Social Learning in Budget Formulation: A Case of Adaptation to Natural Disasters*

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Abstract

This paper studies social learning behaviours among policymakers when formulating a budget. Focusing on the disaster prevention policy, we model local governments' expenditures as a response to the expected future disaster risk. Through this model, we associate the correlation of the expenditures among local governments with the connection in the social learning about the risk. We estimate the social learning network using administrative data on the expenditures over 20 years. The result shows a sparse network among local governments. Moreover, by investigating the determinants of the connection, we find that the inflow of internal migration increases the local government's attention to their origin and that the higher risk of future earthquakes decreases the attention to others. Given previous studies finding that those with catastrophe experiences become more risk-tolerant, our results further show that such an experience induces more attention to others through changes in their risk preference.

Keywords: disaster prevention, policymaker, network estimation, social learning

JEL Classification: C51, D83, H54, H84

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1 Introduction

The budget allocation for a policy domain is not solely determined by the essential costs of individual policies in that domain. Rather, the government's comprehension about the issue has a significant top-down influence on the allocated budget amount: for instance, the extent to which the government estimates the risks of climate change unavoidably shapes the allocation of expenditures towards the domain of climate change mitigation. However, many of the challenges the government faces are inherently difficult to envision accurately. Issues like climate change, AI risks, and the economic dominance of tech giants — these globally crucial challenges involve intricate structures, rendering precise comprehension a formidable task. In making decisions to address these challenges, social learning among policymakers plays a vital role. As we witnessed during the COVID-19 pandemic, many countries adopted the travel ban policy after observing other countries' outbreaks. The social learning involves not only leveraging insights from other nations to achieve a more accurate understanding of the issues but also aligning with the international community by incorporating their perspectives on the problems.

However, little is known about the role of social learning in budget formulation or forming attitudes toward policy. The social learning about the effectiveness of a specific policy is studied in the past literature, such as Hjort et al. (2021); Vivalt, Coville and KC (2022); Vivalt and Coville (2023), and the same topic is broadly examined in political science as a driving force of policy diffusion.[1] Our emphasis goes beyond the adoption of individual policies and pertains to the upstream determination of the significance of a particular issue. In this regard, social learning remains a substantial force. It is known that past experience is a decisive factor in the policy attitude: for example, Malmendier, Nagel and Yan (2021) show that the monetary policies favoured by central bankers are influenced by their personal experiences with inflation. However these studies do not take the influence of others' opinions into account.

Our focus lies in understanding the influence of others' opinions and susceptibility to

[1] See Volden, Ting and Carpenter (2008); Gilardi (2010); Gilardi and Wasserfallen (2019), for example.

influence during the budget formulation in a specific area. Among many significant issues these days, we spotlight disaster prevention, which lacks clear evidence to base and is less influenced by partisanship. We establish a model where individual local governments act as policy entities that determines disaster prevention expenditures through social learning by referencing others' belief about the severity of future disasters. This model allows us to associate the correlation of the expenditures among local governments with the connection in the social learning about the risk. Using LASSO as in Manresa (2016), we estimate a high-dimensional linear model, where we regress the expenditure of one local government on the expenditures of the others, to recover the social learning network: in other words, which local governments refer to whose beliefs.

Besides the social learning network itself, we focus on two factors as the determinants of the network structure. The first one is the population move between prefectures. Like the recent surge in migration between nations, there are a lot of population movements between prefectures in Japan. We hypothesise that such a move transfers social identity from the hometown, which causes prefecture i facing a larger population from the other prefecture j to pay more attention to j's belief when forming their own belief about future disasters. While it is evident that the areas with many immigrants suffer from cultural or religious influence, we attempt to uncover that they impact the seemingly unrelated and obviously necessary policies, such as disaster prevention, by changing the information source in social learning.

As another factor, we study the radical change in the social learning network after a significant event. It is known that a severe event like a financial crisis or a catastrophic disaster often changes human behaviours, such as investment, by altering their risk attitude. In our case, it is possible that a catastrophic disaster changes the basic level of the attitude toward future disasters and makes the local governments gather information about it in different ways. In particular, we test if the Great East Japan Earthquake in 2011 changed the way to collect the information of others. In addition to that, Hanaoka, Shigeoka and Watanabe (2018) shows that the citizens who suffered from the Great East Japan Earthquake in 2011 became more risk-tolerant after the disaster. Given their results, we consider a direct effect of the 2011 disaster and an indirect effect through changing the risk-aversion on the social learning network.

We use Japanese administrative data to estimate the empirical social learning networks. The data contains each local government's expenditure on disaster prevention and damages by natural disasters over 20 years. We focus on non-infrastructural expenditure (soft policy) to capture governments' immediate updates and avoid political partisanship. Our estimation recovers the sparse networks about the severity of future disasters for two sample periods: *pre-2011* and *post-2011*. We do not find any exceptionally influential group of local governments. By analysing the mechanism of the connections in the recovered networks, we find that a larger move from a prefecture j in i induces more attention to j by i. Furthermore, this effect is quadratic: the marginal influence of the movers is increasing. In other words, we do find evidence of the power of the movers in the attention paid by a government. As we focus on disaster prevention, which heavily relies on geographical factors, it is surprising that such a soft power influences the actual policies. As to the impact of a catastrophic event, we do not find any direct change in the network connection after the Great East Japan Earthquake in 2011. However, we do find that the more risk-averse a prefecture is, the less attention it pays to other prefectures given the risks of future earthquakes. Given the result of Hanaoka, Shigeoka and Watanabe (2018), this implies that the prefecture that suffered from the disaster more severely pays more attention to others.

This paper contributes to several flows of literature. First, it contributes to the literature on social learning about the effectiveness of specific policies as we described above. Our current paper shows evidence that social learning plays a major role even in the upper stream of the policymaking process. Second, for the experience effect literature, such as Greenwood and Nagel (2009); Koudijs and Voth (2016); Kuchler and Zafer (2019); Malmendier, Nagel and Yan (2021), our current paper highlights the impact of social learning.

Our model of optimal disaster prevention comes from the literature about the adaptation behaviour to future disasters. Some studies have developed dynamic models that incorporate adaptation behaviour and calibrate these models using macroeconomic data (de Bruin, Dellink and Tol, 2009; Agrawala et al., 2010; Felgenhauer and Webster, 2014). Fried (2021) focuses on the effectiveness of seawalls and uses dynamic models to evaluate it. More recently, a growing number of applied microeconomic studies have attempted to quantify the reduction in the future economic damage resulting from adaptation. Barreca et al. (2016); Auffhammer (2022); Carleton et al. (2022) study the adaptation to heat waves and Taraz (2017) considers irrigation investments as a form of adaptation to droughts and floods. To the best of our knowledge, however, there is no empirical paper clarifying the role of social learning in environmental policies while social learning surely plays an important roll as we discussed previously.[2][3]

We contribute to the literature on behavioural changes after catastrophic disasters. Some studies use survey data to reveal how social and risk preferences changed due to natural disasters such as earthquakes and typhoons (Goebel et al., 2015; Chuang and Schechter, 2015; Hanaoka, Shigeoka and Watanabe, 2018; Bourdeau-Brien and Kryzanowski, 2020). These studies suggest that the structural parameters of economic models, which are usually assumed to remain unchanged over time, may change due to disaster experience. Our paper reveals behavioural changes through changes in the information sources, which are also usually treated as an unaltered object. Moreover, other studies investigate how the experience of disasters affects the perception of future disasters (Brown et al., 2018; Gao, Liu and Shi, 2020). On the contrary, our study focuses on objectively observable behavioural responses of policymakers, which themselves affect future disaster risks and are more directly important to society.

The remainder of the paper is organised as follows. Section 2 explains the institutional background while Section 3 illustrates the data. The model and estimation method are discussed in Section 4, while we show the results in Section 5. Section 6 concludes the study with discussions. The appendix exhibits further data details and robustness checks.

[2] A general framework of the effects from other people can be regarded as peer effects. See Bramoullé, Djebbari and Fortin (2020) for a review.

[3] A few papers consider how the past disaster experience affects the expenditure on disaster prevention and the caused damages (Hsiang and Narita, 2012; Gallagher, 2014; Hsiang and Jina, 2014).

2 Institutional Background

2.1 Natural Disasters in Japan

Japan suffers from piles of natural disasters. Japan has heavy rains and subsequent floods and landslips, because it is an island country located just above subtropical areas and most of the land is in the typical path of typhoons. Moreover, since mountains cover three-quarters of Japanese land, heavy rain often causes landslips and flows into rivers in a short time, which leads to a lot of floods. Also, Japanese mountainous land results from the four tectonic plates touching each other under the land. This geological feature makes Japan famous for frequent large earthquakes: about 20% of the earthquakes of magnitude over 6 happen around Japan. Besides the earthquakes themselves, the subsequent tsunamis, occurring when a large earthquake happens in the ocean near land — a shake of the seabed creates a wave, and it comes to the land as a tsunami — are also notorious for their severe damages due to the difficulty of the prevention. These natural disasters cause human damages and the destruction of houses and infrastructures.

It is worth noting that Japan has experienced two recent major earthquakes: "Hanshin-Awaji Dai-Shinsai" and the "Great East Japan Earthquake." "Hanshin-Awaji Dai-Shinsai" (a catastrophe in the Hanshin and Awaji area) happened on 17 January 1995. The magnitude was 7.2, and the largest seismic intensity (SI) scale observed was seven, the largest in the scale (Ministry of Transport, 1996).[4] This happened just beneath the Osaka metropolitan area, and 6,434 people were killed, about 44 thousand people were injured, and more than 10 thousand houses collapsed (Ministry of Transport, 1996; Fire and Disaster Management Agency, 2006). Since this happened in the coastal urban area, a lot of railway infrastructure was damaged, liquefaction of artificial islands occurred, and many lifelines stopped. The total cost was estimated up to JPY 9.6 trillion (Ministry of Transport, 1996). About two decades later, the largest earthquake Japan has ever experienced occurred on 11 March 2011 in northern Japan, named the Great East Japan Earthquake (*Higashi-Nihon Dai-Shinsai* in Japanese). The magnitude was 9.0 and the

[4]See Table A2 about the SI scale.

largest SI observed was seven, and the following largest tsunami was 9.3 metres high (Fire and Disaster Management Agency, 2013; Ministry of Internal Affairs and Communications, 2022). This series of disasters, especially the tsunamis, destroyed the northeastern part of Japan: about 18 thousand people died, about three thousand people were reported missing, 129 thousand houses collapsed completely, and more than one million houses were damaged (Fire and Disaster Management Agency, 2013). This tsunami damaged the nuclear power plant in Fukushima, which triggered radiological damage. As shown, damages from natural disasters in Japan are huge.

These massive damages show that it is still difficult, even impossible, to prepare well for future disasters in Japan, which is a member of G7 with a high standard of technology. This is because of the difficulty in predicting future disasters, as exemplified in cases of earthquakes and weather forecasts.[5][6] Hence, even in a country that suffers from severe disasters like Japan, the policy about its disaster prevention cannot be based on rigorous scientific evidence and instead the government has to learn the appropriate policy, including its direction and the expenditure on it, from its own experience and the opinions of the others: in other words, the (social) learning plays a large role in the disaster prevention policy.

Due to a lack of solid scientific prediction and the resulting difficulty in preparing well enough for future disasters, the Japanese government has at best learnt lessons from catastrophic experiences. After Hanshin-Awaji Dai-Shinsai, the government updated several laws and guidelines so that they can react to disasters more quickly and more appropriately to each type of disaster, such as earthquakes, floods, and volcanic eruptions.[7]

[5] Although the government offers a warning a few seconds to a minute earlier than a large earthquake in the very short-term, in the medium run, due to complications of the mechanism of earthquakes, it is impossible to predict ones based on the current technology of seismology (Hasegawa, Saito and Nishimura, 2015).

