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【Abstract】

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Our findings support those other studies that have used hypothetical and experimental data, which suggest that experiencing a large-scale disaster changes individuals' risk and time preferences.

Furthermore, the observed households' consumption and asset allocation behavior fitted in a life-cycle consumption model show that a large-scale disaster affects households facing different future risks of similar disasters differently even if they are not physically affected by the focal disaster.

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Preference Parameter Changes in Life-cycle Consumption Models: the Measurement-error-robust Approach[1]

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Summary: This study proposes 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 findings support those other studies that have used hypothetical and experimental data, which suggest that experiencing a large-scale disaster changes individuals' risk and time preferences. Furthermore, the observed households' consumption and asset allocation behavior fitted in a life-cycle consumption model show that a large-scale disaster affects households facing different future risks of similar disasters differently even if they are not physically affected by the focal disaster.

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1   Introduction

To evaluate a policy that focuses on recovery from a large-scale disaster, understanding not only indi-
vidual 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' deci-
sions 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 those
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, and 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 reveal
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-cycle

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[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

consumption models to address the issue 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, and 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 under- or overestimate 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 the weak stationarity of measurement errors. In addition to stationarity, existing works assume independence between

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Euler equation.

the 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 the 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.

The parameter sets 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. The 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 the heterogeneous impacts of a disaster on 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

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the 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 the proofs for the propositions in these Sections are given in the 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, and 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 the bias of respondents' behaviors that might arise from the special experimental environment.[3]

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[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

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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.

For the earthquake risk measures, we use the data on probabilistic earthquake hazards published by the Japan Seismic Hazard Information Station (JSHIS). We adopt two probabilities: a location will be hit by an earthquake with a Japan Meteorological Agency (JMA) seismic intensity larger than 5 upper in the next 30 years and a JMA seismic intensity larger than 6 lower in the next 30 years.[5] 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 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

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[5]See the Data section for more details.

[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.

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

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

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

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

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

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

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[7] Assuming CRRA-type utility may be too restrictive, since all households are assumed to have identical preference

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 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

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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.

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

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

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 on 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. The 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 is 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:

$$E\left[\log\beta + \log(1+R_{i,t+1}) - \gamma\log\left(\frac{C_{i,t+1}^{\mathrm{obs}}}{C_{i,t}^{\mathrm{obs}}}\right) + \log g(Z_i) - \log E[g(Z_i)]\right] \le 0, \qquad (5)$$

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 a time trend that occurs when the experiences of respondents 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 $E(\eta_{i,t}/\eta_{i,t+1}) \le 1$ 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 the expectation of (the inverse of) the growth in measurement errors is smaller than one, which 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 assumes a multiplicative variant of the Berkson measurement error, say, $C_{i,t} = C_{i,t}^{\mathrm{obs}}\eta_{i,t}$, the restriction becomes that $E(\eta_{i,t+1}/\eta_{i,t})$ is smaller than one, which 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 $\rho_{i,t}^{\mathrm{obs}}(\theta) = \beta(1+R_{i,t+1})\left(C_{i,t+1}^{\mathrm{obs}}/C_{i,t}^{\mathrm{obs}}\right)^{-\gamma}$. 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 $E\{\log\rho_{i,t}^{\mathrm{obs}}(\theta) + \log g(Z_{i,t}) - \log E[g(Z_{i,t})]\} \le 0$. 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 also holds 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, $\Theta_I = \{\theta : E[m_i(\theta)] \leq 0\}$. 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, which includes the future earthquake risks faced by each household.

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

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

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 the independence restriction nor the distributional assump-

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[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.

tions 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:

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

(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 $E\{\log \rho_{i,t}^{\text{obs}}[\theta(w)] + \log g(Z_{i,t}) - \log E[g(Z_{i,t})|W_{i,t} = w]\} \leq 0$. 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. 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 $E\{\rho_{i,t}[\theta(w)] - 1|Z_{i,t}W_{i,t} = w\} = 0$. Moreover, $\theta_0(w)$ belongs to the set of parameters satisfying (7).*

Proposition 4. *Proposition 3 also 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 use the sample of nuclear families with at least one child whose head is working age during the sample periods from 2007 to 2015, namely a household head no older than 51 and no younger than 16 in 2007. To apply our theoretical model, we focus on households who satisfy the following characteristics. First, following Attanasio and Weber (1995) and Vissing-Jørgensen (2002), we drop observations for which the observed income and consumption growth ratios in 2009 and 2012 are less than 0.2 or above five (73 households) to exclude obvious reporting and coding errors. Second, following Alan et al. (2009), we exclude households that have no saving during the sampling periods (186 households) to

exclude any households that may be liquidity constrained in the sample periods. Third, 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 data show skeptical evidence of the risk-sharing hypothesis, especially when households are liquidity constrained. For example, Kohara, Ohtake, and Saito (2006), Ichimura, Sawada, and Shimizutani (2008), and Sawada and Shimizutani (2008) provide empirical evidence using Japanese data, while Ogaki and Zhang (2001) and Zhang and 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 is $2,864$ 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, 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 the 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

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[11]In particular, we exclude households whose houses fully or partially collapsed.
[12]https://www.e-stat.go.jp/SG1/estat/eStatTopPortal.do.

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
Future risk 6 lower	0.35	0.26	0.25	0.00	0.96
Future risk 5 upper	0.74	0.81	0.25	0.03	0.99
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
Future risk 6 lower	0.39	0.36	0.25	0.00	0.97
Future risk 5 upper	0.76	0.86	0.25	0.03	1.00
Consumption rate					
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
Return (%)					
R_{2009}	-0.215	0.193	0.908	-4.646	0.243
R_{2010}	-1.359	0.065	3.169	-17.242	0.088
R_{2012}	3.202	0.026	7.303	0.026	40.062
R_{2013}	0.142	0.026	0.268	0.026	1.494

Note: Annual income is pre-tax annual household income of the previous year. Saving indicates the amount of household total saving at the moment of the response. Both are given in 10 thousand Japanese yen.

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]

The third panel of Table 1 shows the descriptive statistics for the growth rates of consumption.

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[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 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.

The mean consumption rates are stable over time, showing that consumption is smoothed. The growth rates of consumption are slightly higher after the earthquake. It derives a conjecture that households may become risk tolerant and/or have a lower discount factor.

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.

Then, household-specific return R_i is calculated as

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

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[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.

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 household-specific 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 a 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 of 5 upper and 6 lower.

The JSHIS website provides a user-friendly digital hazard map of these data, which can be easily accessed by everyone. 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

[15]It may be more appropriate to use the subjective future earthquake risk perceived by households, because 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.1 presents the geographic distributions of future earthquake risks.

Table 1 also provides the descriptive statistics of households' future earthquake risks in 2009 and 2012. According to the descriptive statistics, the distribution of future risks seems to shift rightwards after the disaster. Figure A.2 illustrates the future risk shifts, showing the relationship between the probabilistic seismic hazards of 2009 and 2012. The future risks faced by each household are not the same across these two years. Although the small changes in the future earthquake risks between before and after the earthquake indicate that the local moments capture almost the same households across these years, the results should be compared carefully, especially for those households whose 6 lower risk in 2009 lies between 0.2 and 0.8 and for those households whose 5 upper risk in 2009 lies between 0.5 and 0.9. Thus, the interpretation of the results should focus on the localizing points outside these intervals.

Figure A.3 displays the positive correlation between the 5 upper and 6 lower earthquake risks. In particular, households facing a high 6 lower risk of around 0.9 also face a 5 upper risk of above 0.9, while those facing a low 5 upper risk of around 0.1 also face a low 6 lower risk of under 0.1.

Figure A.4 illustrates the 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. Following Alan et al. (2009) and Gayle and Khorunzhina (2017), the set of instruments include the number of children, lagged household-specific returns, and a constant; the future earthquake risks (5 upper and 6 lower) are also included for the localization.

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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/.

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 6 lower and 5 upper probabilistic seismic hazard measures are adopted as the localizing variables.

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, that is, $\epsilon_{i,j} \sim N(\mu, \nu)$, and includes ν as an additional parameter to be estimated. To check the validity of these assumptions on the measurement errors, we present the confidence sets derived from the moment inequalities (5) for the constant coefficients models and (7) 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 cross-validation. First, we estimate the parameters for a specific value of the localizing parameter $W = w$, which we denote $\hat{\theta}_1(w)$, by using the bandwidth calculated by rule of thumb. In particular, we adopt continuously updating GMM (CUGMM) to obtain the estimates, as suggested by Hansen, Heaton, and Yaron (1996). Second, $\hat{\theta}_1(w)$ is plugged into the local GMM objective function so that it can be seen as a function of the bandwidths. We find the bandwidths that minimize the objective function, which we denote $\hat{h}_1$. The final estimation results are then estimated by using $\hat{h}_1$ instead of the rule of thumb bandwidth in the first step.

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 derived from the moment inequalities are shown. Figure A.5 illustrates the relationship between the confidence set and estimated parameter values. The GMM-D and GMM-LN estimates are out of 95% confidence set in 2009, while both estimates belong to the confidence

Table 3: Estimation of Euler equation

	$\hat{\beta}$		$\hat{\gamma}$		$\hat{\nu}$		$value$	
	2009 (1)	2012 (2)	2009 (3)	2012 (4)	2009 (5)	2012 (6)	2009 (7)	2012 (8)
GMM-D	0.990 (0.074)	0.990 (0.376)	2.659 (0.601)	7.554 (0.697)			0.220 reject	0.000 accept
GMM-LN	0.990 (0.092)	0.990 (0.104)	3.077 (0.538)	4.016 (0.488)	0.027 (0.0119)	0.0178 (0.0151)	0.481 reject	0.000 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.

set after the earthquake. The results in columns (3) and (4) suggest that households become risk averse after the disaster. However, it is not possible to compare the parameters before and after the earthquake because the 2012 results is not accepted by the test for measurement errors. To study the heterogeneity and analyze households that do not violate the confidence set, we then conduct a local GMM analysis.

7.2 Results of the Varying Coefficients Model

We adopt the future earthquake risk (6 lower and 5 upper) variables as the localizing variables and estimate the parameters at equally spaced 99 localizing points in the $[0.01, 0.99]$ interval.[17] Figures A.6, A.7, A.8, and A.9 present the estimation results for the 6 lower future risk of the GMM-D and GMM-LN estimators and 5 upper future risk of the GMM-D and GMM-LN estimators, respectively. In these figures, the results for each localizing point are displayed only when the estimates both before and after the earthquake belong to the 95% confidence set derived by moment inequalities (7). In other words, we show the results of the localizing points in which our moment inequality does not reject the additional distributional assumptions imposed on the GMM-D and GMM-LN estimators.

7.2.1 Results for 6 Lower Future Risk

The GMM-D estimates of the discount factor parameter β in the left panel of Figure A.6 suggest that the discount factor of most households in 2009 are close to one and do not change in 2012. The only exception is households whose future earthquake risks lie between 0.94 and 0.97. The discount factors of these households are lower after the earthquake. However, the 95% confidence intervals of the estimated discount factor overlap, which suggests that the change in parameters might not be

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[17]As shown in descriptive statistics of Table 1, we have no observations who face a future earthquake risk higher than 0.98. Thus, we can ignore the results obtained from local points above 0.98.

statistically significant. Overall, we can conclude that no subpopulation shows any significant discount factor changes.

