Can an economic structural model support hypothetical and experimental evidence? Preference parameters before and after the Great East Japan Earthquake [1]

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Summary: This study proposes the measurement error robust Euler equation approaches to estimate households' preference parameters before and after a large-scale disaster, namely the Great East Japan Earthquake of 2011. Our finding supports other studies using hypothetical and experimental data that suggest experiencing a large-scale disaster changes individuals' risk and time preferences. Furthermore, revealed households consumption and asset allocation behavior fitted in a life-cycle consumption model exhibits that a large-scale disaster affects households facing different future risks of similar disasters differently even if they are not physically damaged by the disaster.

Keywords: preference parameters; Euler equation; measurement error; large-scale disasters; local GMM

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1 Introduction

To evaluate a policy that focuses on recovery from a large-scale disaster, understanding not only individual economic behavior but also household behavior after the disaster is important. A growing body of the literature finds that an individual's preference parameters such as risk and time preferences change after experiencing an unexpected natural disaster.[1] In the literature, two main approaches elicit preference parameters. The first approach uses data collected from field experiments, such as in the studies presented by Eckel, El-Gamal, and Wilson (2009), Cameron and Shah (2015), Sawada and Kuroishi (2016), and Cassar, Healy, Kessler, and Carl (2017). The second approach elicits preference parameters from hypothetical questions, for example Callen (2015), Goebel, Krekel, Tiefenbach, and Ziebarth (2015), and Hanaoka, Shigeoka, and Watanabe (in press). There are three important open questions in the literature. First, since experiments and hypothetical questions target individuals' decisions rather than those of households, whether and how natural disasters affect households' preference parameters are not evident. Second, there may be gaps between respondents' behaviors in hypothetical or experimental settings and their actual economic behaviors. Third, no clear lines exist between affected and not affected by a disaster, which makes the definition of the treatment controversial. In addition, preference parameters in a specific context may offer a stronger measure for that particular context (see Rabin, 2000, Rabin & Thaler, 2001, Cox & Sadiraj, 2006, Schechter, 2007, Dohmen et al., 2011), which suggests, for example, that preference parameters elicited in a financial context such as a lottery, game, or bet scenario may have less predictive power in another context. To reveal households' preference parameters with respect to consumption and saving allocation plans, it is thus preferable to investigate them in a consumption and saving context.

This study empirically investigates how preference parameters such as relative risk aversion and the time discount factor are affected by a large-scale disaster by using household panel data that reveals actual households' consumption and saving behaviors. We adopt life-cycle consumption models, in which risk and time preferences determine consumption, saving, and the other asset allocation plans of economic agents.[2] We propose a new identification strategy for preference parameters in life-

[1]While preference parameters are typically treated as constant over time (e.g., Stigler & Becker, 1977), a large number of studies have questioned the time- and event-invariant parameter assumption. For example, Fehr and Hoff (2011) summarize that preference parameters are not only variable over time but also affected by the event a person has experienced.

[2]The risk preference parameter we use in this study is the Arrow–Pratt measure of relative risk aversion. This measure has been used as the risk aversion parameter in both experimental and hypothetical settings. In the literature using hypothetical questions, Cramer, Hartog, Jonker, Praag, and Mirjam (2002) show an approximation procedure for the Arrow–Pratt absolute measure of risk aversion, which is adopted, for example, by Hanaoka et al. (in press) in the natural disaster context. In the literature on field experiments, the Arrow–Pratt measure of relative risk aversion is used by Cameron and Shah (2015) by adopting the estimation method proposed by Schechter (2007). Sawada and Kuroishi (2016) also use the Arrow–Pratt measure estimated by using the log-linearized intertemporal consumption

cycle consumption models because of the measurement errors that exist in consumption data (see, for example, Runkle, 1991 who confirms the existence of measurement errors in consumption data when testing the permanent income hypothesis). Since neglected measurement errors may seriously inhibit the ability to obtain consistent parameter estimates, one needs an econometric approach that delivers parameter estimates robust to measurement errors under plausible assumptions. In particular, under our approach, measurement errors can be arbitrarily correlated with any other variables including true consumption. Since it seems to be implausible to assume independence between latent true consumption and its measurement error in economic data (e.g., Bound & Krueger, 1991, Bound, Brown, Duncan, & Rodgers, 1994, Chen, Hong, & Tamer, 2005), allowing arbitrary dependency between them is an important and challenging task.

By using Keio Household Panel Survey (KHPS) data and the Great East Japan Earthquake that occurred in March 2011, we find that the disaster affects households' risk and time preference parameters even if households did not lose properties because of the disaster. Moreover, the observed effect is heterogeneous with respect to a household's future risk of being hit by severe earthquakes. In particular, households facing a high risk of earthquakes become risk averse compared with households facing a low risk of earthquakes. This result is consistent with German evidence reported by Goebel et al. (2015) and Bauer, Braun, and Kvasnicka (2017) in the sense that the Great East Japan Earthquake affected the risk attitudes of households facing the risk of a similar disaster in the future even if they did not directly experience the disaster themselves. For instance, Goebel et al. (2015) find that the Great East Japan Earthquake affected the risk attitudes of Germans, while Bauer et al. (2017), using German housing price data, find that the prices of houses close to nuclear power plants declined significantly. Our result is also consistent with Ishino, Kamesaka, Murai, and Ogaki (2012) and Sekiya et al. (2012), who analyze the earthquake from a psychological perspective. Our simulation shows that the risk and time preference parameters estimated from data before the earthquake can severely underestimate the consumption expenditure of households after the disaster.

This study contributes to the literature technically and empirically as follows. Its technical contribution is that we propose a new identification strategy for the preference parameters in life-cycle consumption models when consumption is contaminated by dependent measurement errors. It reveals the set of parameters characterized by moment inequalities evaluated with the observed consumption, to which the true parameters belong. The only assumption required in this study is weak stationarity of measurement errors. In addition to the stationarity, existing works assumes independence between

Euler equation.

measurement errors and other variables in the model and/or parametric distribution of measurement errors. For example, Alan and Browning (2010) develop a simulation-based approach in which they assume the distribution of expectation errors to be a mixture of two log-normals. Alan, Attanasio, and Browning (2009) propose exact generalized method of moments (GMM) approaches, called GMM-LN estimator, in which the log-normality of measurement errors is assumed (see, also Ventura, 1994). Alan et al.'s (2009) so called GMM-D estimator exploits the first-order condition of the utility maximization problem with respect to consumption that is two periods ahead (see also Chioda, 2004). By using two Euler equations, they show that measurement errors are differenced out in the Euler equation if they are independent of all other variables including consumption. The recent approach of Gayle and Khorunzhina (2017) also uses information on additional time periods that comes from habit formation in preferences. Their independence assumption is mild in the sense that they only assume independence between the growth rates of consumption and measurement errors. Without habit formation, however, this approach fails to identify the time discount factor.

Therefore, parameter set identified by our methods can be used as the test for assumptions set on existing methods. Testing the independence and distributional assumptions are important because they might be unreasonable in life-cycle consumption models. For example, measurement errors seem to depend on the level of consumption or the wealth of households. For example, the accuracy of the consumption measurement depends on the wealth of households, when poorer households tend to grasp their expenditure more clearly than wealthy households. Since a 10% measurement error at a high level of consumption is larger than that at a low level, households with higher expenses may have a much larger measurement error than those with lower expenses. Confidence sets for parameters satisfying moment conditions can be inferred by existing methods such as Chernozhukov, Hong, and Tamer (2007).

Preference parameters in life-cycle consumption models have been widely studied by using household panel data (see Attanasio & Weber, 2010 and the references therein). To the best of our knowledge, however, this is the first study adopting such models that focus on the impact of natural disasters on preference parameters. This study also contributes to the literature by revealing heterogeneous impacts of a disaster to households' preference parameters. We allow preference parameters to depend on households' future earthquake risks rather than how those households are affected by a specific disaster. This is because the extent to which a natural disaster affects households' preferences may also depend on the initial level of preference parameters. Households that face a similar future earthquake risk may tend to have similar risk preferences through residential sorting. In addition, We exclude possibilities of other paths such as belief updates and substantial income and property damage through which the economic behavior of households changes.

The remainder of this paper is organized as follows. In Section 2, we present the empirical background of the study. Section 3 presents the economic model. Sections 4 and 5 describe the analytical strategy and our estimator. All proofs for the propositions in these Sections are given in Appendix. In Section 6, we present the data. The empirical results are presented in Section 7. The conclusion and policy implications of the study are discussed in Section 8.

2 Empirical Background and Our Strategy

2.1 Hypothetical Questions and Field Experiments

The design of hypothetical questions and field experiments enables researchers to elicit a variety of deep parameters. These are widely adopted to study the effect of a large-scale disaster on preference parameters to identify the causal effect. However, at least three arguments remain controversial and not yet settled. First, households may face different budget constraints compared with individuals participating in experiments or responding to questionnaires. Economic decisions are often budget constrained, and a household's decision is made following agreement between its members. Even if just one member of the household increases his/her consumption, the other members may have to decrease their amount under the household's budget constraints. As a result, an individual change in the risk aversion parameter may not affect consumption in the economy. Therefore, it would be informative to analyze household data to derive households' preference parameters to understand their decisions and the consumption path of an economy after large-scale disasters.

Second, for respondents, answering hypothetical questions or attending experiments can be a special experience that biases their economic attitudes and behaviors. Several studies insist that the risk measures obtained by hypothetical survey questions or experiments are reliable predictors of actual risk-taking behaviors (e.g., Anderson & Mellor, 2009,Barsky, Juster, Kimball, & Shapiro, 1997,Donkers, Melenberg, & Van Soest, 2001,Dohmen, Falk, Huffman, & Sunde, 2012). However, collecting data by using hypothetical questions or experiments has also been criticized because of the gaps that appear between respondents' answers to the hypothetical questions and their actual economic behaviors as well as bias of respondents' behaviors that might arise from the special experimental environment.[3]

[3]For example, on the use of hypothetical questions, when evaluating non-market goods such as environmental goods, Hausman (2012) finds that when researchers elicit respondents' willingness to pay through questionnaires, there is a huge difference between their answers and the actual payment for the goods. One main reason for this difference is that

Third, field experiments are problematic for analyzing the effect of disasters when the treatment is difficult to define. To identify the causal effect, experimental studies divide the target population into treated and untreated groups. However, severe disasters may affect people not only physically, but also mentally. For example, as noted in the Introduction, Goebel et al. (2015) and Bauer et al. (2017) find that the Great East Japan Earthquake affected German risk attitudes, implying that seemingly uninvolved respondents are still affected when researchers define a large-scale disaster as the treatment.[4]

2.2 The Great East Japan Earthquake and Related Studies

The Great East Japan Earthquake hit the eastern coast of Japan on March 11, 2011. The earthquake caused a tsunami, which caused more than $15,800$ deaths, $2,500$ missing persons, $6,000$ injuries, $450,000$ evacuations, and the Fukushima nuclear accident. The disaster caused power outages and water shortages not only on the eastern coast of Japan but also in the areas surrounding Tokyo. These events were repeatedly broadcasted across Japan. Therefore, the Great East Japan Earthquake may have affected not only the households living in those areas hit by the disaster but also the entire population of Japan.

