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

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**Abstract**

This paper studies social learning 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 between local governments with the connection in the social learning about the risk. We use Japanese administrative data over 20 years to estimate a sparse social learning network. Moreover, as the network formation determinants, we find significant effects of (1) the inflow of internal migration between local governments, (2) the risk of future earthquakes, and (3) the risk preference of the local citizens.

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. At the same time, 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. Even in this regard, the broadly-speaking 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 between 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 hazards 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 shows a non linearity: the marginal influence of the movers is increasing. This finding is consistent with the existing literature about the non linear increment in the influence of the minority group size (Kanter, 1977; Dahlerup, 1988; Centola et al., 2018). 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 a constant 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 Disasters in Japan

Japan suffers from piles of natural hazards. 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 all 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 perfectly against future hazards for Japan, which is a member of G7 with a high standard of technology. This is because of the difficulty in predicting future hazards, 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 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 hazards, 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 natural hazards more quickly and more appropriately.[7] Furthermore, they changed the building resistant standard against

[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).

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.

To reduce the vulnerability to natural hazards, the government can take two types of policies ranging 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 hazards. 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.

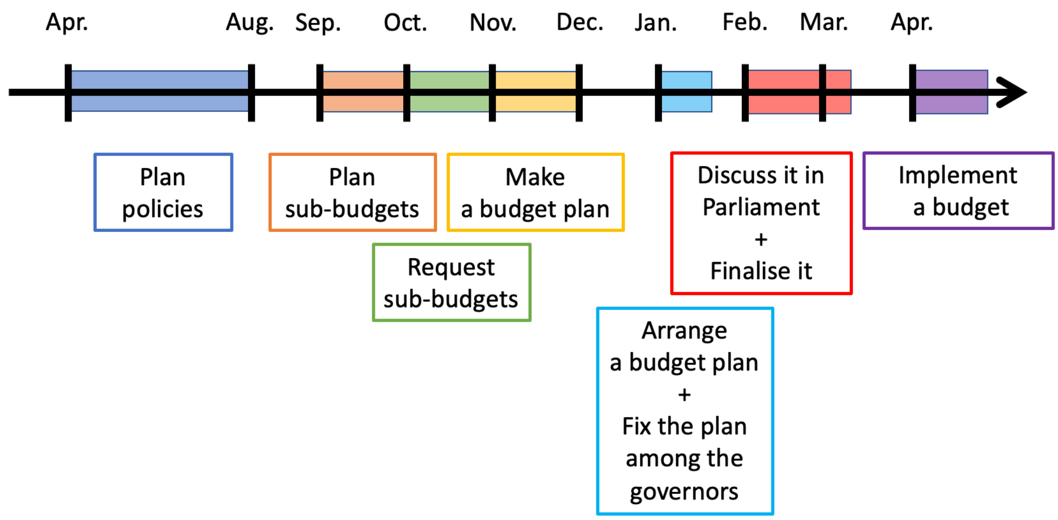



Figure 1. Typical Timeline of Budget Planning by a Local Government

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 hazards, 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 $P_{\text{SI, aggregate calculation}}$ 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.[25] Panel A summarises information on the budget and various damages from natural disasters in each prefecture each year. On average, the

[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 $\lambda$ 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.

[25] In Appendix A, Table A3 shows the summary statistics of the additional variables that are mainly used for robustness checks.