The GMM-D estimates of the risk aversion parameters in the right panel of Figure A.6 suggest that most households whose future earthquake risk is above 0.2 become risk averse after the earthquake. Figure A.6 shows that the 95% confidence intervals in 2009 and 2012 do not overlap for those households. In particular, in 2012, households whose earthquake risk lies between 0.94 and 0.97 have high $\hat{\gamma}$ values compared with households whose risk is outside this interval. Close inspection reveals that the municipalities in which the corresponding households live are located along the Pacific Ocean in Aichi and Shizuoka prefectures. In particular, these municipalities face high risks of subsequent disasters such as tsunamis, so that government offices of these municipalities publish hazard maps for future disasters to inform and alert their residents. A similar tendency of the risk aversion parameter changes is also exhibited by households with a future risk between 0.28 and 0.31. However, as shown in Figure A.2, some households with a future risk in 2012 lying between 0.28 and 0.31 experience future risk shifts, indicating that the preference parameter changes for those households may be induced not only by the disaster but also by the risk shifts. Overall, the results suggest that earthquakes make most households risk averse. The effect is heterogeneous and households may become more risk averse after a disaster if they live in places at risk of a future natural disaster that may bring about severe damage.

Figure A.7 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 panel of Figure A.7). The risk aversion parameter in the right panel of Figure A.7 illustrates that households whose future risk lies above 0.97 become risk averse. Although the change is not as drastic as the GMM-D results, it is significant. Some households with a future risk below 0.8 also become risk averse. However, since households with future risks between 0.2 and 0.8 experience future risk shifts, these parameter changes may not only be induced by the earthquake. Thus, the GMM-LN results also suggest that households become more risk averse after a disaster if they live in places at a high risk of future natural disasters.

7.2.2 Results for 5 Upper Future Risk

Figures A.8 and A.9 present the estimation results of GMM-D and GMM-LN, respectively, when the 5 upper future risk is used as the localizing variable. The results for the discount factor (the left panel of Figures A.8 and A.9) show that there are few differences in the discount factors before and after the earthquake.

The GMM-D estimates of the risk aversion parameters in the right panel of Figure A.8 suggest that households who face 5 upper earthquake risks lying above 0.97 become significantly risk averse after the disaster. The GMM-LN estimates in the right panel of Figure A.9 also illustrate that these households become risk averse. However, the 95% confidence intervals overlap, which suggests that the change in parameters might not be statistically significant for the latter estimates. This finding is consistent with the results obtained from the 6 lower earthquake risk, because the 6 lower risk of these households is distributed above 0.60 and the risk averseness changes captured by the GMM-LN estimators are less than those captured by the GMM-D estimators. Since households with future risks between 0.5 and 0.9 experience future risk shifts, the parameter changes captured in this interval may not only be induced by the earthquake.

The interesting results obtained by using 5 upper risks as the localizing variable can be found when we focus on households who face future risks between 0.03 and 0.15 (see the right panel of Figure A.9). Although these households become risk averse after an earthquake, the parameter change might not be statistically significant for most. Indeed, significant parameter changes are reported only for households with 5 upper risks of 0.03, 0.04, and 0.14. The municipalities in which the corresponding households live are located in Ishikawa, Toyama, Fukuoka, Kagoshima, and the inland of Fukushima, which do not face the Pacific Ocean. The half of these municipalities do not even face the ocean, indicating that they are not exposed to disasters such as tsunamis. Overall, the results from the 5 upper localization suggest that an earthquake does not affect the risk averseness of households that live in places at a low risk of future natural disasters.

7.2.3   Consumption Prediction

We next compare actual consumption with predicted consumption for each point of future earthquake risks. Actual consumption is the observed households' non-durable consumption in 2013. To predict the non-durable consumption of each household, we fit the observed household-specific return in 2012 as a proxy for the return in 2013, non-durable consumption in 2012, and the estimated preference parameters before and after the disaster to the Euler equation. Figure A.10 illustrates the absolute mean difference in the consumption forecast errors in 10,000 Japanese yen. That is, this figure shows the absolute mean of the consumption forecast errors based on the before-disaster parameter estimates minus that based on the after-disaster parameter estimates (updated preferences hereafter). The positive values in the figure show the lower forecasts errors for forecasts based on the updated preferences, thus favoring the preference parameter estimates after the disaster to make an accurate prediction.

Overall, the updated preferences make fewer forecasts errors. In particular, the two left panels of Figure A.10 show the preference for the updated preferences of households with 5 upper future earthquake risks below 0.2. According to our estimation results, these households become risk averse after the disaster. Although the risk preference changes may be non-significant for most of these households, as shown in Figure A.9, the difference improves the consumption prediction slightly. For households with 6 lower future earthquake risks above 0.9, the prediction errors after the earthquake are smaller when the parameter estimates are based on the GMM-D estimators (see the upper right panel of Figure A.10). However, this is not the case for the GMM-LN estimators (see the bottom right panel of Figure A.10), indicating the preference for a prediction based on the before-disaster preferences. However, the absolute error difference in the latter case is much smaller than that in the former case. Therefore, although the updated preferences do not uniformly dominate those based on preferences beforehand, they can be used to avoid the serious under- or overestimation of consumption after the disaster.

Figure A.11 presents the conditional mean of actual and predicted consumption expenditure, where consumption is predicted by using the updated preferences. To calculate the conditional mean, we adopt the Nadaraya–Watson kernel estimator. The two upper (lower) panels are the results from the GMM-D (GMM-LN) setup, left for the 5 upper future earthquake risk and right for the 6 lower risk. Overall, the prediction captures the consumption differences according to the future earthquake risks well. For 5 upper future risks, although it fails to predict the sharp consumption fall (compared with the others) of households around the 0.45 risk, it does capture the tendency of upward consumption above the 0.6 risk. For 6 lower future risks, the prediction captures the peaks of consumption around the 0.1, 0.5, and 0.75 future risks well. In sum, using the updated preferences can improve the consumption predictions after a disaster in terms of the mean absolute error, and such predictions capture the broad consumption tendency of households depending on the future risks of similar disasters.

8   Conclusion

In this study, we analyzed the risk preference parameters and discount factors before and after the Great East Japan Earthquake to answer three questions insufficiently addressed by existing works.

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 capturing the parameter changes caused by other macroeconomic shocks, we used local GMM estimators. By proposing a new moment inequality approach, 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 subpopulations that do not violate the moment inequality. We then limited ourselves to analyzing the localizing points where the moment inequality is not violated, finding that households globally became risk averse after the Great East Japan Earthquake. The effect is heterogeneous; in particular, households living in high-risk areas became drastically risk averse, whereas the risk averseness of households who live in low-risk areas does not change significantly. Thus, households may become more risk averse after a disaster if they live in places at risk of future natural disasters that may bring about severe damage.

The observed preference parameter changes are consistent with those found by existing works. While Hanaoka et al. (in press) find a subpopulation that becomes risk tolerant after the Great East Japan Earthquake, we found one that became risk averse. Our result is nevertheless consistent with the finding of Hanaoka et al. (in press) in that both studies show risk parameter changes 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. Our results together with existing results such as Goebel et al. (2015) and Hanaoka et al. (in press) provide suggestions to the research questions above. Question (i): Studying individual data may be insufficient to predict changes in households' risk preferences. Question (ii): the effect of the disaster on questionnaire responses and behavior in experiments is not always the same as that on real-life economic behavior. Although hypothetical questions and experiments are useful when researchers are interested in examining whether a large-scale disaster affects respondents' mindsets, additional evidence would be required. Question (iii): a large-scale disaster affects not only those individuals who suffer from it directly, but also those 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 consumption predictions

based on the parameters derived from ex-ante analyses are less precise than those derived with updated preferences. 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 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, while the risk preference parameters for households facing a low risk of a similar disaster do not change significantly.

Our results also suggest that ignoring the indirect effects of unexpected events can derive confounding estimation results. 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 large-scale disaster can affect seemingly untreated individuals or households differently. Therefore, careful interpretation is required when designing studies that rely on a clear distinction between treated and untreated groups such as experimental studies when the treatment is related to unexpected natural disasters.

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 $\log C_{i,t+1}/C_{i,t} = \log C_{i,t+1}^{obs} - \log C_{i,t}^{obs} + \log\left(\eta_{i,t}/\eta_{i,t+1}\right)$. 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

$$\log E[\rho_{i,t}(\theta_0)g(Z_{i,t})] = \log E[g(Z_{i,t})]$$

$$E[\log\beta_0(1 + R_{i,t+1}) - \gamma_0\log\left(C_{i,t+1}/C_{i,t}\right) + \log g(Z_{i,t})] \leq \log E[g(Z_{i,t})]$$

$$E[\log\beta_0(1 + R_{i,t+1}) - \gamma_0\log\left(C_{i,t+1}^{\text{obs}}/C_{i,t}^{\text{obs}}\right) - \gamma_0\log\left(\eta_{i,t}/\eta_{i,t+1}\right) + \log g(Z_{i,t})] \leq \log E[g(Z_{i,t})]$$

$$E[\log\beta_0(1 + R_{i,t+1}) - \gamma_0\log\left(C_{i,t+1}^{\text{obs}}/C_{i,t}^{\text{obs}}\right) + \log g(Z_{i,t}) - \log E[g(Z_{i,t})]] \leq 0.$$

This shows that θ_0 belongs to the parameter set satisfying (5). $\square$

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 $\log C_{i,t+1}/C_{i,t} = \log C_{i,t+1}^{obs} - \log C_{i,t}^{obs} + \log(\eta_{i,t}/\eta_{i,t+1})$. 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

$$\log E\{\rho_{i,t}(\theta_0(w))g(Z_{i,t})\mathbb{1}[W_{i,t}=w]\} = \log E\{g(Z_{i,t})|W_{i,t}=w]\}$$

$$E\{\log \beta_0(w)(1+R_{i,t+1})g(Z_{i,t})\mathbb{1}[W_{i,t}=w] - \gamma_0(w)\log(C_{i,t+1}/C_{i,t})\} \leq \log E[g(Z_{i,t})|W_{i,t}=w]$$

$$E\{\log \beta_0(w)(1+R_{i,t+1})g(Z_{i,t})\mathbb{1}[W_{i,t}=w] - \gamma_0(w)\log\left(C_{i,t+1}^{obs}/C_{i,t}^{obs}\right) - \gamma_0(w)\log(\eta_{i,t}/\eta_{i,t+1})\}$$

$$\leq \log E[g(Z_{i,t})|W_{i,t}=w]$$

$$E\{\log \beta_0(w)(1+R_{i,t+1})g(Z_{i,t}) - \gamma_0(w)\log\left(C_{i,t+1}^{obs}/C_{i,t}^{obs}\right) - \log E[g(Z_{i,t})|W_{i,t}=w]|W_{i,t}=w\} \leq 0,$$

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

Supplemental Tables

Tables A.1–A.8 present the estimation results of the localized GMM-D and GMM-LN estimators. The first column in each table shows the future earthquake risk as the localizing point. Figure A.6 are made by using the results shown in Tables A.1 and A.2. Similarly, Figures A.7, A.8, and A.9 are made by using the results shown in Tables A.5 and A.6, A.3 and A.4, and A.7 and A.8, respectively.

Table A.1: Local GMM-D estimation of preference parameters: 6 lower future earthquake risk.

