount factor makes it possible to consider the uncertainty after disasters in our model.

Then, since the random term is assumed to be an i.i.d extreme value I, the probability of choosing the residential state $s_{\tau+1}$ after the state s_τ is formulated as follows (Equation(3)):

$$P^d(s_{\tau+1} \mid s_\tau) = \frac{e^{\frac{1}{\mu}\{v(s_{\tau+1}|s_\tau) + \beta V^d(s_{\tau+1})\}}}{\sum\limits_{s'_{\tau+1} \in S(s_\tau)} e^{\frac{1}{\mu}\{v(s'_{\tau+1}|s_\tau) + \beta V^d(s'_{\tau+1})\}}} \tag{3}$$

We assume a Markov process in which the affected household n makes sequential choices of residential status in each period, taking into account future residential status, and arrives at final residential status. By introducing a discount factor, we describe the recursive choice of residence with a view to the future and the short-sighted decision-making that must be made in response to uncertain situations.

The choice probability of such a dynamic residential choice path $\sigma = [s_1, ..., s_T](s_T = d = (T, l))$ is expressed as the product of the residential state choice probabilities at each time point τ (Equation (3)) as Equation (4)

$$P_n(\sigma_n) = \prod_{\tau=1}^{T-1} P^d(s_{\tau+1} \mid s_\tau) \tag{4}$$

Then, since ε is assumed to be Gumbel distribution, Equation (2) is transformed into the form of log-sum (Equation (5)).

$$V^d(s_\tau) = \begin{cases} \mu \ln \sum_{s_{\tau+1} \in S(s_\tau)} \delta_{s_\tau}^{s_{\tau+1}} \cdot e^{\frac{1}{\mu}\{v(s_{\tau+1}|s_\tau) + \beta V^d(s_{\tau+1})\}} & (s_\tau \neq d) \\ 0 & (s_\tau = d) \end{cases} \tag{5}$$

where $\delta_{s_\tau}^{s_{\tau+1}}$ is an indicator that equals one if the state $s_{\tau+1}$ is connected to the state s_τ, and 0 otherwise. There is no node following the node d at the last time step, $V^d(d)$ is always equals zero.

Since the cyclic structure of the residential path is eliminated in the time-space network, the expected utility $V^d(s_\tau)$ can be calculated by a simple backward induction method by repeatedly using Equation (5).

Estimation

We estimate the parameters of the recursive migration choice model formulated in the previous section by the maximum likelihood method. When the instantaneous utility $u(s_{\tau+1} \mid s_\tau)$ is expressed as a linear sum of the parameters and explanatory variables, the log-likelihood function LL is defined as follows according to Equation (4).

$$LL(\theta, \beta) = \ln \prod_{n=1}^{N} P_n(\sigma_n) = \sum_{n=1}^{N} \sum_{t=1}^{T-1} \frac{1}{\mu} (v_n(s_{\tau+1} \mid s_\tau) + \beta V_n^d(s_{\tau+1}) \text{-} V_n^d(s_\tau)) \tag{6}$$

N is the total number of affected households observed (the total number of path data), and T is the number of time steps (i.e., the number of states included in a residential choice path σ).

Sampling Alternatives

In this section, we explain the sampling method of alternatives for residential locations. In the decision-making process to choose a place to live in, it is not practical to assume that a person identifies all possible cities and selects a single place, so we sample a set of alternative places. In this model, the sampling procedure is based on the Markov Chain Monte Carlo (MCMC) method. The sampling procedure is as follows.

1. Randomly draw one city r_i from the set of all possible alternatives and set it as the initial state.
2. Randomly select another city r_j.
3. Calculate the ratio of the choice probabilities of the two extracted cities, $\gamma = \frac{PD(r_j)}{PD(r_i)}$.
4. Generate ε, a uniform random number in $(0, 1)$. If $\gamma > \varepsilon$, replace r_i with r_j and return

to 2. If $\gamma < \varepsilon$, return to 2 without replacement.

These steps 2-4 are first repeated many times to relax the initial conditions and then sampled at sufficiently large intervals while repeating many times.

EMPIRICAL ANALYSIS

In this chapter, we estimate the parameters of the long-term recursive migration choice model presented above using actual data on the 10-year residential histories of the victims of the Great East Japan Earthquake, and discuss the results.

The massive earthquake occurred in 2011 and affected vast areas of Japan. The earthquake caused the tsunami, and many people in that area lost their houses. In addition, the tsunami triggered the nuclear accident in Fukushima prefecture. In order to protect residents in areas surrounding the power station, the Government established the Areas of Evacuation Order, forcing about 110,000 people to evacuate from their hometowns. Because of this complex disaster, many people experienced intra-regional or inter-regional migration. Although the evacuation orders have been gradually lifted, more than 40,000 Fukushima citizens, including the voluntary evacuees who are not officially ordered to evacuate, are displaced even ten years after the disaster.