Sawada and Kuroishi (2016) investigate how risk and time preference parameters are differently affected by the level of housing damage. The authors conduct a field experiment after the disaster and find that the disaster affected the present bias parameter negatively. Hanaoka et al. (in press) focus on the link between individuals' hypothetically elicited risk aversion parameters and the seismic intensity of the earthquake experienced by them, finding that men who experience an earthquake of large seismic intensity become risk tolerant. Goebel et al. (2015) analyze the risk and political attitudes of Germans by using a questionnaire and find that the Great East Japan Earthquake and the subsequent disaster affected the risk attitudes of Germans. Bauer et al. (2017) find a significant causal decline in the prices of houses close to nuclear power plants in the wake of the Great East Japan

answers to hypothetical questions do not change respondents' lives in the real world. Studies that use experimental data are less likely to suffer from this hypothetical bias problem because researchers can modify the rewards given to participants according to their behavior in the experiment. However, experimental studies are still not free from bias. The special experimental environment can bias respondents' behaviors. For example, an experimental environment in which respondents earn and use money may make subjects behave differently from their daily lives because it does not necessarily reflect real-world consumption, saving, and budget constraints. In addition, respondents can change their behavior strategically to control the result of the experiment if they recognize the purpose of the study.

[4] From this view of the effect of a large-scale disaster, our study does not intend to identify the causal effects by defining treated and untreated households. To identify the causal effects of experiencing large-scale disasters, some authors focus on the causal change in household behavior that is theoretically related to preference parameters. For example, Berlemann, Steinhardt, and Tutt (2015) report that suffering from a flood causes individuals' saving to decrease. However, to understand the economy after a large-scale disaster, structural parameters would be more informative (e.g., Heckman, 2010).

Earthquake. This result indirectly supports the non-behavioral findings of Goebel et al. (2015) because if Germans changed their risk parameters as Goebel et al. (2015) point out, the shape of the housing price function should vary after the disaster. Ishino et al. (2012) and Sekiya et al. (2012) suggest that the psychological impact of the earthquake was not limited to individuals who physically experienced the disaster, showing that it also affected individuals facing future risks of similar large-scale disasters. Overall, although no studies directly analyze the preference parameters before and after the disaster by using household data, research adopting hypothetical questionnaires, experiments, and the analysis of housing price data implies that the disaster changed Japanese households' preference parameters.

2.3 Our Strategy

To focus on the finding that the Great East Japan Earthquake affected individuals facing future risks of similar large-scale disasters discussed above, we allow the preference parameters to vary with respect to the future earthquake risk of households. To allow these preference parameters to differ for households living in different potential earthquake risk areas, we use the localized moment restrictions directly implied by the Euler equation and adopt the local GMM estimator developed by Lewbel (2007). By localizing the moment conditions, we only assume that households that have similar characteristics hold the same information and the same prediction about their future.

To derive the earthquake risk measures, we use the data on probabilistic earthquake hazards published by the Japan Seismic Hazard Information Station (JSHIS). We adopt the probabilities that a location will be hit by a Japan Meteorological Agency (JMA) seismic intensity larger than 5 upper earthquake in the next 30 years.[5] Figure A.1 shows the relationship between the probabilistic seismic hazards of 2009 and 2012. Although the reported future risks faced by each household are not the same across these two years, the observed change in the future earthquake risk between before (2009) and after (2012) the earthquake is small. Since each household's future earthquake risk differs little across 2009 and 2012, the local moments capture the same households across these years, indicating that comparing the parameter estimates in 2009 and 2012 at a specific future risk is possible. Note that our estimation strategy allows belief (i.e., perceived risk) updates, meaning that preference changes do not come from updated perceived risk.

By exploiting the advantage of using household survey data, we focus on households whose properties are undamaged and examine how their preference parameters are affected by the earthquake. In particular, we estimate the preference parameters before and after the earthquake. We use short

[5]See the Data section for more details.

periods of data to avoid confusing the effect of the earthquake with other shocks. Chamberlain (1984) and Hayashi (1985) find that the use of short-period panel data requires imposing a complete market assumption to apply the Fubini theorem on the orthogonality condition.[6] The assumption that all households in Japan hold the same information and the same prediction about their future is, however, a strong one. Hence, introducing heterogeneous preference parameters depending on the future earthquake risk faced by households moderates this assumption.

3 Economic Model

To understand the extent to which households' tastes change through their preference parameters, we specify households' behavior by using life-cycle consumption models. We assume that a household chooses the intertemporal allocation of consumption and investment that maximizes its expected utility, is not subject to liquidity constraints, and has an additive budget over time. Further, utility is intertemporally additive, that is, it has no habit formation specification.

At time t, household i chooses (non-durable) current and future consumption $C_{i,t}$ and investment plan $Q_{i,t} = \sum_{j=1}^{N} A_{i,j,t}$, which is a summation of N assets $A_{i,j,t}$, to maximize the expected utility function given information set I_t available at time t. Households' expected utility maximization problem is

$$\max E\left[\sum_{t=0}^{\infty} \beta^t U(C_{i,t}, \omega_i, \gamma) \middle| I_{i,t}\right],$$

$$\text{s.t.} \qquad Q_{i,t+1} \leq Q_{i,t}(1 + R_{i,t}) + W_{i,t} - C_{i,t} \tag{1}$$

where $0 < \beta < 1$ is the discount factor, and $U(\cdot)$ represents a strictly concave utility function with the household fixed effect ω_i and utility curvature parameter $0 < \gamma < \infty$. The household's returns $R_{i,t}$ at time t consist of the weighted average returns of its assets, where the weight is quantity. W_t is labor income at time t.

The first-order condition of the maximization problem is

$$E\left[\beta(1 + R_{i,t+1})\frac{U'(C_{i,t+1}, \omega_i, \gamma)}{U'(C_{i,t}, \omega_i, \gamma)} - 1 \middle| I_{i,t}\right] = 0, \qquad (j = 1, \ldots, N) \tag{2}$$

[6] We set up the intertemporal optimization problem faced by each household. The Euler equation describes each household's consumption and saving path. The limitation of such data, however, restricts us to summing over time to obtain the sample analogue of the Euler equation. Individual households' intertemporal allocations of consumption and saving are modeled by Runkle (1991), for example.

where $U'(\cdot)$ is the first derivative of $U(\cdot)$ with respect to consumption. Households decide their intertemporal allocation of consumption and saving to hold the first-order condition.

Specifically, we assume the utility function to be the constant relative risk aversion (CRRA) type: $U(C_{i,t}, \omega_i, \gamma) = (1-\gamma)^{-1}(C_{i,t}^{1-\gamma} - 1)\exp(\omega_i)$. Since γ represents the Arrow–Pratt measure of relative risk aversion under CRRA utility, we call it the risk parameter.[7] The first derivative of the utility function is $U'[C_{i,t}, \omega_i, \gamma] = C_{i,t}^{-\gamma}\exp(\omega_i)$. Then, the first-order conditions (2) become

$$E\left\{ \beta(1+R_{i,t+1})\left(C_{i,t+1}/C_{i,t}\right)^{-\gamma} - 1 \,\middle|\, I_{i,t} \right\} = 0, \qquad (i = 1, \ldots, N). \tag{3}$$

The information set at time t consists of all the variables known by households, that is, $I_{i,t} = \{R_{i,s}, C_{i,s}, Z_{i,s}, \nu_{i,s}\}_{s=t_0}^{t}$, where Z_s is a vector of the variables observable by the researchers, $\nu_{i,s}$ represents the variables observable by the households but not the researchers, and t_0 is the initial period.

3.1 Belief Updates

The main question we consider concerns the occurrence of unexpected events such as natural disasters that influence the behaviors of economic agents. There are two potential paths through which an unexpected event affects household behaviors. Facing an influential unexpected event may first change the subjective beliefs in the occurrence frequency of such events. Second, it may change the preference parameters such as the discount factor β and risk averseness γ in utility. When an unexpected event changes the subjective beliefs and preference parameters, the optimal consumption path chosen to satisfy the first-order condition (3) before such an unexpected event is no longer optimal after the event.[8]

In this study, we allow our model to be flexible with respect to the belief update to focus on the preference parameters. We assume that households have homogeneous subjective beliefs about the future state, according to which they build their expectations. Households are adaptive to unexpected

[7] Assuming CRRA-type utility may be too restrictive, since all households are assumed to have identical preference parameters. We moderate this assumption by considering the varying coefficients model in which we allow the preference parameters to differ across households' characteristics.

[8] Formally, we define *belief* as the conditional distribution of the future state of the world. Suppose, for simplicity, that the future state of the world considered at time t is discrete and finite, which we denote as $s_t \in \{1, 2, \ldots, S\}$. Then, one's belief is the conditional probability of the future state is $P(s_t|I_t)$, where information set I_t includes all the information about the economic variables that are consequences of the realized state at time t. Equation (3) can be rewritten as $\sum_{s_t=1}^{S}\left[\beta(1+R_{t+1})(C_{t+1}/C_t)^{-\gamma} - 1\right] P(s_t|I_t) = 0$, for $i = 1, \ldots, N$, where future variables R_{t+1} and C_{t+1} are considered to be P-measurable real-valued functions defined on future states. A belief update caused by an event at time t indicates that the belief of a future state considered after the event at a certain time period is different from that considered in a state in which no such an event had taken place. From the above representation of the first-order condition, it is obvious that a future consumption path chosen without a belief update is different from that chosen with such an update.

events in the current time period that change their subjective beliefs about future states, which means that they adjust the allocation path after experiencing such an unexpected event.

Note that the observed data on the economic variables reflect the actual beliefs and preferences of households. Thus, under our model assumptions and given homogeneous subjective beliefs, the preference parameters can be obtained without any knowledge of the belief. Estimating the preference parameters before and after an unexpected event implicitly allows the beliefs to be different. Then, the preference differences captured by the estimation before and after the event are not the consequence of neglecting the possibility of a belief update.

4 Constant Coefficients Model

In this section, we consider the identification and estimation of the econometric model of the Euler equation (3) under which the preference parameters are implicitly assumed to be constant across all households. We moderate this assumption by allowing heterogeneous preference parameters in the next section.

Our baseline econometric model is implied by (3): for any observable subset of information set, say $Z_{i,t} \in I_{i,t}$, the law of iterated expectations yields

$$E\left\{ \beta(1+R_{i,t+1})\left(C_{i,t+1}/C_{i,t}\right)^{-\gamma} - 1 \,\middle|\, Z_{i,t} \right\} = 0, \qquad (i = 1, \ldots, N). \tag{4}$$

4.1 Measurement Error

Estimators based on the baseline econometric model (4) are not consistent when consumption data are contaminated by measurement errors. Thus, we explicitly define an econometric representation of the Euler equation by replacing unobserved true consumption with the observed consumption and measurement errors to deal with this problem.

Let true consumption, $C_{i,t}$, be observed with multiplicative error $\eta_{i,t}$, so that the observed consumption is given by $C_{i,t}^{\text{obs}} = C_{i,t}\eta_{i,t}$. The multiplicative measurement error of consumption is standard in the literature of life cycle consumption models. For notational simplicity, we denote the measurement error of log consumption by $\epsilon_{i,t} \equiv \log C_{i,t}^{\text{obs}} - \log C_{i,t} = \log \eta_{i,t}$.

Assumption 1 (Measurement error)**.** *For each household, $\epsilon_{i,t}$ is weak stationary.*

Assumption 1 does not require any independence between the errors and other variables. For example, it allows measurement errors to depend on the level of consumption, demographic characteristics, and even unobservable households' characteristics. Stationarity assumption also allows serial correlation of measurement errors that occurs if the household tends to over- or under-report the level of consumption. In existing methods, serial correlation of measurement errors are not allowed except in Gayle and Khorunzhina (2017).

Under Assumption 1, we can transform (4) into moment inequalities expressed in terms of the observed consumption:

$$E\left[\log\beta + \log(1+R_{i,t+1}) - \gamma\log\left(\frac{C^{\text{obs}}_{i,t+1}}{C^{\text{obs}}_{i,t}}\right) + \log g(Z_i) - \log E[g(Z_i)]\right] \leq 0, \tag{5}$$

for any measurable transition function $g(\cdot)$. The derivation of (5) is shown in the proof of Proposition 1 below.