[6] These days, quite accurate weather forecasts are available in the short term, but still precision of long-term weather forecasts is nearly impossible, according to the Met Office, the national meteorological service for the UK. See `https://www.metoffice.gov.uk/research/climate/seasonal-to-decadal/long-range/user-guide`

[7] More concretely, the government updated the Basic Act on Disaster Management, a law governing how to react to catastrophes. They also updated the Disaster Management Basic Plan to have a comprehensive plan for each type of disaster, earthquakes, storm and flood damages, and volcanic disaster, separately so that the government can respond appropriately to specific features of each type. The Japanese government summarises the change on their website: `https://www.bousai.go.jp/kaigirep/hakusho/h17/bousai2005/html/honmon/hm120702.htm` (in Japanese, last access on 25 August 2023).

Furthermore, they changed the building resistant standard against earthquakes, given about 80% of the deaths were due to collapses of housings. After the Great East Japan Earthquake, whose damages were mainly triggered by the tsunamis, the government focused more on preventing tsunami and flood damages such as creating embankments and flood control dams, in addition to non-infrastructural changes including updating evacuation instructions in the local areas. As seen, catastrophic events have triggered policy changes in the field of disaster prevention.

The disaster-preventive policies range from large infrastructural investments to relatively smaller non-infrastructural preparations. The former contains building seawalls against tsunamis, creating retaining walls to prevent landslips, and aseismic reinforcing work of old buildings, while the latter includes implementing disaster-related education programmes for residents, making localised evacuation manuals and maps, and hiring experts on crisis management.[8] In this paper, we focus on non-infrastructural expenditures for several reasons. First, infrastructural policies are planned well in advance, say a few years, so reactions to past earthquakes are expected to be slow, while for non-infrastructural ones, responses to earthquakes should be much quicker. This feature makes it easier to identify whether the effects come from recent disasters. Second, these expenditures are usually not on political issues – contrary to other policies such as large infrastructural investment. We can exclude strategic interaction among policymakers, politicians, and voters, and our model can focus on policymaking simply based on policymakers' decisions. Third, infrastructural expenses depend more heavily on each specific local situation than non-infrastructural ones. For example, a seawall could be effective only when a tsunami occurs, but an evacuation manual can work for any type of disaster. Therefore, we focus on non-infrastructural expenditures.

2.2 Budget Planning in Japan

In the analysis, we view local governments at the prefecture level as the unit of decision-makers and in this section, we describe the role of central and local governments. Japan

[8] See the budget of Saitama prefecture in 2021 as an example (in Japanese, last access was on 29th April 2023): `https://www.pref.saitama.lg.jp/documents/193830/05kikikanribousaibu03.pdf`.

has 47 prefectures with an average size of 8043 square kilometres and a population of about three million (Soga, 2019), and each has its own autonomy to decide its local policies. Although there is a lot of overlap, the basic idea is that the central government is in charge of national-level benefits, such as defence, pension system, business and sightseeing. On the contrary, the local prefectures are responsible for citizens' daily-basis benefits in a wider range, such as constructing high schools and public primary education, police, infrastructural investment including road construction and riparian improvement, public health, and welfare (Soga, 2019).[9][10] A local government's budget for these services comes from the local government's income, a transfer from the central government and local bonds. The former is mainly from local tax, which primarily consists of residential tax (both for individuals and businesses), property tax, and car tax, which are generally identified by their locations in local areas. The revenue from these taxes varies according to how wealthy the residents are and how many businesses are operating in the local areas. As a result, there is a huge disparity in the size of the revenues among prefectures. However, they need to provide a minimum service, such as maintaining education and others described above, so the central government provides the transfer to cover some expenses out of national tax revenue. One is called "a local allocation tax grant," and each local government can decide how to use it. There is another type of large transfer, called "national treasury distributions," which restricts the purpose of the expense. The local governments' income is the combination of these sources.

Both central and local governments use their budgets in disaster prevention, but their roles differ. The central government determines a principal plan and the standard of prevention, and the local governments manage its administration and implementation, in addition to making detailed plans based on local characteristics (Fire and Disaster Management Agency, 2019). For example, the central government creates the resistance standard of buildings against earthquakes as a law, while local governments create measures against more specific disasters expected in each area, such as earthquakes (in all

[9] For details, see the website of the Ministry of Internal Affairs and Communications: `https://www.soumu.go.jp/iken/jokyo_chousa.html` (Last access: 29 July 2023).

[10] Each municipality in a prefecture is in charge of more localised services, such as public assistance, public insurance, water and sewer, waste disposal, and fire-fighting.

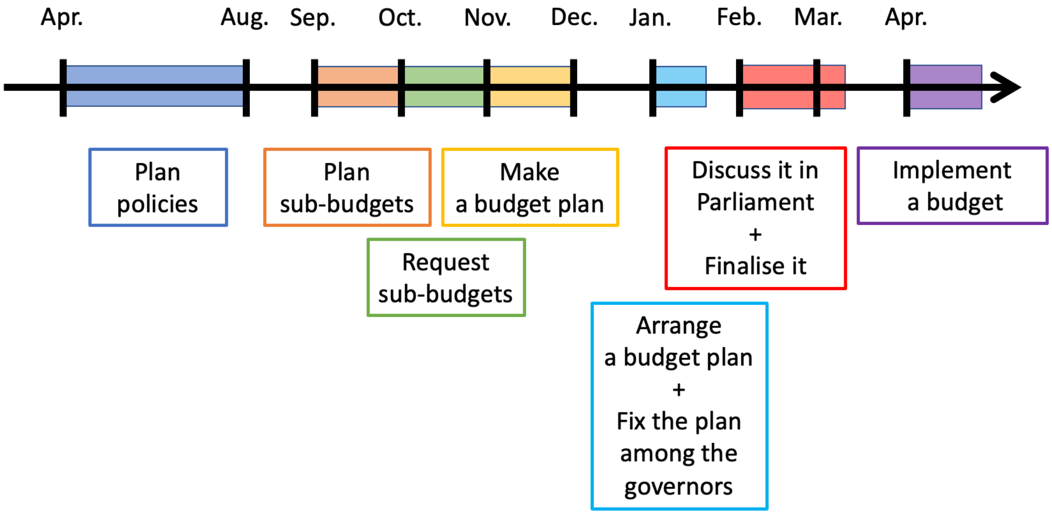

Figure 1. Typical Timeline of Budget Planning by a Local Government

prefectures but localised), tsunamis, disasters related to nuclear power plants, volcano eruptions, and other natural disasters. As a result, although all prefectures meet a minimum level of prevention of natural disasters, there is a large room in adjusting the plan and a large variation in how much each local government is prepared for incoming but unpredictable natural disasters. This attitude towards the expenditure on disaster prevention and making Japan more resistant to disasters is common across political parties.[11] Therefore, it is unlikely that disaster prevention is central to political discussions. This feature is suitable in our context where we want to avoid political strategical interaction.

Planning a budget takes a year to be completed.[12] Figure 1 shows a typical timeline of budget planning by a local government. In a typical local government, policymakers start planning a policy in their prefecture at the beginning of a fiscal year, April, which lasts until August.[13] Then, they make a budget plan in each division and submit a request to the budget division in their prefecture by around October. After the budget division

[11] A research laboratory in Waseda University in Japan summarises the arguments on the disaster prevention before the House of Councillors election in 2022. See https://maniken.jp/kurabete_erabu/seisaku11/ (in Japanese, last access: 25 August 2023).

[12] The timeline differs among central and local governments, where the former takes longer.

[13] This information is based on the website of Chiyoda ward in Tokyo https://city-chiyoda.j-server.com/LUCCHIYOAI/ns/tl.cgi/https://www.city.chiyoda.lg.jp/koho/kuse/zaise/hense-kate.html?SLANG=ja&TLANG=en&XMODE=0&XCHARSET=utf-8&XJSID=0 (in Japanese, last access: 25 August 2023) and Nippon Consultants Group, Inc. http://c.ncnavi.jp/bel/demo/contents/046kanko/html/3_02/3_2_03_03.html (in Japanese, last access: 25 August 2023).

receives the requests, they start making a budget for the prefecture by the end of the year and make some adjustments early in the next year before finalising it on the governors' side. Next, the governors submit this budget plan to a local council in the middle of February to March, and after the discussion there and the vote, the plan is finalised as a prefecture.

3 Data

In our empirical analysis, we use several Japanese administrative data sets. First, to measure how much each prefecture spends on disaster prevention, we utilise the Local Government Finance Survey (*Chihou Zaisei Joukyou Chousa*), collected by the Ministry of Internal Affairs and Communications of Japan. This administrative data includes prefecture-level information about its fiscal situation over the fiscal years from 1989 to 2021.[14] It possesses various details on incomes and expenditures in a local government in a given fiscal year, such as how much it earns from each income source and how much it spends on each expenditure category.[15] In our analysis, we use the income of prefectures to capture the difference in the budget size and the expenditure on disaster prevention in the category of general affairs expenses, which is used for non-infrastructural policies.

Second, the primary source of information on disaster damage is the White Paper on Fire Service (*Shoubou Hakusho* in Japanese), issued by the Fire and Disaster Management Agency, Ministry of Internal Affairs and Communications of Japan. This data set contains annual records of the estimated monetary value of the damage caused by natural disasters, including earthquakes, tsunamis, storms, torrential rains, floods, storm surges, volcanic eruptions and other unusual natural phenomena. It also has other damage information, such as the number of deaths, people reported missing, and major and minor injuries in each prefecture. We use the data of the calendar years from 1989 to 2021.

We supplement these two administrative data sets, which we use to estimate the net-

[14] In Japan, a fiscal year starts at the beginning of April and finishes at the end of March.

[15] The latter typically has 24 categories, including opening congress, general affairs, sanitation, construction, agriculture, business, education, and other items, and each may have more detailed subcategories. The number of categories varies depending on the years of the records.

work, with several administrative and survey data to explain the factors of the network estimated. First, we use the information about the long-term predicted probability of earthquakes in Japan. As we discussed above, earthquakes can be predicted at a certain level of precision in the long term. National Research Institute for Earth Science and Disaster Resilience publicises the prediction data called Japan Seismic Hazard Information Station (J-SHIS).[16] The data contains the probability of earthquakes every year, and we employ the data from 2008 to 2020.[17] This data set contains information on predicted probabilities of earthquakes equal to or larger than the seismic intensity (SI, *Shindo* in Japanese) 5 Lower (5−), 5 Upper (5+), 6 Lower (6−), and 6 Upper (6+), occurring in 30 years, for each 250-metre square mesh across Japan.[18] This probability is calculated with a range, and we use two measures: the average and maximum cases.[19] We further summarise the information into two variables at each prefecture level using the mesh data described below — the maximum and average probabilities in the prefecture. We denote this variable as $D_{\text{SI, aggregate calculation}}$ for SI $\in \{5-, 5+, 6-, 6+\}$, aggregate $\in \{[a]verage, [m]aximum\}$, and calculation $\in \{[a]verage, [m]aximum\}$, where aggregate refers to methods of aggregation over the prefecture, while calculation refers to the method of pick a value out of predicted range of the probabilities. To aggregate this mesh-level data into the prefecture-level information, we use the mesh code of each prefecture, released by the Japanese Statistics Bureau.[20]

Second, as we discussed in the introduction, we collect data on internal migration in Japan to examine the effects of movers. We use the Report on Internal Migration in Japan, collected by the Japanese Statistics Bureau. This data contains information on internal migration from 1954, including the annual number of movers between prefectures.