Web Survey and Data

We conducted a web survey to collect longitudinal data on the post-disaster residence after the Great East Japan Earthquake. The survey was conducted in January in 2021, using a major Web survey company in Japan, and 1,700 samples currently living in six Tohoku prefectures or seven Kanto prefectures were obtained. Screening condition is that people who lived in the coastal area severely damaged by the tsunami (eight cities in Iwate prefecture and ten cities in Miyagi prefecture, 500 samples, respectively), or people who lived in Fukushima prefecture then and have experienced evacuation from the nuclear power plant accident (700 samples). A summary of the survey items is as follows.

1. Current family information (family members, residence location, residence type, income, and properties)
2. Family information at the time of the disaster (family members, residence location, residence type, income, properties, and damage of the disaster)
3. Residential biography from 2011 to 2020 (residence location, residence type, family structure, and subsidies and compensation)

We estimate parameters for 285 samples who properly answered the questions about their residence and relocation timing in their 10-year residential biography.

Figure 2 shows examples of residential trajectories from the web survey. For example, sample 2 was affected by the disaster in Kesennuma City and was forced to evacuate. After living in a post-disaster public-funded rental accommodation in Itabashi Ward in Tokyo for about five years, she returned to Kesennuma City in 2018 and rebuilt her house through the group relocation project. In the case of sample 3, he lived in his own house in Namie Town at the time of the earthquake. After the nuclear accident, he had to move out and spent five years in a post-disaster public-funded rental accommodation in Fukushima City, changing his job to work there. After that, in 2016, he rebuilt his house in Iwaki City, which is within commuting distance from Namie town, and is now working in Namie Town. He might anticipate the partial lifting of the evacuation order of Namie Town in March 2017. On the other hand, sample 4, affected by the disaster in Namie Town, lived in public housing in Kashiwazaki City in Saitama Prefecture for eight years

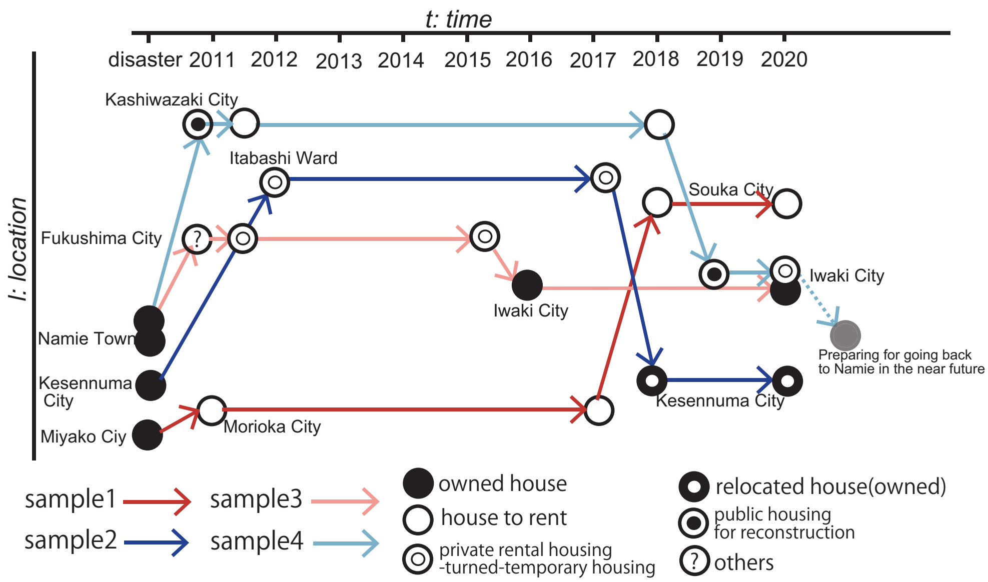


FIGURE 2 Examples of residential trajectories after large-scale disasters

and moved to public housing in Iwaki City in 2019. This household is currently constructing their house on their property in Namie. They seem to have moved to Iwate City close to Namie Town to return to Namie Town shortly.