Assumption 1 does not allow measurement errors to have time trend, which occurs when experiences of responding questionnaire mitigate measurement errors over time. Thus, we make an alternative assumption that arrows time trend in measurement errors. Inequality (5) can be derived under Assumption 2 below instead of Assumption 1.

Assumption 2. *For each household, $E(\eta_{i,t}/\eta_{i,t+1})$ exist and $E(\eta_{i,t}/\eta_{i,t+1}) \leq 1$ for all t.*

Assumption 2 does not require stationarity in $\eta_{i,t}$, so that $\eta_{i,t}$ are allowed to have any form of time trend. The cost of allowing errors to have a time trend is the restriction that expectation of (the inverse of) the growth in measurement errors is smaller than one, that is the case when measurement errors tend to increase over time. The restriction on the growth in measurement errors depends on the definition of the measurement error. If one assume a multiplicative variant of Berkson measurement error, say, $C_{i,t} = C^{\text{obs}}_{i,t}\eta_{i,t}$, the restriction become that $E(\eta_{i,t+1}/\eta_{i,t})$ is smaller than one, that is the case when measurement errors tend to decrease over time.

4.2 Identification

We now discuss the identification of preference parameters, that is, the discount factor β and risk parameter γ in (4). In particular, we show that the true parameters satisfying the baseline moment conditions (4), if they exist, belong to an informative parameter set consistent with the moment inequalities defined in (5).

Let $\theta = \{\beta, \gamma\}$. For notational simplicity, we define $\rho_{i,t}(\theta) = \beta(1+R_{i,t+1})\left(C_{i,t+1}/C_{i,t}\right)^{-\gamma}$ and $\rho^{\text{obs}}_{i,t}(\theta) = \beta(1+R_{i,t+1})\left(C^{\text{obs}}_{i,t+1}/C^{\text{obs}}_{i,t}\right)^{-\gamma}$. Then, our baseline model (4) can be expressed by $E(\rho_{i,t}(\theta) -$

$1|Z_{i,t}) = 0$, and the moment inequality (5) is $E\{\log \rho^{\text{obs}}_{i,t}(\theta) + \log g(Z_{i,t}) - \log E[g(Z_{i,t})]\} \leq 0$. Let the true preference parameter vector be $\theta^0 \equiv \{\beta^0, \gamma^0\}$, that is, $\theta^0 = \{\theta : E[\rho_{i,t}(\theta) - 1|Z_{i,t}] = 0\}$.

For the identification, we need the following assumptions in addition to Assumption 1 or 2.

Assumption 3 (Completeness)**.** *$E[\rho_{i,t}(\theta) - 1|Z_{i,t}] = 0$ implies $\rho_{i,t}(\theta) - 1 = 0$ almost surely (a.s.) for some t.*

Assumption 4 (Rank)**.** *$E[(1, C_{i,t+1}/C_{i,t})'(1, C_{i,t+1}/C_{i,t})]$ has full rank for all t.*

The completeness restriction in Assumption 3 is satisfied, for example, when the joint distribution of $\{C_{i,t}, C_{i,t+1}, R_{i,t+1}\}$ belongs to exponential families. Other sufficient conditions can be found, for example in Hu and Shiu (2017). Although the completeness assumption seems to be restrictive, existing works such as Gayle and Khorunzhina (2017) also assume completeness to identify the preference parameters in the Euler equation with habit-formed utility (see also the references in Gayle & Khorunzhina, 2017).

The rank condition in Assumption 4 requires the consumption growth rates to vary across households. The rank condition is violated, for example, when all households have equivalent consumption growth rates, meaning that the second moment of the consumption growth rate is equal to the square of its first moment.

Proposition 1. *Suppose Assumptions 1, 3, and 4 hold. Then, θ_0 is identified if $E(\rho_{i,t}(\theta_0) - 1|Z_{i,t}) = 0$. For any measurable function $g(\cdot)$, θ_0 belongs to the set of parameters satisfying (5).*

Proposition 2. *Proposition 1 hold under Assumptions 2, 3, and 4.*

The first statement in Proposition 1 about the identification of the preference parameters is not new. For example, Gayle and Khorunzhina (2017) shows the identification of the parameters in the Euler equation under habit forming utility by assuming the completeness and rank restrictions. We show the identification results to clarify the true parameter in which we are interested.

The second part of Proposition 1 states that the true parameter vector satisfying the Euler equation is consistent with the moment inequality (5). The results of Propositions 1 and 2 are useful in at least two senses. First, the parameter set satisfying these inequalities pins down the potential parameter space that contains the true parameters, which is obtained by using the information provided by the data and weak assumption on measurement errors. These initial results may help proceed further research, for example, by determining the initial optimization values. Second, our results can be used as a sensitivity analysis of other approaches, when a set of those assumptions used in such approaches nest our assumption set on the measurement errors. For example, one can check whether the point estimates of Alan et al. (2009) belong to the parameter set obtained by using our approach.

4.3 Estimation

We adopt the method developed by Chernozhukov et al. (2007) to derive the 95% confidence set for the preference parameters γ and β that satisfy the moment inequality (5).

Let $m_i(\theta)$ be the vector of the moment functions and Θ_I denote the parameter values that satisfy the moment restrictions, that is, $\Theta_\mathrm{I} = \{\theta : E[m_i(\theta)] \leq 0\}$. In our case, the moment restriction is (5). The confidence region is denoted as $C_n(c) \equiv \{\theta \in \Theta : nQ_n(\theta) \leq c\}$, where $Q_n(\theta) \equiv \| \max(n^{-1} \sum_{i=1}^n m_i(\theta), 0)\|^2$ and c is a consistent estimate of the α-quantile of $\sup_{\theta \in \theta_I} nQ_n(\theta)$. We follow the subsampling method of Chernozhukov et al. (2007) to obtain c, and calculate it by using $B_n = 100$ draws of subsamples of size $b = n/2$.[9] We begin with a starting value $\hat{c}_0$ of c.[10] We compute $\sup_{\theta \in C_n(c_0)} bQ_{j,b}(\theta)$ for each subsample $j = 1, \ldots, B_n$, where $Q_{j,b}(\theta)$ denotes the criterion function evaluated by using the jth subsample. Then, we calculate $\hat{c}_1$ as the α-quantile of these quantities. Similarly, we calculate $\hat{c}_2$ and $\hat{c}_3$. The critical value is set to be $c = \min(\hat{c}_1, \hat{c}_2, \hat{c}_3)$.

5 Varying Coefficients Model

We moderate the assumption of homogeneous preference parameters by using the localized Euler equation. For the localizing variables, say, W_i, we adopt different variables according to the aim of our analysis. These are the earthquake risk faced by household i and the seismic intensity that household i experienced during the Great East Japan Earthquake.

Instead of the constant risk parameters γ and β, we suppose that the risk parameters are a function of W. The utility maximization problem conditioned by $I_{i,t}$ and $W_{i,t}$ yields the Euler equation: $E[\beta(w)(1 + R_{i,t+1})(C_{i,t+1}/C_{i,t})^{-\gamma(w)} - 1|I_{i,t}, W_{i,t} = w] = 0$, which directly implies

$$E\{[\beta(w)(1 + R_{i,t+1})(C_{i,t+1}/C_{i,t})^{-\gamma(w)} - 1]|Z_{i,t}, W_{i,t} = w\} = 0, \tag{6}$$

[9] Since there is no general theory to choose the size of the subsample, we follow Gayle and Khorunzhina (2017). Another example is $n/4$, which is used by Ciliberto and Tamer (2009).

[10] We randomly choose 100 sets of the initial parameter values, which we denote $\bar{\Theta}$. The starting value $\hat{c}_0$ is chosen to be $\inf_{\theta \in \bar{\theta}} nQ_n(\theta)$. Attanasio and Weber (2010) review the literature on consumption-based estimates of the relative risk aversion parameter and show estimates that range between 1 and 3. Less empirical evidence has been accumulated for the discount factor, since it is not identified by using the conventional log-linear method. According to Alan et al., 2009, who provide a rare example, β is around 0.95, and it is not plausible for β to be close to zero. Therefore, each $\theta \in \bar{\Theta}$ is randomly chosen from $[0.5, 1]$ for β and $[1, 3]$ for γ.

for $Z_{i,t} \in I_{i,t}$. Equation (6) is the localized variant of the baseline model (4). Note that equation (6) is directly implied by the first-order condition (3) as long as the localizing variable W_i is in the household's information set. Otherwise, the population of interest should be those with a localizing variable equal to w.

We derive the moment inequalities evaluated by the observed consumption when consumption is contaminated by multiplicative measurement errors. In particular, we derive the moment restriction under Assumption 1 or 2, in which neither independence restriction nor distributional assumptions are set on the measurement errors. Under Assumption 1 or 2, we can transform (6) into moment inequalities expressed in terms of the observed consumption:

$$E\left\{\log \beta(w)(1+R_{i,t+1}) - \log E[g(Z_{i,t})|W_{i,t}=w] - \gamma(w)\log\left(\frac{C^{\text{obs}}_{i,t+1}}{C^{\text{obs}}_{i,t}}\right) + \log g(Z_{i,t}) \middle| W_{i,t}=w\right\} \leq 0. \tag{7}$$

The derivation of (7) is shown in the proof of Propositions 3 and 4.

The identification of the preference parameters that satisfy (6) is analogous to that in the constant coefficients model described above. In particular, we show that the true parameters satisfying (6), if they exist, belong to an informative parameter set consistent with the moment inequality defined in (7).

Let $\theta(w) = \{\beta(w), \gamma(w)\}$. Then, our baseline moment restriction (6) can be expressed by $E[\rho_{i,t}(\theta(w)) - 1|Z_{i,t}, W_{i,t} = w] = 0$, and the moment inequality (7) can be expressed by $E\{\log \rho^{\text{obs}}_{i,t}(\theta(w)) + \log g(Z_{i,t}) - \log E[g(Z_{i,t})|W_{i,t} = w]\} \leq 0$. Let the true preference parameter vector be $\theta^0(w) \equiv \{\beta^0(w), \gamma^0(w)\}$, that is, $\theta^0(w) = \{\theta(w) : E[\rho_{i,t}(\theta(w)) - 1|Z_{i,t}, W_{i,t} = w] = 0\}$.

The identification of the varying coefficients model is given in Propositions 3 and 4 below. To identify the varying coefficients model, we need the following assumption, which is a localized variant of Assumption 3.

Assumption 5 (Local Completeness). *$E[\rho_{i,t}(\theta(w)) - 1|Z_{i,t}W_{i,t} = w] = 0$ implies $\rho_{i,t}(\theta(w)) - 1 = 0$ a.s. for some t.*

Proposition 3. *Suppose Assumptions 1, 4, and 5 hold. Then, $\theta_0(w)$ is identified if $E[\rho_{i,t}(\theta(w)) - 1|W_{i,t} = w] = 0$. Moreover, $\theta_0(w)$ belongs to the set of parameters satisfying (7).*

Proposition 4. *Proposition 3 holds under Assumptions 2, 4, and 5.*

The 95% confidence set for the preference parameters γ and β that satisfy the moment inequality

(7) can be derived by adopting the method developed by Chernozhukov et al. (2007). The derivation of the confidence set is the same as that in the constant coefficients model explained above except that the conditional expectation is estimated by using non-parametric kernel methods.

6 Data

6.1 Data Sources

Five data sources are used in this study. The first is KHPS data, which include household behavior and information on households' assets. The second data source is the average interest rates of deposits posted at financial institutions by type of deposit from 2007 to 2015. These data are available from the website of the Bank of Japan. The third data source is the average price and yield of securities, which is published by the Tokyo Stock Exchange. The fourth is the probabilistic seismic hazard data published by the JSHIS. The fifth data source is the observed seismic intensity caused by the Great East Japan Earthquake.

