Does Memory of Earthquakes Affect Risk Tolerance?

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Abstract

Using data on earthquakes that have affected Japan over the past 100 years and self-reported risk tolerance, this paper finds a positive impact of "life-long" earthquake memory on risk tolerance. The results are robust with several alternative specifications. The paper also finds that earthquake memory is positively related to the share of risky financial assets in household financial assets.

Keywords Experience, Earthquakes, Risk tolerance, Household financial investment

JEL codes D14, D81, Q54

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This research utilizes the micro data from the Preference Parameters Study of Osaka University's 21st Century COE Program 'Behavioral Macro-Dynamics Based on Surveys and Experiments', its Global COE project 'Human Behavior and Socioeconomic Dynamics' and JSPS KAKENHI 15H05728 'Behavioral-Economic Analysis of Long-Run Stagnation'. The views presented in this paper are those of the author, and should not be attributed to the International Monetary Fund.

1 Introduction

While standard economic models assume that risk preference may not change over the life time, it is plausible to think that it does in response to an event or experience. Such a change in risk preference is likely to have important implications for the aggregate economy through financial and entrepreneurial behaviors, as those behaviors are affected by risk preference.

In the financial area, a sharp shock to markets and/or economic conditions could alter households' risk tolerance. Studies in the financial area typically support the view that a negative financial experience may reduce risk tolerance (e.g., Guiso, Sapienza, and Zingales (2018), Necker and Ziegelmeyer (2016)).

In the non-financial area, natural disasters may also change people' risk tolerance as they are traumatic events for many people. Given the important economic implications of changes in risk tolerance, many researchers have empirically investigated the impact of natural disasters on risk tolerance, but their results are inconclusive in terms of the direction of the impact. Some studies find a positive impact of natural disasters on risk tolerance, while others indicate the opposite (summarized, e.g., by Schildberg-Horisch (2018), Chuang and Schechter (2015)). Convergence of the results needs to be reached empirically, because as noted by Schildberg-Horisch (2018), within the field of economics there are no established theoretical predictions about whether natural disasters increase or decrease people's risk tolerance.

In light of this situation, this paper contributes to reconciling these results by taking an approach different from that adopted by existing studies. The approach adopted here differs in two important ways. First, the paper tests the impact of "life-long" earthquake memory on risk tolerance. This is also the main contribution of the paper as it is the first attempt in the field to examine the impact of life-long memory. Past studies have examined relatively short-term impacts of natural disasters, and in most cases, they have focused on a single disaster. The extensive earthquake data for Japan provided by the Japan Meteorological Agency, which covers 100 years from 1919, allows the paper to test the long-term impact of earthquakes using a sample larger than past studies.

Second, while all previous studies used risk tolerance that was based on experimental data (either hypothetical or real choices of lotteries in most cases) in testing the impact of natural disasters, this paper uses a self-reported risk tolerance variable ranging between 0 and 10. Both risk tolerance based on experimental data and self-reported risk tolerance have strengths and weaknesses (e.g., while cognitive skills affect the results for the former, interpretation of the question may differ across respondents for the latter). One way of comparing the two measures could be judging which measure has stronger power in predicting actions, and there is no evidence of any advantage of risk tolerance based on experimental data. This paper, however, does not argue that the self-reported risk tolerance variable is a superior measure than risk tolerance based on experimental data. Rather, the paper intends to fill a gap, because to my knowledge, no past studies have examined the impact of natural disasters on self-reported risk tolerance.

To capture life-long earthquake memory, this paper calculates the weighted frequency of experienced earthquakes in a flexible manner, following the methodology proposed by

Malmendier and Nagel (2011). The current paper does not predetermine the parameter that governs weights attached to past earthquakes, but estimates the parameter that fits the data best. This approach could be seen as a generalization of (most) past studies, which tested the impact of a recent event, effectively meaning that the weight on the recent event is 1, while the weights on other past events are zero.

The current paper finds that life-long earthquake memory has a positive impact on risk tolerance. This is consistent with Hanaoka, Shigeoka, and Watanabe (2018) who also used data for Japan and examined the impact of the devastating earthquake of 2011, and with Page, Savage, and Torgler (2014) and Eckel, El-Gamal, and Wilson (2009) who reported a positive impact using advanced economy data (Australia and the United States, respectively). The results do not change much when controlling for prefecture fixed effects, providing evidence against the argument that the estimated positive impact could arise from potential endogeneity that more risk tolerant households might be staying in more earthquake-prone prefectures. The results are also robust with other alternative specifications.

Importantly, the current paper also confirms that earthquake memory affects actual financial behavior. Specifically, the results indicate that an increase in the weighted annual frequency of experienced earthquakes by 0.1 point is estimated to raise the share of risky financial assets in household total financial assets by 13.3 percentage points.

The paper proceeds as follows. The next section presents a literature review, Section 3 describes the data, and Section 4 introduces the econometric model and reports the results. The final section provides concluding comments.

2 Related Literature

In the financial area, literature has reported relatively consistent results on the direction of the impact of a negative financial event on risk tolerance. Guiso, Sapienza, and Zingales (2018), Dohmen, Lehmann, and Pignatti (2016), and Necker and Ziegelmeyer (2016) reported that experience of a financial crisis lowers risk tolerance, while Bucciol and Miniaci (2018) and Sahm (2012) reported weaker macroeconomic conditions reduce risk tolerance.[1,2] By taking a very long-term view, Malmendier and Nagel (2011) reported results consistent with these studies. They showed that those who have experienced higher stock returns in their life time tend to show greater risk tolerance to financial risks, and argued that this observation is at least partly driven by changes in expectations about stock returns but did not exclude a possible impact of experiences on risk preferences.

By contrast, studies on the impact of natural disasters on risk tolerance have provided

[1]In an experimental setting, Cohn, Engelmann, Fehr, and Marechal (2015) presented the results that a negative financial shock makes financial professionals less risk tolerant.

[2]While some studies, e.g., Chiappori and Paiella (2011) and Brunnermeier and Nagel (2008), reported changes in wealth do not lead to changes in risk tolerance, these results do not necessarily contradict with those reporting significant association because the latter often supports an important role played by negative emotions instead of changes in financial variables themselves.

divergent results (Schildberg-Horisch (2018) and Chuang and Schechter (2015)).[3] As summarized in Table 1, while several studies reported that natural disasters may result in increases in risk tolerance (e.g., Hanaoka, Shigeoka, and Watanabe (2018), Page, Savage, and Torgler (2014)), others find the opposite (e.g., Cameron and Shah (2015)). In all of these studies, risk tolerance measures are based on experimental data (lottery choices in most cases).

There are three key messages from the past studies collected in Table 1.

1. All studies using advanced-economy data (Japan, Australia, and United States) reported increases in risk tolerance (first three rows in the table).