## Table 1. Summary Statistics

| | Mean | sd | Min | 25% | Median | 75% | Max | N |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Prefecture-Year-Level Records** | | | | | | | | |
| Income (in billion yen) | 1095 | 1052 | 312 | 584.1 | 763.6 | 1131 | 10139 | 1551 |
| Expenditure on Disaster Prevention (in billion yen) | 2.713 | 11.82 | .2006 | .9542 | 1.558 | 2.932 | 15.32 | 1551 |
| Ratio of Expenditure on Disaster Prevention to Income (%) | .2652 | .4924 | .0337 | .1175 | .18 | .3149 | 15.32 | 1551 |
| Damages by Natural Disasters | | | | | | | | |
| Estimated Monetary Damage | 325.3 | 3929 | 0 | 1.803 | 5.71 | 18.02 | 136970 | 1546 |
| Monetary Damage Rate (%)[a] | 36.06 | 296.6 | 0 | .2149 | .762 | 2.18 | 5357 | 1546 |
| N of Human Damage[b] | 20.02 | 373.7 | 0 | 0 | 1 | 3 | 11770 | 1551 |
| N of Deaths | 18.01 | 329 | 0 | 0 | 1 | 3 | 10154 | 1551 |
| N of People Reported Missing | 2.011 | 51.69 | 0 | 0 | 0 | 0 | 1616 | 1551 |
| N of People with Injuries[c] | 72.88 | 1027 | 0 | 2 | 8 | 29 | 39488 | 1551 |
| N of People with Severe Injuries[d] | 36.14 | 1003 | 0 | 0 | 1 | 6 | 39488 | 1551 |
| N of People with Minor Injuries[d] | 36.74 | 192.8 | 0 | 1 | 6 | 21 | 4274 | 1551 |
| **Panel B: Pair-of-Prefectures-Level Records** | | | | | | | | |
| Distances between Capital Cities Prefectures (in kilometres) | 519.7 | 355.2 | 11 | 242 | 445 | 724 | 2244 | 1081 |
| Move Rates between Prefectures (%) | | | | | | | | |
| Pre 2011 | .0219 | .07381 | .000149 | .00153 | .00485 | .01771 | 1.442 | 2162 |
| Post 2011 | .01877 | .06769 | .000134 | .00129 | .00404 | .01426 | 1.401 | 2162 |
| **Panel C: Prefecture-level Records** | | | | | | | | |
| Risk Preference (Transformed Reservation Price)[e] | | | | | | | | |
| Pre 2011 Disaster[f] | .8115 | .03122 | .7439 | .791 | .8148 | .8305 | .8882 | 1551 |
| Post 2011 Disaster[g] | .7524 | .04935 | .6154 | .7231 | .7597 | .7887 | .837 | 1551 |
| Predicted Probability of Earthquakes in the Maximum Case[h] | | | | | | | | |
| Maximum of Each Prefecture | | | | | | | | |
| Seismic Intensity of 6 Upper ($P_{6+,mm}$) | | | | | | | | |
| Pre 2011 | .1941 | .2425 | 0 | .009965 | .09872 | .2715 | .9223 | 188 |
| Post 2011 | .327 | .2323 | .01574 | .1306 | .2585 | .5237 | .9252 | 423 |
| Seismic Intensity of 6 Lower ($P_{6-,mm}$) | | | | | | | | |
| Pre 2011 | .5099 | .2775 | .03696 | .2763 | .4876 | .7327 | .9707 | 188 |
| Post 2011 | .6035 | .2414 | .1036 | .4233 | .6513 | .7785 | .997 | 423 |
| Seismic Intensity of 5 Upper ($P_{5+,mm}$) | | | | | | | | |
| Pre 2011 | .6214 | .3922 | 0 | .2049 | .8034 | .945 | .9993 | 188 |
| Post 2011 | .8432 | .1412 | .4188 | .7761 | .8751 | .9593 | 1 | 423 |
| Seismic Intensity of 5 Lower ($P_{5-,mm}$) | | | | | | | | |
| Pre 2011 | .955 | .07081 | .585 | .9378 | .9883 | .9979 | 1 | 188 |
| Post 2011 | .965 | .03937 | .8143 | .9453 | .9752 | .9985 | 1 | 423 |

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 does not have any other prefectures in the same area, so the number of observations in the corresponding row is smaller. As written in Footnote ??, the records in 1978, 1979, and 1980 do not distinguish major and minor injuries. In this table, we regard both as severe injuries.

a: We use the maximum case, defined in Footnote 19.

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

f: 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.