Risk	$\hat{\beta}$				$\hat{\gamma}$			
	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev
0.01	0.990	0.084	0.990	0.398	2.660	0.674	7.645	0.725
0.02	0.990	0.084	0.990	0.396	2.659	0.674	7.632	0.723
0.03	0.990	0.084	0.990	0.395	2.659	0.673	7.620	0.722
0.04	0.990	0.084	0.990	0.394	2.660	0.672	7.607	0.721
0.05	0.990	0.084	0.990	0.392	2.661	0.672	7.595	0.719
0.06	0.990	0.084	0.990	0.391	2.664	0.670	7.582	0.718
0.07	0.990	0.084	0.990	0.389	2.666	0.669	7.570	0.716
0.08	0.990	0.084	0.990	0.388	2.669	0.667	7.557	0.715
0.09	0.990	0.084	0.990	0.386	2.672	0.665	7.545	0.713
0.10	0.990	0.084	0.990	0.385	2.676	0.663	7.533	0.712
0.11	0.990	0.084	0.990	0.383	2.679	0.661	7.521	0.710
0.12	0.990	0.084	0.990	0.382	2.681	0.658	7.508	0.709
0.13	0.990	0.084	0.990	0.380	2.683	0.654	7.496	0.707
0.14	0.990	0.083	0.990	0.378	2.684	0.651	7.484	0.706
0.15	0.990	0.083	0.990	0.377	2.683	0.647	7.473	0.705
0.16	0.990	0.082	0.990	0.375	2.680	0.643	7.461	0.703
0.17	0.990	0.082	0.990	0.374	2.675	0.638	7.449	0.702
0.18	0.990	0.081	0.990	0.396	2.669	0.633	7.534	0.711
0.19	0.990	0.080	0.990	0.402	2.661	0.628	7.605	0.720
0.20	0.990	0.079	0.990	0.399	2.650	0.623	7.591	0.718
0.21	0.990	0.078	0.990	0.367	2.635	0.617	7.403	0.696
0.22	0.990	0.077	0.990	0.365	2.617	0.611	7.392	0.695
0.23	0.990	0.075	0.990	0.364	2.594	0.605	7.381	0.694
0.24	0.990	0.073	0.990	0.362	2.568	0.599	7.370	0.692
0.25	0.990	0.071	0.990	0.360	2.538	0.593	7.359	0.691
0.26	0.990	0.069	0.990	0.359	2.504	0.587	7.348	0.690
0.27	0.990	0.067	0.990	0.357	2.466	0.581	7.338	0.688
0.28	0.990	0.065	0.990	0.696	2.425	0.575	13.203	1.191
0.29	0.990	0.063	0.990	0.557	2.382	0.569	10.814	1.052
0.30	0.990	0.061	0.990	0.545	2.342	0.564	11.219	1.054
0.31	0.990	0.059	0.990	0.529	2.308	0.559	11.307	1.040
0.32	0.990	0.058	0.990	0.387	2.269	0.554	7.935	0.741
0.33	0.990	0.056	0.990	0.368	2.223	0.548	7.650	0.721
0.34	0.990	0.054	0.990	0.350	2.170	0.541	7.419	0.703
0.35	0.990	0.052	0.990	0.334	2.113	0.535	7.234	0.687
0.36	0.990	0.050	0.990	0.318	2.053	0.530	7.084	0.673
0.37	0.990	0.048	0.990	0.305	1.994	0.525	6.964	0.661
0.38	0.990	0.047	0.990	0.294	1.946	0.520	6.866	0.651
0.39	0.990	0.045	0.990	0.285	1.893	0.515	6.785	0.643
0.40	0.990	0.044	0.990	0.277	1.874	0.500	6.721	0.636
0.41	0.990	0.045	0.990	0.271	1.878	0.478	6.670	0.630
0.42	0.990	0.040	0.990	0.266	1.735	0.455	6.630	0.626
0.43	0.990	0.038	0.990	0.263	1.674	0.448	6.600	0.623
0.44	0.990	0.014	0.990	0.260	0.363	0.235	6.578	0.621
0.45	0.990	1.383	0.990	0.258	34.801	3.075	6.563	0.619
0.46	0.990	0.010	0.990	0.257	0.238	0.150	6.555	0.618
0.47	0.990	0.010	0.990	0.257	0.194	0.168	6.554	0.618
0.48	0.990	0.065	0.990	0.257	2.359	0.541	6.560	0.618
0.49	0.990	0.075	0.990	0.258	2.682	0.601	6.572	0.619
0.50	0.990	0.075	0.990	0.260	2.678	0.600	6.588	0.621

Table A.2: Local GMM-D estimation of preference parameters: 6 lower future earthquake risk.

	$\hat{\beta}$				$\hat{\gamma}$			
Risk	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev
0.50	0.990	0.075	0.990	0.260	2.678	0.600	6.588	0.621
0.51	0.990	0.075	0.990	0.262	2.674	0.599	6.609	0.623
0.52	0.990	0.075	0.990	0.265	2.669	0.599	6.640	0.625
0.53	0.990	0.075	0.990	0.269	2.667	0.598	6.675	0.628
0.54	0.990	0.074	0.990	0.273	2.662	0.597	6.718	0.631
0.55	0.990	0.074	0.990	0.278	2.659	0.597	6.765	0.635
0.56	0.990	0.074	0.990	0.284	2.654	0.596	6.825	0.640
0.57	0.990	0.074	0.990	0.293	2.648	0.595	6.905	0.645
0.58	0.990	0.073	0.990	0.300	2.642	0.595	6.979	0.650
0.59	0.990	0.073	0.990	0.311	2.639	0.594	7.081	0.657
0.60	0.990	0.073	0.990	0.390	2.635	0.594	7.673	0.701
0.61	0.990	0.073	0.990	0.329	2.628	0.593	7.276	0.671
0.62	0.990	0.072	0.990	0.338	2.624	0.592	7.380	0.678
0.63	0.990	0.072	0.990	0.306	2.620	0.592	7.010	0.649
0.64	0.990	0.072	0.990	0.308	2.614	0.591	7.034	0.651
0.65	0.990	0.072	0.990	0.309	2.610	0.590	7.047	0.652
0.66	0.990	0.072	0.990	0.309	2.606	0.590	7.051	0.653
0.67	0.990	0.071	0.990	0.309	2.600	0.589	7.052	0.653
0.68	0.990	0.071	0.990	0.309	2.597	0.589	7.054	0.653
0.69	0.990	0.071	0.990	0.309	2.592	0.588	7.056	0.652
0.70	0.990	0.071	0.990	0.309	2.586	0.588	7.058	0.652
0.71	0.990	0.070	0.990	0.309	2.583	0.587	7.061	0.652
0.72	0.990	0.070	0.990	0.310	2.578	0.586	7.067	0.652
0.73	0.990	0.070	0.990	0.311	2.572	0.586	7.077	0.653
0.74	0.990	0.070	0.990	0.312	2.567	0.585	7.092	0.654
0.75	0.990	0.069	0.990	0.315	2.562	0.585	7.112	0.655
0.76	0.990	0.069	0.990	0.318	2.557	0.584	7.140	0.657
0.77	0.990	0.069	0.990	0.322	2.552	0.584	7.178	0.660
0.78	0.990	0.069	0.990	0.327	2.547	0.583	7.227	0.663
0.79	0.990	0.069	0.990	0.333	2.543	0.583	7.290	0.668
0.80	0.990	0.068	0.990	0.341	2.538	0.582	7.371	0.674
0.81	0.990	0.068	0.990	0.352	2.533	0.582	7.473	0.683
0.82	0.990	0.068	0.990	0.365	2.528	0.581	7.604	0.693
0.83	0.990	0.068	0.990	0.381	2.523	0.581	7.771	0.707
0.84	0.990	0.067	0.990	0.401	2.519	0.580	7.981	0.725
0.85	0.990	0.067	0.990	0.425	2.514	0.580	8.243	0.747
0.86	0.990	0.067	0.990	0.452	2.509	0.579	8.564	0.774
0.87	0.990	0.067	0.990	0.380	2.505	0.579	8.594	0.769
0.88	0.990	0.067	0.990	0.170	2.500	0.578	5.175	0.488
0.89	0.990	0.066	0.990	0.162	2.495	0.578	4.984	0.494
0.90	0.990	0.066	0.990	0.169	2.491	0.577	5.091	0.506
0.91	0.990	0.066	0.990	0.176	2.486	0.577	5.208	0.516
0.92	0.990	0.066	0.990	0.183	2.481	0.576	5.328	0.526
0.93	0.990	0.065	0.990	0.190	2.476	0.576	5.448	0.536
0.94	0.990	0.121	0.563	0.291	3.378	0.756	19.091	1.193
0.95	0.990	0.130	0.563	0.291	3.470	0.792	19.013	1.195
0.96	0.990	0.123	0.563	0.292	3.381	0.768	18.953	1.197
0.97	0.990	0.128	0.564	0.293	3.589	0.705	18.914	1.199
0.98	0.990	0.125	0.990	0.189	3.538	0.695	6.547	0.598
0.99	0.990	0.123	0.990	0.191	3.505	0.690	6.647	0.606

Table A.3: Local GMM-D estimation of preference parameters: 5 upper future earthquake risk.

	$\hat{\beta}$				$\hat{\gamma}$			
Risk	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev
0.01	0.990	0.080	0.990	0.210	2.780	0.608	4.547	1.056
0.02	0.990	0.080	0.990	0.209	2.779	0.609	4.522	1.033
0.03	0.990	0.080	0.990	0.209	2.778	0.609	4.521	1.007
0.04	0.990	0.080	0.990	0.210	2.777	0.609	4.547	0.979
0.05	0.990	0.080	0.990	0.212	2.777	0.609	4.598	0.950
0.06	0.990	0.080	0.990	0.201	2.776	0.610	4.441	0.965
0.07	0.990	0.080	0.990	0.211	2.776	0.610	4.574	0.978
0.08	0.990	0.080	0.990	0.489	2.775	0.610	10.308	1.056
0.09	0.990	0.016	0.990	0.158	0.094	0.260	4.887	0.689
0.10	0.990	0.076	0.990	0.173	2.695	0.562	5.178	0.681
0.11	0.990	0.075	0.990	0.194	2.585	0.614	5.541	0.679
0.12	0.990	0.079	0.990	0.220	2.806	0.543	5.978	0.685
0.13	0.990	0.079	0.990	0.249	2.799	0.544	6.486	0.698
0.14	0.522	0.327	0.990	0.316	29.882	1.433	7.567	0.722
0.15	0.990	0.076	0.736	0.352	2.678	0.556	10.613	1.007
0.16	0.990	0.074	0.990	0.450	2.618	0.564	9.923	0.861
0.17	0.990	0.080	0.990	0.518	2.764	0.612	11.262	0.952
0.18	0.990	0.080	0.990	0.409	2.763	0.612	7.896	0.776
0.19	0.990	0.080	0.990	0.411	2.762	0.612	7.855	0.771
0.20	0.990	0.080	0.990	0.417	2.761	0.613	7.846	0.769
0.21	0.990	0.080	0.990	0.422	2.760	0.613	7.869	0.772
0.22	0.990	0.081	0.990	0.428	2.801	0.616	7.912	0.778
0.23	0.990	0.081	0.990	0.435	2.808	0.617	7.977	0.787
0.24	0.990	0.082	0.990	0.443	2.815	0.617	8.060	0.798
0.25	0.990	0.082	0.990	0.451	2.822	0.618	8.152	0.810
0.26	0.990	0.082	0.990	0.459	2.828	0.618	8.249	0.823
0.27	0.990	0.082	0.990	0.467	2.834	0.618	8.336	0.835
0.28	0.990	0.082	0.990	0.471	2.840	0.618	8.388	0.842
0.29	0.990	0.083	0.990	0.474	2.845	0.618	8.413	0.846
0.30	0.990	0.083	0.990	0.475	2.849	0.618	8.412	0.846
0.31	0.990	0.083	0.990	0.473	2.853	0.618	8.383	0.842
0.32	0.990	0.083	0.990	0.470	2.859	0.618	8.336	0.835
0.33	0.990	0.083	0.990	0.465	2.859	0.617	8.275	0.826
0.34	0.990	0.083	0.990	0.460	2.862	0.617	8.209	0.817
0.35	0.990	0.083	0.990	0.455	2.861	0.617	8.145	0.807
0.36	0.990	0.083	0.990	0.449	2.859	0.616	8.084	0.798
0.37	0.990	0.083	0.990	0.444	2.855	0.616	8.028	0.789
0.38	0.990	0.083	0.990	0.439	2.850	0.616	7.975	0.781
0.39	0.990	0.083	0.990	0.434	2.843	0.616	7.927	0.774
0.40	0.990	0.081	0.990	0.430	2.804	0.611	7.885	0.767
0.41	0.990	0.081	0.990	0.426	2.800	0.610	7.849	0.761
0.42	0.990	0.081	0.990	0.422	2.794	0.610	7.821	0.756
0.43	0.990	0.081	0.990	0.419	2.786	0.610	7.800	0.752
0.44	0.990	0.081	0.990	0.416	2.777	0.610	7.788	0.750
0.45	0.990	0.081	0.990	0.414	2.767	0.610	7.785	0.749
0.46	0.990	0.080	0.990	0.413	2.757	0.610	7.792	0.749
0.47	0.990	0.080	0.990	0.412	2.745	0.610	7.811	0.750
0.48	0.990	0.080	0.990	0.412	2.732	0.611	7.842	0.754
0.49	0.990	0.080	0.990	0.413	2.718	0.612	7.885	0.758
0.50	0.990	0.080	0.990	0.414	2.701	0.613	7.941	0.765

Table A.4: Local GMM-D estimation of preference parameters: 5 upper future earthquake risk.