2. Studies that reported declines in risk tolerance all used data from nonadvanced economies (bottom half of the table).

3. Analysis using nonadvanced-economy data reported divergent results.

On the third point, while the majority of the studies in this field have used experimental data from developing countries, Schildberg-Horisch (2018) suggested that analyses using such data—but with tools typically developed for advanced economies—might be more likely to produce noisy results and thus contribute to the divergent results.[4] Researchers have also expressed skepticism about data based on *real* (not hypothetical) experiments, by pointing out, for example, the limited sample size (because of costs) and lack of stable responses (e.g., Mata, Frey, Richter, Schupp, and Hertwig (2018), Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011)). However, risk tolerance based on experimental data has merit in terms of the objectivity of the questions. For example, lottery choices are objective and not subject to multiple interpretations. Self-reported risk tolerance may not be subject to many of these shortcomings listed above, but each respondent might interpret the question differently (e.g., in the current study, a midpoint of the self-reported risk tolerance variable equal to 5 smight be interpreted differently).

Previous studies have examined relatively short-term impacts of natural disasters on risk tolerance. This is because most of them focused on the impact of a recent disaster (e.g., the 2004 Indian Ocean tsunami in Cassar, Healy, and von Kessler (2017) and Ingwersen (2015)). An exception is Cameron and Shah (2015) who also tested the impact of disaster history over 30 years. The limited availability of risk tolerance data (because the sample size of experimental data tends to be small) and the focus on a recent disaster give a relatively small sample size, at most around 3,000 (except for Ingwersen (2015)).

This paper is closely related to Hanaoka, Shigeoka, and Watanabe (2018) who also examined the impact of earthquakes using Japanese data, but the two papers are different in two ways. First, this paper tests the impact of the memory of earthquakes over individuals' lifetimes, while Hanaoka, Shigeoka, and Watanabe (2018) focused on a

[3]Research on the impact of conflicts on risk tolerance has also been inconclusive. While Voors, Nillesen, Verwimp, Bulte, Lensink, and Soest (2012) found increases in risk tolerance, Moya (2018), Callen, Isaqzadeh, Long, and Sprenger (2014), and Kim and Lee (2014) provided evidence of the opposite.

[4]For example, Vieider (2018), Andersson, Holm, Tyran, and Wengstrom (2016), and Chuang and Schechter (2015) also made the point that experimental data may be noisy.

Table 1 Literature on Natural Disasters' Impact on Risk Tolerance

	Nature of disaster	Country	Sample size
Increases in risk tolerance			
Hanaoka, Shigeoka, and Watanabe (2018)	Earthquake	Japan	3,352
Page, Savage, and Torgler (2014)	Flood	Australia	171
Eckel, El-Gamal, and Wilson (2009)	Hurricane	US	923
Ingwersen (2015)	Tsunami	India	11,890
Willinger, Bchir, and Heitz (2013)	Volcanic eruption	Indonesia	131
Bchir and Willinger (2013)	Mud flow and volcanic eruption	Peru	173
Declines in risk tolerance			
Cameron and Shah (2015)	Earthquake/Flood	Indonesia	1,538
Reynaud and Aubert (2020)	Flood	Vietnam	1,850
Chantarat, Chheng, Minea, Oum, Samphantharak, and Sann (2015)	Flood	Vietnam	256
Samphantharak and Chantarat (2015)	Flood	Thailand	374
van den Berg, Fort, and Burger (2009)	Hurricane	Nicaragua	84
	Crop and live stock losses (e.g., by drought)	Peru	82
Cassar, Healy, and von Kessler (2017)	Tsunami	Thailand	332

Notes: For the sample size, the maximum size in the main regression(s) in each paper is reported.

single event, the 2011 Great East Japan Earthquake.[5] Second, this paper tests the long-term impact of earthquakes by constructing the weighted frequency of experienced earthquakes for each respondent, not the short-term impact or impact over several years as examined in Hanaoka, Shigeoka, and Watanabe (2018).

3 Data

The empirical analysis in this paper relies on two datasets. The first contains self-reported risk tolerance data provided by the Japan Household Panel Survey on Consumer Preferences and Satisfaction (JHPS-CPS). The second contains earthquake seismic intensity data released by the Japan Meteorological Agency.

3.1 Self-reported Risk Tolerance Data

The JHPS-CPS is a household panel dataset for Japan that started in 2003. It contains preference-related variables, as well as standard demographic variables. In light of its strength in covering preference-related variables, several recent studies have also investigated the impact of economic and non-economic events on preferences (e.g., Akesaka (2019), Shigeoka (2019), Hanaoka, Shigeoka, and Watanabe (2018)).

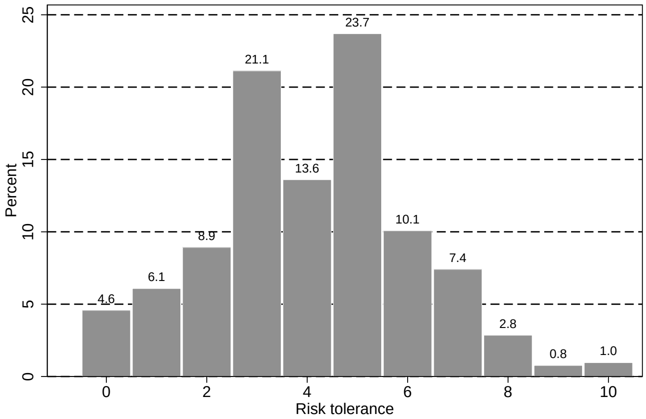
As the key variable, this paper uses the self-reported risk tolerance variable reported by respondents, motivated by the fact that previous studies (in Table 1) have all used a risk-tolerance measure based on experimental data. In the JHPS-CPS, each respondent selects an integer between 0 and 10, with 0 indicating the highest degree of risk aversion, and 10 indicating the highest degree of risk tolerance, in response to the following question:

As the proverb says, "Nothing ventured, nothing gained", there is a belief that in order to achieve results, you need to take risks. On the other hand, as another proverb says, "A wise man never courts danger", meaning that you should avoid risks as much as possible. Which way of thinking is closest to the way you think? On a scale of 0 to 10, with "10" being completely in agreement with the thinking "Nothing ventured, nothing gained", and "0" being completely in agreement with the thinking "A wise man never courts danger", please rate your behavioral pattern.

Choosing this risk tolerance variable also maximizes the sample size and increases statistical power as this is the preference variable reported for the longest period of time (seven years between 2004 and 2010) in the JHPS-CPS. This variable is distributed widely from 0 to 10; however, more than half of the respondents selected a value in the range 3 to 5 (Figure 1).

[5] The 2011 Great East Japan Earthquake was the most devastating earthquake in recent history in Japan. It occurred on March 11 2011, causing more than 15,000 deaths.