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

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

expenditure on disaster prevention is about JPY 2.7 billion (about USD 18.4 million), 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.[26] 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,

[26]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.

while one of SI6+ is quite unlikely. The predicted probability of earthquakes also changed 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 Reduction-Recovery Model

Here, we describe how the government decides to invest in the disaster reduction and the recovery. We index the time period by $t$ while we focus on the problem of one government and so omit the index of the government.

First, we introduce a disaster preparedness, which is denoted by $Q_t$. This represents the effort level for future disasters. The government chooses $Q_t$ each time to reduce the expected disaster damages. This preparedness is not a free lunch. We assume that the government balances the trade-offs of the current output level and the reduction in the future capital by choosing the disaster preparedness. To prepare well for future disasters, we must pay attention to future event in case and requires some extra activities not directly related to the current production. In our model, this reduction in the current output is represented as the detriment in the total factor productivity. When we write the consumption by $c_t$ and the investment in the recovery by $I_{t+1}$, the budget constraint at time $t$ is written as follows: for some $\alpha \in [0, 1]$,

$$c_t + I_{t+1} = \frac{F}{Q_t} k^{\alpha}.$$

At the same time, $Q_t$ works to reduce the disaster damage. We consider the natural hazards make damage to the capital in contrast to the existing literature which considers they harms the output. This modification allows us to consider the catastrophic hazards in a natural way. In other words, we can include the fat-tailed nature of the natural hazards damage in the model. When we write the level of capital at time $t$ by $k_t$, the investment in the recovery by $I_{t+1}$, and the natural hazard severity by $M_{t+1}$, the capital grows in the following manner:

$$k_{t+1} = \frac{Q_t}{M_{t+1}} k_t I_{t+1}^{\eta},$$

where $\eta$ represents the effectiveness of the recovery investment. Here we include the investment term in the multiplicative way because the recovery investment is aimed to work in a combination with the existing capital, not the linearly additive way.

Under the above budget constraint and the law of motion of capital, the government tries to maximize the expected lifetime utility in the infinite time horizon problem while facing the uncertainty over the distribution of the severeness of future disasters. The problem at time $t$ is written in the following form: the expectation is taken to the realization of $M_{t+1}$,

$$\max_{c_t, I_{t+1}, Q_t} \quad \mathbb{E}_t \left[ \sum_{n=0}^{\infty} \beta^n \frac{c_{t+n}^{1-\zeta} - 1}{1 - \zeta} \right]$$

$$\text{s.t.} \quad \begin{cases} c_t + I_{t+1} = \frac{F}{Q_t} k^{\alpha} \\ k_{t+1} = \frac{Q_t}{M_{t+1}} k_t I_{t+1}^{\eta}. \end{cases}$$

Now we describe about the severity of the natural hazard, $M_{t+1}$. The government does not know the realization of this value when making the consumption decision. It knows what family of distribution $M_{t+1}$ follows but does not know the exact distribution: i.e. the government knows how to parametrize the distribution but does not know the true parameter of the distribution. This type of uncertainty is known as *structural uncertainty* in literature. As following the literature, we split the problem of learning the parameter and the consumption decisions: when solving the utility maximization problem, the government uses one parameter and in the learning stage, the government uses the available data to update the parameter. In this section, we focus on the decision stage.

We assume that $M_{it+1}$ follows a Pareto distribution whose support is $[\bar{Q}, \infty]$ and the scale parameter is denoted by $\xi > 0$. This represents the possibility of catastrophe: with some probability, natural hazards completely disrupt the economy like Great East Japan earthquake.

Except the direct investment of the recovery term, the damage of the disaster is measure as the ratio of the damage on the capital: $\frac{k_{it+1}-k_{it}}{k_{it}} = \frac{Q_{it}}{M_{it+1}}$. When we assume $M_{it+1}$ follows a Pareto distribution and $Q_{it} < \bar{Q}$, this damage ratio might take almost zero with small probability. This is clear in Figure 2: where we plot the histogram of the simulated damage rate. We plot the values of $\frac{Q_{it}}{m_{it+1}}$ for each draw of $M_{it+1}$ which follows a Pareto distribution with $\bar{Q} = 5$ and $\xi = 5$ and for $Q_{it} = 5$. Note that this is the best case: $Q_{it}$ attains the largest value, $\bar{Q}$. You see that, even in the best case, the economy might suffer from almost half destruction from natural hazard under our model with some positive probability.