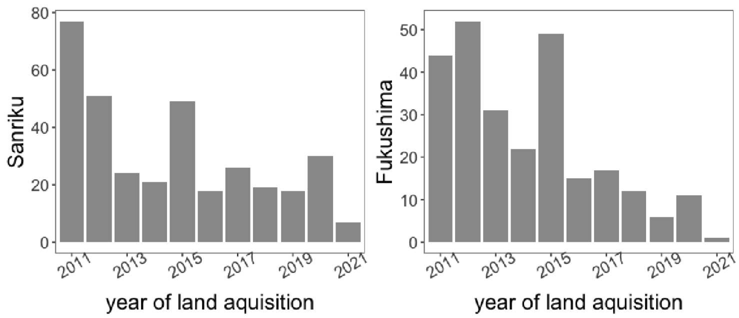
As shown in these examples, disaster victims dynamically choose their residential locations following the changes over time in factors such as life cycles, reconstruction projects, and the lifting of evacuation orders while thinking about their final housing recovery in the future.

Figure 3 shows the results of basic analysis of the web survey. Figure 3-A shows those who purchased, received, or inherited land in 2011 or later in the Sanriku area (N=340) and Fukushima prefecture (N=260). In Sanriku, the largest number of respondents acquired land in 2011, immediately after the disaster, followed by 2012 and 2015. On the other hand, more people in Fukushima Prefecture acquired land in 2012 and 2015 than in 2011. It means their housing reconstruction was more delayed than those in Sanriku. In both Sanriku and Fukushima Prefectures, land acquisition was active immediately after the disaster and again in 2015, four years later.

Figure 3-B shows income groups as of 2011 and whether the households currently reside in the same municipality as at the time of the earthquake. A higher percentage of households in the income group of 5 million yen or more (4.5.6) moved out of the home municipality than households in the income group of 5 million yen or less (1.2.3). Households with lower incomes are more likely to stay in their former places of residence, maybe because they own land and buildings there and temporary housing or low-cost reconstruction public housing are available.

Next, we look at people who were affected by the disaster to the extent that they had to move into temporary housing or were ordered to evacuate, or who acquired their own house after the earthquake. The percentage of households that moved out of their original residence was 34.2% for households that owned their own house in 2011 (N=379) and 47.5% for households that lived in rented housing (N=653). The out-migration rate was higher in the latter group.

Figure 3-C plots the rents of households living in rented housing in both 2011 and 2021,

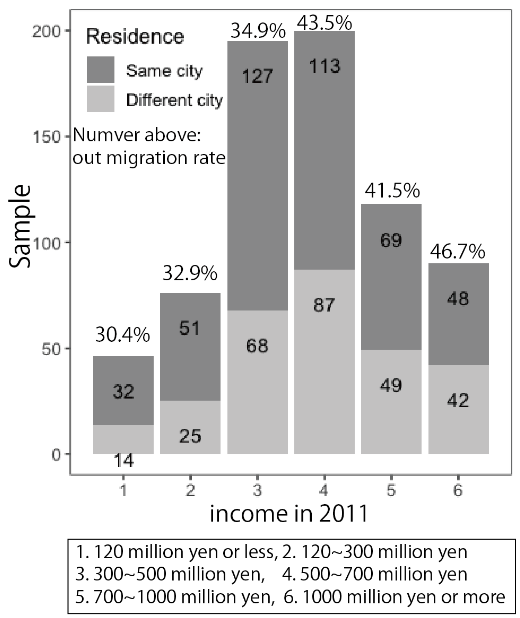


A. The year of land aquisition (Left: Sanriku, Right: Fukushima)

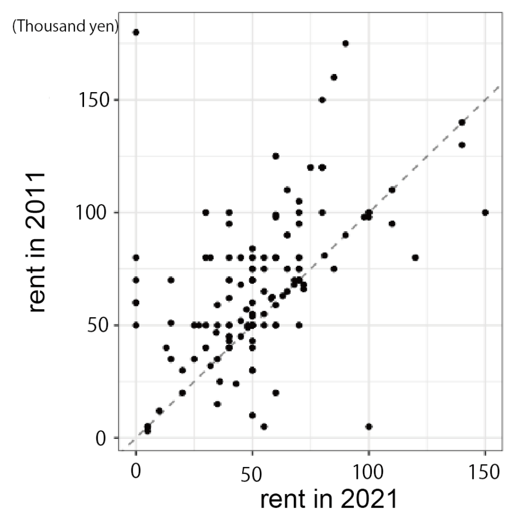
D. Migration and household structure

Migration	Keep*1	Divided*2	Integrated*3
none	72	4	20
once	54	25	17
twice	27(0.49)	16(0.29)	21(0.38)
3 times	15(0.56)	9(0.33)	7(0.26)
4 times	5(0.33)	8(0.53)	5(0.33)

*1) Who has kept the household structure for 10 years
*2) *3) Who has experienced household division or integration



B. Income groups and out migration



C. Rents of 2011 and 2021

FIGURE 3 Results of basic analysis of the web survey

showing that many plots are above the straight line where the rents in 2011 and 2021 are the same. It indicates that many households have higher rents now than before the earthquake. It suggests that non-homeowning households tend to move out of the home municipality to cities with higher rents.