The KHPS is a panel survey of household behavior and social attitudes that has been conducted since 2004. The survey respondents of the KHPS are selected by two-stage stratified sampling. The number of survey respondents was $4,005$ in 2004. The KHPS added new cohorts in 2007 and 2012 ($1,419$ respondents in 2007 and $1,012$ respondents in 2012). The survey subjects of the KHPS are men and women aged 20 to 69. The KHPS data consist of information on households' consumption, saving, security, debt, socio-demographic characteristics, and city of residence. The survey is conducted in January, and respondents are asked to report consumption details for January and their current saving, security, debt, and socio-demographic characteristics.

6.2 Data Used in the Study

The findings of Sekiya et al. (2012), Ishino et al. (2012), Goebel et al. (2015), and Bauer et al. (2017) imply that the Great East Japan Earthquake affected not only those individuals who experienced the earthquake, tsunami, and nuclear accident but also who did not. To analyze the indirect effect of the disaster, we do not limit our focus to households living in eastern Japan. Our data thus covers households across Japan.

We are interested in the effect of experiencing an earthquake on the preference parameters. From our economic model, households that have different statuses are assumed to face different future wage paths. Therefore, we focus on households expected to face a similar economic environment. First, we focus on data on nuclear families with at least one child from 2007 to 2015. We retain those households with a working age head during the sample periods, namely a household head no older than 51 and no younger than 16 in 2007. Second, following Attanasio and Weber (1995) and Vissing-Jørgensen (2002), we drop observations for which the observed income and consumption growth ratio is less than 0.2 or above five (73 households) to exclude obvious reporting and coding errors. Third, we exclude any households that may be liquidity constrained in the sample periods. Following Alan et al. (2009), we also exclude households that have no saving (186 households). Fourth, we remove households whose properties were substantially damaged by the earthquake (one household).[11]

While the exclusion of households with an abrupt consumption growth ratio is standard in the literature, such an exclusion according to income and properties may be non-standard. Under the permanent income or risk-sharing hypotheses, unexpected income shocks do not affect household consumption. However, empirical studies using Japanese datashow skeptical evidence of the risk-sharing hypothesis, especially when households are liquidity constrained. For example, Kohara, Ohtake, & Saito, 2006, Ichimura, Sawada, & Shimizutani, 2008, and Sawada & Shimizutani, 2008 provide empirical evidence using Japanese data, while Ogaki & Zhang, 2001 and Zhang & Ogaki, 2004) test the risk-sharing and permanent income hypotheses. Therefore, we concentrate on those households whose economic environment was not substantially affected by the earthquake and who were not liquidity constrained.

We remove households that did not submit the questionnaire at least once from 2007 to 2015. The original sample size was $2,864$ for 2007, $3,691$ for 2008, $3,422$ for 2009, $3,207$ for 2010, $3,030$ for 2011, $2,865$ for 2012, $3,568$ for 2013, $3,305$ for 2014, and $3,124$ for 2015. The number of households that submitted all questionnaires in the period is $2,658$. The number of nuclear family households that satisfy the conditions stated above is 278. The first and second panels of Table 1 present the summary statistics of the household characteristics in 2009 and 2012, respectively.

6.3 Consumption

For the composition of consumption, we follow Hall (1978) and the empirical evidence presented by Khvostova, Larin, and Novak (2016) and Gayle and Khorunzhina (2017). Our consumption includes non-durable consumption and services, which is a standard definition used in time-separable utility models (e.g., Attanasio & Weber, 1995, Vissing-Jørgensen, 2002, and Alan, 2012). Household consumption is the sum of expenditure on food consumed at home and away from home, lighting, heating,

[11] In particular, we exclude households whose houses fully or partially collapsed.

Table 1: Summary statistics of the data used in the study

	mean	median	std.dev	min	max
2009					
Age of the household head	42.04	5.73	42	29	52
Number of children	2.01	0.69	2	1	5
Saving	606.49	712.37	400	20	5252
Annual Income	816.24	397.67	736	179	4065
2012					
Age of the household head	45.04	5.73	45	32	55
Number of children	2.03	0.71	2	1	5
Saving	694.96	832.19	460	5	6940
Annual Income	822.47	330.52	750	180	1900
Consumption Rate					
C_{2009}/C_{2008}	1.050	0.337	1.009	0.102	2.903
C_{2010}/C_{2009}	1.025	0.293	0.980	0.481	2.767
C_{2013}/C_{2012}	1.054	0.297	1.019	0.374	3.000
C_{2014}/C_{2013}	1.062	0.271	1.013	0.402	2.186
Return					
R_{2009}	-0.002	0.009	0.002	-0.046	0.002
R_{2010}	-0.014	0.032	0.001	-0.172	0.001
R_{2012}	0.032	0.073	0.000	0.000	0.401
R_{2013}	0.001	0.003	0.000	0.000	0.015

water, fuel, public transport, and communication services. Data on consumption are deflated by using the consumer price index at the prefecture level.[12]

In contrast to a large number of studies that use Panel Study of Income and Dynamics (PSID) such as Shapiro (1984), Runkle (1991), Alan et al. (2009), and Alan and Browning (2010), we do not focus on food consumption. A notable reason is that the utility function we adopt does not have a habit formation specification, meaning that current consumption affects utility only in the current period. Gayle and Khorunzhina (2017) use the PSID and show that habit formation is an important determinant of food consumption patterns. Alternatively, Khvostova et al. (2016) use Russian panel data that contain rich information on non-durable consumption other than food and find that habit formation is not significant. Therefore, we follow the results of Khvostova et al. (2016) to compose consumption.[13]

[12] https://www.e-stat.go.jp/SG1/estat/eStatTopPortal.do.

[13] A growing body of the literature has offered empirical evidence of habit formation for consumption. The existence of habit formation is inconclusive, however, and may depend on the types of consumption and data sets used. For example, Dynan (2000) finds no habit formation on foods by using the PSID, Carrasco, Labeaga, and J David (2005) and Browning and Collado (2007) show habit formation for food but a non-significant habit pattern in transport by using Spanish panel data, Leth-Petersen (2007) shows habit formation for gas for heating by using Danish panel data, and Guariglia and Rossi (2002) show habit patterns in food consumption by using British panel data. However, the empirical results of Khvostova et al. (2016) and Gayle and Khorunzhina (2017) are obtained by adopting measurement

The third panel of Table 1 shows the descriptive statistics for the growth rates of consumption. The mean consumption rates are stable over time, showing that consumption is smoothed. When we examine the subtle difference before and after the earthquake, we find that the consumption growth rate before 2011 is slightly lower, which suggests that households show risk tolerance and/or lower discounting behavior.

6.4 Household-Specific Returns

Household-specific returns $R_{i,t}$ are calculated by using the average interest rates of deposits data, average price and yield data, and households' saving and asset amounts included in the KHPS data.

The average interest rates of deposits data show the average interest rate of the Bank of Japan's clients.[14] We calculate households' interest rates for deposits by using the average interest rates of deposits data, which include the average interest rates for three deposit amounts: less than $300,000$ JPY, from $300,000$ to $1,000,000$ JPY, and more than $1,000,000$ JPY. Households' interest rates for deposits are calculated as

$$\begin{aligned} r_{i,saving,t} = &\ \mathbb{1}\{saving_{i,t} < 300,000 \text{ JPY}\} r(300,000,t) \\ &+ \mathbb{1}\{300,000 \text{ JPY} \leq saving_{i,t} < 1,000,000 \text{ JPY}\} r(1,000,000,t) \\ &+ \mathbb{1}\{1,000,000 \text{ JPY} \leq saving_{i,t}\} r(1,000,000+,t), \end{aligned} \tag{8}$$

where $r(300,000,t)$ is the average interest rate for a deposit for which the amount is less than $300,000$ JPY when time is equal to t, $r(1,000,000,t)$ is the average interest rate for a deposit for which the amount is more than $300,000$ but less than $1,000,000$ JPY when time is equal to t, and $r(1,000,000+,t)$ is the average interest rate for a deposit for which the amount is less than $1,000,000$ JPY when time is equal to t.

The average price and yield data published by the Tokyo Stock Exchange consist of average yield for securities traded in the first and second sections of the Exchange. In this study, we use the annual average price and yield of securities, say, $r_{i,security,t}$, which are the weighted average of the monthly average price and yield as the return to securities.

error-robust methods, which are not used in other works. They are also the earliest studies using the exact Euler equation non-linear GMM method that no distributional assumption on the measurement errors is set. Therefore, we follow their results.

[14]These include city banks, regional banks, the second association of regional banks, trust banks, credit unions, and the Shoko Chukin bank. City banks include Mizuho Bank, Bank of Tokyo-Mitsubishi UFJ, Sumitomo Mitsui Banking Corporation, Resona Bank, and Saitama Resona Bank. Regional banks are member banks of the Regional Banks Association of Japan. Trust banks are those that in addition to banking businesses operate trust businesses based on the Act on Provision, etc. of Trust Business by Financial Institutions and are not categorized as city or trust banks.

Then, individual return R_i is calculated as

$$R_{i,t} = r_{i,saving,t}\frac{A_{i,saving,t}}{A_{i,saving,t} + A_{i,security,t}} + r_{i,security,t}\frac{A_{i,security,t}}{A_{i,saving,t} + A_{i,security,t}}, \tag{9}$$

where $A_{i,saving,t}$ is household i's saving at time t and $A_{i,security,t}$ is household i's securities at time t. The fourth panel of Table 1 shows the descriptive statistics of individual returns.

6.5 Future Earthquake Risk

The effect of the shock caused by the Great East Japan Earthquake can differ depending on the future earthquake risks faced by households. To capture this difference, we allow the discount rate and risk preference parameters to differ with respect to earthquake risk.

Table 2: JMA seismic intensity scale

	JMA seismic intensity	
	5 Upper	6 Lower
Human perception and reaction	Many people find it difficult to move; walking is difficult without holding onto something stable.	It is difficult to remain standing.
Wooden houses		
High earthquake resistance		Slight cracks may form in walls.
Low earthquake resistance	Cracks may form in walls.	Cracks are more likely to form in walls. Large cracks may form in walls. Tiles may fall, and buildings may lean or collapse.
Reinforced-concrete buildings		
High earthquake resistance		Cracks may form in walls, crossbeams, and pillars.
Low earthquake resistance	Cracks may form in walls, crossbeams, and pillars.	Cracks are more likely to form in walls, crossbeams, and pillars.

Source: http://www.jma.go.jp/jma/en/Activities/inttable.html

To measure the future earthquake risk, we use the probabilistic seismic hazard data published by the JSHIS. We adopt the probabilities that a location will be hit by a JMA seismic intensity larger than 5 upper (hereafter 5 upper) earthquake and JMA seismic intensity larger than 6 lower (hereafter 6 lower) earthquake in the next 30 years as the earthquake risk for each household. JMA seismic intensity is the measure of the seismic intensity at a particular location, which ranges from 0 to 7. The value is mainly related to land acceleration caused by the earthquake. Table 2 describes the seismic intensity 5 upper and 6 lower.

We use the probabilistic seismic hazard data of the JSHIS. The JSHIS website provides a user-friendly digital hazard map of these data, which can be accessed by households. Moreover, earthquake risks are routinely announced in Japan. Therefore, it is reasonable to assume that households have sufficient information about earthquake risks.[15] Since the KHPS data provide information on the city in which respondents live, we calculate the probabilistic seismic hazard for each household by using the Geographic Information System of the University of Tokyo.[16] Figure A.2 presents the geographic distributions of future earthquake risks.