### 4.1.1 Solution

We have one state variable, $k_t$, and the value function is defined as $V(k_t)$ and we write it by $V_{t+1}$, The corresponding Bellman equation is written as follows:

$$V(k_t) = \max_{c_t, I_{t+1}, Q_t} \frac{c_{t+n}^{1-\zeta} - 1}{1-\zeta} + \beta \mathbb{E}_t \left[ V(k_{t+1}) \right].$$

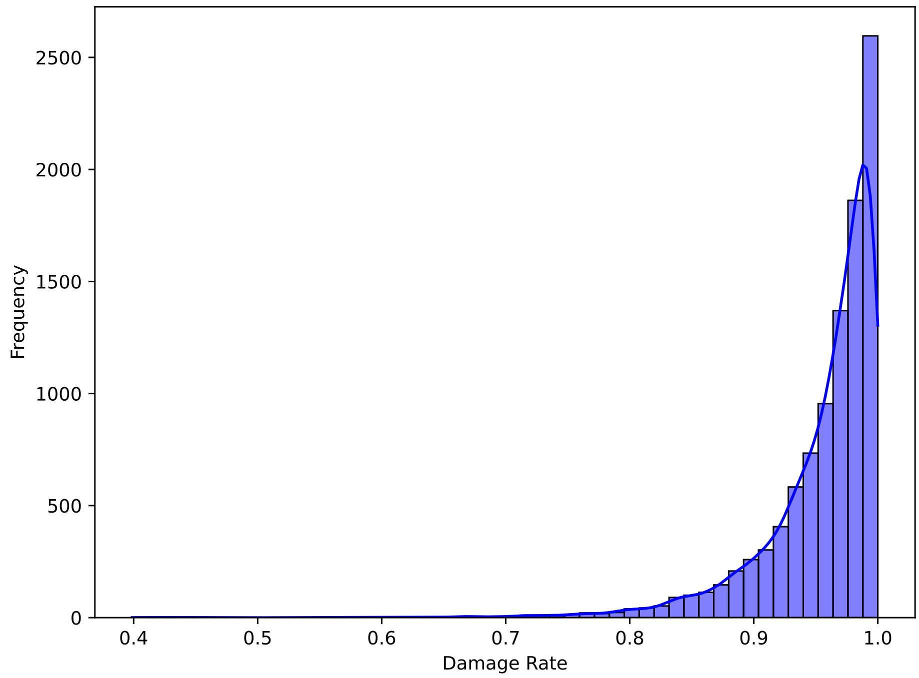



Figure 2. Simulated histogram of the damage rate. We draw $M_{it+1}$ from a Pareto distribution with $\bar{Q} = 5$ and $\xi = 5$. The damage rate is $\frac{Q_{it}}{M_{it+1}}$ where $Q_{it} = 5$. The total number of draws is $10,000$.

The F.O.C. gives us

$$- c_t^{-\zeta} + \beta \mathbb{E}_t \left[ \eta \frac{Q_t k_t}{M_{t+1}} I_{t+1}^{\eta-1} V'_{t+1} \right] = 0, \tag{1}$$

$$- c_t^{-\zeta} \frac{F k_t^{\alpha}}{Q_t^2} + \beta \mathbb{E}_t \left[ \frac{k_t I_{t+1}^{\eta}}{M_{t+1}} V'_{t+1} \right] = 0. \tag{2}$$

By envelope theorem, we have

$$V'_t = c_t^{-\zeta} \frac{\alpha F k_t^{\alpha-1}}{Q_t} + \beta \mathbb{E}_t \left[ \frac{Q_t I_{t+1}^{\eta}}{M_{t+1}} V'_{t+1} \right]. \tag{3}$$