Table D in Figure 3 shows the change in household type with the number of times the household moved after the earthquake (0-4 times). It shows that many cases of migration are accompanied by a change in family structure. Therefore, it is essential to consider the change in family structure when predicting the number of people and households after the earthquake, which is the planning unit for reconstruction projects. Capturing the changes in family structure in our model is a future challenge.

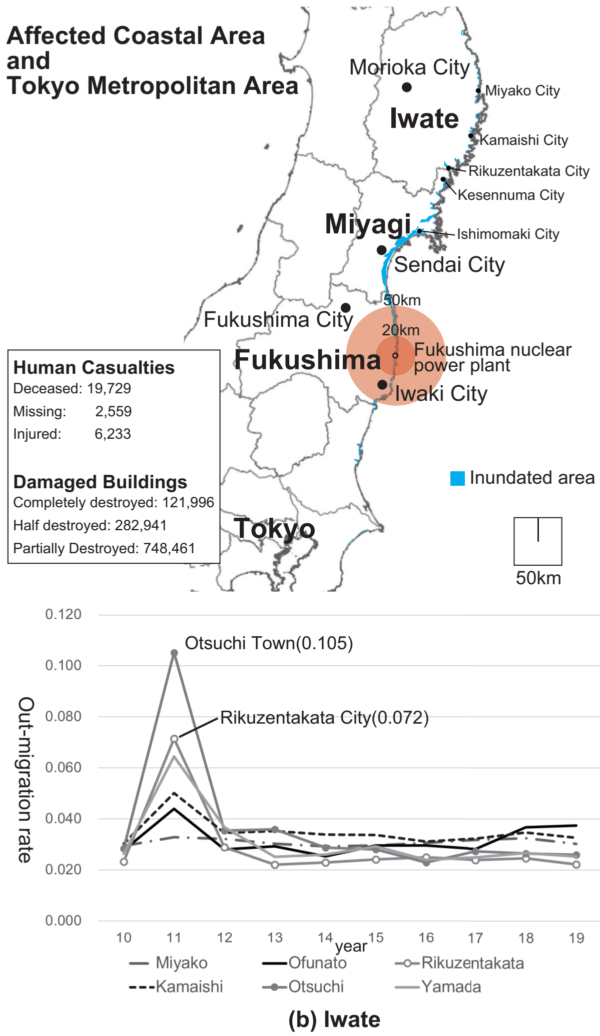


FIGURE 4 Affected area and out-migration rate to population in 2010 (a)(b)(c)

Basic analysis based on statistical data

In this section, we present the outcome of the basic statistical analysis conducted as a basis for setting up the model to estimate the parameters. For the analysis of population movement, we used the National Census and data on migration provided by the Ministry of Internal Affairs and Communications.

Figures 4(a), (b), and (c) show the ratio of out-migration to the 2010 population in Miyagi, Iwate, and Fukushima prefectures, respectively. The percentage of out-migration in 2011 is extremely high (about 10%) in Yamamoto Town, Minamisanriku Town, Onagawa Town in Miyagi Prefecture, and Otsuchi Town in Iwate Prefecture. In all the municipalities, the out-migration rate rose sharply in 2011, but in most of them, the out-migration rate settled down to the pre-earthquake level in 2012. On the other hand, in Onagawa, Minamisanriku, and Yamamoto, the out-migration rate remained high for three years.