Figure A.3 illustrates mean consumption. The left-hand figure shows the mean consumption conditional on the probability of being hit by a 5 upper future earthquake risk, while the right-hand figure shows that conditional on a 6 lower risk. These figures show that the change in consumption before and after the earthquake is heterogeneous. Households that face a lower earthquake risk decrease their consumption, while those that face a higher risk increase their consumption on average. This finding suggests that the heterogeneous effects of earthquakes on the preference parameters vary according to the future earthquake risks faced by households.

7 Results

In this section, we present the estimation results for the constant and varying coefficients models. We use the number of children and earthquake risks (5 upper and 6 lower) as instrumental variables.

We first present the estimation results of the GMM-D and GMM-LN estimators proposed by Alan et al. (2009) to study the average effect of the disaster. Then, we present the results of the localized GMM-D and GMM-LN estimators to study the heterogeneity of the disaster's impact. In the local GMM analysis, the 5 upper probabilistic seismic hazard measure is adopted as the localizing variable.

GMM-D and GMM-LN are measurement error-robust estimators derived from the moment conditions (4) and (6). The GMM-D estimator assumes measurement errors to be stationary and independent of all components in the information set including the lagged value of measurement errors, consumption, interest rate, and instruments. In addition to stationarity and independence, the GMM-LN estimator requires the measurement error to follow a normal distribution with the same variance across households. To check the validity of these assumptions on the measurement errors, we present

[15] It may be more appropriate to use the subjective future earthquake risk perceived by households, because the perception of objective risk would differ across households. It would thus be interesting to investigate whether future risk perception relative to objective risk can explain the risk aversion parameter with respect to consumption and investment allocation. This is left for future research.

[16] http://newspat.csis.u-tokyo.ac.jp/geocode/.

the confidence sets derived from the moment inequalities (5) and (**??**) for the constant coefficients models and (7) and (**??**) for the varying coefficients models. Note that our moment inequality approaches require milder assumptions on the measurement errors. Therefore, when the GMM-D and GMM-LN estimates lie outside the confidence sets, we can conclude that the results are unreliable.

The bandwidths for the non-parametric kernel estimation of the localized models are obtained by using an iteration procedure. First, the parameters for a specific value of the localizing parameter $W = w$ are obtained from the local GMM estimation, which we denote $\hat{\theta}_1(w)$. In particular, we adopt continuously updating GMM (CUGMM) to obtain the estimates, as suggested by Hansen, Heaton, and Yaron (1996). Second, the local GMM objective function is regarded as a function of the bandwidths by plugging $\hat{\theta}_1(w)$, and we find bandwidths that minimize the objective function. We denote the minimizer by $\hat{h}_1$. Third, we obtain $\hat{\theta}_2(w)$, which is the local CUGMM estimates by using $\hat{h}_1$. Iterating the second and third steps derives bandwidth $\hat{h}_M$ and the following local CUGMM estimator $\hat{\theta}_{M+1}(w)$. We iterate $M = 10$ times to obtain our results.

Table 3: Estimation of Euler equation

	$\hat{\beta}$		$\hat{\gamma}$		$\hat{\nu}$		*value*	
	2009	2012	2009	2012	2009	2012	2009	2012
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GMM-D	0.990	0.990	2.639	7.607			0.185	0.000
	(0.079)	(0.385)	(0.628)	(0.704)			reject	accept
GMM-LN	0.990	0.990	3.204	5.251	0.028	0.024	0.520	0.000
	(0.112)	(0.137)	(0.610)	(0.528)	(0.013)	(0.013)	reject	accept

Note: Standard errors are in parentheses. Tests in columns (7) and (8) are rejected when the test statistics exceed 0.073 and 0.017, respectively.

7.1 Results of the Constant Coefficients Model

Table 3 presents the estimation results for the preference parameters in the Euler equation of the constant coefficients models. The estimated values and standard deviations of the parameters are presented in columns (1)–(6). In columns (7) and (8), the values of the test statistics for the 95% confidence set and test results are shown. Figure A.4 illustrates the relationship between the confidence set and estimated parameter values. For the 95% confidence sets derived from the moment inequalities, the estimated parameters of the GMM-D and GMM-LN estimators are not included in the set in 2009. After the earthquake, the GMM-D and GMM-LN parameters are included in the confidence set. However, it is not possible to compare the parameters before and after the earthquake because both the 2009 and the 2012 results are not accepted according to the test for measurement errors. To study the heterogeneity and analyze households that do not violate the confidence set, we therefore conduct a local GMM analysis to examine the difference in detail.

7.2 Results of the Varying Coefficients Model

7.2.1 Estimation results

We adopt the future earthquake risk (5 upper) variable as the localizing variable and estimate the parameters at equally spaced 99 points in the $[0.01, 0.99]$ interval.

Table 4: Test for measurement error

localizing points	[0.01, 0.24] (1)	[0.25, 0.49] (2)	[0.50, 0.74] (3)	[0.75, 0.99] (4)
local GMM-D				
2009	0.00	0.08	1.00	1.00
2012	1.00	1.00	1.00	1.00
local GMM-LN				
2009	0.32	0.24	1.00	1.00
2012	1.00	1.00	1.00	1.00

Note: Proportion of localizing points where estimated parameters are included in 95% confidence set.

Table 4 presents the summary statistics of the test for measurement errors.[17] We calculate the proportion of localizing points where the estimated parameters are included in the 95% confidence set. For example, column (1) shows the proportion of localizing points in the interval $[0.01, 0.24]$ (24 points) where the estimated parameters are included in the 95% confidence set. The specification of local GMM-D and GMM-LN is rejected for about half the localizing points in 2009. However, in the interval $[0.50, 0.99]$ in columns (3) and (4), the estimated parameters are included in the 95% confidence sets at all localizing points. In this interval, our moment inequality does not reject the additional distributional assumptions imposed on the GMM-D and GMM-LN estimators. Therefore, we concentrate on the results localized at the points in the $[0.50, 0.99]$ interval.

Figure A.5 presents the estimation results of GMM-D. The discount factor parameters β in the left-hand panel of Figure A.5 suggest that households whose risk runs from 0.7 to 0.8 had a lower discount rate in 2009. In 2012, the discount factor of these households increased. However, the 95% confidence intervals of the estimated discount factor overlap, which suggests that the change in parameter might not be statistically significant. Overall, it is difficult to conclude that a subpopulation changed its discount factor because the observed parameter changes are small compared with the standard errors.

[17]Complete results are provided in the Appendix.

For the risk aversion parameters of GMM-D in the right-hand panel of Figure A.5, households whose future earthquake risk is above 0.5 become risk averse after the earthquake. Figure A.5 shows that the 95% confidence intervals in 2009 and 2012 do not overlap for most households. In particular, in 2012, households whose earthquake risk runs from 0.8 to 0.9 had high $\hat{\gamma}$ values compared with households whose risk is outside this interval. The estimated values suggest that earthquakes make most households risk averse. In particular, households facing a higher risk of earthquakes became more risk averse than other households.

Figure A.6 presents the estimation results of GMM-LN. The estimated value of GMM-LN is similar to that of GMM-D. There are few differences in the discount factors before and after the earthquake (see the left-hand panel of Figure A.6). From the risk aversion parameter in the right-hand panel of Figure A.6, households facing a high risk of a future earthquake became more risk averse than other households. The only exception is that the 95% confidence intervals for households facing a $[0.95, 1.0]$ risk overlap. An additional difference is the smaller standard error of GMM-LN compared with GMM-D.

The varying coefficients model thus reveals the heterogeneous effects of the disaster on households' parameters. The estimated values suggest that the parameter changes of some subpopulations are larger than others. The estimated parameter change suggests that households living in regions at risk of an sivere earthquake are more risk averse than those living in safer areas. In other words, households facing a relatively high earthquake risk are more affected by earthquakes compared with others. The observed parameter change is consistent with the empirical results reported by Goebel et al. (2015) and Bauer et al. (2017). Hence, our results support the findings of studies that report a change in the time or risk preference parameters. While other unexpected events occurred in 2011 could have made households risk averse, the observed heterogeneity of the risk preference change, which was also observed in Germany, suggests that the disaster affected risk preferences to some extent.

We next conduct a simple simulation study. We compare the conditional mean of actual consumption with that of predicted consumption for 2013. To calculate the conditional mean, we adopt earthquake risk as the localizing variable as before. We predict the non-durable consumption of each household by using the Euler equation with an estimated value of β and γ before and after the earthquake, the actual amount of non-durable consumption in 2012, and the interest rates. Figure A.7 presents the conditional mean of actual and predicted consumption expenditure. Overall, these predictions overestimate the actual consumption of households whose risk score is around 0.5, while they underestimate the actual consumption of households whose risk score is around 0.9 regardless of the information adopted in the prediction. In the GMM-D setup presented in the upper three panels of Figure A.7, the parameters after the earthquake (the middle panel) predicts the consumption expenditure of households precisely when risk scores run from 0.6 to 0.8. By contrast, the parameters before the earthquake (the left panel) severely underestimates the consumption of households whose risk score is around 0.6 and above 0.8. A similar tendency is also observed for the GMM-LN prediction in the lower three panels of Figure A.7. However, there is little difference in the predicted consumption for the GMM-LN prediction. To sum up, although the predictions using parameters after the earthquake do not uniformly dominate those based on parameters beforehand, the parameters after the earthquake can be used to avoid the serious under- or overestimation of consumption after the disaster.

8 Conclusion

In this study, we analyzed the risk preference parameters and discount factors before and after the Great East Japan Earthquake to answer the three main questions that hypothetical data and experimental studies reporting evidence of preference changes fail to address sufficiently. These questions are (i) is it sufficient to analyze individual-level data, (ii) do studies that use hypothetical questions or experiments provide reasonable results, and (iii) does a large-scale disaster affect only those individuals who directly suffer from it? To answer these three questions, we adopted household panel data and a structural model to estimate the preference parameters. Further, to analyze the effect of the disaster and avoid confusing parameter changes caused by it and other macroeconomic shocks, we used a local GMM estimator. Our results are robust to the measurement error of reported consumption. While the parameters based on constant coefficient models are not included in the 95% confidence set derived from the measurement error-robust moment inequality approach, we found one subpopulation that does not violate the moment inequality. We then limited ourselves to analyze the localizing points where the moment inequality is not violated, finding that households globally became risk averse after the Great East Japan Earthquake. However, households living in high-risk areas became drastically risk averse, whereas those living in very high-risk areas did not show such a drastic change in risk averseness. Our results are thus consistent with those of existing works such as Goebel et al. (2015) who adopt a questionnaire to elicit risk aversion.

In addition, we observed preference parameter changes, again consistent with existing works. While Hanaoka et al. (in press) find a subpopulation who become risk tolerant after the Great East Japan Earthquake, we found one that became risk averse. Our result is nevertheless consistent with Hanaoka et al. (in press) in the sense that both studies show evidence that a subpopulation changed its risk parameter after the Great East Japan Earthquake. Although such parameter changes caused by large-scale disasters have been reported by studies based on hypothetical questions, no research has thus far provided evidence of a preference change by using structural models and household behavioral data. Further, the observed sign of the parameter change is consistent with Goebel et al. (2015), who find that the disaster affected risk attitudes in Germany. The similarity between our result and those of Goebel et al. (2015) and Hanaoka et al. (in press) provides a suggestion to the first research question above (question (i)). Studying individual data may be insufficient to predict changes in households' risk preferences. In answer to question (ii), hypothetical questions or experiments are useful when researchers are interested in whether a large-scale disaster affect respondents' minds. However, the effect of the disaster on questionnaire responses and behavior in experiments is not always the same as real-life economic behavior. Additional evidence would thus be required. In answer to question (iii), a large-scale disaster affects not only those individuals who suffer from it directly, but also individuals facing a high risk of a similar disaster.