Figure 1 Distribution of Risk Tolerance Variable



Notes: The data source is JHPS-CPS (2004–2010). 0 indicates the highest degree of risk aversion, while 10 indicates the highest degree of risk tolerance.

3.2 Earthquake Seismic Intensity Data

The Japan Meteorological Agency has recorded all earthquakes in Japan that have occurred since 1919, with data on earthquake location and seismic intensity. Seismic intensity is the scale of the ground motion (acceleration) and is measured using a 10-point scale (0, 1, 2, 3, 4, 5 Lower, 5 Upper, 6 Lower, 6 Upper, and 7) at each monitoring site located across Japan. Table 2, which summarizes typical human response and perception by seismic intensity, gives us a better sense of the severity of various seismic intensity levels. Through September 1996 (since 1919), the Japan Meteorological Agency was using 8 scales (0, 1, 2, 3, 4, 5, 6, and 7), and was not recording the breakdown of seismic intensity 5 (5 Lower and 5 Upper) and seismic intensity 6 (6 Lower and 6 Upper).

As noted earlier, this paper examines whether memory of earthquakes affects risk tolerance. For this reason, we use data on strong earthquakes, more specifically, earthquakes with seismic intensity of 5 or higher (i.e., "5 Lower" or higher) because seismic intensity 5 Lower is the level where "Many people were frightened" (see "5 Lower" row in Table 2) and thus people are more likely to remember earthquakes with seismic intensity of 5 or higher. The Japan Meteorological Agency notes that in the case of an earthquake with seismic intensity of 5 or higher, elevators stop automatically while water and electricity supply may be suspended. Such events may also strengthen people's memory.

This paper counts the main earthquake and aftershocks as one earthquake. In Japan, a single name is often given to a series of earthquakes (main earthquake and subsequent aftershocks), and thus people may remember the series as one earthquake. Specifically, we do not include an earthquake if the previous earthquake in the same prefecture occurred within one year because the Japan Meteorological Agency suggests that aftershocks may occur up to one year after the main earthquake.[6] As we will see, the results are not sensitive to this assumption of a one-year cutoff.

[6] For example, `https://www.data.jma.go.jp/svd/eqev/data/aftershocks/kiso_aftershock.html`

Table 2 Seismic Intensity and Human Perception and Reaction

Seismic intensity	Human perception and reaction
0	Imperceptible to people, but recorded by seismometers.
1	Felt slightly by some people staying quiet in buildings.
2	Felt by many people keeping quiet in buildings. Some people may have been awoken.
3	Felt by most people in buildings. Felt by some people walking. Many people were awoken.
4	Most people felt startled. Felt by most people walking. Most people were awoken.
5 Lower	Many people were frightened and felt the need to hold onto something stable.
5 Upper	Many people found it difficult to move; walking was difficult without holding onto something stable.
6 Lower	It was difficult to remain standing.
6 Upper	It was impossible to remain standing or move without crawling. People may have been thrown through the air.
7	

Notes: The source is "Tables explaining the JMA Seismic Intensity Scale" released by the Japan Meteorological Agency (https://www.jma.go.jp/jma/en/Activities/inttable.html). Seismic intensity is measured by the ground motion (acceleration) at a site where a seismic intensity meter is installed, and is not determined from the observed phenomena described in this table.

The paper also excludes earthquakes observed at remote islands because the vast majority of residents in the prefecture to which such remote islands belong would not have felt these earthquakes, and therefore are unlikely to remember them (because the earthquake locations are extremely distant).[7]

3.3 Weighted Frequency of Earthquakes

This paper calculates the weighted frequency of earthquakes (with seismic intensity 5 or higher) for each respondent over their lifetime. This variable is intended to capture respondents' memory of earthquake experience.

Specifically, the paper follows Malmendier and Nagel (2011), assuming that the weighted frequency for respondent i in year t takes the form of a weighted average:

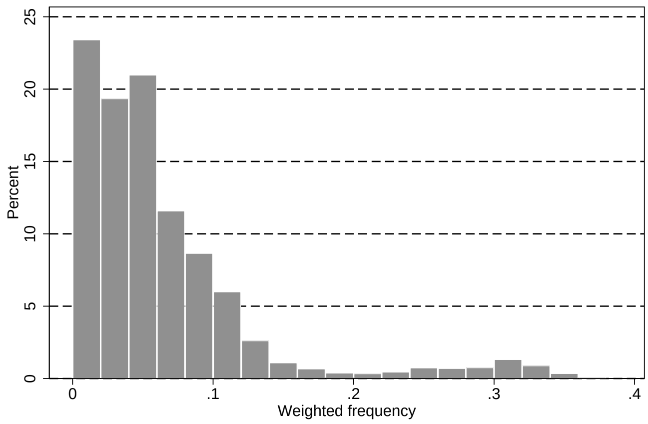
$$F_{i,t}(\lambda) = \sum_{k=1}^{age_{i,t}-1} w_{i,t}(k,\lambda)E_{t-k}, \tag{1}$$

where $w_{i,t}(k,\lambda)$ is the weight, and E_{t-k} is the number of earthquakes (with seismic intensity 5 or higher) in year $t-k$ in the prefecture in which respondent i resides,[8] but is not the number of earthquakes the respondent actually experienced as such information is unavailable (this paper will return to this issue).

[7] Specifically, remote islands that belong to the following three prefectures are excluded: Tokyo, Kagoshima, and Okinawa.

[8] This paper removes an observation from the sample if a respondent moved to another prefecture during the sample period.

Figure 2 Distribution of Weighted Frequency of Earthquakes in 2004–2010 (at $\lambda = 0$)



The function form of $w_{i,t}(k, \lambda)$ is

$$w_{i,t}(k, \lambda) = \frac{(age_{i,t} - k)^{\lambda}}{\sum_{k=1}^{age_{i,t}-1} (age_{i,t} - k)^{\lambda}}, \tag{2}$$

where λ determines the shape of $w_{i,t}$. A positive λ implies higher weights for more recent earthquake experiences, whereas a negative λ suggests the opposite ($\lambda = 0$ implies equal weights for each year in the past). For example, if $\lambda = 0.5$ and the age is 40 years, the weight assigned to one year ago is 3.8 percent, while that assigned to 20 years ago declines to 2.7 percent.

The methodology using equation (1) could be seen as a generalization of (most of the) past studies. These studies examined the impact of a recent disaster, which effectively means that the weight for that disaster is 1, while the weights for other past events are zero. This is equivalent to setting λ equal to a large positive value.

Variation of the weighted frequency $F_{i,t}$ is needed for the regression analysis (below) to identify the impact of $F_{i,t}$ on the risk tolerance. By plotting the distribution of $F_{i,t}$ evaluated at $\lambda = 0$ for the full JHPS-CPS sample (2004–2010), Figure 2 confirms the existence of sufficient variation.