Risk	$\hat{\beta}$				$\hat{\gamma}$			
	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev
0.50	0.990	0.080	0.990	0.414	2.701	0.613	7.941	0.765
0.51	0.990	0.079	0.990	0.416	2.685	0.614	8.013	0.773
0.52	0.990	0.079	0.990	0.418	2.665	0.616	8.103	0.783
0.53	0.990	0.076	0.990	0.422	2.596	0.615	8.214	0.796
0.54	0.990	0.076	0.990	0.883	2.581	0.618	22.585	1.651
0.55	0.990	0.075	0.990	0.865	2.571	0.620	22.331	1.628
0.56	0.990	0.076	0.990	0.850	2.571	0.623	22.213	1.610
0.57	0.990	0.076	0.990	0.837	2.566	0.625	22.203	1.594
0.58	0.990	0.075	0.990	0.827	2.568	0.627	22.288	1.582
0.59	0.990	0.075	0.990	0.819	2.568	0.628	22.449	1.573
0.60	0.990	0.075	0.990	0.815	2.575	0.629	22.702	1.568
0.61	0.990	0.075	0.990	0.815	2.585	0.630	23.087	1.566
0.62	0.990	0.076	0.990	0.397	2.602	0.632	8.479	0.807
0.63	0.990	0.077	0.990	0.366	2.618	0.634	8.008	0.752
0.64	0.990	0.077	0.990	0.364	2.625	0.635	8.002	0.751
0.65	0.990	0.077	0.990	0.363	2.625	0.637	7.996	0.749
0.66	0.990	0.077	0.990	0.362	2.620	0.639	7.992	0.748
0.67	0.990	0.077	0.990	0.361	2.610	0.640	7.988	0.746
0.68	0.990	0.076	0.990	0.360	2.525	0.696	7.983	0.745
0.69	0.990	0.074	0.990	0.359	2.479	0.693	7.977	0.743
0.70	0.990	0.080	0.990	0.357	2.510	0.740	7.972	0.742
0.71	0.990	0.086	0.990	0.356	2.556	0.780	7.965	0.740
0.72	0.990	0.086	0.990	0.355	2.559	0.779	7.956	0.738
0.73	0.990	0.076	0.990	0.354	2.450	0.705	7.946	0.737
0.74	0.990	0.076	0.990	0.352	2.458	0.702	7.934	0.735
0.75	0.990	0.075	0.990	0.780	2.461	0.692	21.311	1.586
0.76	0.990	0.075	0.990	0.774	2.465	0.684	21.709	1.577
0.77	0.990	0.076	0.990	0.766	2.501	0.668	21.890	1.565
0.78	0.990	0.071	0.990	0.132	2.506	0.631	4.328	0.593
0.79	0.990	0.072	0.990	0.498	2.528	0.630	11.570	1.026
0.80	0.990	0.072	0.990	0.491	2.550	0.628	11.281	1.005
0.81	0.990	0.073	0.990	0.497	2.574	0.625	11.288	1.005
0.82	0.990	0.074	0.990	0.142	2.609	0.620	4.494	0.585
0.83	0.990	0.075	0.990	0.160	2.645	0.615	4.913	0.595
0.84	0.990	0.075	0.990	0.201	2.649	0.615	5.640	0.670
0.85	0.990	0.075	0.990	0.209	2.652	0.615	5.864	0.694
0.86	0.990	0.075	0.990	0.265	2.653	0.614	8.078	0.706
0.87	0.990	0.075	0.990	0.172	2.652	0.614	6.071	0.704
0.88	0.990	0.075	0.990	0.256	2.652	0.614	6.929	0.764
0.89	0.990	0.075	0.990	0.304	2.651	0.614	7.737	0.834
0.90	0.990	0.075	0.990	0.395	2.651	0.614	9.103	0.969
0.91	0.990	0.075	0.990	0.507	2.650	0.614	11.000	1.133
0.92	0.990	0.075	0.990	0.565	2.650	0.614	17.567	1.215
0.93	0.990	0.075	0.990	0.156	2.650	0.614	5.316	1.497
0.94	0.990	0.075	0.990	0.178	2.649	0.614	5.878	1.157
0.95	0.990	0.075	0.990	0.151	2.649	0.614	5.244	1.211
0.96	0.990	0.075	0.990	0.211	2.649	0.613	5.676	3.127
0.97	0.990	0.075	0.680	0.270	2.648	0.613	10.580	2.725
0.98	0.990	0.075	0.887	0.274	2.647	0.613	9.632	1.104
0.99	0.990	0.075	0.952	0.406	2.645	0.613	7.417	3.833

Table A.5: Local GMM-LN estimation of preference parameters: 6 lower future earthquake risk.

	$\hat{\beta}$				$\hat{\gamma}$				$\hat{\nu}$			
Risk	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev
0.01	0.990	0.092	0.990	0.114	2.805	0.641	5.879	0.481	0.027	0.014	0.021	0.009
0.02	0.990	0.092	0.990	0.114	2.807	0.641	5.871	0.481	0.027	0.014	0.021	0.009
0.03	0.990	0.092	0.990	0.114	2.811	0.641	5.867	0.481	0.027	0.014	0.021	0.009
0.04	0.990	0.093	0.990	0.115	2.817	0.640	5.863	0.481	0.027	0.014	0.021	0.009
0.05	0.990	0.093	0.990	0.115	2.823	0.640	5.868	0.481	0.027	0.014	0.021	0.009
0.06	0.990	0.093	0.990	0.115	2.832	0.639	5.876	0.481	0.027	0.014	0.021	0.009
0.07	0.990	0.094	0.990	0.115	2.842	0.638	5.898	0.481	0.027	0.014	0.021	0.009
0.08	0.990	0.094	0.990	0.114	2.854	0.637	5.952	0.481	0.027	0.014	0.021	0.009
0.09	0.990	0.095	0.990	0.123	2.867	0.636	4.893	0.488	0.027	0.014	0.021	0.013
0.10	0.990	0.095	0.990	0.124	2.883	0.634	4.893	0.488	0.027	0.014	0.021	0.013
0.11	0.990	0.096	0.990	0.124	2.899	0.633	4.887	0.488	0.027	0.014	0.021	0.013
0.12	0.990	0.097	0.990	0.124	2.917	0.631	4.880	0.488	0.027	0.014	0.021	0.013
0.13	0.990	0.097	0.990	0.125	2.936	0.629	4.871	0.489	0.027	0.013	0.021	0.013
0.14	0.990	0.098	0.990	0.125	2.956	0.628	4.863	0.489	0.027	0.013	0.021	0.014
0.15	0.990	0.099	0.990	0.125	2.975	0.626	4.855	0.489	0.027	0.013	0.021	0.014
0.16	0.990	0.100	0.990	0.125	2.997	0.624	4.847	0.490	0.027	0.013	0.021	0.014
0.17	0.990	0.101	0.990	0.126	3.021	0.623	4.839	0.490	0.027	0.013	0.021	0.014
0.18	0.990	0.102	0.990	0.126	3.047	0.621	4.832	0.490	0.027	0.013	0.021	0.014
0.19	0.990	0.103	0.990	0.126	3.074	0.619	4.825	0.491	0.027	0.013	0.021	0.014
0.20	0.990	0.104	0.990	0.126	3.104	0.617	4.818	0.491	0.027	0.013	0.021	0.014
0.21	0.990	0.105	0.990	0.126	3.135	0.616	4.814	0.491	0.027	0.013	0.021	0.014
0.22	0.990	0.106	0.990	0.127	3.169	0.614	4.809	0.492	0.027	0.013	0.021	0.014
0.23	0.990	0.108	0.990	0.127	3.206	0.613	4.807	0.492	0.026	0.013	0.021	0.014
0.24	0.990	0.108	0.990	0.127	3.220	0.612	4.805	0.492	0.026	0.013	0.021	0.014
0.25	0.990	0.108	0.990	0.127	3.205	0.614	4.807	0.492	0.026	0.013	0.021	0.014
0.26	0.990	0.107	0.990	0.128	3.191	0.615	4.812	0.492	0.026	0.013	0.021	0.014
0.27	0.990	0.106	0.990	0.128	3.178	0.616	4.821	0.492	0.026	0.013	0.021	0.014
0.28	0.990	0.106	0.990	0.130	3.167	0.618	5.114	0.484	0.027	0.013	0.020	0.013
0.29	0.990	0.105	0.990	0.131	3.157	0.619	5.179	0.484	0.027	0.013	0.021	0.013
0.30	0.990	0.104	0.990	0.134	3.152	0.621	5.520	0.480	0.027	0.013	0.021	0.012
0.31	0.990	0.104	0.990	0.125	3.140	0.625	6.325	0.485	0.027	0.013	0.021	0.010
0.32	0.990	0.103	0.990	0.055	3.126	0.629	11.799	0.430	0.027	0.013	0.022	0.006
0.33	0.990	0.103	0.990	0.128	3.113	0.633	5.894	0.446	0.027	0.013	0.023	0.011
0.34	0.990	0.103	0.990	0.134	3.101	0.637	5.488	0.465	0.027	0.013	0.022	0.012
0.35	0.990	0.103	0.990	0.032	3.091	0.640	12.289	0.254	0.027	0.013	0.022	0.006
0.36	0.990	0.102	0.990	0.108	3.059	0.658	4.091	0.482	0.027	0.013	0.018	0.016
0.37	0.990	0.103	0.990	0.108	3.078	0.667	4.088	0.482	0.027	0.013	0.018	0.016
0.38	0.990	0.108	0.990	0.095	3.156	0.677	5.807	0.438	0.027	0.013	0.016	0.008
0.39	0.990	0.110	0.990	0.094	3.188	0.684	5.983	0.435	0.027	0.013	0.016	0.008
0.40	0.990	0.158	0.990	0.093	4.247	0.608	6.138	0.433	0.025	0.010	0.016	0.007
0.41	0.990	0.181	0.990	0.090	4.591	0.642	8.559	0.416	0.025	0.010	0.015	0.004
0.42	0.990	0.201	0.990	0.082	4.840	0.673	6.733	0.463	0.025	0.010	0.016	0.005
0.43	0.990	0.220	0.990	0.077	5.062	0.704	7.046	0.456	0.025	0.010	0.016	0.004
0.44	0.990	0.276	0.990	0.107	5.552	0.800	8.148	0.394	0.024	0.010	0.015	0.004
0.45	0.990	0.315	0.980	0.003	5.838	0.875	18.979	0.024	0.024	0.010	0.012	0.001
0.46	0.990	0.358	0.990	0.163	6.134	0.960	3.361	0.468	0.024	0.011	0.020	0.017
0.47	0.818	0.478	0.989	0.042	7.485	1.395	19.131	0.381	0.019	0.010	0.012	0.001
0.48	0.868	0.494	0.990	0.177	7.496	1.374	3.458	0.542	0.020	0.010	0.021	0.017
0.49	0.897	0.472	0.990	0.058	7.281	1.301	15.987	0.407	0.021	0.010	0.011	0.002
0.50	0.565	0.311	0.990	0.053	12.301	1.316	16.681	0.399	0.015	0.004	0.011	0.002

Table A.6: Local GMM-LN estimation of preference parameters: 6 lower future earthquake risk.