[16]The data is publicly available at `https://www.j-shis.bosai.go.jp/` (Last access: 14 August 2023).

[17]The data in 2015 is missing, and data in several years contain the predictions based on two different methods. We use the first method if several are available.

[18]See Appendix Table A2 for the reference of earthquake sizes in Japan.

[19]According to J-SHIS, when evaluating the major active fault zones in the long term, we often obtain the estimate of mean recurrence and the time of the latest event as an interval. In the average case, the model uses the earthquake occurrence probability based on the median values of the respective ranges of the recurrence interval and the time of the latest event. In contrast, in the maximum case, the model utilises the smallest value from mean recurrence intervals and the oldest time of the latest event to avoid the underestimation and potentially obtain the highest probability.

[20]See `https://www.stat.go.jp/data/mesh/m_itiran.html` for their website (Last access was on 30th August 2023).

We use data from 1995 to 2021 and calculate the ratio of movers in each prefecture based on the total population data for each year. For the regression analysis, we take the average of the move rate within the years before 2011 and after 2011 and make the variable $Move\ Rate$ in the percentile scale.

Third, we employ the data about the risk preference of individuals residing in Japan to see whether the risk attitudes of local residents change their social learning behaviours. Although we cannot observe the risk preference of policymakers directly, we proxy it with the attitudes of those sampled from the prefecture. We use the Japan Household Panel Survey on Consumer Preferences and Satisfaction (JHPS-CPS), which contains panel records of national representatives. Following Hanaoka, Shigeoka and Watanabe (2018), we construct a measure of risk aversion: a transformed reservation price of a lottery.[21][22][23] If the measure is larger, a respondent is more risk averse. Since this survey is at an individual level, we calculate their weighted averages at the prefecture level, where the weight is the sampling weight offered in the survey data.

Finally, we use the information on the distance between the prefectures' capitals issued by the Geospatial Information Authority of Japan.[24]

We merge these data sets to make prefecture-level panel data. Table 1 shows the summary statistics of the data. Panel A summarises information on the budget and various damages from natural disasters in each prefecture each year. On average, the expenditure on disaster prevention is about JPY 2.7 billion (about USD 18.4 million),

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[21] The original question in the questionnaire asks a respondent their willingness to pay for a lottery with which they win JPY 100,000 (about USD 730) with the probability of a half or nothing otherwise. There are eight prices in the list, JPY 10, 2,000, 4,000, 8,000, 15,000, 25,000, 35,000, and 50,000, and the respondents are asked to choose whether they are willing to buy this lottery at each price or not. Then, following Cramer et al. (2002), we calculate reservation price λ and transform it into $R = 1 - \lambda/(\alpha Z)$, where $\alpha = 0.5$ and $Z =$ JPY 100,000 in our case.

[22] We calculate the risk preference based on the programming code of Hanaoka, Shigeoka and Watanabe (2018), offered on American Economic Association website. See `https://doi.org/10.1257/app.20170048`.

[23] Hanaoka, Shigeoka and Watanabe (2018) creates the other measure of risk aversion, which is absolute risk aversion based on Arrow-Pratt measure (Pratt, 1964). To construct this, following Hanaoka, Shigeoka and Watanabe (2018), we calculate the Arrow-Pratt measure of absolute risk aversion: $R = (\alpha Z - \lambda)/\{(1/2)(\alpha Z^2 - 2\alpha Z\lambda + \lambda^2)\}$. We conduct the analyses with this measure as well, and the results are qualitatively the same.

[24] See `https://www.gsi.go.jp/KOKUJYOHO/kenchokan.html` (Last access was on 29th April 2023). The distances are calculated based on the shortest distance (geodesic length) in the spheroid (GRS80) to examine how physical closeness affects the selection of information sources.

Table 1. Summary Statistics

	Mean	sd	Min	25%	Median	75%	Max	N
Panel A: Prefecture-Year-level Records								
Income (in billion yen)	1,095	1,052	312.0	584.1	763.6	1,131	10,139	1,551
Expenditure on Disaster Prevention (in billion yen)	2.713	11.82	0.201	0.955	1.558	2.927	408.6	1,551
Ratio of Expenditure on Disaster Prevention to Income (%)	0.265	0.492	0.034	0.117	0.180	0.314	15.32	1,551
Damages by Natural Disasters								
Estimated Monetary Damage (in billion yen)	325.3	3,924	0.000	1.806	5.710	17.99	136,970	1,546
Monetary Damage Rate (%)[a]	36.06	296.6	0.000	0.215	0.762	2.180	5,357	1,546
N of Human Damage[b]	20.02	373.7	0	0	1	3	11,770	1,551
N of Deaths	18.01	329.0	0	0	1	3	10,154	1,551
N of People Reported Missing	2.011	51.69	0	0	0	0	1,616	1,551
N of People with Injuries[c]	72.88	1,027	0	2	8	29	39,488	1,551
N of People with Severe Injuries[d]	36.14	1,003	0	0	1	6	39,488	1,551
N of People with Minor Injuries[d]	36.74	192.8	0	1	6	21	4,274	1,551
N of House Damage[e]	1,509	16,222	0	0	0	171.5	485,135	1,551
N of Houses Complete Destroyed	99.47	2,280	0	0	0	0	84,636	1,551
N of Houses Half Destroyed	239.4	4,230	0	0	0	0	147,370	1,551
N of Houses Partially Destroyed	888.1	10,070	0	0	0	21	221,917	1,551
N of Houses Flooded above the Floor	63.96	468.5	0	0	0	8	16,051	1,551
N of Houses Flooded below the Floor	218.2	1,022	0	0	0	81	21,726	1,551
Agricultural Field Damage (in hectare)[f]	134.3	982.3	0.000	0.000	0.000	2.030	24,276	1,551
Rice Paddy Lost or Buried (in hectare)	25.38	402.1	0.000	0.000	0.000	0.000	15,307	1,551
Rice Paddy Flooded (in hectare)	57.42	588.8	0.000	0.000	0.000	0.000	19,639	1,551
Field Lost or Buried (in hectare)	20.02	234.6	0.000	0.000	0.000	0.000	6,337	1,551
Field Flooded (in hectare)	31.49	237.4	0.000	0.000	0.000	0.000	3,914	1,551
Panel B: Pair-of-Prefectures-level Records								
Distances between Capital Cities Prefectures (in kilometres)	519.7	355.2	11	242	445	724	2244	1,081
Move Rates between Prefectures (%)								
Pre 2011	0.022	0.074	0.000	0.002	0.005	0.018	1.442	2,162
Post 2011	0.019	0.068	0.000	0.001	0.004	0.014	1.400	2,162
Panel C: Prefecture-level Records								
Risk Preference (Transformed Reservation Price[g])								
Pre 2011 Disaster[h]	0.812	0.032	0.744	0.791	0.815	0.829	0.888	47
Post 2011 Disaster[i]	0.752	0.050	0.615	0.726	0.760	0.787	0.837	47
Predicted Probability of Earthquakes in the Average Case[j]								
Average over Each Prefecture								
Seismic Intensity of 5 Lower ($D_{5-,aa}$)								
Pre 2011	0.548	0.264	0.099	0.330	0.480	0.773	0.975	47
Post 2011	0.583	0.224	0.151	0.389	0.567	0.770	0.990	47
Seismic Intensity of 5 Upper ($D_{5+,aa}$)								
Pre 2011	0.226	0.194	0.022	0.069	0.122	0.418	0.649	47
Post 2011	0.343	0.248	0.048	0.125	0.243	0.583	0.875	47
Seismic Intensity of 6 Lower ($D_{6-,aa}$)								
Pre 2011	0.108	0.132	0.004	0.014	0.035	0.166	0.542	47
Post 2011	0.144	0.150	0.008	0.029	0.066	0.278	0.502	47
Seismic Intensity of 6 Upper ($D_{6+,aa}$)								
Pre 2011	0.015	0.025	0.000	0.002	0.005	0.016	0.125	47
Post 2011	0.032	0.042	0.001	0.005	0.008	0.054	0.179	47

Notes. 1 USD is approximately equivalent to 140 JPY. Japan has 47 prefectures, so in the first row, the number of observations is $1,081 = 47 * 46/2$. In Panel B, we omit the move rate between the same prefectures, and so the number of observations is $2,162 = 47 * 47 - 47$. See Figure A1 and Table A1 for the definition of the same area. See Table A3 for the summary statistics of those used in the robustness checks.

a: Monetary damage Rate is the estimated monetary damage divided by income and multiplied by 100 to be converted into a percent unit.

b: The number of human damage is the sum of the number of deaths and people reported missing.

c: The number of people with injuries is the sum of The number of people with severe and minor injuries.

d: People with severe injuries are defined as those who have been injured due to the disaster, are taking or need to take medical treatment and are expected to require treatment for at least one month, while people with severe injuries are defined as those who have been injured due to the disaster, are taking or need to take medical treatment and are expected to require treatment for less than one month (Fire and Disaster Management Agency, 1970).

e: N of House Damage is the sum of the number of houses half destroyed, the number of houses partially destroyed, the number of houses flooded above the floor, and the number of houses flooded below the floor.

f: Agricultural field damage is the sum of the amount of rice paddy lost or buried, the amount of rice paddy flooded, the amount of field lost or buried, and the amount of field flooded.

g: This variable measures the willingness to pay for a lottery with which they win JPY 100,000, following Hanaoka, Shigeoka and Watanabe (2018).

h: The survey containing this variable was conducted between January and February, so this was done before the 2011 earthquakes which occurred on 11 March 2011.

i: The survey containing this variable was conducted between January and February 2021.

j: We use the average case, defined in Footnote 19.

which accounts for about 0.26% of total expenditure. However, the amount varies from 0.03% to 15%, depending on the prefecture and year. Despite the frequency of natural disasters in Japan, Japan is quite resistant to them — Most of the measures on damages, including monetary damage, human damage, and building and field damage, exhibit the amount of zero. However, they become large from the median and huge at the maximum, which suggests that some catastrophes caused most of the damage. The Great East Japan Earthquake in 2011 is such an event: it caused damage of JPY 137 trillion in one year in one prefecture. This gigantic earthquake and the following tsunamis increased the number of deaths and people reported missing.[25] In the following analysis, we use the sum of the number of deaths, people reported missing, and people with minor and major injuries as an indicator of human damage. Also, we use agricultural field damage, which is the sum of the amount of rice paddy lost or buried, the amount of rice paddy flooded, the amount of field lost or buried, and the amount of field flooded.

In Panel B, we show the statistics of the characteristics of pairs of prefectures. As shown in Figure A1, Japan is a long country, so some pairs are close to each other while others are far away, which creates variation in who are neighbours. Move rate, defined by the ratio of the movers to one prefecture from another prefecture to the total population of the former, varies across pairs of prefectures. Some pairs do not exhibit much inflow, while some prefectures attract a lot from the paired prefecture, up to 1.4% of the destination population.

The first part of Panel C presents the prefecture-level records. The first section shows the risk preference measure before and after the catastrophe in 2011 separately. As discussed in Hanaoka, Shigeoka and Watanabe (2018), we see people tend to be more risk-tolerant after 2011, which is reflected in the smaller value of the transferred price in post-2011. The second part of Panel C illustrates how likely a large earthquake will happen in thirty years. As we can see, an earthquake of SI5$-$ is very likely to happen, while one of SI6+ is quite unlikely. The predicted probability of earthquakes also changed

[25] The numbers shown in Table 1 are slightly different from Section 2, because the former is the summary of the statistics in one year, while the latter exhibits the accumulation of total damage by the Great East Japan Earthquake in 2011, some of which were identified after 2011.

from 2010 to 2020: almost all measures increase. We can see earthquakes of SI5$-$ are not too rare, with the average predicted probability from 55% to 58% in 30 years, while SI6+ is quite infrequently. As a result, people might be getting accustomed to relatively smaller earthquakes while still not to ones like SI6+. Therefore, in the main analysis, we focus on the predicted probability of earthquakes of the SI of 6 Lower (SI6$-$) and use the other measures in the robustness checks.