3.4 Summary Statistics

Table 3 reports means by year (2004–2010) for the combined JHPS-CPS and earthquake data. The total sample size, excluding those with missing data, is 17,175, which is larger than that in previous studies (Table 1). While the means are relatively stable across years, the risk tolerance in 2009 is around 4.0 and lower by 0.2 points or more compared with other years (first row of the table), which may reflect the economic downturn during the global financial crisis.

When $\lambda = 0$ (equal weight for each year in the past), the weighted frequency of earthquakes is about 0.07 in 2010, meaning that households experienced an earthquake with seismic intensity of 5 or higher 0.07 times each year on average (i.e., experienced such an earthquake once in 14 years on average). The weighted frequency of earthquakes increases to 0.069 in 2009 from 0.064 in 2008 (when $\lambda = 0$). This is because in 2008, as many as 9 prefectures were hit by earthquakes with seismic intensity of 5 or higher, which is greater than the average of 3.3 prefectures per year over the period 1919–2018.[9]

4 Empirical Analysis

This section presents the econometric model and empirical results.

4.1 Econometric Model

With the weighted frequency of earthquakes introduced in Section 3.3, I estimate the following equation while simultaneously searching for the value of λ that minimizes the sum of the squared residuals ($= \varepsilon_{i,t}^2$) across households (i.e., across i):

$$RiskTolerance_{i,t} = \theta_0 + \theta_1 F_{i,t}(\lambda) + \theta_2 Z_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where $RiskTolerance_{i,t}$ is respondent i's risk tolerance variable introduced earlier, and θ_1 is the coefficient of primary interest.

$Z_{i,t}$ is a vector of control variables comprising household real income in the previous year ($y_{i,t-1}$), household real net worth in year t ($rnetworth_{i,t}$) (both deflated by the 2018 CPI for Japan), and other controls, including the age of the main earner, age squared, dummy variables denoting the sex of the respondent, marriage status and whether the respondent has a bachelor degree, number of family members, eight occupation dummies of the main earner[10], 10 region dummies[11], and year dummies. I removed an observation from the sample if the respondent moved to another prefecture during the sample period (2004–2010).

4.2 Does Self-reported Risk Tolerance Explain Behavior?

Before reporting the main results, this subsection investigates if the self-reported risk tolerance variable can explain actions that have implications for the aggregate economy. Self-reported risk tolerance may differ from actual behavior (e.g., Malmendier and Nagel (2011)), leading to a concern about whether self-reported risk tolerance can explain risk-taking behavior accurately. While past studies reported that risk aversion expressed in survey responses does so (e.g., Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011), Guiso and Paiella (2008), Donkers, Melenberg, and Van Soest (2001), Barsky, Juster, Kimball, and Shapiro (1997)), we still need to confirm the validity of the self-reported risk tolerance variable used in the current analysis. Data on risky behavior, such

[9] The weighted frequency in 2008 does not reflect earthquakes that occurred in 2008, as it is calculated with the earthquakes through 2007.

[10] The eight occupations are clerical worker, sales worker, manager, professional and technical worker, service worker, craftsperson, farmer, and not employed.

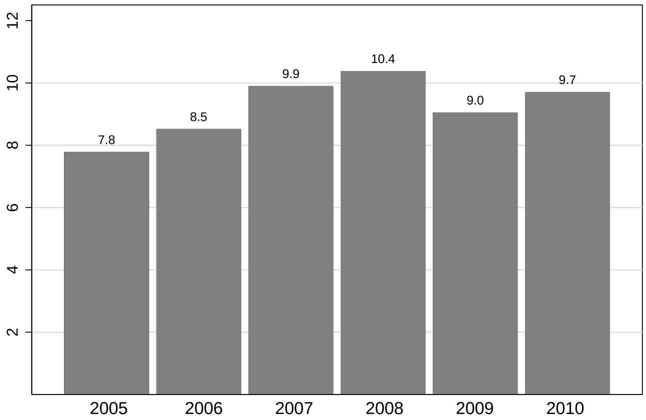
[11] The ten regions are Hokkaido, Tohoku, Kanto, Koshinetsu, Hokuriku, Tokai, Kinki, Chugoku, Shikoku, and Kyushu.

Table 3 Means of Key Variables

	2004	2005	2006	2007	2008	2009	2010
Risk tolerance	4.24	4.19	4.15	4.14	4.12	3.95	4.15
Weighted frequency of earthquakes: $\lambda = 0$	0.051	0.055	0.063	0.062	0.064	0.069	0.068
Weighted frequency of earthquakes: $\lambda = 0.5$	0.058	0.063	0.074	0.073	0.076	0.081	0.080
Weighted frequency of earthquakes: $\lambda = -0.5$	0.043	0.047	0.051	0.050	0.052	0.055	0.054
age	49.5	51.1	50.9	52.4	53.6	51.1	52.0
dummy of male	0.52	0.51	0.53	0.51	0.50	0.51	0.51
dummy of marriage	0.78	0.79	0.79	0.80	0.81	0.80	0.80
dummy of bachelor's degree	0.22	0.21	0.23	0.22	0.22	0.25	0.26
family size	3.44	3.44	3.52	3.51	3.43	3.45	3.44
household real income last year (in million yen, deflated by 2018 CPI)	6.82	7.04	7.07	6.98	6.85	6.51	6.46
household real net worth (in million yen, deflated by 2018 CPI)	24.7	27.0	25.6	27.4	27.8	25.1	25.0
Number of observations (respondents)	2413	1701	2178	1894	1719	3922	3348

Notes: The sample is the JHPS-CPS data in 2004–2010.

Figure 3 Average Share of Risky Financial Assets in Total Household Financial Assets



Notes: The sample is JHPS-CPS 2004–2010.

as smoking and drinking, are available in the JHPS-CPS, and empirical analysis confirms that self-reported risk tolerance has impact on such behavior (details not reported here).

A more important question, however, is whether self-reported risk tolerance affects household investment in risky financial assets because such investment could have macroeconomic impact. The JHPS-CPS enables us to conduct this analysis as it contains data on whether households own risky financial assets and on the share of risky financial assets in total financial assets. The JHPS-CPS defines risky financial assets as follows: trusts, stocks, derivatives, corporate bonds, foreign currency deposits, and foreign bonds. In Japan, the rate of financial penetration is low. Indeed, in the sample (JHPS-CPS 2004–2010), the share of households that own such risky financial assets is around 26 percent, which is substantially lower than the share of households in the United States around 50 percent that own shocks directly or indirectly (see, e.g., Board of Governors of the Federal Reserve System (2017)). The average share of risky financial assets in total household financial assets is also relatively low around 9 percent, although it was on an upward trend between 2005 and 2010 (Figure 3) except for the period during the global financial crisis.