	$\hat{\beta}$				$\hat{\gamma}$				$\hat{\nu}$			
Risk	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev
0.50	0.565	0.311	0.990	0.053	12.301	1.316	16.681	0.399	0.015	0.004	0.011	0.002
0.51	0.990	0.195	0.990	0.175	4.799	0.638	2.948	0.725	0.021	0.009	0.025	0.022
0.52	0.990	0.038	0.987	0.023	1.599	0.327	21.451	0.201	0.010	0.023	0.011	0.002
0.53	0.990	0.342	0.990	0.020	20.882	1.147	21.873	0.174	0.010	0.002	0.011	0.001
0.54	0.990	0.055	0.891	0.022	2.294	0.644	21.291	0.207	0.026	0.014	0.011	0.001
0.55	0.990	0.057	0.719	0.032	2.323	0.709	18.821	0.356	0.026	0.015	0.010	0.001
0.56	0.990	0.057	0.990	0.091	2.227	0.537	1.493	0.421	0.021	0.016	0.021	0.045
0.57	0.990	0.086	0.990	0.007	2.876	0.709	24.679	0.069	0.025	0.013	0.010	0.001
0.58	0.990	0.076	0.990	0.143	2.740	0.690	7.894	0.578	0.025	0.013	0.010	0.005
0.59	0.990	0.077	0.897	0.113	2.770	0.677	12.037	0.699	0.025	0.012	0.012	0.003
0.60	0.990	0.078	0.990	0.098	2.805	0.684	8.598	0.516	0.025	0.012	0.010	0.003
0.61	0.990	0.084	0.990	0.102	2.934	0.710	7.037	0.583	0.026	0.012	0.010	0.003
0.62	0.990	0.094	0.990	0.109	3.173	0.761	6.870	0.594	0.026	0.012	0.010	0.004
0.63	0.990	0.086	0.990	0.096	1.949	0.767	5.501	0.547	0.023	0.031	0.010	0.005
0.64	0.990	0.034	0.990	0.085	0.933	0.369	4.642	0.719	0.010	0.061	0.010	0.006
0.65	0.990	0.051	0.990	0.084	1.170	0.530	4.664	0.738	0.010	0.059	0.010	0.006
0.66	0.990	0.049	0.990	0.082	1.214	0.526	4.600	0.757	0.010	0.054	0.010	0.006
0.67	0.990	0.047	0.990	0.081	1.196	0.528	4.520	0.774	0.010	0.053	0.010	0.006
0.68	0.990	0.045	0.990	0.081	1.180	0.525	4.431	0.788	0.010	0.053	0.010	0.007
0.69	0.990	0.043	0.990	0.081	1.129	0.474	4.321	0.797	0.010	0.054	0.010	0.007
0.70	0.990	0.150	0.990	0.082	7.191	0.814	4.229	0.803	0.024	0.005	0.010	0.007
0.71	0.990	0.031	0.990	0.084	0.861	0.321	4.240	0.811	0.010	0.066	0.010	0.007
0.72	0.990	0.031	0.990	0.086	0.836	0.322	4.221	0.819	0.010	0.068	0.010	0.008
0.73	0.990	0.030	0.990	0.090	0.813	0.321	4.160	0.827	0.010	0.071	0.010	0.008
0.74	0.990	0.029	0.990	0.129	0.784	0.330	4.715	0.861	0.010	0.073	0.011	0.009
0.75	0.990	0.026	0.965	0.150	0.710	0.322	12.305	0.924	0.010	0.080	0.010	0.002
0.76	0.990	0.023	0.990	0.132	0.686	0.278	3.144	0.770	0.010	0.076	0.010	0.018
0.77	0.990	0.022	0.990	0.128	0.663	0.243	3.276	0.769	0.010	0.074	0.010	0.017
0.78	0.990	0.021	0.990	0.166	0.644	0.224	4.389	1.161	0.010	0.074	0.015	0.011
0.79	0.990	0.021	0.990	0.276	0.632	0.215	7.074	1.237	0.010	0.074	0.010	0.007
0.80	0.990	0.564	0.990	0.272	8.558	1.127	7.361	1.232	0.024	0.009	0.010	0.007
0.81	0.990	0.158	0.990	0.233	4.206	0.619	6.946	1.195	0.025	0.011	0.010	0.007
0.82	0.990	0.141	0.990	0.220	3.944	0.597	6.293	1.152	0.025	0.011	0.011	0.008
0.83	0.990	0.131	0.990	0.199	3.770	0.584	5.425	1.063	0.025	0.011	0.010	0.010
0.84	0.990	0.020	0.990	0.174	0.767	0.237	4.464	0.919	0.010	0.056	0.010	0.013
0.85	0.990	0.021	0.990	0.157	0.702	0.216	4.038	0.841	0.010	0.069	0.011	0.014
0.86	0.990	0.021	0.990	0.216	0.647	0.219	4.086	1.241	0.010	0.080	0.016	0.012
0.87	0.990	0.098	0.990	0.137	3.199	0.543	4.031	1.017	0.025	0.012	0.015	0.009
0.88	0.990	0.725	0.990	0.146	21.601	1.717	4.157	0.984	0.013	0.003	0.015	0.011
0.89	0.990	0.080	0.990	0.170	2.856	0.505	4.432	0.905	0.024	0.012	0.016	0.012
0.90	0.990	0.072	0.990	0.177	2.696	0.488	4.576	0.856	0.023	0.013	0.016	0.012
0.91	0.990	0.067	0.990	0.270	2.567	0.474	4.627	1.017	0.023	0.013	0.016	0.017
0.92	0.990	0.063	0.990	0.264	2.485	0.466	4.854	0.914	0.022	0.013	0.016	0.016
0.93	0.990	0.032	0.990	0.103	0.808	0.294	2.876	0.663	0.010	0.074	0.013	0.015
0.94	0.990	0.057	0.985	0.099	2.318	0.451	2.832	0.742	0.021	0.014	0.010	0.017
0.95	0.990	0.057	0.990	0.120	0.707	0.438	3.008	0.805	0.010	0.157	0.011	0.016
0.96	0.990	0.051	0.990	0.177	2.159	0.437	3.966	1.046	0.020	0.015	0.017	0.015
0.97	0.990	0.049	0.864	0.185	2.091	0.430	6.838	1.119	0.020	0.016	0.012	0.006
0.98	0.990	0.062	0.990	0.160	0.834	0.530	5.125	1.079	0.010	0.126	0.016	0.008
0.99	0.990	0.046	0.990	0.155	1.991	0.420	5.110	1.042	0.019	0.017	0.016	0.007

Table A.7: Local GMM-LN estimation of preference parameters: 5 upper future earthquake risk.

Risk	$\hat{\beta}$				$\hat{\gamma}$				$\hat{\nu}$			
	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev
0.01	0.990	0.019	0.990	0.020	0.667	0.309	18.929	0.171	0.011	0.066	0.017	0.002
0.02	0.988	0.020	0.864	0.014	0.702	0.332	20.352	0.138	0.010	0.064	0.017	0.002
0.03	0.987	0.021	0.990	0.058	0.764	0.367	3.322	0.802	0.012	0.058	0.039	0.009
0.04	0.987	0.023	0.952	0.069	0.842	0.412	3.543	0.847	0.016	0.050	0.034	0.009
0.05	0.987	0.025	0.990	0.059	0.926	0.461	2.474	0.610	0.019	0.044	0.016	0.020
0.06	0.987	0.028	0.990	0.062	1.012	0.506	2.633	0.604	0.021	0.039	0.026	0.016
0.07	0.990	0.034	0.990	0.069	1.136	0.514	2.618	0.571	0.025	0.035	0.026	0.015
0.08	0.990	0.031	0.990	0.081	1.142	0.557	2.982	0.653	0.024	0.032	0.035	0.014
0.09	0.990	0.030	0.990	0.086	1.134	0.554	2.993	0.685	0.024	0.033	0.035	0.014
0.10	0.990	0.029	0.990	0.086	1.122	0.540	2.651	0.712	0.023	0.034	0.026	0.017
0.11	0.990	0.028	0.990	0.075	1.095	0.509	2.638	0.619	0.021	0.036	0.027	0.019
0.12	0.990	0.027	0.990	0.081	1.064	0.472	2.966	0.645	0.018	0.038	0.034	0.017
0.13	0.990	0.026	0.990	0.083	1.039	0.434	3.096	0.622	0.016	0.040	0.037	0.017
0.14	0.990	0.025	0.990	0.088	1.008	0.397	3.192	0.568	0.013	0.041	0.035	0.018
0.15	0.990	0.024	0.990	0.068	0.970	0.367	2.673	0.509	0.010	0.043	0.035	0.014
0.16	0.990	0.079	0.990	0.101	2.750	0.525	4.049	0.489	0.027	0.013	0.018	0.015
0.17	0.990	0.079	0.990	0.101	2.749	0.529	4.047	0.489	0.027	0.013	0.018	0.015
0.18	0.990	0.080	0.990	0.101	2.749	0.533	4.045	0.489	0.027	0.013	0.018	0.015
0.19	0.990	0.080	0.990	0.101	2.751	0.537	4.044	0.489	0.027	0.013	0.018	0.015
0.20	0.990	0.081	0.990	0.101	2.754	0.540	4.041	0.489	0.027	0.013	0.018	0.015
0.21	0.990	0.081	0.990	0.101	2.756	0.543	4.039	0.489	0.027	0.013	0.018	0.015
0.22	0.990	0.082	0.990	0.101	2.796	0.529	4.037	0.489	0.027	0.013	0.018	0.015
0.23	0.990	0.083	0.990	0.102	2.804	0.533	4.036	0.489	0.027	0.013	0.018	0.015
0.24	0.990	0.084	0.990	0.097	2.815	0.538	2.963	0.536	0.027	0.013	0.041	0.019
0.25	0.990	0.085	0.990	0.102	2.830	0.544	4.032	0.489	0.027	0.013	0.018	0.015
0.26	0.990	0.086	0.990	0.171	2.850	0.550	4.698	0.728	0.027	0.013	0.016	0.009
0.27	0.990	0.088	0.990	0.124	2.877	0.557	2.817	0.658	0.028	0.013	0.020	0.020
0.28	0.990	0.090	0.990	0.102	2.914	0.565	4.027	0.489	0.028	0.013	0.018	0.015
0.29	0.990	0.093	0.990	0.102	2.960	0.576	4.025	0.489	0.028	0.013	0.018	0.015
0.30	0.990	0.097	0.990	0.102	3.017	0.587	4.024	0.489	0.028	0.013	0.018	0.015
0.31	0.990	0.094	0.990	0.102	2.948	0.583	4.022	0.489	0.028	0.013	0.018	0.015
0.32	0.990	0.083	0.990	0.102	2.745	0.562	4.020	0.489	0.027	0.013	0.018	0.015
0.33	0.990	0.075	0.990	0.102	2.581	0.547	4.018	0.489	0.027	0.014	0.018	0.015
0.34	0.990	0.114	0.990	0.102	3.278	0.647	4.017	0.489	0.028	0.013	0.018	0.016
0.35	0.990	0.112	0.990	0.102	3.235	0.650	4.016	0.489	0.028	0.013	0.018	0.016
0.36	0.990	0.079	0.990	0.103	2.654	0.569	4.016	0.489	0.027	0.013	0.018	0.016
0.37	0.990	0.081	0.990	0.103	2.688	0.575	4.014	0.489	0.027	0.013	0.018	0.016
0.38	0.990	0.083	0.990	0.103	2.716	0.579	4.013	0.489	0.027	0.013	0.018	0.016
0.39	0.990	0.084	0.990	0.103	2.742	0.583	4.012	0.489	0.027	0.013	0.018	0.016
0.40	0.990	0.086	0.990	0.103	2.771	0.587	4.011	0.489	0.027	0.013	0.018	0.016
0.41	0.990	0.089	0.990	0.103	2.829	0.592	4.010	0.489	0.027	0.013	0.018	0.016
0.42	0.990	0.091	0.990	0.103	2.861	0.595	4.009	0.489	0.026	0.013	0.018	0.016
0.43	0.990	0.089	0.990	0.103	2.835	0.595	4.009	0.489	0.027	0.013	0.018	0.016
0.44	0.990	0.089	0.990	0.103	2.819	0.596	4.008	0.488	0.027	0.013	0.018	0.016
0.45	0.990	0.088	0.990	0.103	2.808	0.597	4.009	0.488	0.027	0.013	0.018	0.016
0.46	0.990	0.087	0.990	0.103	2.799	0.595	4.008	0.488	0.026	0.013	0.018	0.016
0.47	0.990	0.076	0.990	0.103	2.567	0.582	4.008	0.488	0.026	0.014	0.018	0.015
0.48	0.990	0.081	0.990	0.103	2.686	0.586	4.008	0.488	0.026	0.013	0.018	0.015
0.49	0.990	0.080	0.990	0.103	2.667	0.581	4.008	0.488	0.026	0.013	0.018	0.015
0.50	0.990	0.089	0.990	0.103	2.778	0.645	4.008	0.488	0.027	0.013	0.018	0.015