4 Model and Empirical Strategy

This section presents a model for determining the optimal adaptation level for local governments. In Section 4.1, we formulate the dynamic problem of determining the level of adaptation in response to future expected disasters. Section 4.2 describes how the belief of a prefecture about the future disaster risk is incorporated into the others' beliefs. The model also directly connects to our empirical strategy.

4.1 Adaptation Problem

Here, we describe how investment in disaster prevention decreases future damage and how the local government determines the optimal level of investments toward future disasters. First, we have two types of investments: one is the soft adaptation, such as making evacuation manuals and evacuation drills, and the other is the hard adaptation, such as constructing seawalls and embankments and seismic reinforcement work. Investing in these two adaptations accumulates the disaster prevention capital, which is hard to observe directly. We denote the accumulation of the soft adaptation, that of the hard adaptation, and the disaster prevention capital of prefecture i at time t by A_{it}, B_{it}, and Q_{it}, respectively. We model the capital accumulation process in local government i using a Cobb-Douglas function:

$$Q_{it} = K_i A_{it}^{\alpha_i} B_{it}^{1-\alpha_i}.$$

where K_i is the factor productivity specific to i representing the disaster preparedness in i, which is formed through the long-run experiences of past disasters. K_i is hard to change, and we assume that this is constant over the sample period.[26] α_i is the parameter governing the rate of substitution between the soft and hard adaptations. Local government accumulates the soft and hard capitals by investments a_{it} and b_{it}:

$$A_{it} = (1 - \delta_i)A_{it-1} + a_{it}$$
$$B_{it} = (1 - \delta_i)B_{it-1} + b_{it},$$

where δ_i is the depreciation parameter.

Disaster damage takes variable forms, including human damage, like the number of deaths and the number of people reported missing, the physical damage to the buildings, and the monetary damages computed from these damages. This multi-dimensional feature of the disaster damage is expressed by the loss of capital in our model. In particular, we consider an optimal growth model, including accumulating the disaster prevention capital. For brevity, we now remove the notation i when obvious. Let k_t be such capital at the time t, c_t be the consumption at time t, and I_{t+1} be the amount of the investment on the capital made at time t. The optimisation problem of a local government at time τ is written as the following:

$$\max_{c_t, I_{t+1}, a_{t+1}, b_{t+1}} \sum_{t=\tau}^{\infty} \beta^{t-\tau} u(c_t)$$

$$\text{s.t.} \begin{cases} c_t + I_{t+1} + a_{t+1} + b_{t+1} \leq f(k_t) \\ k_{t+1} = \frac{Q_t}{\mu_\tau} k_t + I_{t+1} \\ Q_t = K A_t^{\alpha} B_t^{1-\alpha} \\ A_t = (1 - \delta)A_{t-1} + a_t \\ B_t = (1 - \delta)B_{t-1} + b_t, \end{cases}$$

[26] As we discuss later, K changes after huge disasters, such as the ones discussed in Section 2. In the estimation, we assume K is constant throughout the pre-2011 periods and the post-2011 periods, but it can be different over the two sample periods.

where we assume $f(k) = \ln k$. μ_τ is the parameter of how severe the expected future disasters are. When the government expects severe disaster damage will be realised in the future, this parameter takes the larger values and discounts the effectiveness of the disaster prevention capital. For a fixed time period τ and a local government i, $\mu_{i\tau}$ is just a parameter of the problem that determines the optimal level of investment in disaster preventive adaptations. We show how the value of $\mu_{i\tau}$ is updated in Subsection 4.2.

We make a policy rule to determine the sequences of the investments, $\{a_{t+1}, b_{t+1}\}$, from the severeness of the future expected disasters, μ_τ. To express the stickiness of the government's budget, we approximate the sequence of the investments by the values constituting a steady state of the model. Our specification gives the following affine policy rules with respect to μ_τ:

$$a_\tau = L^{1a}\mu_{\tau-1} + L^{2a},\ b_\tau = L^{1b}\mu_{\tau-1} + L^{2b}, \tag{1}$$

where

$$L^{1a} = \frac{\delta}{\beta\left(\frac{1-\alpha}{\alpha}\right)^{1-\alpha} K},\ L^{2a} = \frac{\delta\alpha}{\frac{1}{\beta} - 1 + \delta}$$

$$L^{1b} = \frac{\delta}{\beta\left(\frac{1-\alpha}{\alpha}\right)^{-\alpha} K},\ L^{2b} = \frac{\delta(1-\alpha)}{\frac{1}{\beta} - 1 + \delta}.$$

At time τ, Each local government i determines the amount of investments according to this affine rule given $\mu_{i\tau}$.

Optimal policy given in Equation (1) tells us that the disaster preparedness K works as a substitute for the adaptations in our model: when an area has a higher level of disaster preparedness, this area does not invest in the adaptations so much as the other area facing the lower level of disaster preparedness. Knowledge about investment in the adaptations and disaster preparedness in each region allow each government to retrieve the expected severity of future disasters, which varies among local governments. K behaves as an inverse weight on the observed value of the amount of the investment to retrieve the unobserved value of μ_τ.

4.2 Social Learning

Now, we define how to learn the severity of future disasters. Let the true severeness be $m^\star$ and local government i's belief over this state at time t be h_{it}. We define the individual parameter μ_{it} as the first order moment of the distribution h_{it}. At time $t+1$, given the information in hand, local government i retrieves the realised parameter value as $M_{it+1} \equiv \frac{Q_{it}k_{it}}{k_{it+1}-I_{it+i}}$. We model this value as the signal about the true value, $m^\star$: in other words, $M_{it+1} \sim H(\cdot; m^\star)$. h_{it} is updated following two steps:

1. i performs the Bayesian update to obtain $\tilde{h}_{it+1}$
2. When we denote the random variable following h_{it+1} by $m^\star_{it+1}$, our model specifies it by a linear combination of the random variables $\tilde{m}^\star_{it+1} \sim \tilde{h}_{it+1}$ and $m^\star_{jt} \sim h_{jt}$: $m_{it+1} = \gamma_{ii}\tilde{m}_{it+1} + \sum_{j\neq i} \gamma_{ij} m_{jt}$.

This gives the linear update rule about μ_{it}: $\mu_{it+1} = \gamma_{ii}\mathbb{E}_{m\sim\tilde{h}_{it+1}}[m] + \sum_{j\neq i}\gamma_{ij}\mu_{jt}$. These simple heuristics, non-fully Bayesian updates, are inspired by the model in Jadbabaie et al. (2012). Practically, it seems impossible for local governments to collect all the necessary information to conduct a full Bayesian update, so the governments need to rely on easy-to-use information like the one-dimensional object μ_{jt} when updating their own parameters.

Now, we consider the Bayesian update using own observation. We assume a Gaussian prior over $m^\star$ at the start of the learning process, $N(\mu_{i0}, \iota^2_{i0})$, and also a Gaussian disturbance, i.e. $M_{it+1} = m^\star + \epsilon$ where $\epsilon \sim N(0, \sigma^2_{it})$ for all t. This set up gives us a Gaussian posterior distribution: $N(\frac{\iota^2_{i0}M_{i1}+\sigma^2_{i0}\mu_{i0}}{\iota^2_{i0}+\sigma^2_{i0}}, \frac{\iota^2_{i0}\sigma^2_{i0}}{\iota^2_{i0}+\sigma^2_{i0}})$. Then, due to the reproducibility of Gaussian distribution, the distribution obtained after social learning is also Gaussian:

$$
\begin{aligned}
&h_{i1} = N\left(\mu_{i1}, \iota^2_{i1}\right), \\
&\text{where } \mu_{i1} = \gamma_{ii}\frac{\sigma^2_{i0}\mu_{i0} + \iota^2_{i0}M_{i1}}{\iota^2_{i0} + \sigma^2_{i0}} + \sum_{j\neq i}\gamma_{ij}\mu_{j0}, \qquad \iota^2_{i1} = \frac{\gamma^2_{ii}\iota^2_{i0}\sigma^2_{i0}}{\iota^2_{i0} + \sigma^2_{i0}} + \sum_{j\neq i}\gamma^2_{ij}\iota^2_{j0}.
\end{aligned}
$$

When we fix σ^2_{it} for all t, the weight on the prior mean at time $t+1$, $\frac{\sigma^2_{it}}{\sigma^2_{it}+\iota^2_{it}}$, becomes closer to 1 as the learning proceeds: the local government becomes less careful of the observation and finally ignores it. While this is an appropriate behaviour in the infinite horizon, given the time scale of our sample period, it seems reasonable to assume that σ_{it}^2 is adjusted to keep the weight away from 1 during the sample period. As one way to achieve this, we assume that the ratio $\frac{\sigma_{it}^2}{\iota_{it}^2}$ is constant for all the time periods. This makes the weight on the prior mean constant, denoted by w. This gives us the following update rule about μ_{it}:

$$
\begin{aligned}
\mu_{it+1} &= \gamma_{ii}\mathbb{E}_{m\sim\tilde{h}_{it+1}}[m] + \sum_{j\neq i}\gamma_{ij}\mu_{jt} \\
&= \gamma_{ii}\left(w\mu_{it} + (1-w)M_{it+1}\right) + \sum_{j\neq i}\gamma_{ij}\mu_{jt} \qquad (2)
\end{aligned}
$$

4.3 Empirical Strategy

We focus on the investment in the soft adaptations, a_{it+1}, as we discussed in Section 2. Our estimation takes two steps: in the first stage, we estimate the reduced form parameters denoted by ξ_{ij}, which is composed of γ_{ij} and i and j dependent terms, L_i^{1a} and L_j^{1a}, and then in the second stage, we decompose ξ_{ij} to uncover the determinants of γ_{ij}.

Based on the optimal policy in Equation (1) and the update rule about the mean in Equation (2), we have the following relationship between the current and the past levels of the investments:

$$
\begin{aligned}
&\frac{a_{it+1} - L_i^{2a}}{L_i^{1a}} = \gamma_{ii}\left(w\mu_{it} + (1-w)M_{it+1}\right) + \sum_{j\neq i}\gamma_{ij}\frac{a_{jt} - L_j^{2a}}{L_j^{1a}} \\
&\Rightarrow\ a_{it+1} = w\gamma_{ii}a_{it} + \sum_{j\neq i}\gamma_{ij}\frac{L_i^{1a}}{L_j^{1a}}a_{jt} + z_i^a + L_i^{1a}\gamma_{ii}(1-w)M_{it},
\end{aligned}
$$

where $z_i^a = (1-w\gamma_{ii})L_i^{2a} - L_i^{1a}\sum_{j\neq i}\gamma_{ij}\frac{L_i^{1a}}{L_j^{1a}}$. Note that M_{it} is just a summation of the true state $m^\star$, which is not dependent on time, and is an independent noise. Hence, we have the following regression equation: where the parameters are $\xi_{ij} = \gamma_{ij} \frac{L_i^{1a}}{L_j^{1a}}$,

$$a_{it+1} = \sum_j \xi_{ij} a_{jt} + \tilde{z}_i^a + \epsilon_{it+1}. \tag{3}$$

Using the estimates of these ξ_{ij}, which are denoted by $\hat{\xi}_{ij}$, we clarify the determinants of the social learning network. In particular, as we discussed in Section 1, we mainly focus on the impacts of the population moves between prefectures and the catastrophic disaster.