The results in Table 4 confirm that self-reported risk tolerance has a significant impact on risky financial investment. The first column of the table reports the results for the regression of the dummy of owning risky financial assets on self-reported risk tolerance; the coefficient on the latter is positive and significant at the 1 percent level. The coefficient on the risk tolerance variable remains significant, when using the share of risky financial assets in total household financial assets (in percent) as the dependent variable (second column).

Table 4 Impact of Self-reported Risk Tolerance on Financial Investment

VARIABLES	(1) OLS Dummy of risky financial assets	(2) OLS Share of risky financial assets
$RiskTolerance_t$	0.0068	0.54
	(0.0021)***	(0.11)***
Observations	17,175	13,042
R-squared	0.151	0.088

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2004–2010. The dependent variable is the dummy of owning risky financial assets in the first column and and the share of risky financial assets in the second column. Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1.

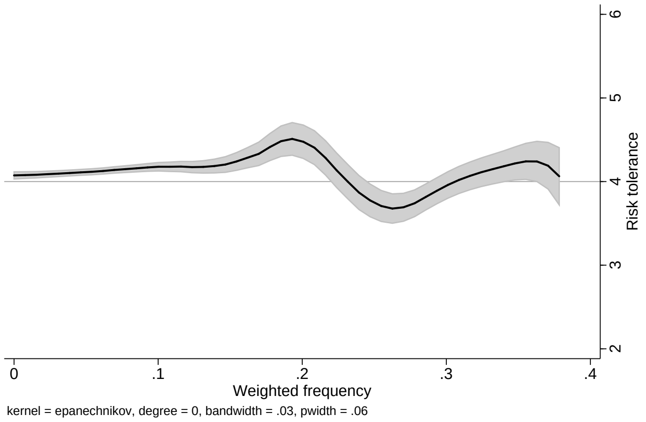
4.3 Main results

The results support the hypothesis that the impact of earthquake memory on risk tolerance is positive. Figure 4 plots a nonparametric estimation of the association between the weighted frequency of earthquakes and risk tolerance. The figure shows positive relation between the two where the weighted frequency is lower than 0.2, but this relation appears to disappear where the weighted frequency is higher than 0.2. Given that the fraction of observations with the weighted frequency greater than 0.2 is relatively small around 5 percent (Figure 2), the relation could be estimated to be positive by formal regression analysis. Table 5 revisits the issue with regressions that also control for other factors including individually-specific factors. The first column of the table shows that at $\lambda = 0$ (meaning equal weight for each year), the coefficient on the weighted frequency is indeed positive and significant. More importantly, at the solution value of λ that minimizes the sum of the squared residuals in equation (3), the coefficient on the weighted frequency is significant at the 1 percent level (second column of the table).[12] The coefficient on the weighted frequency implies that an increase in the weighted frequency by 0.1 points raises the risk tolerance variable by about 0.2 points. This, together with the estimate in Section 4.2, suggests that a 0.1-point increase in the weighted annual frequency of earthquakes will increase the share of risky financial assets by about 0.1 ($\approx 0.2 \times 0.54$) percentage point. However, whether earthquake memory affects actual financial behavior needs to be tested explicitly (see Section 4.6).

Although future financial variables (income and wealth) could affect risk tolerance, including them does not change the results. So far, the regressions have controlled for household real income in the previous year ($y_{i,t-1}$) and household real net worth in year t ($rnetworth_{i,t}$). The third column of Table 5 reports that adding future financial variables

[12] The solution value of λ is slightly negative at -0.33, and its standard error is 0.22, implying that $\lambda = 0$ cannot be rejected. However, the statistical significance of the weighted frequency is not sensitive to the value of λ. At the solution of $\lambda \pm 2\times$standard deviation of λ, the coefficient on the weighted frequency remains significant (results not reported here).

Figure 4 Weighted Frequency of Earthquakes in 2004–2010 (at $\lambda = 0$) and Risk Tolerance (with 95 percent confidence interval)



Notes: The figure plots the estimated polynomial (solid line) and the 95 percent confidence interval (shaded).

$y_{i,t}$ and $rnetworth_{i,t+1}$ (both divided by 10,000) does not change the results much and that the coefficient on the weighted frequency remains significant with these variable. (The results do not change substantially either when adding $y_{i,t+1}$ and $rnetworth_{i,t+2}$, and further $y_{i,t+2}$ and $rnetworth_{i,t+3}$ (details not reported here)).

4.4 Alternative Specifications

The results do not change much with alternative specifications: including prefecture fixed effects, changing the weight function, the threshold level of seismic intensity or the way earthquakes are counted, and scaling the weighted frequency of earthquakes by prefecture size. The results provide no evidence of selection bias.

4.4.1 Prefecture Fixed Effects

Controlling for 47 prefecture dummies instead of region dummies (included in the estimations above) does not change the results much. Although the statistical significance is lower, the coefficient on the weighted frequency remains significant (Table 6). These results provide evidence against the argument that the estimated positive impact could arise from potential endogeneity that more risk tolerant respondents might stay in more earthquake-prone prefectures.

4.4.2 Alternative Discount Function

Next, we examine if the results change with an alternative weight function. Although equation (2) has the benefit of flexibility (Malmendier and Nagel (2011)), consider the following weight in year $t - k$ with δ as a constant discount factor (δ), which is typical

Table 5 Impact of Lifetime Weighted Frequency of Earthquakes

VARIABLES	(1) OLS Risk tolerance $\lambda = 0.0$	(2) OLS Risk tolerance λ at solution	(3) OLS Risk tolerance
Weighted frequency of earthquakes F_t ($\lambda = 0.0$)	1.78		
	(0.72)**		
Weighted frequency of earthquakes F_t (λ at solution)		1.90	2.02
		(0.73)***	(0.87)**
household real income in year t (y_t) divided by 10,000			-0.12
			(0.79)
household real net worth in year $t+1$ ($rnetworth_{t+1}$) divided by 10,000			-0.08
			(0.09)
Observations	17,175	17,175	12,517
R-squared	0.048	0.048	0.04

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2004–2010. The dependent variable is self-reported risk tolerance. Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1. The estimated value of λ in the second column of Table 5 is used in the last column.

Table 6 Estimation Results with Prefecture Fixed Effects

VARIABLES	(1) OLS Risk tolerance $\lambda = 0.0$ With dums of 47 prefectures	(2) OLS Risk tolerance λ at solution With dums of 47 prefectures
Weighted frequency of earthquakes F_t ($\lambda = 0.0$)	2.97	
	(1.40)**	
Weighted frequency of earthquakes F_t (λ at solution)		2.52
		(1.11)**
Observations	17,175	17,175
R-squared	0.052	0.052

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2004–2010. The dependent variable is self-reported risk tolerance. Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1 and 47 prefecture dummies (instead of region dummies).