Table A.8: Local GMM-LN estimation of preference parameters: 5 upper future earthquake risk.

|	$\hat{\beta}$				$\hat{\gamma}$				$\hat{\nu}$			
Risk	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev	2009	std.dev	2012	std.dev
0.50	0.990	0.089	0.990	0.103	2.778	0.645	4.008	0.488	0.027	0.013	0.018	0.015
0.51	0.990	0.088	0.990	0.103	2.748	0.654	4.008	0.488	0.027	0.013	0.018	0.015
0.52	0.990	0.099	0.990	0.104	2.941	0.688	4.008	0.487	0.026	0.013	0.018	0.015
0.53	0.990	0.096	0.990	0.104	2.882	0.683	4.008	0.487	0.026	0.013	0.018	0.015
0.54	0.990	0.100	0.990	0.104	2.938	0.694	4.008	0.487	0.026	0.013	0.018	0.015
0.55	0.990	0.098	0.990	0.104	2.889	0.688	4.009	0.487	0.026	0.013	0.018	0.015
0.56	0.990	0.098	0.990	0.104	2.891	0.698	4.010	0.487	0.026	0.013	0.018	0.015
0.57	0.990	0.098	0.990	0.104	2.884	0.700	4.011	0.486	0.026	0.014	0.018	0.015
0.58	0.990	0.098	0.990	0.104	2.877	0.701	4.012	0.486	0.026	0.014	0.018	0.015
0.59	0.990	0.098	0.990	0.104	2.869	0.701	4.014	0.486	0.026	0.014	0.018	0.015
0.60	0.990	0.098	0.990	0.104	2.860	0.701	4.015	0.486	0.026	0.014	0.018	0.015
0.61	0.990	0.093	0.990	0.104	2.813	0.673	4.017	0.486	0.026	0.013	0.018	0.015
0.62	0.990	0.110	0.990	0.104	2.447	1.309	4.018	0.485	0.027	0.019	0.018	0.015
0.63	0.990	0.111	0.990	0.104	2.450	1.336	4.019	0.485	0.027	0.019	0.018	0.015
0.64	0.990	0.112	0.990	0.104	2.457	1.361	4.480	0.470	0.027	0.020	0.021	0.011
0.65	0.990	0.108	0.990	0.105	2.455	1.299	4.457	0.471	0.027	0.019	0.021	0.011
0.66	0.990	0.109	0.990	0.106	2.481	1.353	4.424	0.472	0.027	0.019	0.021	0.011
0.67	0.990	0.099	0.990	0.107	2.457	1.121	4.379	0.473	0.027	0.018	0.021	0.012
0.68	0.990	0.100	0.990	0.107	2.550	1.203	4.334	0.475	0.027	0.017	0.020	0.012
0.69	0.990	0.085	0.990	0.107	2.348	0.931	4.310	0.475	0.027	0.017	0.020	0.012
0.70	0.990	0.085	0.990	0.108	2.342	0.924	4.509	0.470	0.027	0.017	0.021	0.011
0.71	0.990	0.072	0.990	0.108	2.222	0.828	4.774	0.464	0.026	0.016	0.021	0.010
0.72	0.990	0.061	0.990	0.039	2.193	0.721	17.438	0.330	0.025	0.015	0.012	0.044
0.73	0.990	0.064	0.988	0.007	2.233	0.705	31.755	0.059	0.025	0.015	0.010	0.432
0.74	0.990	0.051	0.990	0.105	1.948	0.523	4.038	0.486	0.016	0.016	0.017	0.015
0.75	0.990	0.073	0.990	0.102	2.556	0.637	4.060	0.482	0.026	0.013	0.017	0.015
0.76	0.990	0.070	0.990	0.103	2.502	0.615	4.829	0.469	0.025	0.013	0.015	0.012
0.77	0.990	0.070	0.990	0.096	2.512	0.605	3.920	0.472	0.025	0.013	0.016	0.012
0.78	0.990	0.071	0.990	0.088	2.524	0.595	3.571	0.484	0.025	0.013	0.017	0.013
0.79	0.990	0.071	0.990	0.100	2.534	0.584	4.279	0.488	0.025	0.013	0.015	0.014
0.80	0.990	0.071	0.990	0.005	2.541	0.573	24.487	0.031	0.025	0.013	0.015	0.002
0.81	0.990	0.071	0.990	0.146	2.543	0.562	6.033	0.507	0.025	0.013	0.016	0.011
0.82	0.990	0.071	0.990	0.111	2.542	0.551	5.982	0.508	0.025	0.013	0.015	0.008
0.83	0.990	0.071	0.990	0.006	2.537	0.541	23.756	0.042	0.025	0.013	0.015	0.002
0.84	0.990	0.070	0.990	0.168	2.530	0.532	5.738	0.499	0.025	0.013	0.015	0.010
0.85	0.990	0.070	0.990	0.214	2.635	0.518	7.098	0.626	0.024	0.012	0.017	0.008
0.86	0.990	0.071	0.990	0.199	2.660	0.515	6.807	0.610	0.024	0.012	0.016	0.008
0.87	0.990	0.072	0.990	0.190	2.706	0.514	6.822	0.608	0.024	0.012	0.016	0.008
0.88	0.990	0.072	0.990	0.119	2.725	0.512	5.489	0.579	0.025	0.012	0.014	0.007
0.89	0.990	0.065	0.990	0.113	2.561	0.499	4.993	0.569	0.025	0.012	0.014	0.008
0.90	0.990	0.061	0.879	0.003	2.535	0.498	35.111	0.028	0.025	0.012	0.010	0.001
0.91	0.990	0.057	0.990	0.135	2.467	0.493	5.747	0.620	0.026	0.012	0.014	0.007
0.92	0.990	0.054	0.990	0.155	2.414	0.489	5.648	0.616	0.026	0.012	0.013	0.009
0.93	0.990	0.077	0.990	0.141	3.189	0.519	4.803	0.827	0.026	0.010	0.010	0.011
0.94	0.990	0.518	0.990	0.132	10.488	1.306	4.526	0.740	0.018	0.005	0.010	0.010
0.95	0.990	0.110	0.986	0.159	3.244	0.830	5.186	1.482	0.029	0.012	0.013	0.008
0.96	0.990	0.121	0.990	0.174	3.301	0.840	5.689	1.840	0.029	0.013	0.015	0.007
0.97	0.990	0.124	0.990	0.177	3.358	0.828	5.724	1.904	0.029	0.012	0.015	0.007
0.98	0.990	0.116	0.990	0.181	3.408	0.802	5.757	1.948	0.029	0.012	0.015	0.007
0.99	0.990	0.114	0.990	0.181	3.477	0.793	5.747	1.914	0.029	0.011	0.015	0.007