The policy implications of our findings are clear. Since preference parameters can change after a large-scale disaster even if the disaster does not damage households' lives or property directly, policymakers must consider preference changes after a large-scale disaster when evaluating the effect of a policy implemented after its occurrence. Our simulation results suggest that predictions based on parameters derived from ex-ante analyses can seriously underestimate household consumption after a disaster. Additionally, both our results and existing works such as Hanaoka et al. (in press) and Goebel et al. (2015) suggest that policymakers can improve recovery policy by accounting for the characteristics of the target population. Specifically, households facing a high risk of a similar disaster become more risk averse compared with others. However, for households whose risk score is around 0.5, the parameters estimated before the earthquake provide a slightly better prediction of consumption expenditure.

Our results also suggest that experimental social sciences studies may be biased. It is common to consider that unexpected events such as natural disasters do not affect untreated objects, except for objects theoretically proven to interact with the treated objects such as land prices and neighboring households. However, our results suggest that a huge disaster can affect seemingly untreated individual or household behavior differently. Therefore, ignoring the indirect effect of such unexpected events can bias the analysis.

Finally, we discuss the limitations of this study and future research directions. First, we focused on nuclear households that have at least one child. Whether the Great East Japan Earthquake and other large-scale disasters affect households with different characteristics in the same manner is unclear. Second, our strategy did not identify the causal change induced by the Great East Japan Earthquake even though the observed heterogeneity after the disaster implies causality. Therefore, developing a method that can identify the causal change in the structural parameters of economic models would be ideal (e.g., Heckman, 2010). Third, we used short-period panel data to estimate the parameters by using the Euler equation to focus on the effect of the earthquake. While we moderated the assumption by adopting localized moment conditions, it would be ideal to use long-term panel data in the estimation.

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Appendix

Proof of Propositions 1 and 2

Proof. We first show the identification of θ_0. Consider that $\bar{\theta}_0 \equiv \{\bar{\beta}_0, \bar{\gamma}_0\}$ also satisfies $E(\rho_{i,t}(\bar{\theta}_0) - 1|Z_{i,t}) = 0$. Then, Assumption 3 implies $\rho_{i,t}(\theta_0) = \rho_{i,t}(\bar{\theta}_0)$ a.s. Taking the logs of both sides yields $\log(\beta_0/\bar{\beta}_0) - (\gamma_0 - \bar{\gamma}_0)\log\left(C_{i,t+1}/C_{i,t}\right) = 0$ a.s. Multiplying $\log\left(C_{i,t+1}/C_{i,t}\right)$ for both sides yields $\log(\beta_0/\bar{\beta}_0)\log\left(C_{i,t+1}/C_{i,t}\right) - (\gamma_0 - \bar{\gamma}_0)[\log\left(C_{i,t+1}/C_{i,t}\right)]^2 = 0$ a.s. Then, the rank restriction in Assumption 4 implies $\beta_0 = \bar{\beta}_0$ and $\gamma_0 = \bar{\gamma}_0$.

We now show that θ_0 belongs to the parameter set satisfying (5). Applying the law of iterated expectations to (4) yields $E\{[\rho_{i,t}(\theta_0) - 1]g(Z_t)\} = 0$ for any measurable transition function $g(\cdot)$. According to the definition of measurement errors in consumption, we have $\log C_{i,t+1}/C_{i,t} = \log C^{obs}_{i,t+1} - \log C^{obs}_{i,t} + \log\left(\eta_{i,t}/\eta_{i,t+1}\right)$. Under Assumption 1, we have $E[\log\left(\eta_{i,t}/\eta_{i,t+1}\right)] = E(\epsilon_{i,t} - \epsilon_{i,t+1}) = 0$ and under Assumption 2 we have $E[\log\left(\eta_{i,t}/\eta_{i,t+1}\right)] \leq \log E[(\eta_{i,t}/\eta_{i,t+1})] \leq 0$. By using these and from the concavity of the logarithm function and Jensen's inequality, we obtain

$$\begin{aligned}
\log E[\rho_{i,t}(\theta_0)g(Z_{i,t})] &= \log E[g(Z_{i,t})] \\
E[\log\beta_0(1+R_{i,t+1}) - \gamma_0\log\left(C_{i,t+1}/C_{i,t}\right) + \log g(Z_{i,t})] &\leq \log E[g(Z_{i,t})] \\
E[\log\beta_0(1+R_{i,t+1}) - \gamma_0\log\left(C^{\text{obs}}_{i,t+1}/C^{\text{obs}}_{i,t}\right) - \gamma_0\log\left(\eta_{i,t}/\eta_{i,t+1}\right) + \log g(Z_{i,t})] &\leq \log E[g(Z_{i,t})] \\
E[\log\beta_0(1+R_{i,t+1}) - \gamma_0\log\left(C^{\text{obs}}_{i,t+1}/C^{\text{obs}}_{i,t}\right) + \log g(Z_{i,t}) - \log E[g(Z_{i,t})]] &\leq 0.
\end{aligned}$$

This shows that θ_0 belongs to the parameter set satisfying (5). □

Proof of Propositions 3 and 4

Proof. We first show the identification of $\theta_0(w)$. Consider that $\bar{\theta}_0(w) \equiv \{\bar{\beta}_0(w), \bar{\gamma}_0(w)\}$ also satisfies the baseline local moment restriction, that is, $E[\rho_{i,t}(\bar{\theta}_0(w)) - 1|Z_{i,t}, W_{i,t} = w] = 0$. Then, Assumption 5 implies $\rho_{i,t}(\theta_0(w)) = \rho_{i,t}(\bar{\theta}_0(w))$ a.s. Taking the logs of both sides yields $\log(\beta_0(w)/\bar{\beta}_0(w)) - (\gamma_0(w) - \bar{\gamma}_0(w))\log\left(C_{i,t+1}/C_{i,t}\right) = 0$ a.s. Multiplying $\log\left(C_{i,t+1}/C_{i,t}\right)$ for both sides of this equation yields $\log(\beta_0(w)/\bar{\beta}_0(w))\log\left(C_{i,t+1}/C_{i,t}\right) - (\gamma_0(w) - \bar{\gamma}_0(w))[\log\left(C_{i,t+1}/C_{i,t}\right)]^2 = 0$ a.s. The rank restriction in Assumption 4 implies $\beta_0(w) = \bar{\beta}_0(w)$ and $\gamma_0(w) = \bar{\gamma}_0(w)$.

We now show that $\theta_0(w)$ belongs to the parameter set satisfying (7). Applying the law of iterated expectations to (6) yields $E\{[\rho_{i,t}(\theta(w)) - 1]g(Z_{i,t})\mathbb{1}[W_{i,t} = w]\} = 0$ for any transition function $g(\cdot)$, where $\mathbb{1}[W_{i,t} = w]$ is the indicator function taking one if $W_{i,t} = w$ and zero otherwise. According to the definition of measurement errors in consumption, we have $\log C_{i,t+1}/C_{i,t} = \log C^{obs}_{i,t+1} - \log C^{obs}_{i,t} + \log(\eta_{i,t}/\eta_{i,t+1})$. Under Assumption 1, we have $E[\log(\eta_{i,t}/\eta_{i,t+1})] = E(\epsilon_{i,t} - \epsilon_{i,t+1}) = 0$ and under Assumption 2 we have $E[\log(\eta_{i,t}/\eta_{i,t+1})] \leq \log E[\log(\eta_{i,t}/\eta_{i,t+1})] \leq 0$. From the concavity of the logarithm function and Jensens inequality, we obtain

$$
\begin{aligned}
&\log E\{\rho_{i,t}(\theta_0(w))g(Z_{i,t})\mathbb{1}[W_{i,t} = w]\} = \log E\{g(Z_{i,t})|W_{i,t} = w]\} \\
&E\{\log \beta_0(w)(1 + R_{i,t+1})g(Z_{i,t})\mathbb{1}[W_{i,t} = w] - \gamma_0(w)\log(C_{i,t+1}/C_{i,t})\} \leq \log E[g(Z_{i,t})|W_{i,t} = w] \\
&E\{\log \beta_0(w)(1 + R_{i,t+1})g(Z_{i,t})\mathbb{1}[W_{i,t} = w] - \gamma_0(w)\log\left(C^{\text{obs}}_{i,t+1}/C^{\text{obs}}_{i,t}\right) - \gamma_0(w)\log(\eta_{i,t}/\eta_{i,t+1})\} \\
&\leq \log E[g(Z_{i,t})|W_{i,t} = w] \\
&E\{\log \beta_0(w)(1 + R_{i,t+1})g(Z_{i,t}) - \gamma_0(w)\log\left(C^{\text{obs}}_{i,t+1}/C^{\text{obs}}_{i,t}\right) - \log E[g(Z_{i,t})|W_{i,t} = w]|W_{i,t} = w\} \leq 0,
\end{aligned}
$$

This shows that $\theta_0(w)$ belongs to the parameter set satisfying (7). □

Supplemental Tables

Tables A.1 and A.2 present estimation results of localized GMM-D and GMM-LN estimators. Figures A.5 and A.6 are made by using the results shown in Tables A.1 and A.2, respectively. Tables presents estimation results for discount factors for 2009 and 2012 (β_{09} and β_{12}, respectively) and risk parameters for 2009 and 2012 (γ_{09} and γ_{12}, respectively). SE in tables stands for standard errors. Table A.2 also shows results of additional parameters for 2009 and 2012 (ν_{09} and ν_{12}, respectively). The first column in each tables shows the localizing points.

Table A.1: Local GMM D Estimation of Euler Equation. Bandwidth selected by iteration.

	β_{09}	SE	β_{12}	SE	γ_{09}	SE	γ_{12}	SE
0.50	0.990	0.106	0.990	0.392	2.896	0.848	8.340	0.670
0.51	0.990	0.107	0.990	0.391	2.879	0.868	8.328	0.668
0.52	0.990	0.107	0.990	0.390	2.852	0.892	8.316	0.666
0.53	0.990	0.107	0.990	0.388	2.823	0.906	8.303	0.663
0.54	0.990	0.105	0.990	0.387	2.793	0.909	8.291	0.661
0.55	0.990	0.103	0.990	0.386	2.767	0.902	8.281	0.659
0.56	0.990	0.101	0.990	0.385	2.747	0.892	8.272	0.657
0.57	0.990	0.100	0.990	0.384	2.733	0.882	8.266	0.655
0.58	0.990	0.099	0.990	0.383	2.723	0.874	8.264	0.654
0.59	0.990	0.098	0.990	0.383	2.716	0.867	8.268	0.653
0.60	0.990	0.097	0.990	0.382	2.712	0.862	8.280	0.652
0.61	0.990	0.097	0.990	0.382	2.709	0.857	8.305	0.652
0.62	0.990	0.096	0.990	0.383	2.709	0.853	8.351	0.654
0.63	0.990	0.098	0.990	0.386	2.723	0.864	8.436	0.658
0.64	0.990	0.096	0.990	0.386	2.711	0.845	8.419	0.657
0.65	0.990	0.096	0.990	0.387	2.713	0.842	7.533	0.697
0.66	0.990	0.095	0.990	0.387	2.716	0.839	7.529	0.696
0.67	0.990	0.095	0.990	0.386	2.720	0.836	7.525	0.696
0.68	0.848	0.142	0.990	0.386	3.641	0.887	7.521	0.695
0.69	0.432	0.241	0.990	0.385	5.839	1.418	7.517	0.694
0.70	0.871	0.191	0.990	0.385	3.499	1.228	7.513	0.693
0.71	0.881	0.193	0.990	0.385	3.446	1.268	7.510	0.693
0.72	0.892	0.193	0.990	0.385	3.384	1.302	7.507	0.692
0.73	0.904	0.190	0.990	0.384	3.310	1.334	7.503	0.691
0.74	0.918	0.186	0.990	0.380	3.224	1.368	7.555	0.674
0.75	0.933	0.179	0.990	0.231	3.126	1.401	7.439	0.470
0.76	0.949	0.170	0.990	0.369	3.014	1.436	9.164	0.687
0.77	0.965	0.158	0.990	0.297	2.883	1.467	9.721	1.962
0.78	0.983	0.140	0.990	0.285	2.726	1.477	9.727	1.866
0.79	0.990	0.094	0.988	0.277	3.005	0.613	9.758	1.810
0.80	0.990	0.053	0.990	0.272	2.735	0.496	9.773	1.784
0.81	0.990	0.067	0.990	0.218	2.750	0.560	9.928	1.419
0.82	0.990	0.065	0.989	0.218	2.706	0.598	9.921	1.440
0.83	0.990	0.073	0.990	0.213	2.863	0.599	9.980	1.413
0.84	0.990	0.075	0.990	0.215	2.870	0.631	9.925	1.451
0.85	0.990	0.061	0.990	0.206	2.386	0.580	10.000	1.418
0.86	0.990	0.058	0.979	0.225	2.547	0.546	10.000	1.555
0.87	0.990	0.079	0.990	0.215	2.970	0.614	9.936	1.499
0.88	0.990	0.084	0.986	0.245	2.780	0.617	9.845	1.744
0.89	0.990	0.103	0.990	0.242	3.092	0.633	9.799	1.752
0.90	0.990	0.049	0.990	0.235	2.637	0.431	9.807	1.692
0.91	0.990	0.083	0.990	0.235	2.749	0.619	9.835	1.715
0.92	0.990	0.042	0.990	0.131	2.488	0.366	6.494	0.488
0.93	0.990	0.061	0.990	0.295	2.518	0.555	7.556	0.511
0.94	0.990	0.061	0.990	0.133	2.505	0.559	6.459	0.477
0.95	0.990	0.062	0.990	0.298	2.500	0.564	7.567	0.507
0.96	0.990	0.063	0.990	0.297	2.498	0.572	7.514	0.506
0.97	0.990	0.064	0.990	0.289	2.497	0.583	7.334	0.504
0.98	0.990	0.021	0.990	0.215	0.098	0.335	7.357	0.465
0.99	0.990	0.086	0.990	0.241	2.884	0.759	7.248	0.472