Table 7 Estimation Results with Alternative Weight Function

VARIABLES	(1) OLS Risk tolerance δ at solution	(2) OLS Risk tolerance
Weighted frequency of earthquakes F_t (δ at solution)	1.96	2.00
	(0.72)***	(0.87)**
household real income in year t (y_t) divided by 10,000		-0.13
		(0.79)
household real net worth in year $t+1$ ($rnetworth_{t+1}$) divided by 10,000		-0.08
		(0.09)
Observations	17,175	12,517
R-squared	0.048	0.04

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2004–2010. The dependent variable is self-reported risk tolerance. Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1. The estimated value of δ in the first column is used in the second column.

in the economics literature:

$$w_{i,t}(k,\delta) = \frac{\delta^k}{\sum_{k=1}^{age_{i,t}-1} \delta^k}. \tag{4}$$

This function means that memory depreciates at the constant rate at $1-\delta$ every year.

The results are robust to the alternative weight function. The first column of Table 7 shows that the coefficient on the weighted frequency of earthquakes is significant at the 1 percent level. The key coefficient remains significant (although its statistical significance is somewhat weaker) even when adding future financial variables (last two columns of the table).

4.4.3 Alternative Seismic Intensity Levels

The results show robustness with an alternative threshold level of seismic intensity. So far, the analysis has used data on earthquakes with seismic intensity of 5 or higher, namely, "5 Lower" or higher. Now change this threshold level to "5 Upper" or higher. There is a data issue with this change because as noted in Section 3.2, through September 1996 (since 1919) the Japan Meteorological Agency was not recording the breakdown of seismic intensity 5 (5 Lower and 5 Upper). Given this data limitation, when calculating the weighted frequency of earthquakes with seismic intensity of 5 Upper or higher, include i) all the earthquakes with seismic intensity of 6 (6 Lower) or higher since 1919; and ii) those with seismic intensity of 5 Upper or higher after September 1996. As data on earthquakes with seismic intensity of 5 Upper are unavailable between 1919 and September 1996 (only those with seismic intensity of "5" are available during this period),

Table 8 Estimation Results with Alternative Cutoff Level of Seismic Intensity

VARIABLES	(1) OLS Risk tolerance λ at solution 5 Upper or higher	(2) OLS Risk tolerance δ at solution 5 Upper or higher
Weighted frequency of earthquakes F_t (λ at solution; Intensity 5 Upper or higher)	2.56	
	(1.30)**	
Weighted frequency of earthquakes F_t (δ at solution; Intensity 5 Upper or higher)		3.42
		(1.78)*
Observations	17,175	17,175
R-squared	0.048	0.048

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2004–2010. The dependent variable is self-reported risk tolerance. Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1.

this creates a measurement error problem and works in the direction of reducing the size of the coefficient on the weighted frequency. The mean value in the sample (across households) of the weighted frequency of earthquakes with seismic intensity of 5 Upper or higher evaluated at $\lambda = 0$ (equal weight for each past year) is 0.018 and as low as about a quarter of the weighted frequency of earthquakes with seismic intensity of 5 or higher (evaluated at $\lambda = 0$).

Despite the low value of the weighted frequency of earthquakes with seismic intensity of 5 Upper or higher, which also reflects the measurement error problem, its coefficient is positive and significant, when using weight function (2) (first column of Table 8). Using an alternative weight function (4) gives similar results (second column).

4.4.4 Alternative Method of Counting Earthquakes

The results are also not sensitive to the way that earthquakes are counted. The first column of Table 9 shows that, using the weight function (2) with λ, the coefficient on the weighted frequency remains significant even when excluding earthquakes for which the previous earthquake occurred within two years. The results are similar when using the weight function (4) with δ (second column) and excluding earthquakes for which the previous earthquake occurred within half a year (last two columns).

4.4.5 Earthquake Frequency Scaled by Prefecture Size

The weighted frequency of earthquakes with seismic intensity of 5 or higher introduced earlier may involve some measurement issues. As noted in Section 3.3, the number of earthquakes used to calculate the weighted frequency is the number of earthquakes

Table 9 Estimation Results with Alternative Counting of Earthquakes

VARIABLES	(1) OLS Risk tolerance λ at solution Exc. 2 yrs	(2) OLS Risk tolerance δ at solution Exc. 2 yrs	(3) OLS Risk tolerance λ at solution Exc. 6 months	(4) OLS Risk tolerance δ at solution Exc. 6 months
Weighted frequency of earthquakes F_t (λ at solution; Exc. quakes within 2 yrs)	1.66 (0.79)**			
Weighted frequency of earthquakes F_t (δ at solution; Exc. quakes within 2 yrs)		1.63 (0.83)*		
Weighted frequency of earthquakes F_t (λ at solution; Exc. quakes within 6 months)			1.58 (0.70)**	
Weighted frequency of earthquakes F_t (δ at solution; Exc. quakes within 6 months)				1.61 (0.66)**
Observations	17,175	17,175	17,175	17,175
R-squared	0.048	0.048	0.048	0.048

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2004–2010. The dependent variable is self-reported risk tolerance. Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1.

Table 10 Impact of Lifetime Weighted Frequency of Earthquakes Scaled by Prefecture Size

VARIABLES	(1) OLS Risk tolerance λ at solution	(2) OLS Risk tolerance δ at solution
Weighted frequency of earthquakes F_t (λ at solution)	0.52 (0.28)*	
Weighted frequency of earthquakes F_t (δ at solution)		0.53 (0.27)**
Observations	17,175	17,175
R-squared	0.048	0.048

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2004–2010. The dependent variable is self-reported risk tolerance. Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1. The weighted frequency is scaled by prefecture size (measured in 10,000 square kilometers).

observed in the prefecture in which the respondent resides, not that actually experienced by them because the latter information is not available.

People may not remember clearly an earthquake that occurred in the prefecture in which they reside, if the location of the earthquake is far away from where they live. In such a case, the seismic intensity felt by them could be lower than 5. This may happen more often in large prefectures than in small prefectures, which motivates us to scale the weighted frequency of earthquakes by the size of the prefecture in which the respondent resides.

The results remain strong with this scaling. The first column of Table 10 reports that the coefficient on the "scaled" weighted frequency is significant when equation (2) λ is used for the weight function. The results are similar when equation (4) δ is used (second column of the table).

4.4.6 Potential Sample Bias from Selective Attrition and Mobility

The results might be subject to potential sample selection bias. Specifically, if more risk-averse respondents are more likely to exit the survey, the results will be subject to attrition bias. To examine this possibility, this paper estimates the following equation:

$$Dummy\_Attrition_{i,t+1} = \beta_0 + \beta_1 RiskTolerance_{i,t} + \beta_2 Z_{i,t} + \varepsilon_{i,t}, \tag{5}$$

where $Dummy\_Attrition_{i,t+1}$ is the dummy of attrition set equal to 1 if the respondent left the survey between years t and $t+1$. The mean of $Dummy\_Attrition_{i,t+1}$ in the sample is 0.14, meaning that the attrition rate is 14 percent.