Figures
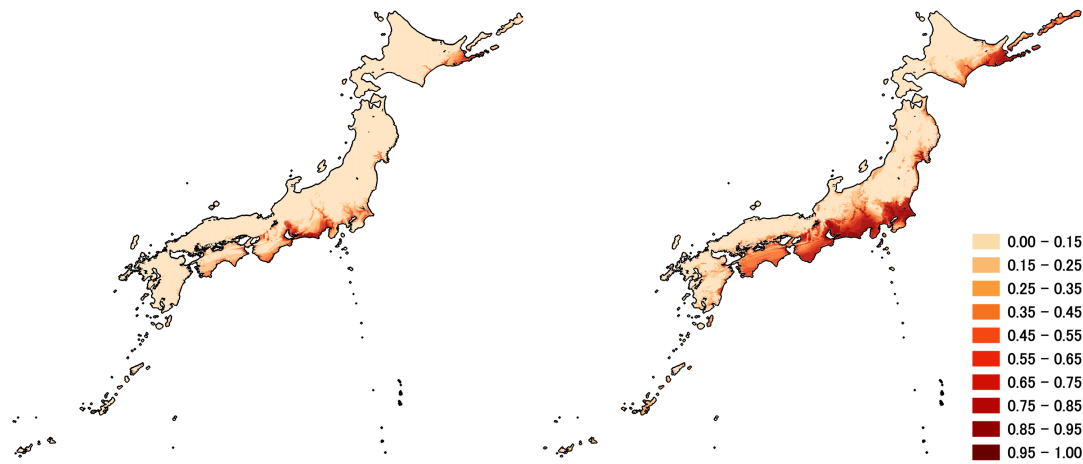
Figure A.1: Geographical distribution of future earthquake risks. The left-hand figure describes the probability that a location suffers an earthquake of a JMA seismic intensity larger than 6 lower in the next 30 years. The right-hand figure describes the probability that a location suffers an earthquake of a JMA seismic intensity larger than 5 upper in the next 30 years.
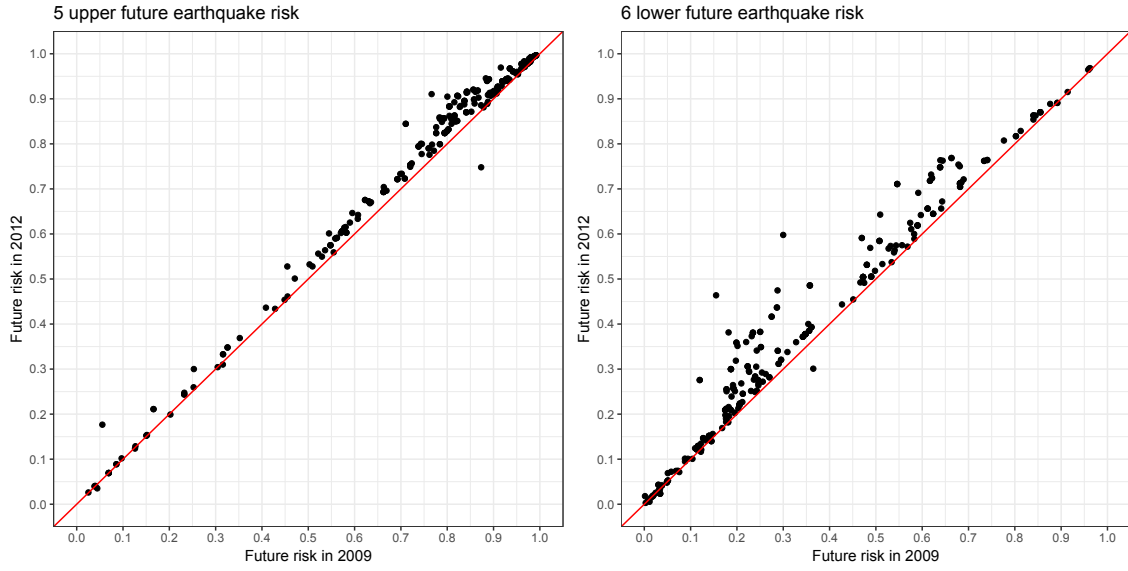
Figure A.2: Relationship between the future earthquake risk measured in 2009 and 2012. The left-hand figure shows the probability of suffering a JMA seismic intensity larger than 5 upper in the next 30 years. The right-hand figure shows the probability of suffering a larger than 6 lower earthquake.
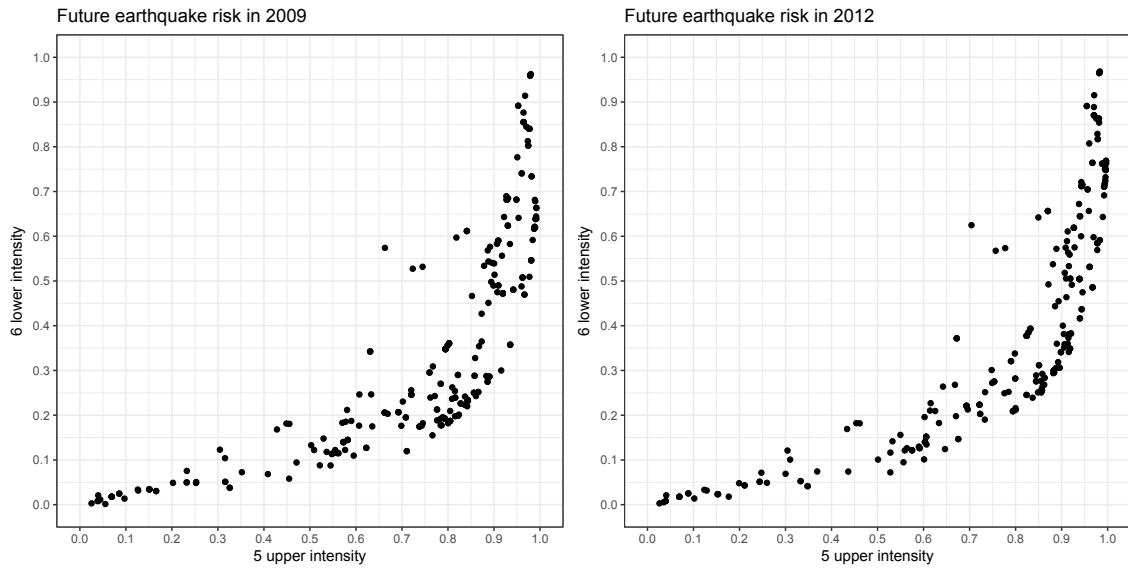
Figure A.3: Relationship between the 6 lower and 5 upper future earthquake risks.
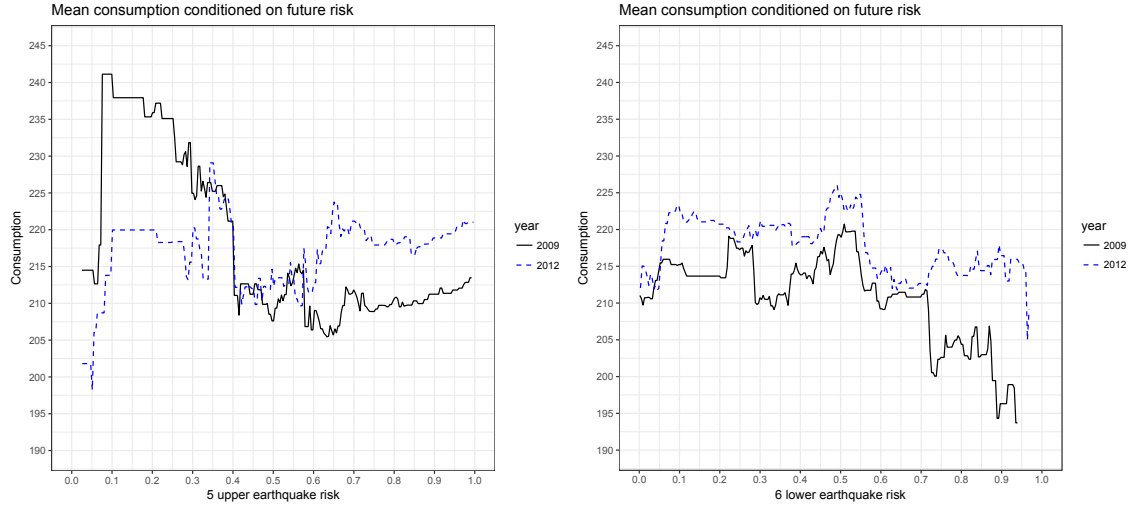
Figure A.4: Average consumption conditional on the risk of being hit by a large-scale earthquake. The left-hand figure describes the local average consumption conditional on the probability that a household suffers an earthquake of a JMA seismic intensity larger than 6 lower in the next 30 years. The right-hand figure describes the local average consumption conditional on the probability that a household suffers an earthquake of a JMA seismic intensity larger than 5 upper in the next 30 years.
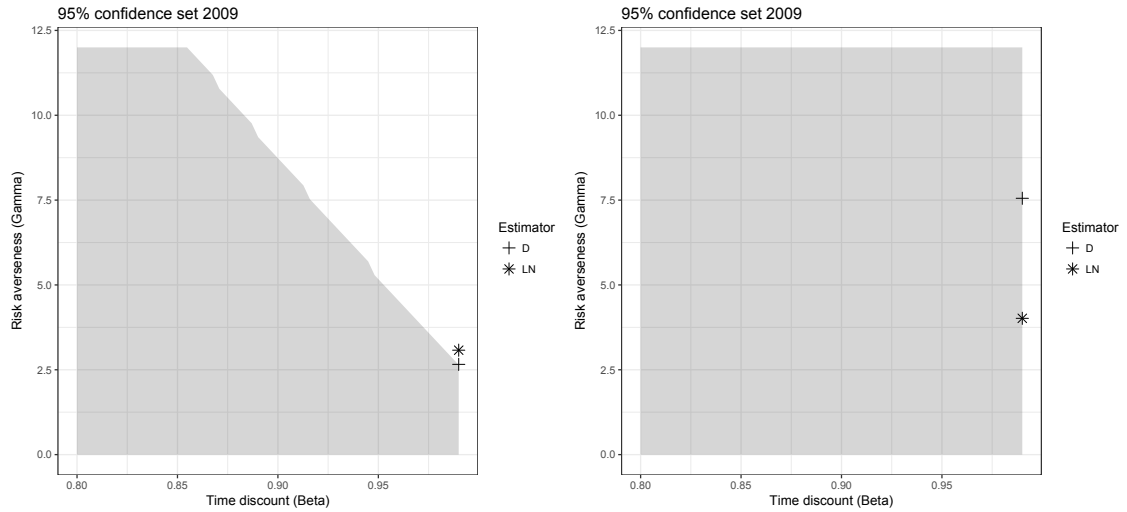
Figure A.5: 95% confidence sets and estimated parameter values. The 95% confidence sets for time discount factors β (vertical line) and risk averseness parameters γ (horizontal line) are shadowed.
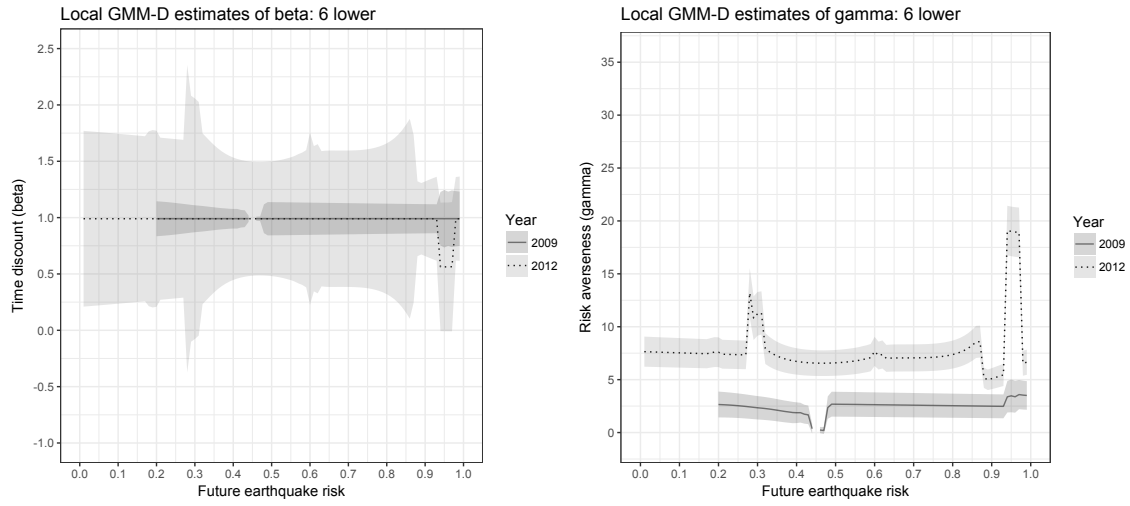
Figure A.6: The local GMM-D estimates and 95% confidence intervals for the 6 lower future risk. Only the estimation results within the 95% confidence sets derived by the moment inequalities are displayed.
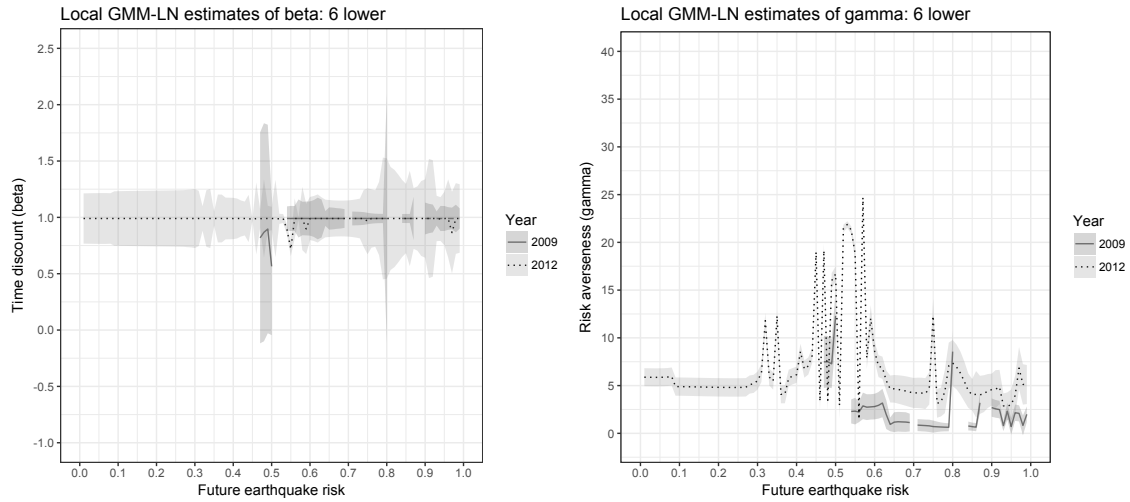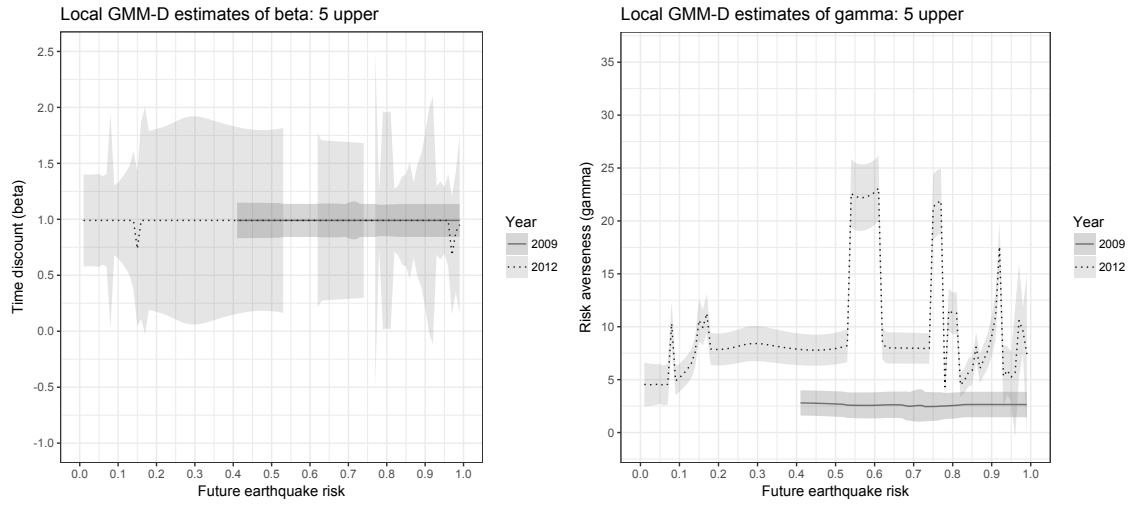