Imagine we have several sets of $\hat{\xi}_{ij}$, estimated using the different sets of time periods. We index them by T. In our following application, this corresponds to the pre-catastrophic disaster period, $T = 1$, and the post-catastrophic disaster period, $T = 2$. Now, our estimated parameters are denoted by $\hat{\xi}_{ijT}$. We specify the log-linear form of γ_{ij} using several sets of variables:

$$\ln \gamma_{ijT} = X'_{ijT}\beta + y_T + \theta_i + \kappa_j + u_{ijT},$$

where X_{ijT} represents the characteristics depending on the learner, the learning target and the period, y_T is the period dummy, θ_i and κ_j are the fixed effect of the local government i and j, and u_{ijT} are a disturbance. By taking the logarithm of the estimated $\hat{\xi}_{ijT}$, we get the estimation equation for the second step: note that $\tilde{\theta}_i = \theta_i + \ln L_i^{1a}$ and $\tilde{\kappa}_j = \kappa_j - \ln L_j^{1a}$,

$$\ln \hat{\xi}_{ijT} = X'_{ijT}\beta + y_T + \tilde{\theta}_i + \tilde{\kappa}_j + u_{ijT}. \tag{4}$$

5 Estimation Result

This section presents the estimation results. As discussed, we use data from 1998 to 2021 and divide our sample into two periods, before and after the Great East Japan Earthquake in 2011. In Section 5.1, for each sample period, we estimate the social learning network separately. Then, in Section 5.2, we examine the determinants of the social learning network: for example, the population moves, and the influence of the earthquake.

5.1 Social Learning Network

By taking the first difference of Equation (3), we eliminate the fixed effect term, $\tilde{z}_i^a$, and then our estimation equation is as follows:

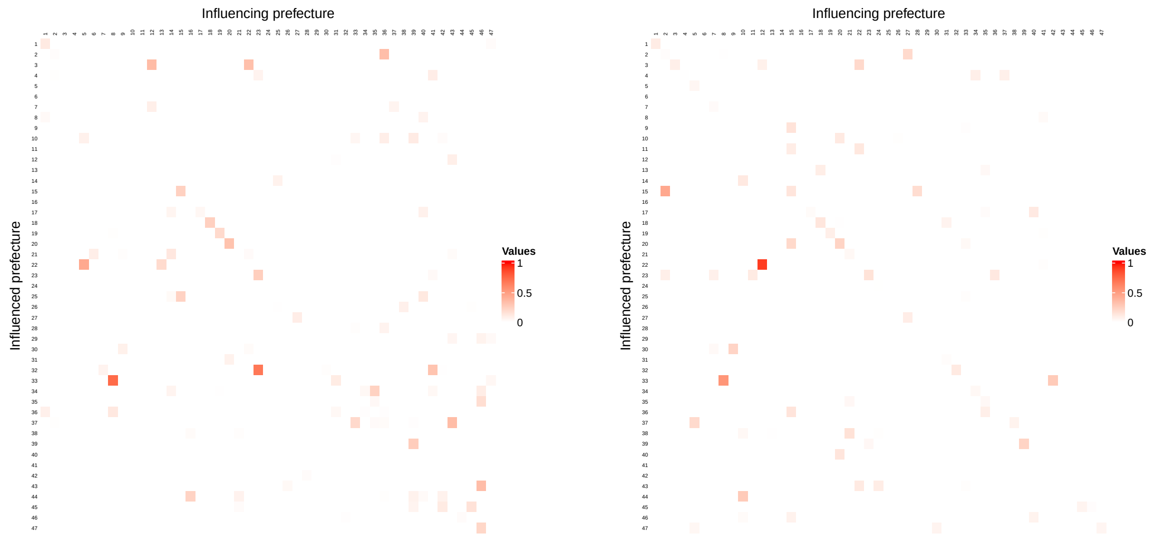
$$a_{it+1} - a_{it} = \sum_j \xi_{ij}(a_{jt} - a_{jt-1}) + \epsilon_{it+1} - \epsilon_{it}.$$

Note that this is a high-dimensional problem. In other words, the number of parameters is $47 \times 47 = 2209$, and it is larger than the number of observations, $47 \times \#$ years, where we have at most 22 years of observations in our pre-2011 sample. This is one of the reasons we use LASSO to estimate the network structure as in Manresa (2016). The other reason is that this methodology corresponds to our hypothesis that the social learning network is sparse: each local government does not have the infinite capability of attention, and instead, it distributes limited attention to a few numbers of selected others.

As to the execution of LASSO, we use cross-validation to pick the best tuning parameter in LASSO. This method gives us the variations of the estimated social learning network due to the different sub-samples in cross-validation. To resolve this variation, we conduct 200 times the same estimation to obtain their mean as our recovered network. To obtain more robust estimation results with a smaller variance of the penalty parameter, we use the logarithm of the non-infrastructural expenditure on the soft adaptation as the measure of a_{it} instead of the raw values.

Figure 2 shows the estimation results of the social networks: Panel (a) is the network obtained before 2011 and Panel (b) is the network obtained after 2011. In both panels, we plot the heatmap of the estimated coefficients $\hat{\xi}_{ij}$. The rows represent the index i, who learns from the others to infer the future disaster risk, and the columns represent the index j, the information source in social learning. The scale of the coefficients is $[0, 1]$, and the larger value corresponds to the darker colour.

First, our estimation reveals that some off-diagonal elements, i.e., the connections to the other prefecture, are positive. This implies that social learning from others' opinions matters in the adaptation policy. Second, our estimation recovers the sparse networks



(a) Before 2011 (b) After 2011

Figure 2. Social learning networks before and after Great East Japan Earthquake. Panel (a) uses 1998 to 2010 and Panel (b) uses 2011 to 2021. The numbers of prefectures are according to the officially determined ones which we show in Section 3. The (i, j) element represents the estimated values of ξ_{ij} in Equation (3).

for both before and after 2011, which means that one local government pays attention to a small number of other local governments. Third, we do not find any exceptionally influential governments or regions: neither Panel (a) nor (b) have a specific column or consequent columns with many non-zero values. These facts intrigue the more detailed analysis of what elements determine the social learning network. What kind of pairs are likely to be connected in the sparse networks? In the next subsection, we investigate these factors by regressing $\hat{\xi}_{ij}$ on several variables.

Lastly, we also note that the diagonal elements likely take non-zero values. Using the pre-2011 sample, we find 124 non-zero values in the estimated coefficients. Among them, the coefficients on the own past expenditure constitute 11.30%, where, if the non-zero values are found randomly, the ratio should be 2.13%, which is equal to $\frac{1}{47} \times 100$. The same ratio is 18.67% when we use the post-2011 sample. This implies that learning from the past plays a more important role than learning from others, which is consistent with the previous literature (Malmendier, Nagel and Yan, 2021).

5.2 Network Mechanism

This subsection presents our analysis of the determinants of the social learning network. In Equation (4), X_{ijT} includes the following variables: The distance between i and j which is computed as the geographical distance between the corresponding city halls. This is written as *Distance*. The ratio of the movers from j to i to the total population in i. Hereafter, we write this by *Move Rate*. The expected risk of the future earthquakes, denoted as $D_{\text{size},\text{XX}}$ for size $\in \{5-, 5+, 6-, 6+\}$ and XX $\in \{aa, am, ma, mm\}$ is also included. In the following regression, we include these measures of the earthquake probabilities for both learning and learned prefectures: the upper subscript *in* and *from* indicate them. We also include the measures of the experienced disaster damages as the control variables: specifically, the number of human damage, the number of injuries, the monetary damage rate, and the size of the agricultural field damage. For the variables that vary each year, we take the average value of them in the sample period, i.e., we take the average among the pre-2011 period and the post-2011 period to compute the value for each sample period.

We have 16 measures of the predicted risk of future earthquakes as we defined in Section 3. Among them, we show the four results obtained when we choose the average risk of SI6− over the prefecture calculated by the average case method. This is because Japanese citizens are accustomed to earthquakes and ones below SI5− do not seem large enough to alter their views of the future disaster risk. At the same time, earthquakes with a larger size, SI6+, are too rare to experience and we face less variation in the probability. As to the calculating methods, it is likely that policymakers would rather measure the entire risk of the prefecture than focus on the single maximum point. We choose the average case method because the maximum case method may overestimate the probability.[27]

Table 2 shows the results when we use $D_{6-,aa}$ as the measure of the future probability of earthquakes. We have three specifications in total. The first column corresponds to the simplest one, where we regress the logarithm of the estimated coefficients in the first

[27]We conduct robustness checks by varying this measure, and the results are qualitatively the same.

Table 2. Factors of Network Formation

	Dependent Variable: $\ln \hat{\xi}_{ijT}$		
	(1)	(2)	(3)
Post 2011	0.370	0.326	0.724
	(0.505)	(0.612)	(0.777)
Move Rate	-21.60*	-24.69**	-24.44**
	(11.18)	(12.07)	(11.77)
Move Rate Squared	167.4**	170.5**	185.5**
	(68.95)	(69.65)	(71.71)
ln Transformed Price (TP)	-6.565	-7.447	-8.603
	(5.354)	(5.828)	(5.972)
$\ln D^{in}_{6-,aa}$	-0.782*	-0.978**	-1.086**
	(0.423)	(0.490)	(0.519)
$\ln D^{from}_{6-,aa}$	-0.185	-0.166	-0.282
	(0.277)	(0.299)	(0.313)
$\ln \mathrm{TP} \times \ln D^{in}_{6-,aa}$	-3.159*	-3.446*	-3.517*
	(1.891)	(2.076)	(2.058)
$\ln \mathrm{TP} \times \ln D^{from}_{6-,aa}$	-0.917	-1.027	-1.642
	(1.149)	(1.243)	(1.347)
FE		√	√
Selection			√
N	165	165	165
adj. R^2	0.855	0.850	0.849

Notes. Standard errors are in parentheses. The superscripts, ***, **, *, denote the statistical significance at the 1, 5, and 10 percent levels, respectively. The regression is based on Equation (4).

stage on the set of variables that we explained above. The second column shows the result where we additionally control for the area-level fixed effects.[28][29] The third column shows the result obtained when we care about the selection bias: because we use LASSO in the first stage, most of the coefficients are estimated as exactly 0. We consider this situation as a selection problem like in the Tobit model, and we conduct Heckman's two-step estimation to avoid selection bias.

The first finding is that the population move from prefecture j to i influences the attention to the prefecture j from i. The squared move rate has a statistically significantly positive coefficient, which implies that the marginal influence of the move rate grows as the move rate increases. We plot the fitted value obtained for column (3) in Figure 3,

[28]We group prefectures into 9 areas following a Japanese standard, as we explain in Appendix A.

[29]Note that, due to the number of observations in the second stage, we use the area-level fixed effects instead of the individual prefecture-level fixed effects. This additionally imposes an assumption that disaster preparedness is common among the prefectures in the same area, based on the model in Subsection 4.1.