Table A.2: Local GMM LN Estimation of Euler Equation. Bandwidth selected by iteration.

	β_{09}	SE	β_{12}	SE	γ_{09}	SE	γ_{12}	SE	ν_{09}	SE	ν_{12}	SE
0.50	0.990	0.098	0.990	0.091	2.839	0.714	4.435	0.563	0.028	0.014	0.022	0.007
0.51	0.990	0.084	0.990	0.084	2.601	0.685	3.997	0.638	0.027	0.014	0.024	0.008
0.52	0.990	0.097	0.990	0.084	2.703	0.703	4.033	0.635	0.026	0.015	0.024	0.008
0.53	0.990	0.091	0.990	0.081	2.561	0.708	3.165	0.681	0.024	0.016	0.026	0.010
0.54	0.951	0.132	0.990	0.084	3.161	0.786	3.665	0.651	0.020	0.014	0.025	0.009
0.55	0.954	0.114	0.990	0.134	2.751	0.735	5.415	0.527	0.017	0.016	0.025	0.012
0.56	0.960	0.107	0.990	0.139	2.678	0.737	1.444	1.588	0.017	0.016	0.024	0.049
0.57	0.957	0.107	0.954	0.188	2.572	0.738	1.547	1.848	0.014	0.017	0.010	0.032
0.58	0.990	0.080	0.990	0.135	2.381	0.622	5.397	0.527	0.020	0.017	0.025	0.012
0.59	0.990	0.084	0.990	0.168	2.492	0.618	1.509	1.877	0.021	0.016	0.025	0.053
0.50	0.990	0.098	0.990	0.136	2.886	0.609	5.385	0.526	0.024	0.014	0.024	0.012
0.61	0.990	0.080	0.990	0.136	2.389	0.603	5.378	0.526	0.020	0.017	0.024	0.012
0.62	0.865	0.234	0.990	0.083	3.695	1.262	4.292	0.616	0.019	0.016	0.024	0.008
0.63	0.990	0.081	0.990	0.137	2.325	0.887	5.363	0.526	0.030	0.017	0.024	0.012
0.64	0.947	0.192	0.990	0.137	3.009	1.422	5.359	0.526	0.025	0.020	0.024	0.012
0.65	0.990	0.083	0.990	0.137	2.309	0.843	5.351	0.526	0.030	0.018	0.024	0.012
0.66	0.984	0.090	0.990	0.138	2.368	0.898	5.344	0.526	0.029	0.018	0.024	0.012
0.67	0.883	0.183	0.990	0.138	3.711	1.342	5.337	0.526	0.020	0.013	0.024	0.012
0.68	0.990	0.076	0.990	0.138	2.496	0.650	5.331	0.525	0.029	0.014	0.024	0.012
0.69	0.990	0.179	0.990	0.139	2.522	2.176	5.324	0.525	0.028	0.029	0.024	0.013
0.70	0.990	0.061	0.990	0.139	2.113	0.687	5.317	0.525	0.025	0.016	0.024	0.013
0.71	0.990	0.171	0.990	0.139	2.470	2.074	5.310	0.525	0.027	0.028	0.024	0.013
0.72	0.990	0.171	0.990	0.139	2.471	2.048	5.303	0.525	0.027	0.028	0.024	0.013
0.73	0.990	0.177	0.990	0.140	2.484	2.093	5.297	0.525	0.027	0.029	0.024	0.013
0.74	0.990	0.101	0.990	0.140	2.412	1.142	5.292	0.525	0.026	0.018	0.024	0.013
0.75	0.990	0.115	0.990	0.135	2.772	0.979	5.092	0.521	0.027	0.016	0.023	0.013
0.76	0.990	0.104	0.990	0.123	2.723	0.862	5.154	0.518	0.026	0.015	0.017	0.011
0.77	0.990	0.104	0.990	0.138	2.737	0.845	5.579	0.559	0.026	0.015	0.019	0.009
0.78	0.990	0.107	0.990	0.118	2.773	0.841	4.772	0.561	0.026	0.015	0.022	0.010
0.79	0.990	0.108	0.990	0.120	2.797	0.830	5.191	0.558	0.026	0.015	0.020	0.012
0.80	0.990	0.110	0.990	0.130	2.821	0.823	5.827	0.587	0.026	0.015	0.015	0.007
0.81	0.990	0.113	0.990	0.083	2.847	0.817	10.000	0.508	0.026	0.015	0.010	0.007
0.82	0.990	0.118	0.990	0.425	2.936	0.834	7.336	0.725	0.026	0.015	0.017	0.019
0.83	0.990	0.111	0.990	0.380	2.830	0.784	7.665	0.678	0.026	0.015	0.015	0.017
0.84	0.990	0.112	0.990	0.162	2.976	0.772	10.000	0.867	0.026	0.014	0.017	0.004
0.85	0.990	0.114	0.990	0.150	2.977	0.756	6.295	0.938	0.026	0.014	0.026	0.006
0.86	0.990	0.116	0.990	0.166	2.995	0.762	7.609	0.714	0.026	0.014	0.016	0.005
0.87	0.990	0.117	0.990	0.152	3.007	0.766	6.699	0.654	0.026	0.014	0.016	0.006
0.88	0.990	0.117	0.990	0.148	3.019	0.772	6.604	0.670	0.026	0.014	0.015	0.006
0.89	0.990	0.113	0.990	0.185	3.018	0.772	10.000	0.796	0.027	0.013	0.015	0.003
0.90	0.990	0.099	0.615	0.160	2.907	0.724	10.000	0.962	0.027	0.013	0.015	0.004
0.91	0.990	0.133	0.990	0.197	3.206	0.775	10.000	0.737	0.026	0.014	0.015	0.003
0.92	0.990	0.077	0.784	0.238	2.794	0.651	9.991	0.993	0.028	0.012	0.014	0.005
0.93	0.990	0.131	0.990	0.229	3.220	0.787	4.852	1.903	0.027	0.014	0.022	0.012
0.94	0.990	0.098	0.990	0.211	2.885	0.730	5.101	2.112	0.028	0.014	0.023	0.009
0.95	0.552	0.444	0.990	0.209	10.000	1.793	5.120	2.150	0.014	0.006	0.023	0.009
0.96	0.990	0.214	0.986	0.208	3.281	1.764	5.132	2.152	0.029	0.022	0.023	0.008
0.97	0.990	0.233	0.984	0.208	3.275	1.952	5.117	2.169	0.029	0.024	0.023	0.008
0.98	0.990	0.237	0.990	0.205	3.274	1.993	5.104	2.174	0.029	0.024	0.023	0.008
0.99	0.990	0.239	0.989	0.204	3.276	2.005	5.139	2.177	0.029	0.024	0.022	0.008

Figures

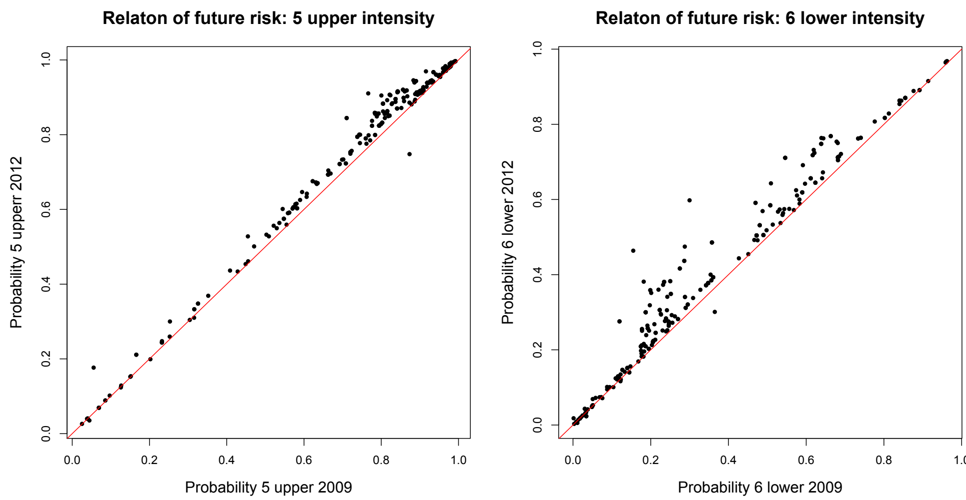

Figure A.1: Relationship between the future earthquake risk measured in 2009 and 2012. The left-hand figure shows the probability of suffering a JMA seismic intensity larger than 5 upper earthquake in the next 30 years. The right-hand figure shows the probability of suffering a larger than 6 lower earthquake.