Figure A.7: The local GMM-LN estimates and 95% confidence intervals for the 6 lower future risk. Only the estimation results within the 95% confidence sets derived by the moment inequalities are displayed.

Figure A.8: The local GMM-D estimates and 95% confidence intervals for the 5 upper future risk. Only the estimation results within the 95% confidence sets derived by the moment inequalities are displayed.
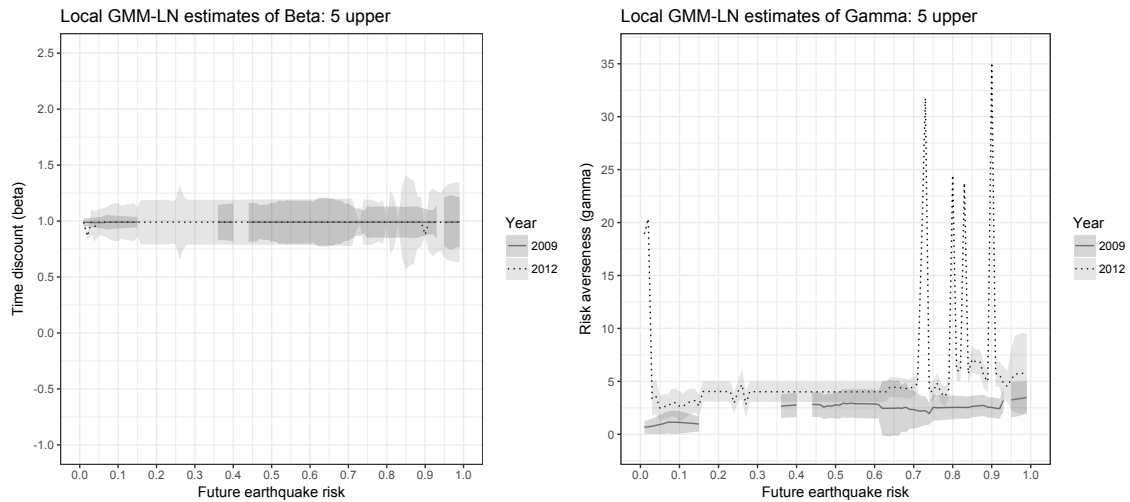

Figure A.9: The local GMM-LN estimates and 95% confidence intervals for the 5 upper future risk. Only the estimation results within the 95% confidence sets derived by the moment inequalities are displayed.
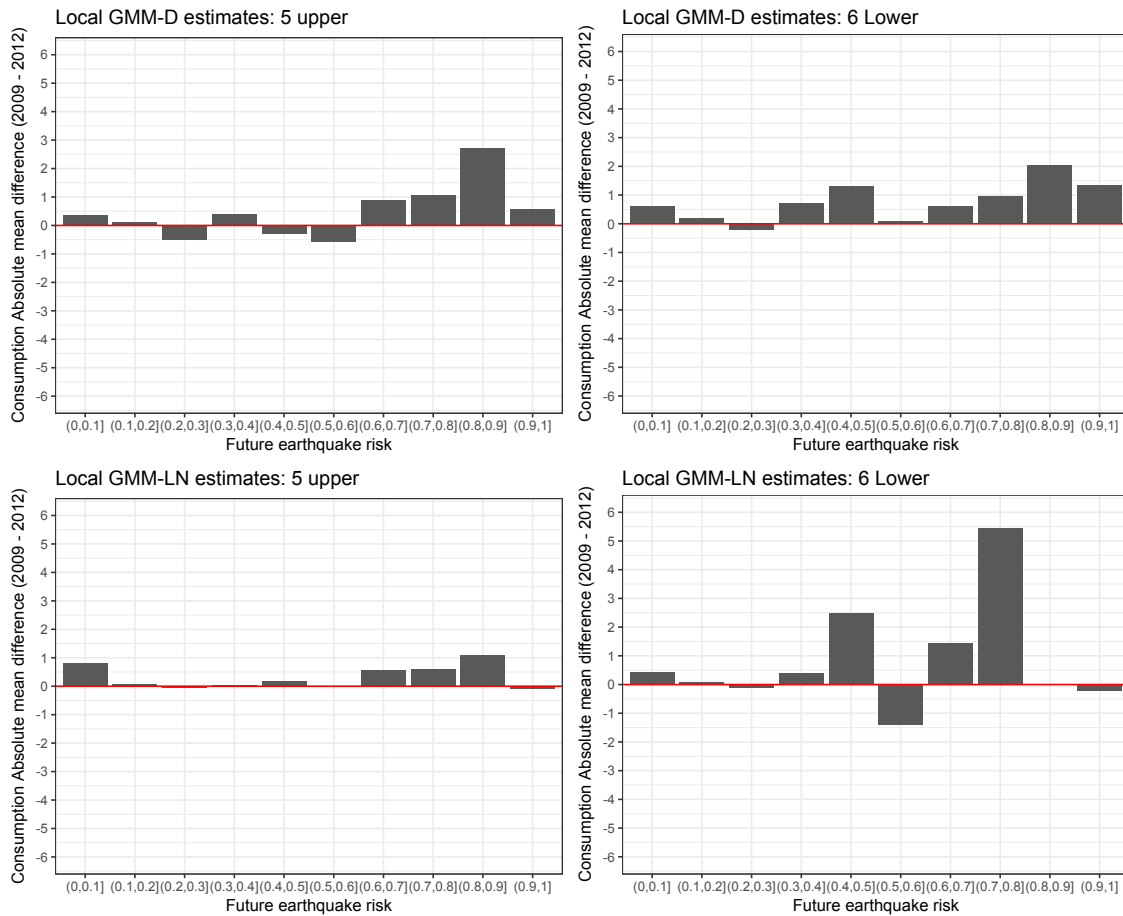
Figure A.10: Absolute mean difference in the consumption forecast errors. The positive values show the preference for a consumption forecast based on the after-disaster parameter estimates.
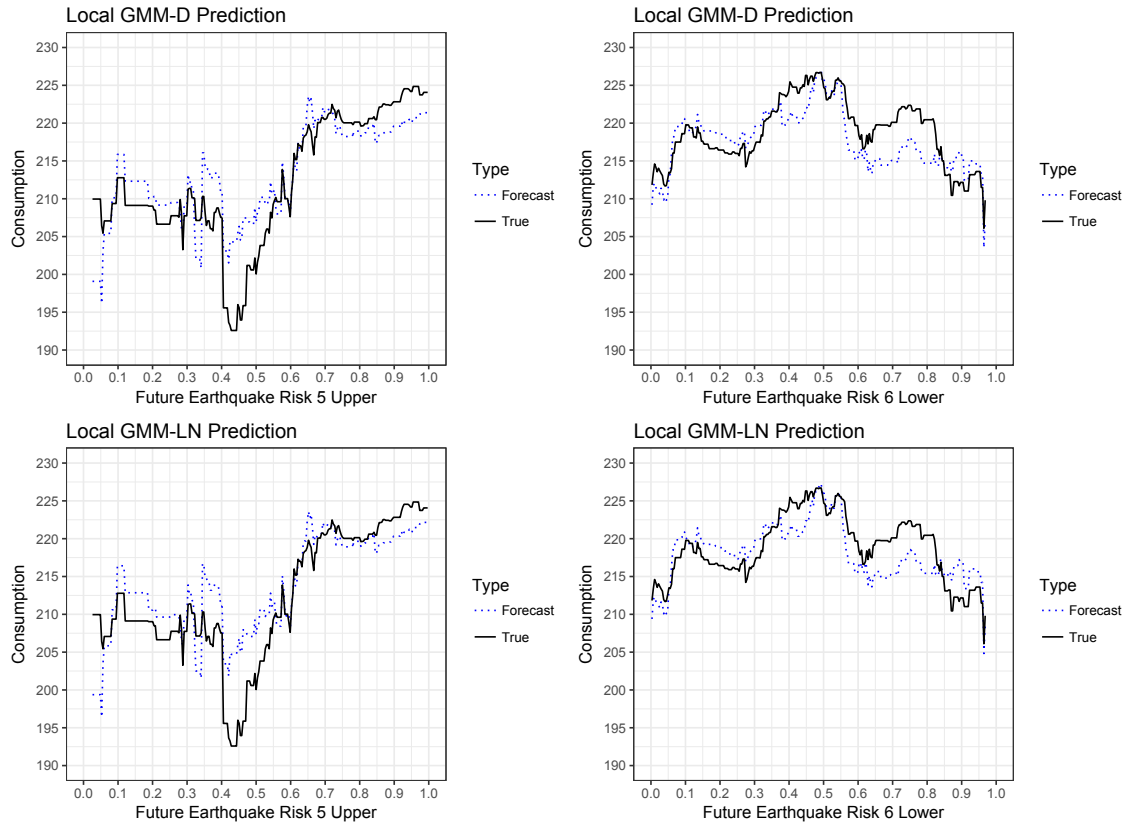
Figure A.11: Conditional mean estimation of consumption with respect to earthquake risk. The two upper (lower) panels show the results from the GMM-D (GMM-LN) setup. The black solid line is obtained by using actual consumption in 2013. The dashed red lines and dotted blue lines are predictions of 2013 consumption, calculated by using the estimated preference parameters before and after the disaster, respectively.