From 1, we know that

$$c_t^{-\zeta} I_{t+1} = \eta \beta \mathbb{E}_t \left[ k_{t+1} V'_{t+1} \right] \tag{4}$$

and from 2, we have

$$c_t^{-\zeta} \frac{F k_t^\alpha}{Q_t} = \beta \mathbb{E}_t \left[ k_{t+1} V'_{t+1} \right]. \tag{5}$$

By combining these and the budget constraint, we get the rule for the investment and the consumption, we split the budget following the effectiveness of the recovery investment, $\eta$:

$$\begin{cases} I_{t+1} = \eta \frac{F}{Q_t} k_t^\alpha \\ C_t = (1-\eta) \frac{F}{Q_t} k_t^\alpha. \end{cases} \tag{6}$$

By (3) and (5), we have

$$k_t V'_t = c_t^{-\zeta} \alpha \frac{F k_t^\alpha}{Q_t} + \beta \mathbb{E}_t \left[ k_{t+1} V'_{t+1} \right] = (1+\alpha) \beta \mathbb{E}_t \left[ k_{t+1} V'_{t+1} \right].$$

By inserting this result into (4) and from (6), we have

$$(1-\eta)^{-\zeta} \left( \frac{F k_t^\alpha}{Q_t} \right)^{-\zeta} \eta \frac{F k_t^\alpha}{Q_t} = \eta \frac{k_t V'_t}{1+\alpha}$$

$$\Rightarrow \; k_t V'_t = (1-\eta)^{-\zeta} (1+\alpha) \left( \frac{F k_t^\alpha}{Q_t} \right)^{1-\zeta}.$$

Again by inserting this result into (5), we have

$$(1-\eta)^{-\zeta} \left( \frac{F k_t^\alpha}{Q_t} \right)^{1-\zeta} = \beta \mathbb{E}_t \left[ (1-\eta)^{-\zeta} (1+\alpha) \left( \frac{F k_{t+1}^\alpha}{Q_{t+1}} \right)^{1-\zeta} \right] \tag{7}$$

$$\Rightarrow \; \frac{1}{1+\alpha} = \beta \mathbb{E}_t \left[ \left( \frac{Q_t}{Q_{t+1}} \right)^{1-\zeta} \left( \frac{k_{t+1}}{k_t} \right)^{\alpha(1-\zeta)} \right]. \tag{8}$$

Now we guess the form of the optimal policy of disaster preparedness. For some $b$ and

$\gamma$, we assume $Q_t = bk_t^\gamma$. Then (7) implies that

$$\frac{1}{1+\alpha} = \beta \mathbb{E}_t \left[ \left( \frac{k_{t+1}}{k_t} \right)^{\alpha(1-\zeta)-\gamma} \right].$$

Now we denote $\omega = \alpha(1-\zeta) - \gamma$. Then,

$$\begin{aligned}
&\frac{1}{1+\alpha} = \beta \mathbb{E}_t \left[ M_{t+1}^{-\omega} \right] Q_t^\omega \left( \eta \frac{Fk_t^\alpha}{Q_t} \right)^{\eta\omega} = \beta \mathbb{E}_t \left[ M_{t+1}^{-\omega} \right] Q_t^{(1-\eta)\omega} (\eta F)^{\eta\omega} k_t^{\alpha\eta\omega} \\
&\Rightarrow \; Q_t^{(1-\eta)\omega} = \frac{(\eta F)^{-\eta\omega}}{1+\alpha} \frac{1}{\beta \mathbb{E}_t \left[ M_{t+1}^{-\omega} \right]} k_t^{-\alpha\eta\omega} \\
&\Rightarrow \; Q_t = \left( \frac{\eta^{-\eta\omega}}{(1+\alpha)\beta \mathbb{E}_t \left[ M_{t+1}^{-\omega} \right]} \right)^{\frac{1}{(1-\eta)\omega}} F^{-\frac{\eta}{1-\eta}} k_t^{-\frac{\alpha\eta}{1-\eta}}.
\end{aligned}$$

Hence, we know that $\gamma = -\frac{\alpha\eta}{1-\eta}$ and so $\omega = \alpha(1-\zeta) + \frac{\alpha\eta}{1-\eta} = \alpha \left( \frac{\eta}{1-\eta} + 1 - \zeta \right)$. And $b$ is the coefficient attached to $k_t^\gamma$. The guess is verified.