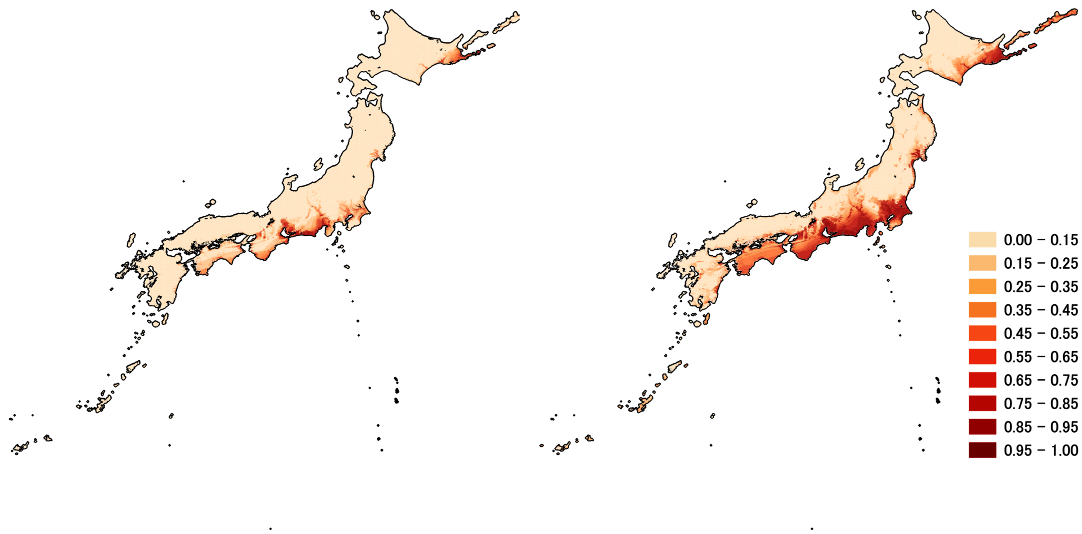

Figure A.2: Geographical distribution of future earthquake risks. The left-hand figure describes the probability that a location suffers an earthquake of JMA seismic intensity larger than 6 lower in the next 30 years. The right-hand figure describes the probability that a location suffers an earthquake of JMA seismic intensity larger than 5 upper in the next 30 years.

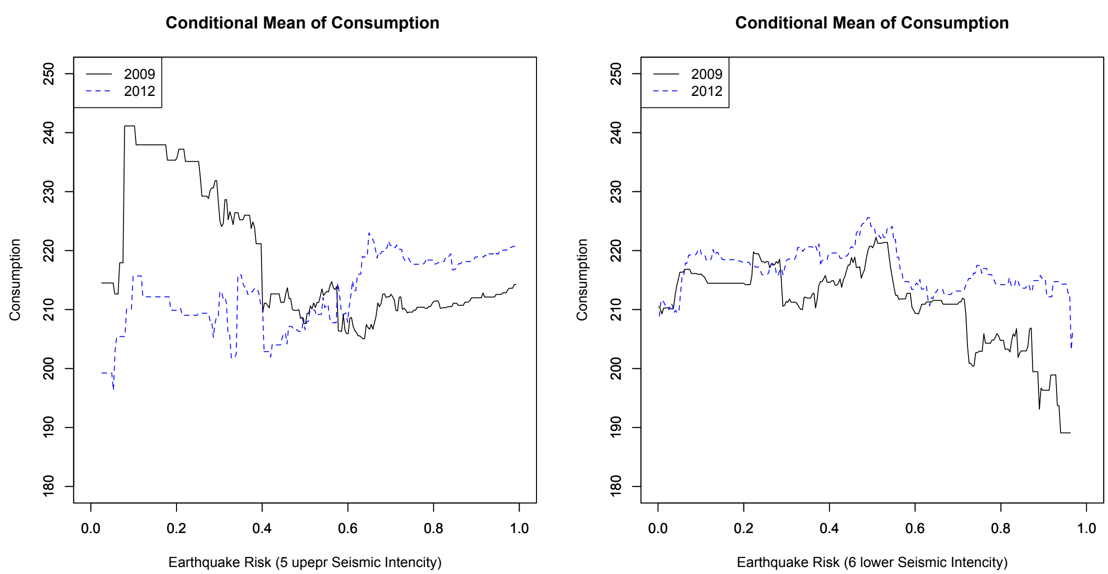

Figure A.3: Average consumption conditional on the risk of being hit by a large-scale earthquake. The left-hand figure describes the local average consumption conditional on the probability that a household suffers an earthquake of JMA seismic intensity larger than 6 lower in the next 30 years. The right-hand figure describes the local average consumption conditional on the probability that a household suffers an earthquake of JMA seismic intensity larger than 5 upper in the next 30 years.

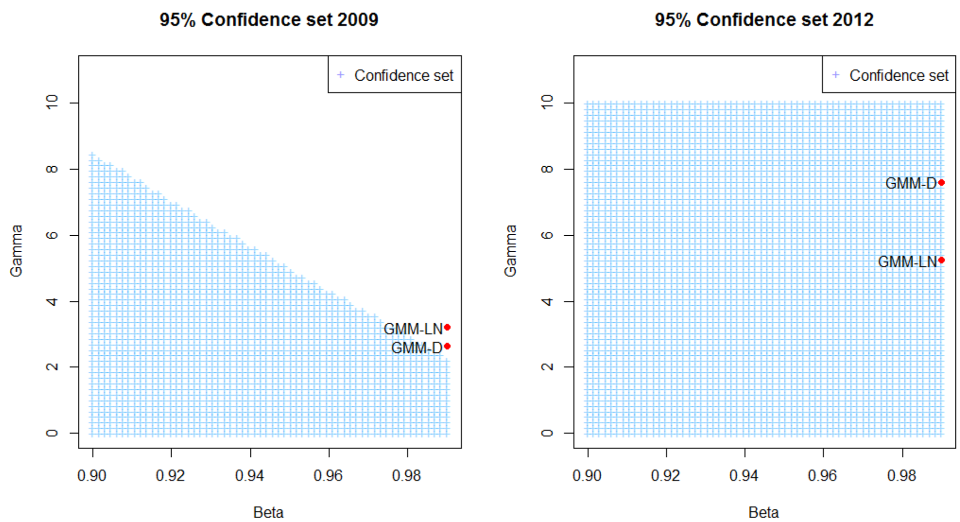

Figure A.4: 95% confidence sets and estimated parameter values.

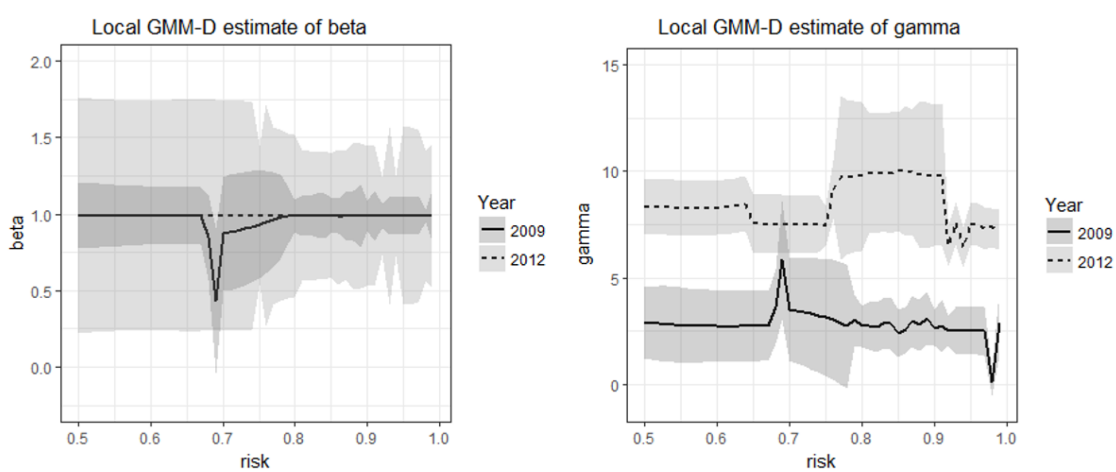

Figure A.5: Estimation results of the local GMM-D estimator.

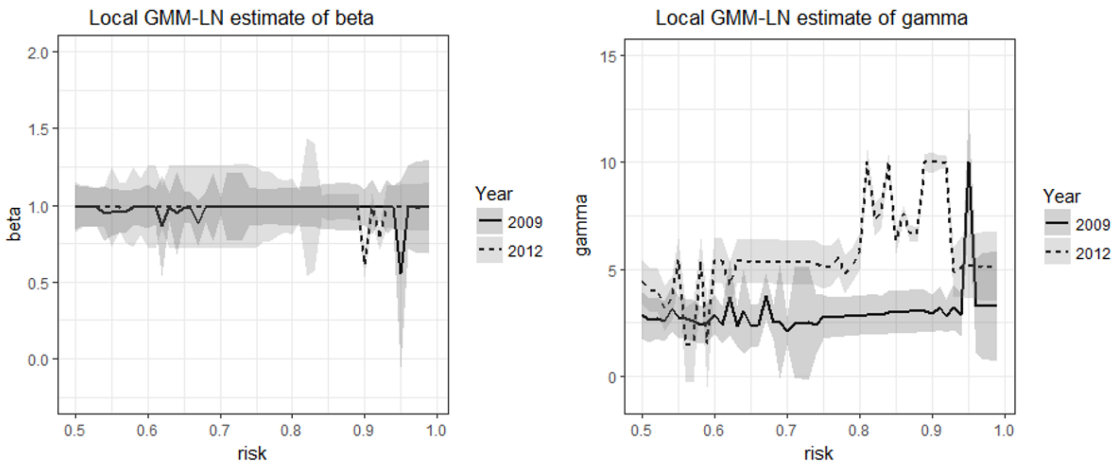

Figure A.6: Estimation results of the local GMM-LN estimator.

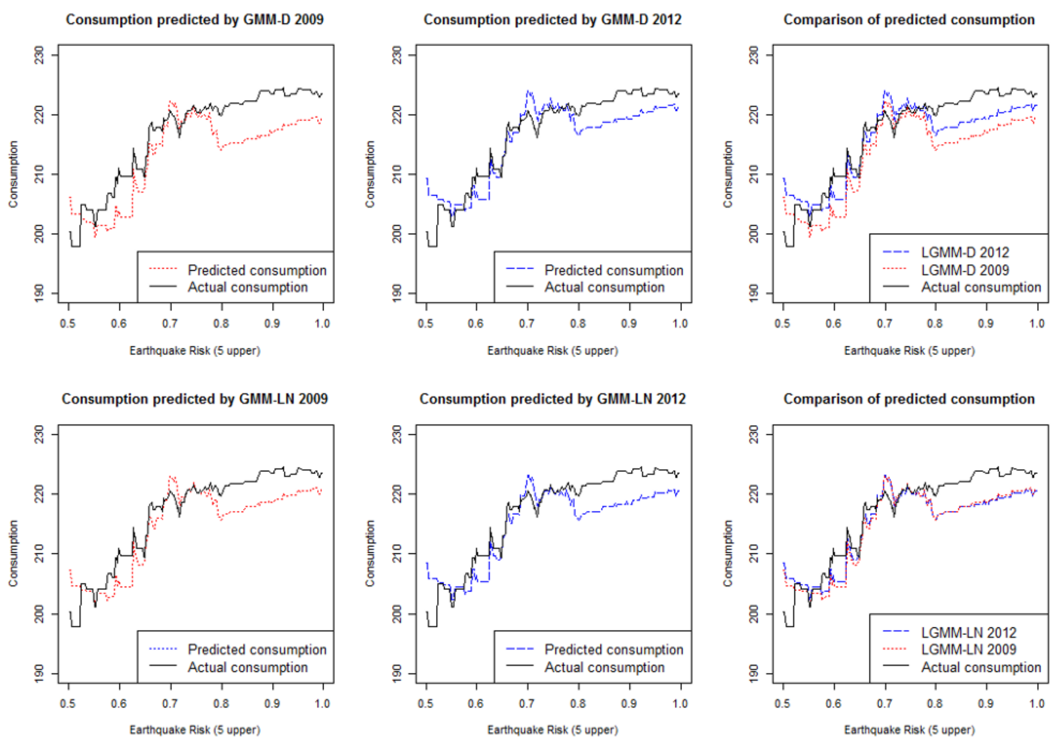

Figure A.7: Conditional mean estimation of consumption with respect to earthquake risk. The upper (lower) three panels are the results from the GMM-D (GMM-LN) setup. The black solid line is estimated by using actual consumption in 2013. The dotted red lines and dashed blue lines are predictions of 2013 consumption, calculated by using the estimated preference parameters before and after the disaster, respectively.