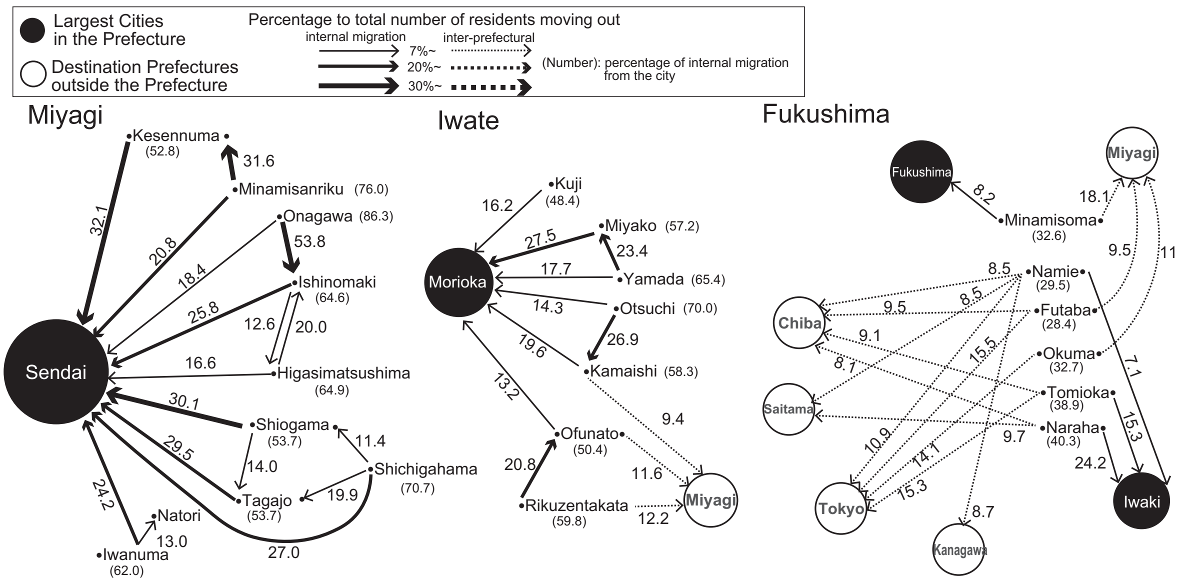


FIGURE 5 Destination cities of out-migration

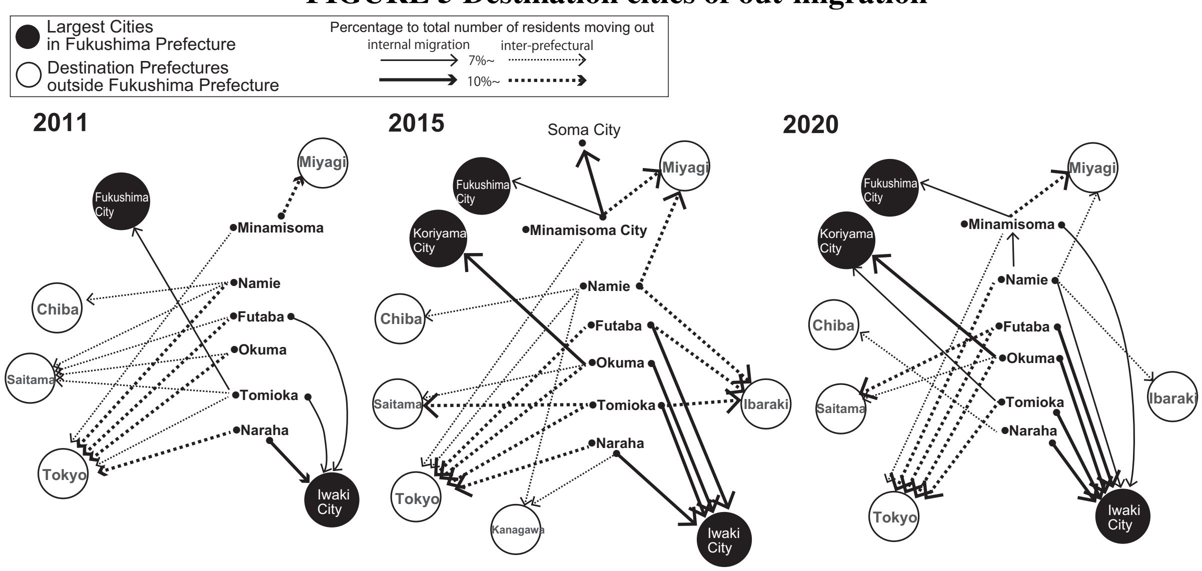


FIGURE 6 Changes in trends of migration over 10 years in Fukushima

On the other hand, Fukushima Prefecture, where the population has moved significantly due to the evacuation from nuclear power plants, shows a different picture from the other two prefectures. In municipalities where evacuation orders were issued, the evacuation orders have been lifted sequentially since 2014. Interestingly, the number of people moving out rose again in the period after the lifting of the evacuation orders, such as in Naraha Town (lifted in September 2015), Minamisoma City (lifted in July 2016), and Tomioka Town (partially lifted in 2017). Note that many households among the nuclear disaster evacuees lived in other cities without transferring their residence records, so caution is required in interpreting the results.

As shown above, there are differences in the population movements in the disaster-affected areas. It can be inferred that factors such as the disaster situation, the content and progress of reconstruction projects, and the lifting of evacuation orders affect the decisions of individuals and households. In order to explain the post-disaster population flow, it is necessary to incorporate these factors into the model.