We take logarithm of both sides.

$$\begin{aligned}
&\ln Q_t = \frac{1}{(1-\eta)\omega} \ln \frac{\eta^{-\eta\omega}}{(1+\alpha)\beta} - \frac{1}{(1-\eta)\omega} \ln \mathbb{E}_t \left[ M_{t+1}^{-\omega} \right] - \frac{\eta}{1-\eta} \ln Fk_t^\alpha \\
&\Rightarrow \; \ln Q_t + \frac{\eta}{1-\eta} \ln Q_t = \frac{1}{(1-\eta)\omega} \ln \frac{\eta^{-\eta\omega}}{(1+\alpha)\beta} - \frac{1}{(1-\eta)\omega} \ln \mathbb{E}_t \left[ M_{t+1}^{-\omega} \right] - \frac{\eta}{1-\eta} \ln \frac{F}{Q_t} k_t^\alpha \\
&\Rightarrow \; \frac{1}{1-\eta} \ln Q_t = \frac{1}{(1-\eta)\omega} \ln \frac{\eta^{-\eta\omega}}{(1+\alpha)\beta} - \frac{1}{(1-\eta)\omega} \ln \mathbb{E}_t \left[ M_{t+1}^{-\omega} \right] - \frac{\eta}{1-\eta} \ln \frac{F}{Q_t} k_t^\alpha \\
&\Rightarrow \; \ln Q_t = \frac{1}{\omega} \ln \frac{\eta^{-\eta\omega}}{(1+\alpha)\beta} - \frac{1}{\omega} \ln \mathbb{E}_t \left[ M_{t+1}^{-\omega} \right] - \eta \ln Y_t
\end{aligned}$$

We replace $\frac{F}{Q_t} k_t^\alpha$ by the observed total output $Y_t$. And from the assumption of the Pareto distribution of $M_{t+1}$, we can compute the expectation as follows: $\xi$ is the scale parameter of the Pareto distribution,

$$\mathbb{E}_t \left[ M_{t+1}^{-\omega} \right] = \frac{\xi}{\omega + \xi} \bar{Q}^{-\omega}$$

Note that $\omega + \xi > 0$ allows the computation. Then the logarithm of the optimal level of disaster preparedness is determined in the following rule: note that $\xi$ is given at this decision,

$$\ln Q_t = \frac{1}{\omega} \ln \frac{\eta^{-\eta\omega}}{(1+\alpha)\beta} + \ln \bar{Q} - \frac{1}{\omega} \ln \frac{\xi}{\omega+\xi} - \eta \ln Y_t \tag{9}$$

We observe that the level of the disaster preparedness is decreasing in the output level. In contrast, the disaster preparedness is increasing in the expected level of disaster severity because disaster severity follows more fat-tailed distribution when $\xi$ is small.

## 4.2 Social Learning

Here we describe how to make inference about the data generating process of $M_{t+1}$. This is represented as a learning process about the true parameter of the Pareto distribution which $M_{t+1}$ follows. This type of learning is considered in a literature as a structural uncertainty and we usually model the process as a Bayesian update given the observation. For example, in Weitzman (2009), the growth of the consumption follows a normal distribution and the government has Pareto distribution as the prior over the variance of the Normal distribution. Weitzman (2009) considers the government updates the prior based on the realized growth of consumption. This learning gives us the fat-tailed posterior distribution over the variance term.