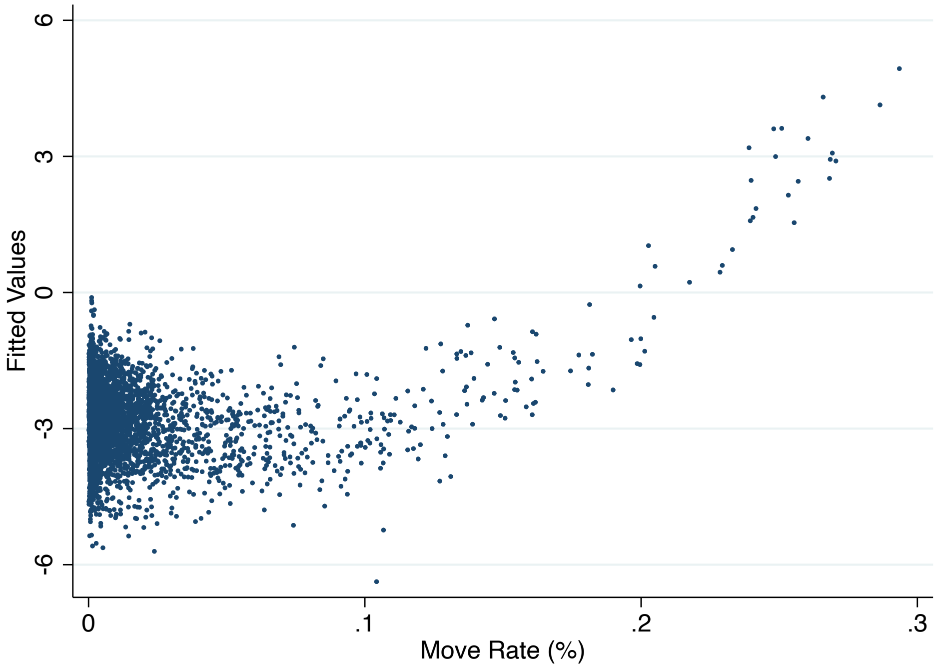


Figure 3. Marginal Influence of Move Rate with SI6− in *aa* Case

We bound the value of the move rate from above by Move Rate = 0.002. See Figure B1 in Appendix B for the results of the other specifications.

which shows that there are pairs of prefectures that increase the strength of the connection from the increasing part of the quadratic function. Specifically, 6.47% of all the pairs have the positive marginal effect of increasing the move rate. This is robust to all the other measures of the future disaster risk and the way of aggregations, shown in Appendix B.[30]

We propose two potential mechanisms which explain the effect of the move rate. One is the soft power, i.e., the atmosphere generated by the demographics. When a prefecture has an amount of move from another prefecture and the movers constitute a community in the prefecture, their voices can make the prefecture as a whole feel sympathy for their origin. In particular, a severe event like a catastrophic disaster incurs sympathy and often leads to an action like fundraising. These intangible feeling generated by the movers has a certain power over the actual policies. The other is the direct influence of the political system. The movers have the political right, and politicians listen to their voices. Under the democratic political system, the distributional change in the demographics should

[30]We note that the coefficients of Move Rate are not always found to be statistically significantly negative.

be reflected by the implemented policy. Our estimation result suggests this obvious conclusion of democracy. The positive coefficient of the Move Rate Squared implies that this power of the community is not linear: As the community grows, the marginal influence of the community also increases.

Given the estimates in Column (3) of Table 2, we compute the change in the weights on prefecture j (γ_{ij}) when the Move Rate for each pair of prefectures increases by 0.1 standard deviations (0.007), which gives the median of the effects equal to -0.144. This implies that the attention paid to j decreases by about 14%. Since the first-order term is estimated imprecisely, we recalculate it by assuming its coefficient is zero. This exercise reduces the value to 0.012, implying an increase in the attention to j by 1.2% when the Move Rate increases by 0.1 standard deviations, which seems more reasonable.

The second finding is that the prefectures facing larger earthquake risks in the future have less attention to the others. This is shown in the estimated coefficients of the set of $\ln D^{in}_{6-,aa}$. For such a prefecture, the information about the own risk is enough to determine the future adaptation level, and the information about others' adaptation is not useful for the inference about the true state and for the future policy. As to the size of the effect, an increase in the probability of the future earthquake by 1% decreases the weight on local government j by 0.061: i.e., 6.1% decrease in attention.

Another factor of a decrease in the attention to others is the risk-aversion of their citizen. The cross term of the measure of the risk aversion and the probability of the future earthquake has a statistically significant negative coefficient. When a prefecture is more risk-averse, the risk of a future disaster decreases the attention to others. Hanaoka, Shigeoka and Watanabe (2018) shows that the citizens of the prefecture that suffered from the catastrophic earthquake in 2011 have become more risk-tolerant. Hence, the current estimation result implies that the prefecture that severely suffered from the earthquake of 2011 pays more attention to the others given the risk of future earthquakes. In contrast to this indirect effect through the change in risk-aversion, we do not find the direct effect of the Great East Japan Earthquake in 2011: The coefficient attached to the dummy variable of post-2011 does not have an effect on the network structure.

Table 3. Heterogeneity in Risk Levels

	Dependent Variable: $\ln \hat{\xi}_{ijT}$								
	$\ln D_{XX,aa} = \ln D_{5-,aa}$			$\ln D_{XX,aa} = \ln D_{5+,aa}$			$\ln D_{XX,aa} = \ln D_{6+,aa}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post 2011	0.310	0.204	0.387	0.373	0.354	0.684	0.329	0.313	0.869
	(0.507)	(0.607)	(0.721)	(0.499)	(0.609)	(0.775)	(0.513)	(0.627)	(0.829)
Move Rate	-18.80*	-20.86*	-20.55*	-19.84*	-22.61*	-22.26*	-22.22*	-26.89**	-27.39**
	(11.11)	(11.94)	(11.84)	(11.02)	(11.82)	(11.59)	(11.30)	(12.09)	(11.83)
Move Rate Squared	151.6**	151.0**	157.4**	157.5**	159.6**	170.8**	167.6**	176.5**	199.5***
	(69.19)	(70.54)	(71.78)	(68.49)	(69.16)	(70.80)	(69.29)	(69.13)	(73.02)
ln TP	-2.080	-2.158	-2.209	-3.894	-4.450	-4.858	-8.502	-10.45	-14.06
	(3.983)	(4.555)	(4.558)	(4.339)	(4.853)	(4.893)	(7.291)	(7.907)	(8.699)
$\ln D^{in}_{XX,aa}$	-1.762	-2.292	-2.459	-1.029*	-1.347*	-1.483*	-0.549	-0.714*	-0.809*
	(1.293)	(1.505)	(1.588)	(0.620)	(0.723)	(0.770)	(0.338)	(0.394)	(0.415)
$\ln D^{from}_{XX,aa}$	-0.623	-0.552	-0.598	-0.268	-0.250	-0.336	-2.248	-2.554	-2.716
	(0.802)	(0.884)	(0.896)	(0.396)	(0.446)	(0.458)	(0.250)	(0.264)	(0.304)
$\ln \text{TP} \times \ln D^{in}_{XX,aa}$	-7.266	-7.726	-7.524	-4.149	-4.578	-4.541	-2.248	-2.554	-2.716
	(5.922)	(6.689)	(6.640)	(2.821)	(3.111)	(3.086)	(1.504)	(1.649)	(1.645)
$\ln \text{TP} \times \ln D^{from}_{XX,aa}$	-2.843	-2.627	-3.258	-1.303	-1.376	-2.012	-0.576	-0.773	-1.653
	(3.442)	(3.766)	(3.966)	(1.638)	(1.792)	(1.930)	(1.040)	(1.124)	(1.284)
FE		✓	✓		✓	✓		✓	✓
Selection			✓			✓			✓
N	165	165	165	165	165	165	165	165	165
adj. R^2	0.852	0.847	0.846	0.854	0.849	0.848	0.853	0.848	0.848

Notes. Standard errors are in parentheses. The superscripts, ***, **, *, denote the statistical significance at the 1, 5, and 10 percent levels, respectively. The regression is based on Equation (4).

Next, we investigate the influence of the size of future earthquakes. Table 3 shows the results obtained when we use a measure of the different SI sizes. As shown, the estimation results of the coefficients of Move Rate and its squared value are similar to those in Table 2. However, the estimation results of the coefficients of $\ln D^{in}$ and its cross terms with $\ln TP$ exhibit clear differences. We do not find that the future earthquake risk of SI5$-$ has an impact on learning behaviour. It seems the information about this level of earthquakes is not surprising to Japanese citizens due to its frequency. On the contrary, we do find the same direction of the impact from the information about the future earthquake risk of SI6+. However, the scale of the influence is reduced. One possible reason for this non-monotonicity is the severeness of such a large earthquake is hard to imagine due to the scarcity of the experience.

6 Discussion and Conclusion

In this paper, using administrative data on the expenditure on disaster prevention by the Japanese local governments, we empirically recover who uses whose information to update the belief about the severity of future disasters. Then, we study what factors determine the connection in the learning network.

First, our estimation reveals that the local governments refer to others' information to infer the uncertain future disaster risk. This is evidence that social learning is crucial in policymaking for complicated problems like disaster prevention policies. Furthermore, we find that the movers from the other area influence the attention to the area. When a prefecture i has more movers from a prefecture j, the government of i is getting to pay more attention to prefecture j. While we do not find the network changes radically due to a catastrophic event, which is the Great East Japan Earthquake in 2011 in our case, we find that, given the risk of future earthquakes, prefectures having suffered from it more severely are more likely to pay more attention to other prefectures through becoming more risk-tolerant.

Our method is not limited to the disaster prevention policy. As discussed in the introduction, many problems must be based on learning, such as climate change, AI risk, and Big Tech's economic dominance. Similar social learning from others, where others often mention the other nation, plays a prominent role in such policy areas. Because any of them will have an enormous impact on the future of the world economy, when deciding the policy direction, the government must acknowledge its own inclination in information usage to make better decisions. At this point, the research about social learning behaviour will help understand the fundamental bias of policymaking.

Besides the necessity of the research on the other issues, climate change and the effectiveness of the adaptation are necessary to be studied more in the future. While our focus is not on a quantitative understanding of the soft adaptations, such as making evacuation manuals, we need to clarify the effectiveness of this type of disaster prevention because they demand less money than the hard adaptations like building seawalls, which are easier to implement in developing countries. In the era of climate change, soft adaptation is becoming more necessary for the fairness to the disaster risk.

References

Agrawala, Shardul, Francesco Bosello, Carlo Carraro, Kelly de Bruin, Enrica De Cian, Rob Dellink, and Elisa Lanzi. 2010. "Plan or React? Analysis of Adaptation Costs and Benefits Using Integrated Assessment Models." , (23).

Auffhammer, Maximilian. 2022. "Climate Adaptive Response Estimation: Short and Long Run Impacts of Climate Change on Residential Electricity and Natural Gas Consumption." *Journal of Environmental Economics and Management*, 114: 102669.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro. 2016. "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century." *Journal of Political Economy*, 124(1): 105–159.

Bourdeau-Brien, Michael, and Lawrence Kryzanowski. 2020. "Natural Disasters and Risk Aversion." *Journal of Economic Behavior & Organization*, 177: 818–835.

Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin. 2020. "Peer Effects in Networks: A Survey." *Annual Review of Economics*, 12: 603–629.

Brown, Philip, Adam J. Daigneault, Emilia Tjernström, and Wenbo Zou. 2018. "Natural Disasters, Social Protection, and Risk Perceptions." *World Development*, 104: 310–325.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E. Kopp, Kelly E. McCusker, Ishan Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Arvid Viaene, Jiacan Yuan, and Alice Tianbo Zhang. 2022. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." *Quarterly Journal of Economics*, 137(4): 2037–2105.

Chuang, Yating, and Laura Schechter. 2015. "Stability of Experimental and Survey Measures of Risk, Time, and Social Preferences: A Review and Some New Results." *Journal of Development Economics*, 117: 151–170.

Cramer, Jan S., Joop Hartog, Nicole Jonker, and C. Mirjam Van Praag. 2002. "Low Risk Aversion Encourages the Choice for Entrepreneurship: An Empirical Test of a Truism." *Journal of Economic Behavior & Organization*, 48(1): 29–36.

de Bruin, Kelly C., Rob B. Dellink, and Richard S. J. Tol. 2009. "AD-DICE: An Implementation of Adaptation in the DICE Model." *Climatic Change*, 95(1): 63–81.