Figure 5 shows major destination cities to which people migrate from coastal cities in the three prefectures in 2012, which shows a marked difference among the three prefectures. In Miyagi Prefecture, where intra-prefectural out-migration was remarkable after the earthquake, we can see that in addition to the tendency to concentrate in Sendai City, the largest city in the Tohoku region, there is also a high tendency to move to the central city in each region. In Iwate and Fukushima Prefectures, the same tendency is observed, but the percentage of out-migration to other prefectures with large cities is higher, especially in Fukushima. We can see a trend of out-migration to Miyagi Prefecture from southern Iwate and northern Fukushima Prefectures and migration to the Tokyo metropolitan area from southern Fukushima Prefecture. From the above analysis, it can be assumed that the residential location choice set of the disaster victims differs greatly depending on the place of residence as of 2011, and we will attempt to reflect this point in the choice sampling.

Figure 6 shows the dynamic change in the destination cities from Fukushima prefecture within ten years after the disaster. Overall, there is no strong trend to which they move; in other words, people move out to various cities. In 2011, people seldom moved within Fukushima prefecture and chose the inter-prefectural migration, especially to the Tokyo metropolitan area. Over time, there has been an increasing migration trend to larger cities within the prefecture, especially to Iwaki City, which is the largest city in Fukushima prefecture and the closest to the area affected by the nuclear accident.

These analyses suggest that the city size and distance have a significant impact on the population movement. In addition, we could confirm the dynamics of out-migration trends with time after disasters. Therefore, in the next section, we propose a model that takes them into account.

Settings of the Case Study

The data acquired by the web survey is used for parameterization and we treat the household as the subject of migration choice.

Time-Space Network

Since the reconstruction period from the Great East Japan Earthquake was politically set at ten years, the target period is ten years from 2011 to 2020. As shown in the results of the basic analysis, there is a significant movement in 2011. Therefore, here, the time of the disaster is set at $t = 1$ and the last period at $T = 14$, assuming the time-space network with four steps/year only in 2011 and one step/year after 2012.

In this model, the value function is discounted by a discount factor β for each step, so it is reasonable to make all the time steps the same length. In reality, the timing of residential decision-making during the reconstruction period and ordinary life is related to the fiscal year due to the renewal of temporary housing, job transfer, advancement to higher education. Moreover, the heterogeneity between the immediate post-disaster period with great uncertainty and the normal period should be considered. In addition, it is difficult to obtain explanatory variables that fluctuate in short time unit such as one month. For these reasons, this paper uses the time-space network described above for estimation. The length of a time unit is to be further studied.

TABLE 1 Explanatory Variables

Population density($10^{-4}/km^2$)	Population density, divided by 10000 for scale adjustment
Distance ($10^{-3}/km$)	Distance between cities, divided by 1000 for scale adjustment
Progress rates	Progress rates of housing reconstruction (cumulative progress rates of public and private housing lots) If not a disaster affected city, nodes in all time steps are set as 1.
High income (dummy)	Annual income of 5 million yen or more as of 2011
Low income (dummy)	Annual income of less than 5 million yen as of 2011
House owner (dummy)	House owner as of 2011
Renter (dummy)	Renter as of 2011
Damaged (dummy)	Dummy for disaster victims (those who were affected to the extent that they had to move into temporary housing or were ordered to evacuate)
Education (dummy)	Dummy for the timing of moving up to elementary school, junior high school, or high school during the targeted period
Destination city (dummy)	Dummy for the location at the last time-step (place of residence 10 years after the disaster)
Destination_early (dummy)	Nodes from the origin up to the year 2013 among the destination city dummies
Home_early (dummy)	Node from the origin up to 2013 among the dummies for the location in 2011

Sampling choice set

The sampling of alternative residential locations for each household is carried out using the method described in the previous chapter. The sampling is based on the residence of each household at the time of the earthquake (2011) (O). The choice probability for each city (D), required in sampling procedure 3 is set as the percentage of out-migration to that city (D) to the total number of out-migration from O. The data on out-migration from each municipality is provided by the Ministry of Internal Affairs and Communications. In this data, the OD of the out-migration is available for each municipality only for 2012 and later, so we used 2012. The scale of cities in the choice set is defined as municipalities for in-prefecture migration and as prefectures for out-of-prefecture migration.

The sampling process 2-4 was repeated 10,000 times to mitigate the effects of the initial conditions, and then three cities were selected at intervals of 1,000 times of this procedure. Each household eventually has a choice set of four cities, including the city chosen in the actual residence history (from one to four cities). The choice set is the same for the entire period.

This sampling method allows us to consider the heterogeneity of choice set according to the residential locations at the time of the earthquake, but further study is needed to take into account the changes in the choice set over time.

Utility function

Explanatory variables of instantaneous utility $x_{s_{\tau+1}|s_\tau}$ presented in Equation (1) is constructed by examining the variables shown in Table 1.