The results provide no evidence of attrition bias. The first column of Table 11 reports

Table 11 Testing Selective Attrition and Mobility

VARIABLES	(1) OLS Dummy of attrition	(2) OLS Dummy of attrition	(3) OLS Dummy of mobility	(4) OLS Dummy of mobility
$RiskTolerance_t$	-0.0009		-0.00005	
	(0.0014)		(0.00004)	
Weighted frequency of earthquakes F_t		-0.08		0.0032
		(0.09)		(0.0048)
Observations	17,175	17,175	17,175	17,175
R-squared	0.0451	0.05	0.00232	0.002

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2004–2010. The dependent variable is the dummy of attrition in the first two columns and the dummy of mobility in the last two columns. Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1. The value of λ estimated in the second column of Table 5 is used for calculating the weighted frequency of earthquakes.

that the coefficient on risk tolerance is insignificant. Replacing risk tolerance with the weighted frequency does not change the results (second column of the table).

Nor does the paper present evidence of bias caused by mobility (moving out of the prefecture). As noted earlier in Section 4.1, this paper dropped an observation from the sample once the respondent moved to another prefecture. This might create a selection bias. However, the results provide no evidence of such bias as replacing the attrition dummy with the dummy indicating that the respondent moved out of the prefecture before the next survey gives an insignificant coefficient on the key dummy (third and fourth columns).[13]

4.5 Heterogeneity

This subsection investigates if the responses of individuals with risk tolerance to earthquake memory may involve heterogeneity. Although the analysis does not find heterogeneous response with respect to age, it finds lower response of risk tolerance for retired households.

4.5.1 Gender

Past studies have confirmed that males are more risk tolerant than females (e.g., Croson and Gneezy (2009), Eckel and Grossman (2008)). Indeed, as shown in the first row of Table 12, the mean value of the self-reported risk tolerance variable is 4.42 for male respondents and higher than that for female respondents at 3.79. More formally, if we

[13] The dummy of mobility is 1 with only two cases in the sample (JHPS-CPS 2004–2010). This is probably because when respondents moved to other prefectures, they were most likely to removed from the survey.

Table 12 Mean of Self-reported Risk Tolerance Variable

	Yes	No
Male	4.42	3.79
Age >=60	3.86	4.23
Retired	3.96	4.13
Bachelor degree	4.39	4.03
Financial industry	4.28	4.11
Homeownership (owning a house)	4.09	4.21

Notes: The sample is JHPS-CPS for the period 2004–2010. As before, the sample excludes households whose main earner has already retired (except for the third row).

regress self-reported risk tolerance on the dummy indicating that the respondent is male (together with other controls), the coefficient on the dummy is positive and significant (not reported here).

The question is whether males' risk tolerance responds more to earthquake memory than that of females. The sample of male respondents gives a higher coefficient on the weighted frequency that that of female respondents (first two columns of Table 13). However, when using the full sample and adding the interaction term of the male respondent dummy and the weighted frequency, the coefficient on this interaction term is negative and significant (third column of Table 13). There is, therefore, no evidence that males' risk tolerance is more responsive to earthquake memory than that of females, contrary to the finding in Hanaoka, Shigeoka, and Watanabe (2018). The difference may be because of the focus in their work on a single but traumatic earthquake (the 2011 Great East Japan Earthquake).

4.5.2 Age

The response of risk tolerance to experience might be weaker for elderly people. This is because it is known that the level of risk tolerance declines with age (e.g., Schildberg-Horisch (2018)), and this patter is confirmed in the current sample (second row of Table 12). The regression analysis, however, provides little support for this view. When including the interaction term of i) the dummy indicating that the age of the main earner is 60 or higher and ii) the weighted frequency, the coefficient on this term is indeed negative but not statistically significant (fourth column of Table 13). Changing the age threshold (e.g., to 55 or 65 from 60) does not change the results much.

4.5.3 Retirement

The level of risk tolerance of retired households may be lower as they cannot absorb shocks with future labor income unlike those who have not retired yet, and thus the risk tolerance could respond less positively to earthquake experience. The results support this hypothesis, giving a negative and significant coefficient on the interaction term of

Table 13 Testing Heterogeneity

VARIABLES	(1) OLS Risk tolerance Males only	(2) OLS Risk tolerance Females only	(3) OLS Risk tolerance Full sample	(4) OLS Risk tolerance	(5) OLS Risk tolerance	(6) OLS Risk tolerance	(7) OLS Risk tolerance	(8) OLS Risk tolerance
Weighted frequency of earthquakes F_t	2.00	1.61	2.18	1.91	1.90	1.86	1.82	1.38
	(1.02)**	(1.02)	(0.83)***	(0.73)***	(0.73)***	(0.75)**	(0.73)**	(0.88)
dummy of male×Weighted frequency of earthquakes F_t			-0.59					
			(0.74)					
dummy of age >=60×Weighted frequency of earthquakes F_t				-0.80				
				(0.73)				
dummy of retirement ×Weighted frequency of earthquakes F_t					-2.29			
					(1.26)*			
dummy of bachelor degree×Weighted frequency of earthquakes F_t						0.12		
						(0.98)		
dummy of financial industry×Weighted frequency of earthquakes F_t							2.86	
							(1.83)	
dummy of financial industry							-0.19	
							(0.19)	
dummy of owning house×Weighted frequency of earthquakes F_t								0.73
								(0.79)
dummy of owning house								-0.07
								(0.08)
Observations	8,778	8,397	17,175	17,175	17,175	17,175	17,175	17,175
R-squared	0.03	0.03	0.05	0.05	0.05	0.05	0.05	0.05

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2004–2010. The dependent variable is self-reported risk tolerance. Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1. The value of λ estimated in the second column of Table 5 is used for calculating the weighted frequency of earthquakes.

i) the dummy indicating that the main earner in the household has already retired and ii) the weighted frequency (fifth column of the table).

4.5.4 Cognitive Ability

Cognitive ability affects risk tolerance. For example, Dohmen, Falk, Huffman, and Sunde (2018) reported that cognitive ability tends to reduce risk tolerance in the context of harmful risky behavior (e.g., drinking), while being positively correlated with, for example, stock market participation. However, the impact of cognitive ability on the *responsiveness* of risk tolerance to experience is unclear, requiring empirical investigation, though cognitive ability might be associated with greater responsiveness to risk aversion to experience.

The empirical analysis does not support the hypothesis that cognitive ability increases responsiveness of risk tolerance. To capture cognitive ability, this paper uses the dummy indicating that the respondent holds a bachelor degree. The sixth column of the table reports that when using the interaction term of the dummy and the weighted frequency of earthquakes, its coefficient is close to zero and insignificant.