In our model, we consider the government conducts the social learning about the distribution: the other governments' observations are also integrated into the belief over the future disaster severity. In particular, we focus on the case of the asymmetric learning: while a government A's observation does influence on the belief of government B, the observation of B does not influence on A's belief. This kind of asymmetric learning is often found in several situation and considered as a important property of the actual social learning (Buechel et al., 2023). In our case, this is represented as the learning process on a social network: where the government is the node and some pair of edges are connected with a directed edges. While we do not consider the binary opinion aggregation, this kind of learning on the social network has a long tradition. To handle this situation, the researchers often consider a heuristics about the belief update process instead of considering the fully Bayesian update: classical exmpla is the famous DeGroot model and the recent examples are Jadbabaie et al. (2012). You can find two surveys Golub and Sadler (2017); Grabisch and Rusinowska (2020).

This is partly because it is difficult to incorporate all the available information into the Bayesian update. Furthermore, the experimental papers give the evidence that the agents do not take the Bayesian update. In particular in our situation, we do focus on the continuous variable choice problem on social network. This non-binary feature makes the Bayesian update much more difficult to tract while Board and Meyer-ter Vehn (2021) analyzes the dynamics of the binary action spread under the fully Bayesian update in social network.

Hence, we do follow the literature to model the social learning process in non-Bayesian way. By introducing the index for each government $i$, from (9), the logarithm of the disaster preparedness is determined in the following way:

$$\ln Q_{it} = D_i + E_i \ln \frac{\xi_{it}}{\omega_i + \xi_{it}} + G_i \ln Y_{it}, \tag{10}$$

where

$$D_i = \frac{1}{\omega_i} \ln \frac{\eta_i^{-\eta_i \omega_i}}{(1+\alpha_i)\beta_i} + \ln \bar{Q},\ E_i = -\frac{1}{\omega_i},\ G_i = -\eta_i.$$

First, we consider the learning target of the social learning is $\ln \frac{\xi_{it}}{\omega_i+\xi_{it}}$ not the scale parameter of the Pareto distribution, $\xi$. Hereafter, we denote $\theta_{it} = \ln \frac{\xi_{it}}{\omega_i+\xi_{it}}$. This is because $\theta_{it}$ is the sufficient statistics for determining the disaster preparedness. The learning of $i$ at the end of $t$ proceeds as follows: (1) from the information of $Q_{jt}$ and $Y_{jt}$ and the parameter values, the government $i$ can retrieve the value of $\theta_{jt}$ using the optimal decision rule, (2) $i$ learns from its own experience of $M_{it+1}$ to update the belief about $\theta_{it}$, which is denoted by $\tilde{\theta}_{it+1}$ and (3) $\tilde{\theta}_{it+1}$ and $\theta_{jt}$ for all $j \neq i$ are linearly combined to generate $\theta_{it+1}$. This process takes the similar form of the learning rule of Jadbabaie et al. (2012) which assure the asymptotic learning occurs under this learning rule when the state space is finite. When we write the weight on other government $j$ of government

$i$ by $\gamma_{ij}$, we can write the learning rule as follows:

$$\theta_{it+1} = \gamma_{ii}\tilde{\theta}_{it+1}(\theta_{it}, M_{it+1}) + \sum_{j \neq i} \gamma_{ij}\theta_{jt}. \tag{11}$$

Here $\tilde{\theta}_{it+1}(\theta_{it}, M_{it+1})$ represents the dependence on the prior and the observation. But we do not specify the exact update rule to this point. Note that we assume that there exists the information delay from the other region. In other words, the government $i$ does include the one period before disaster severeness of the other regions to update its belief. As discussed in Section 2.2, this represents the real budget formulation process.