Estimation Result

In this paper, the following four patterns are estimated and compared; 1. all samples (285), 2. Iwate Prefecture (65), 3. Miyagi Prefecture (108), 4. Fukushima Prefecture (112). In the following, the scale parameter is fixed at $\mu = 1$. Chosen variables and estimated parameters are shown in Table 2. To estimate time discount factor β with 0 to 1 constraints, γ is estimated as $\gamma = \frac{exp(\beta)}{1+exp(\beta)}$.

First of all, the discount factor, an essential factor in this model, is estimated to be 0.725 in Miyagi Prefecture, which is statistically significant, and 0.215 in Fukushima Prefecture, the statistical significance level lower. It indicates that the discount rate in Fukushima is relatively low, which could mean that a myopic residential choice was taking place. In Fukushima Prefec-

TABLE 2 Estimation Result

	All		Iwate		Miyagi		Fukushima	
	parameter	t-value	parameter	t-value	parameter	t-value	parameter	t-value
1)Population density ($10^{-4}/km^2$)	3.028	13.74	28.256	16.01	3.234	11.34	1.811	5.36
2)Progress rates * Damaged * House owner	0.162	1.46	0.034	0.10	0.196	0.98	0.040	0.21
3)Destination_early * High income *Damaged	1.236	9.01	1.709	4.80	1.347	5.67	1.456	5.96
4)Destination city * Education	1.575	8.66	0.828	1.99	1.402	4.84	2.019	5.90
5)Distance ($10^{-3}/km$)	-27.567	-32.43	-42.510	-19.89	-35.824	-19.36	-20.977	-22.66
Discount factor	0.542 (γ=0.168)	0.78	0.000 (γ=-11.657)	-0.13	0.725 (γ=0.970)	4.18	0.215 (γ=-1.297)	-1.41
No. of samples		285		65		108		112
Initial likelihood		-5136.22		-1171.42		-1946.36		-2018.44
Final likelihood		-2492.02		-436.89		-959.84		-974.65
Likelihood ratio		0.51		0.62		0.50		0.51

TABLE 3 Comparison of Parameter Ratios

	all	iwate	miyagi	fukushima
5)Distance / 1)Population	-9.10	-1.50	-11.08	-11.58
5)Distance / 3)High income	-22.29	-24.87	-26.60	-14.41
5)Distance / 4)Education	-17.51	-51.34	-25.55	-10.39
3)High income / 1)Population	0.41	0.06	0.42	0.80
4)Education / 1)Population	0.52	0.03	0.43	1.12
3)High income / 4)Education	0.96	0.72	0.79	2.06

ture, those who suffered from the triple disasters and had to evacuate from nuclear plants due to evacuation orders, and those who evacuated for fear of the risks of contamination from radioactive releases, were forced to focus on the instantaneous utility because of the long period of uncertainty about whether they would be able to return.

The variable 3) in Table 2 is a dummy variable that is set to 1 if the affected high-income household had reached their final residence by 2013. This parameter is statistically significant for all estimation patterns, with a value of 1.347 for Fukushima Prefecture. Looking at the parameter ratios in Table 3 for this variable, it can be said that there is a higher tendency for high-income individuals affected by the disaster to reach their final place of residence at an early stage in Fukushima Prefecture, in comparison to other prefectures. This result is consistent with the fact that high-income people can rebuild their houses on their own regardless of the subsidies and compensation they receive. Actually, low-income people in Iwate and Miyagi prefectures tended to stay in the affected areas, living in temporary housing and waiting for disaster recovery public housing completed. However, victims in the Fukushima nuclear power plant-affected areas were ordered to evacuate, so they had no choice to stay in their original places of residence. Therefore, it is likely that lower-income victims temporarily moved to a municipality where they could receive support and continued their temporary residence while waiting to hear about the situation in the affected hometowns. A more detailed description about the facts above using our model could help examine disaster relief policies that consider diversity in damage and income.

Next, the population density parameter was positively significant, and the distance parameter was negatively significant for all estimation patterns. Looking at the parameter ratios, the ratio of population density to distance in Iwate is very large. This can be attributed to the fact that the target cities of Iwate Prefecture (cities that are always included in the choice set as the origin in history) have a minimal city size. The population density of targeted cities in Iwate is 66.6 people per km^2 on average, while that in Miyagi is 959.3 people per km^2 on average, and that in Fukushima (where all municipalities are included) is 156.8 people per km^2 on average. As for Fukushima Prefecture, the actual average is larger because many of the people in the sample are from cities with relatively large urban areas. On the other hand, the population density of Tokyo, the largest city in the metropolitan area, is 6305.7 persons per km^2, which is extremely large. Therefore, it is assumed that the population density parameter in Iwate is larger than in other prefectures to explain the migration from Iwate to the Tokyo metropolitan area, which has a massive difference in population density.