Felgenhauer, Tyler, and Mort Webster. 2014. "Modeling Adaptation as a Flow and Stock Decision with Mitigation." *Climatic Change*, 122(4): 665–679.

Fire and Disaster Management Agency. 1970. "Saigai Houkoku Toriatsukai Youryou [Disaster Report Handling Guidelines]."

Fire and Disaster Management Agency. 2006. "Hanshin-Awaji Dai-Shinsai Ni Tsuite (Kakutei Hou) [The Great Hanshin-Awaji Earthquake (Final Report)]."

Fire and Disaster Management Agency. 2013. "Higashi-Nihon Dai-Shinsai Kiroku-Shu [Collection of records of the Great East Japan Earthquake]."

Fire and Disaster Management Agency. 2019. "Shoubou Hakusho [White Paper on Fire Service]."

Fried, Stephie. 2021. "Seawalls and Stilts: A Quantitative Macro Study of Climate Adaptation." *Review of Economic Studies*, 89(6): 3303–3344.

Gallagher, Justin. 2014. "Learning about an Infrequent Event: Evidence from Flood Insurance Take-up in the United States." *American Economic Journal: Applied Economics*, 206–233.

Gao, Ming, Yu-Jane Liu, and Yushui Shi. 2020. "Do People Feel Less at Risk? Evidence from Disaster Experience." *Journal of Financial Economics*, 138(3): 866–888.

Gilardi, Fabrizio. 2010. "Who Learns from What in Policy Diffusion Processes?" *American Journal of Political Science*, 54(3): 650–666.

Gilardi, Fabrizio, and Fabio Wasserfallen. 2019. "The Politics of Policy Diffusion." *European Journal of Political Research*, 58(4): 1245–1256.

Goebel, Jan, Christian Krekel, Tim Tiefenbach, and Nicolas R. Ziebarth. 2015. "How Natural Disasters Can Affect Environmental Concerns, Risk Aversion, and Even Politics: Evidence from Fukushima and Three European Countries." *Journal of Population Economics*, 28(4): 1137–1180.

Greenwood, Robin, and Stefan Nagel. 2009. "Inexperienced Investors and Bubbles." *Journal of Financial Economics*, 93(2): 239–258.

Hanaoka, Chie, Hitoshi Shigeoka, and Yasutora Watanabe. 2018. "Do Risk Preferences Change? Evidence from the Great East Japan Earthquake." *American Economic Journal: Applied Economics*, 10(2): 298–330.

Hasegawa, Akira, Haruo Saito, and Takeshi Nishimura. 2015. *Introduction to Modern Earth Science Series Vol. 6 Seismology.* Kyoritsu Shuppan Co., Ltd.

Hjort, Jonas, Diana Moreira, Gautam Rao, and Juan Francisco Santini. 2021. "How Research Affects Policy: Experimental Evidence from 2,150 Brazilian Municipalities." *American Economic Review*, 111(5): 1442–80.

Hsiang, Solomon M., and Amir S. Jina. 2014. "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones." National Bureau of Economic Research Working Paper 20352.

Hsiang, Solomon M., and Daiju Narita. 2012. "Adaptation to Cyclone Risk: Evidence from the Global Cross-section." *Climate Change Economics*, 3(2): 1–28.

Jadbabaie, Ali, Pooya Molavi, Alvaro Sandroni, and Alireza Tahbaz-Salehi. 2012. “Non-Bayesian Social Learning.” *Games and Economic Behavior*, 76(1): 210–225.

Japan Meteorological Agency. 2015. “Tables explaining the JMA Seismic Intensity Scale.” *https://www.jma.go.jp/jma/en/Activities/inttable.html*.

Koudijs, Peter, and Hans-Joachim Voth. 2016. “Leverage and Beliefs: Personal Experience and Risk-Taking in Margin Lending.” *American Economic Review*, 106(11): 3367–3400.

Kuchler, Theresa, and Basit Zafer. 2019. “Personal Experiences and Expectations about Aggregate Outcomes.” *Journal of Finance*, 74(5): 2491–2542.

Malmendier, Ulrike, Stefan Nagel, and Zhen Yan. 2021. “The Making of Hawks and Doves.” *Journal of Monetary Economics*, 117: 19–42.

Manresa, Elena. 2016. “Estimating the Structure of Social Interactions Using Panel Data.” Working paper.

Ministry of Internal Affairs and Communications. 2022. “Reiwa 4 Nen-Ban Chihou-Zaisei Hakusho [White Book of Local Finance in Fiscal Year of 2022].”

Ministry of Transport. 1996. *Heisei 7 Nendo Unyu Hakusho [White Paper on Transport in Fiscal Year of 1995].* Ministry of Finance Printing Bureau.

Pratt, John W. 1964. “Risk Aversion in the Small and in the Large.” *Econometrica*, 122–136.

Soga, Kengo. 2019. *Nihon no Chiho Seihu [Local Governments in Japan].* Chuokoron-Shinsha, Inc.

Taraz, Vis. 2017. “Adaptation to Climate Change: Historical Evidence from the Indian Monsoon.” *Environment and Development Economics*, 22(5): 517–545.

Vivalt, Eva, Aidan Coville, and Sampada KC. 2022. “Weighing the Evidence: Which Studies Count?” working paper.

Vivalt, Eva, and Aidan Coville. 2023. "How Do Policymakers Update Their Beliefs?" *Journal of Development Economics*, 165: 103121.

Volden, Craig, Michael M. Ting, and Daniel P. Carpenter. 2008. "A Formal Model of Learning and Policy Diffusion." *The American Political Science Review*, 102(3): 319–332.

A Additional Tables and Figures

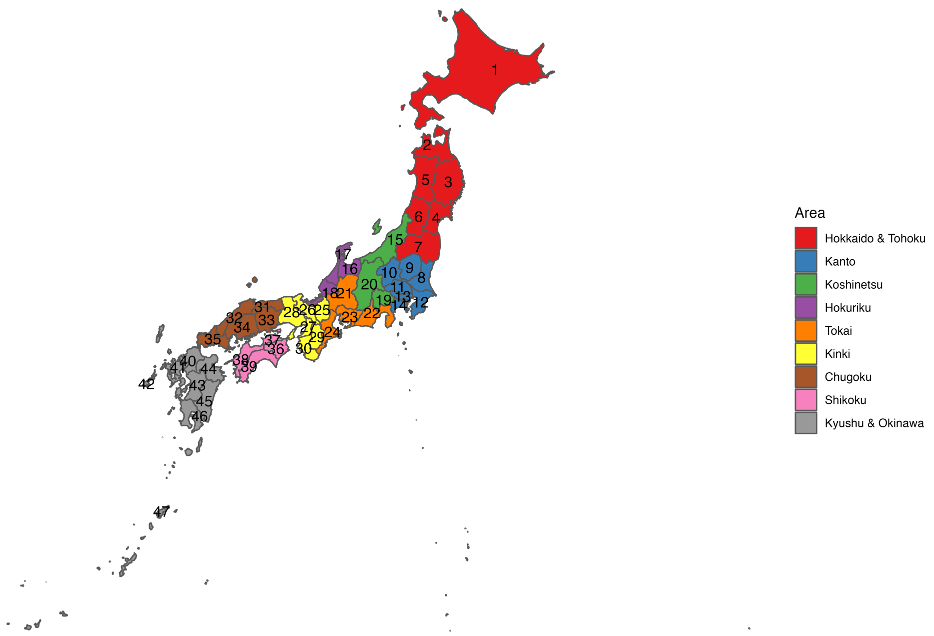


Figure A1. Prefecture Numbers and Regional Division of Japanese Prefectures

The numbers on prefectures correspond to those in the main analysis.

Table A1. Regional Division of Japanese Prefectures

Area	Prefectures in the area
Hokkaido & Tohoku	Hokkaido, Aomori, Iwate, Miyagi, Akita, Yamagata, and Fukushima
Kanto	Ibaraki, Tochigi, Gumma, Saitama, Chiba, Tokyo, and Kanagawa
Koshinetsu	Niigata, Yamanashi, and Nagano
Hokuriku	Toyama, Ishikawa, and Fukui
Tokai	Gifu, Shizuoka, Aichi, and Mie
Kinki	Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama
Chugoku	Tottori, Shimane, Okayama, Hiroshima, and Yamaguchi
Shikoku	Tokushima, Kagawa, Ehime, and Kochi
Kyushu & Okinawa	Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, Kagoshima, and Okinawa

Table A2. Seismic Intensity Scale of Earthquakes in Japan

Panel A: Human perception and reaction

Seismic intensity	Description
0	Imperceptible to people, but recorded by seismometers.
1	Felt slightly by some people keeping quiet in buildings.
2	Felt by many people keeping quiet in buildings. Some people may be awoken.
3	Felt by most people in buildings. Felt by some people walking. Many people are awoken.
4	Most people are startled. Felt by most people walking. Most people are awoken.
5 Lower	Many people are frightened and feel the need to hold onto something stable.
5 Upper	Many people find it hard to move; walking is difficult without holding onto something stable.
6 Lower	It is difficult to remain standing.
6 Upper	It is impossible to remain standing or move without crawling. People may be thrown through the air.
7	It is impossible to remain standing or move without crawling. People may be thrown through the air.

Panel B: Indoor situation

Seismic intensity	Description
0	
1	
2	Hanging objects such as lamps swing slightly.
3	Dishes in cupboards may rattle.
4	Hanging objects such as lamps swing significantly, and dishes in cupboards rattle. Unstable ornaments may fall.
5 Lower	Hanging objects such as lamps swing violently. Dishes in cupboards and items on bookshelves may fall. Many unstable ornaments fall. Unsecured furniture may move, and unstable furniture may topple over.
5 Upper	Dishes in cupboards and items on bookshelves are more likely to fall. TVs may fall from their stands, and unsecured furniture may topple over.
6 Lower	Many unsecured furniture moves and may topple over. Doors may become wedged shut.
6 Upper	Most unsecured furniture moves, and is more likely to topple over.
7	Most unsecured furniture moves and topples over, or may even be thrown through the air.

Panel C: Outdoor situation

Seismic intensity	Description
0	
1	
2	
3	Electric wires swing slightly.
4	Electric wires swing significantly. Those driving vehicles may notice the tremor.
5 Lower	In some cases, windows may break and fall. People notice electricity poles moving. Roads may sustain damage.
5 Upper	Windows may break and fall, unreinforced concrete-block walls may collapse, poorly installed vending machines may topple over, automobiles may stop due to the difficulty of continued movement.
6 Lower	Wall tiles and windows may sustain damage and fall.
6 Upper	Wall tiles and windows are more likely to break and fall. Most unreinforced concrete-block walls collapse.
7	Wall tiles and windows are even more likely to break and fall. Reinforced concrete-block walls may collapse.

Notes. This table is from Japan Meteorological Agency (2015).

Table A3. Summary Statistics (Cont.)