Cognitive ability could be higher for those working in the financial industry as the work in the industry may require high cognitive ability. The interaction term of the dummy indicating that the main earner works in the financial industry and the weighted frequency indeed gives a positive coefficient, though it is slightly below the statistical significance level (seventh column of the table) .

4.5.5 Homeownership

Homeownership might affect the response of risk tolerance to earthquake memory because the potential economic damage of an earthquake is greater for homeowners than for renters. To test this possibility, I include in the regression the interaction term of the dummy of owning a house and the weighted frequency of earthquakes (the dummy or owning a house is also included as a control variable).

The results provide little evidence for the hypothesis that homeownership could change the response of risk tolerance to earthquake memory. The last column of Table 13 indicates that the coefficient on the interaction term is insignificant.

4.6 Impact of Earthquake Memory on Financial Investment Behavior

Whether earthquake memory affects actual financial behavior through changes in risk tolerance is an important economic question because shifts in household financial investment contribute to fluctuations in the macroeconomy. This subsection examines this question by regressing variables that measure risky financial investment on the weighted frequency of earthquakes.

The results confirm that memory of earthquakes has a positive impact on risky financial investment. The first column of Table 14 reports that the coefficient on the weighted frequency is positive and significant at the 10 percent level, when the dummy

Table 14 Impact of Lifetime weighted Frequency of Earthquakes on Financial Investment Behavior

VARIABLES	(1) OLS Dummy of risky fin assets λ at solution	(2) OLS Share of risky fin assets λ at solution
Weighted frequency of earthquakes F_t	0.16	13.29
	(0.09)*	(5.34)**
Observations	32,025	26,231
R-squared	0.15	0.08

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2003–2018 for the first column, and 2005–2018 for the second column. The dependent variable is the dummy of owning risky financial assets in the first column, and the share of risky financial assets in the second column. Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1.

of owning risky financial assets (defined in Section 4.2) is used as the dependent variable and equation (2) is used as the weight function (and λ is estimated).

When the share of risky financial assets is used as the dependent variable, the statistical significance of the coefficient is stronger. The second column of the table reports that the coefficient on the weighted frequency is significant at the 5 percent level. The solution of λ reported in Section 4.3 implies that if one experiences an earthquake with seismic intensity of 5 or higher this year, such an experience increases the weighted frequency by around 0.03. The coefficient reported in the second column of Table 14 indicates that this size of increase, if materializes, is estimated to raise the share of risky financial assets in total financial assets by 0.4 percentage point ($\approx 0.03\times$ 13.3). This magnitude may be non-negligible given that the average share of risky financial assets is only about 9 percent (see Figure 3).

4.7 How Does Earthquake Memory Affect Mental States?

This subsection discusses the potential mechanism through which earthquake memory affects risk tolerance. The psychology literature reports that emotions play an important role in determining risk tolerance (e.g., Loewenstein, Weber, and Hsee (2001)). Negative mental states may reduce cognitive ability, which might eventually increase risk tolerance to risky behavior. Motivated by this notion, this paper examines how earthquake memory affects mental states, while leaving for future research a comprehensive analysis about the impact of earthquake memory on mental states and ultimately on risk tolerance.

Specifically, the paper tests the impact of earthquake memory on the following, whose data are available in JHPS-CPS: 1) sense of fatalism, and 2) mental health.

1. Sense of fatalism. The JHPS-CPS asks each respondent to what extent they agree with the notion that there is no need to think about the future as it is uncertain, with the response being an integer between 1 and 5, with 1 indicating "particularly true for me" and 5 indicating "not true at all for me".

2. Mental health. Three related questions are asked in the JHPS-CPS: whether "feeling stress lately"; whether "feeling depressed lately"; and whether "not being able to sleep well lately" (again the responses are an integer between 1 ("particularly true for me") and 5 ("not true at all for me")). Following Hanaoka, Shigeoka, and Watanabe (2018), this paper constructs a summary index using these three variables, with a lower value of the index meaning that mental health is more of an issue.[14]

The regression results provide little evidence of an effect of earthquake memory on mental states. The first column of Table 15 reports a negative coefficient on the index of fatalism (index of no need to think about the future). Although this is consistent with the hypothesis that higher frequencies of earthquake experiences make people more fatalistic (they are less likely to see the value of thinking about the future), the coefficient is insignificant. The second column of the table reports a negative coefficient on the summary index of mental health, consistent with that reported by Hanaoka, Shigeoka, and Watanabe (2018) who found that experience of an intense earthquake worsened mental health (recall that a lower value indicates less mental health). However, the coefficient is again not significant. Restricting the sample to that of male respondents (as done in Hanaoka, Shigeoka, and Watanabe (2018)) provides similar results (last column of the table).

5 Conclusion

The present paper finds evidence for a positive impact of earthquake memory on self-reported risk tolerance. A key contribution of this study is that it reaches this finding using "life-long" earthquake memory. The extensive earthquake data provided by the Japan Meteorological Agency, which covers 100 years from 1919, allows us to calculate life-long earthquake memory at the household level. The paper also provides evidence of a positive impact of earthquake memory on actions, in particular, household investment in risky financial assets.

An area of future research could be to identify the channel through which earthquake memory affects risk tolerance. Using variables on mental states from the JHPS-CPS, the paper (Section 4.7) investigated the impact of earthquake memory on mental states but did not reach a clear finding. Another area of future research may be to examine the impact of social learning about natural disasters on risk tolerance. While the paper

[14] To construct the summary index, the standardized value is calculated for each variable by subtracting the mean and dividing by the standard deviation, and then the summary index is created by taking the average of these three standardized values. For details, see Hanaoka, Shigeoka, and Watanabe (2018).

Table 15 Impact on Mental States

VARIABLES	(1) OLS Index of no need to think about future	(2) OLS Summary index of mental health	(3) OLS Summary index of mental health Male respondents
Weighted frequency of earthquakes F_t	-0.16	-0.01	-0.60
	(0.33)	(0.35)	(0.52)
Observations	15,232	8,930	4,522
R-squared	0.08	0.03	0.06

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample is JHPS-CPS for the period 2004–2010 (except for 2007) in the first column and 2008–2010 in the last two columns, reflecting the availability of variables on mental states. The dependent variable is the index of agreeing to the notion that there is no need to think about the future in the first column, and the summary index of mental health (feeling stress, feeling depressed, and sleeping problems; see the main text for details). Robust standard errors, which are estimated under the assumption that residuals of the same respondent are correlated across years, are reported in parentheses. To avoid the influence of extreme values, I remove the top and bottom 5 percent of the sample based on real household net worth. Control variables not reported in the table are variables in $Z_{i,t}$ in Section 4.1. The value of λ estimated in the second column of Table 5 is used for calculating the weighted frequency of earthquakes.

tested if a person's *own* memory of earthquakes affects risk tolerance, it is plausible to believe that hearing *others'* experiences of natural disasters may affect risk tolerance.

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