As for the estimation of the discount factor, we obtained significant values in Miyagi Prefecture and informative values in Fukushima Prefecture, but we failed to estimate it reasonably in Iwate Prefecture. The reason for this could be that due to the large population density parameter in Iwate Prefecture, the utility of staying in the Tokyo metropolitan area becomes very large when cities in the metropolitan area are included in the choice set. Note that the utility of moving to the area is not as large as the utility of staying in the affected area because of the distance. Therefore, it is likely that the degree of the consideration of future utility, i.e., the discount rate β, varied greatly depending on whether the households with the metropolitan cities in their choice set chose them or not. In other words, there are varieties between those who chose to stay in the disaster-affected area because it is costly to move to a large city (myopic choice), and those who decided to move to a large city, considering future utility (high utility of staying in a city).

In reality, however, future utility is not only determined by distance and city size. In order to estimate and improve the accuracy of the discount rate for all patterns, firstly, it is necessary to construct a utility function that is not too dependent on one particular variable. It should reflect diverse values of future utility, such as life cycle, attachment to hometown, and properties. In addition, it is necessary to study the estimation structure assuming latent classes, the sampling method for alternatives, and the number of cities in the choice set.

Unfortunately, the parameter of variable 2) in the Table 2, which represents the progress rate of reconstruction, was not significant. This model uses the cumulative progress rate of the prepared number of public or private housing units. However, it does not capture essential factors related to damage and reconstruction, such as evacuation orders and land-use changes between the affected and upland areas. It is necessary to consider other valuable variables to evaluate reconstruction projects.

CONCLUSION

In recent years, disasters have become more frequent and severe worldwide due to climate change, forcing disaster victims to make involuntary or unavoidable choices to migrate. Understanding disaster-induced migration and establishing appropriate assistance schemes are urgently needed. Although individual case studies have revealed the factors that lead to post-disaster migration, previous residential choice models have not described the long-term recursive residential decision-making process. This study developed a long-term recursive migration choice model that considers the decision-making process over decades after a disaster. In this model, victims simultaneously select a location and relocation timing at each time-step, considering the future utility. By introducing a discount factor, future utility is discounted, which enables to describe the choices that must be made under uncertain conditions after a super disaster.

We confirmed the usability of our model by conducting a case study of residential histories for the ten years after the Great East Japan Earthquake and confirmed the possibility of estimating the discount factor. The discount factor was estimated to be lower in Fukushima Prefecture than in others. Disaster victims in Fukushima prefecture could not see any prospect of returning to their hometowns due to the complex disaster including nuclear accident. In addition, it is indicated that there is a higher tendency for high-income people to reach their final place of residence at the early stage in Fukushima than in other prefectures, which suggests that the speed of residential recovery differs depending on income. In the future, we will add an analysis of the amount and timing of housing recovery monetary assistance and compensation payments to nuclear disaster victims, which may be applied to the investigation of a fair distribution of monetary assistance.

In addition, the impact of the time related to education on the timing of residential reconstruction is suggested, so the development of the model that considers the life cycle of households could be meaningful. Although the reconstruction progress rate was not significant in this case study, the model can incorporate variables that differ by location and time, such as the damage situation, the progress rate of reconstruction projects, and the distribution and timing of subsidies. This study helps determine not only the appropriate scale of reconstruction projects but also the effective timing. Moreover, the disaster-affected residents drastically move into large cities after a disaster, and it results in friction, which also happened in Fukushima. By using the model proposed here, it will be possible to perform dynamic control to allow temporary urban functions to serve as buffers and evaluate the next best measures to support residents without relying on excessive reconstruction.

Finally, we summarize the challenges that remained. First, the discount factor introduced in this model is assumed to be constant across time. However, the discount factor in the period of uncertainty immediately after a disaster and that in the reconstruction period several years later are considered different. Hence, developing a framework that considers the time variability of the discount rate is necessary. In addition, the method of describing uncertainty in the post-disaster period needs to be further studied. In this model, uncertainty is expressed only by the discount factor. However, the myopic choice here means "knowing the future utility but valuing the immediate utility," which does not directly reflect the reality of the post-disaster situation where the future situation is completely unforeseeable. One possible countermeasure is to limit the number of alternatives in the immediate aftermath of a disaster, but further study is needed. In the case study, we estimated parameters for each disaster-affected municipality with different types of damage and different geographical environments. However, there is heterogeneity in the characteristics of disaster victims even within the same municipality. In order to estimate the discount factor stably, it could be effective to take into account the latent class. In fact, after the Great East Japan Earthquake, the separation of households co-occurred as the separation of communities due to migration. In order to understand this phenomenon, it will be essential to extend the framework to include the household's life-cycle and describe the choice of household structure that may have coincided with the location choice.

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