	Mean	sd	Min	25%	Median	75%	Max	N
Risk Preference								
Transformed Reservation Price[a]								
Pre 2011 Disaster[b]	0.812	0.032	0.744	0.791	0.815	0.829	0.888	47
Post 2011 Disaster Measure 1 (same in Table 1)[c]	0.752	0.050	0.615	0.726	0.760	0.787	0.837	47
Post 2011 Disaster Measure 2[d]	0.784	0.033	0.677	0.770	0.788	0.802	0.856	47
Absolute Risk Preference[e]								
Pre 2011 Disaster[b]	1.858	0.047	1.750	1.826	1.861	1.887	1.966	47
Post 2011 Disaster Measure 1 (same in Table 1)[c]	1.790	0.098	1.447	1.749	1.822	1.858	1.943	47
Post 2011 Disaster Measure 2[d]	1.832	0.059	1.668	1.801	1.836	1.871	1.939	47

Predicted Probability of Earthquakes in the Average Case[f]								
Maximum of Each Prefecture								
Seismic Intensity of 5 Lower ($D_{5-,ma}$)								
Pre 2011	0.950	0.068	0.751	0.916	0.983	0.998	1.000	47
Post 2011	0.957	0.045	0.841	0.934	0.964	0.998	1.000	47
Seismic Intensity of 5 Upper ($D_{5+,ma}$)								
Pre 2011	0.612	0.147	0.283	0.547	0.689	0.728	0.749	47
Post 2011	0.824	0.156	0.497	0.769	0.860	0.940	1.000	47
Seismic Intensity of 6 Lower ($D_{6-,ma}$)								
Pre 2011	0.494	0.277	0.065	0.247	0.564	0.701	0.965	47
Post 2011	0.580	0.257	0.134	0.382	0.624	0.777	0.958	47
Seismic Intensity of 6 Upper ($D_{6+,ma}$)								
Pre 2011	0.184	0.191	0.015	0.041	0.116	0.211	0.689	47
Post 2011	0.308	0.237	0.024	0.108	0.237	0.501	0.743	47
Predicted Probability of Earthquakes in the Maximum Case[f]								
Average over Each Prefecture								
Seismic Intensity of 5 Lower ($D_{5-,am}$)								
Pre 2011	0.560	0.258	0.118	0.337	0.486	0.778	0.977	47
Post 2011	0.602	0.215	0.189	0.418	0.590	0.779	0.991	47
Seismic Intensity of 5 Upper ($D_{5+,am}$)								
Pre 2011	0.234	0.193	0.025	0.075	0.126	0.421	0.652	47
Post 2011	0.358	0.244	0.060	0.158	0.262	0.595	0.880	47
Seismic Intensity of 6 Lower ($D_{6-,am}$)								
Pre 2011	0.114	0.133	0.004	0.017	0.045	0.171	0.546	47
Post 2011	0.154	0.151	0.012	0.043	0.067	0.297	0.518	47
Seismic Intensity of 6 Upper ($D_{6+,am}$)								
Pre 2011	0.017	0.026	0.000	0.002	0.008	0.018	0.127	47
Post 2011	0.036	0.044	0.002	0.007	0.014	0.057	0.180	47
Maximum of Each Prefecture								
Seismic Intensity of 5 Lower ($D_{5-,mm}$)								
Pre 2011	0.955	0.062	0.784	0.924	0.986	0.998	1.000	47
Post 2011	0.965	0.037	0.848	0.947	0.974	0.998	1.000	47
Seismic Intensity of 5 Upper ($D_{5+,mm}$)								
Pre 2011	0.621	0.136	0.309	0.558	0.696	0.731	0.749	47
Post 2011	0.843	0.138	0.523	0.792	0.881	0.944	1.000	47
Seismic Intensity of 6 Lower ($D_{6-,mm}$)								
Pre 2011	0.510	0.268	0.087	0.262	0.565	0.707	0.966	47
Post 2011	0.603	0.239	0.143	0.437	0.648	0.778	0.961	47
Seismic Intensity of 6 Upper ($D_{6+,mm}$)								
Pre 2011	0.194	0.188	0.015	0.062	0.116	0.219	0.689	47
Post 2011	0.327	0.227	0.030	0.141	0.237	0.519	0.743	47

Notes. 1 USD is approximately equivalent to 140 JPY. Japan is composed of 47 prefectures, so in the first row, the number of observations is $1081 = 47 * 46/2$. See Figure A1 and Table A1 for the definition of the same area. According to this definition, Hokkaido has no other prefectures in the same area, so the number of observations in the corresponding row is smaller.

a: This variable measures the willingness to pay for a lottery with which they win JPY 100,000, following Hanaoka, Shigeoka and Watanabe (2018).

b: This variable is measured in January and February 2011, before the Great East Japan Earthquake on 11 March 2011.

c: This variable is measured in January and February 2021.

d: This variable is the average of ones over three periods, measured in January and February 2012, 2016, and 2021.

e: This corresponds to the absolute risk aversion based on Arrow-Pratt measure (Pratt, 1964). We calculate this measure based on the transformed reservation price, following Hanaoka, Shigeoka and Watanabe (2018).

f: See the definition of the average and maximum cases in Footnote 19.

B Additional Estimation Results

In this appendix chapter we show the robustness of our results. In Table B1, we show the estimation results obtained when we use the other three ways of aggregation of the risk of the future earthquakes. The remaining three are am, ma, and mm. We fix the size of the future earthquakes to SI6− as in the main results in Table 2. We also find that the statistically significant positive coefficients on the squared of Move Rate while the negative coefficients attached to Move Rate is not so robustly found. Furthermore, we find the same directed and similar sized coefficients attached to $\ln D^{in}_{6-,XX}$ and its cross term with $\ln TP$. In Figure B1, we show the same scatter plots as in Figure 3. All of them show that a part of pairs of the local governments suffer from the positive effects of the increasing movers from the other prefecture on the attention to it.

Table B1. Robustness Checks

	Dependent Variable: $\ln \hat{\xi}_{ijT}$								
	$\ln D_{6-,XX} = \ln D_{6-,am}$			$\ln D_{6-,XX} = \ln D_{6-,ma}$			$\ln D_{6-,XX} = \ln D_{6-,mm}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post 2011	0.402	0.382	0.778	0.369	0.374	0.546	0.399	0.397	0.583
	(0.502)	(0.608)	(0.782)	(0.490)	(0.591)	(0.741)	(0.489)	(0.593)	(0.759)
Move Rate	-22.41**	-25.75**	-25.68**	-18.28	-17.98	-17.53	-18.75*	-18.74	-18.24
	(11.19)	(12.12)	(11.84)	(11.09)	(12.21)	(12.15)	(10.97)	(12.14)	(12.10)
Move Rate Squared	170.6**	174.6**	189.8***	148.7**	138.4*	142.7**	150.7**	141.8**	146.1**
	(68.60)	(69.55)	(71.77)	(68.94)	(70.86)	(71.05)	(68.29)	(70.62)	(70.70)
ln TP	-7.269	-8.284	-9.640	-3.827	-4.360	-4.483	-4.203	-4.786	-4.967
	(5.307)	(5.753)	(5.962)	(3.353)	(3.743)	(3.758)	(3.235)	(3.575)	(3.600)
$\ln D^{in}_{6-,XX}$	-0.869**	-1.057**	-1.159**	-2.032**	-2.514**	-2.592**	-2.282**	-2.754***	-2.852***
	(0.439)	(0.507)	(0.534)	(0.951)	(1.026)	(1.057)	(0.960)	(1.024)	(1.068)
$\ln D^{from}_{6-,XX}$	-0.169	-0.156	-0.296	-0.575	-0.595	-0.693	-0.560	-0.612	-0.742
	(0.288)	(0.314)	(0.333)	(0.485)	(0.580)	(0.610)	(0.548)	(0.673)	(0.715)
$\ln \mathrm{TP} \times \ln D^{in}_{6-,XX}$	-3.591*	-3.912*	-4.058*	-8.367**	-9.339**	-9.260**	-9.536**	-10.64**	-10.62**
	(1.964)	(2.134)	(2.133)	(4.134)	(4.458)	(4.444)	(4.100)	(4.309)	(4.300)
$\ln \mathrm{TP} \times \ln D^{from}_{6-,XX}$	-0.884	-1.067	-1.734	-2.197	-2.120	-2.717	-2.109	-2.119	-2.850
	(1.191)	(1.294)	(1.406)	(1.986)	(2.212)	(2.496)	(2.225)	(2.520)	(2.858)
FE		√	√		√	√		√	√
Selection			√			√			√
N	165	165	165	165	165	165	165	165	165
adj. R^2	0.856	0.850	0.850	0.858	0.855	0.854	0.859	0.855	0.854

Notes. Standard errors are in parentheses. The superscripts, ***, **, *, denote the statistical significance at the 1, 5, and 10 percent levels, respectively. The regression is based on Equation (4).

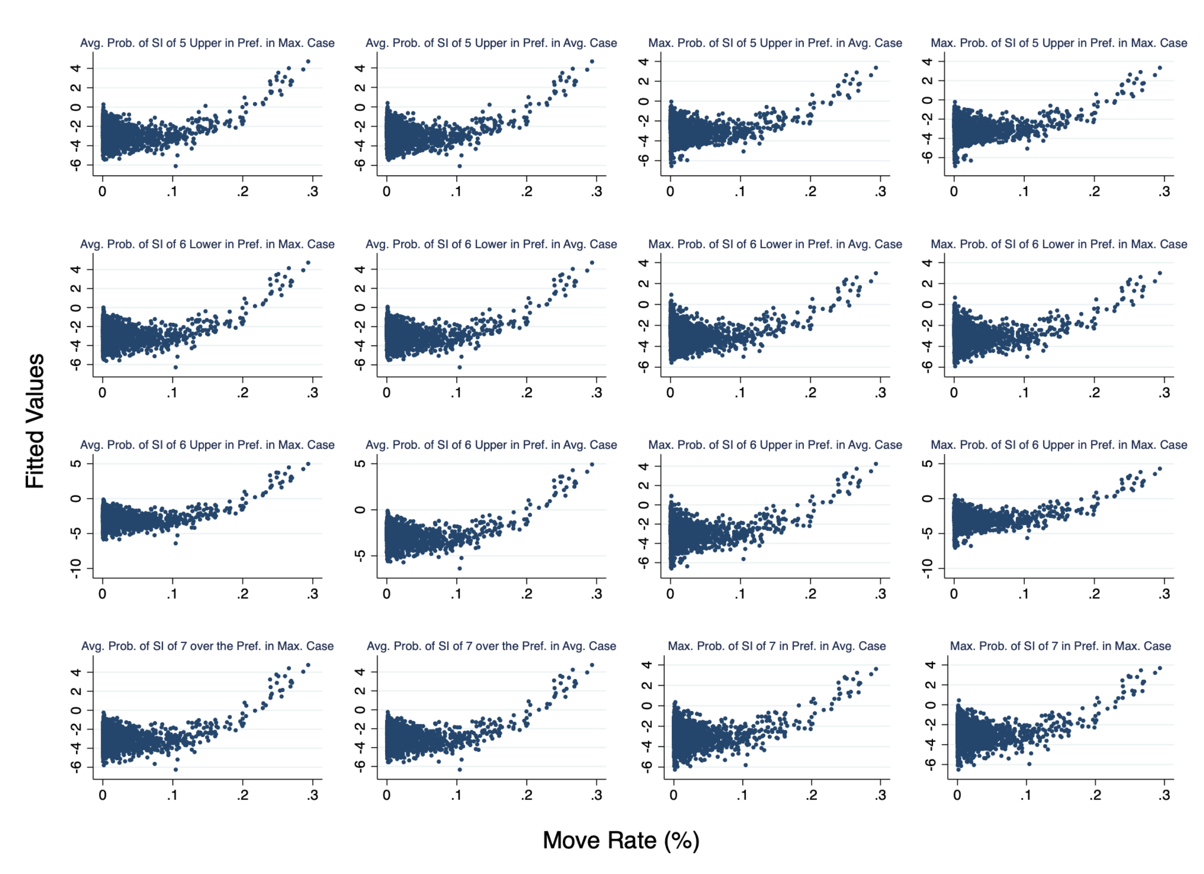


Figure B1. Robustness Check of Marginal Influence of Move Rate