## 4.3 Empirical Strategy

Now we discuss our empirical strategy to uncover the social learning network. By inserting the optimal decision rule (10) into the learning rule (11), we have the following:

$$\begin{aligned} \frac{\ln Q_{it+1} - G_i \ln Y_{it+1} - D_i}{E_i} = \gamma_i i\tilde{\theta}_{it+1}(\theta_{it}, M_{it+1}) + \\ \sum_{j \neq i} \gamma_{ij} \frac{\ln Q_{jt} - G_j \ln Y_{jt} - D_j}{E_j}. \end{aligned} \tag{12}$$

This gives the linear model which connects the disaster preparedness of all the governments:

$$\begin{aligned} \ln Q_{it+1} = D_i - \sum_{j \neq i} \gamma_{ij} \frac{E_i}{E_j} D_j + G_i \ln Y_{it+1} + \sum_{j \neq i} \gamma_{ij} \frac{E_i}{E_j} \ln Q_{jt} \\ - \sum_{j \neq i} \gamma_{ij} \frac{E_i G_j}{E_j} \ln Y_{jt} + E_i \tilde{\theta}_{it+1}(\theta_{it}, M_{it+1}). \end{aligned} \tag{13}$$

By considering the first two terms as the government specific constant and the last term as the error term, this gives us the linear regression model where the explaining variables are $\ln Y_{it+1}$, $\ln Q_{jt}$ for $j \neq i$ and $\ln Y_{jt}$ for $j \neq i$.

$$\ln Q_{it+1} = C_i + G_i \ln Y_{it+1} + \sum_{j \neq i} \delta_{ij} \ln Q_{jt} + \sum_{j \neq i} \lambda_{ij} \ln Y_{jt} + \epsilon_{it+1} \tag{14}$$

where

$$C_i = D_i - \sum_{j \neq i} \gamma_{ij} \frac{E_i}{E_j} D_j, \ \delta_{ij} = \gamma_{ij} \frac{E_i}{E_j}, \ \lambda_{ij} = -\gamma_{ij} \frac{E_i G_j}{E_j}.$$

We have two remarks on this model. First, we can consistently estimate $\delta_{ij}$ because the error term $\epsilon_{it+1}$ is not correlated with $\ln Q_{jt}$ conditional on $\ln Y_{jt}$. But we cannot estimate $G_i$ consistently because $\ln Y_{it+1}$ and $\epsilon_{it+1}$ correlates. Second remark is about the dimensionality of this regression. The right hand side contains all the other governments' disaster preparedness and the outputs for each government $i$. This makes the problem high dimensional: we cannot estimate this equation by ordinary least squares. Instead we use LASSO to recover the network structure following Manresa (2016).

We take the first difference of (14) to make the estimation equation:

$$\Delta \ln Q_{it+1} = G_i \Delta \ln Y_{it+1} + \sum_{j \neq i} \delta_{ij} \Delta \ln Q_{it} + \sum_{j \neq i} \lambda_{ij} \Delta \ln Y_{jt} + \Delta \epsilon_{it+1}.$$

Using the estimates of these $\delta_{ij}$, which are denoted by $\hat{\delta}_{ij}$, we clarify the determinants of the social learning network. Imagine we have several sets of $\hat{\delta}_{ij}$, estimated using the different sets of time periods. We index them by $\tau$. In our following application, this corresponds to the pre-catastrophic disaster period, $\tau = 1$, and the post-catastrophic disaster period, $\tau = 2$. Now, our estimated parameters are denoted by $\hat{\delta}_{ij\tau}$.

Because most of our estimated value is exactly 0 due to the sparse social network, we specify a cutoff model to represent the weights where $\mu$ is the cutoff for non-zero entry:

$$Z_{ij\tau} = X'_{ij\tau}\beta + \kappa_\tau^{time} + \kappa_i^{in} + \kappa_j^{from} + u_{ij\tau}$$

$$\gamma_{ij\tau} = \begin{cases} e^{Z_{ij\tau}} & \text{if } Z_{ij\tau} > \mu \\ 0 & \text{otherwise.} \end{cases}$$

And so the estimated coefficient is modeled as

$$\delta_{ij\tau} = \begin{cases} \frac{E_i}{E_j} e^{Z_{ij\tau}} & \text{if } Z_{ij\tau} > \mu \\ 0 & \text{otherwise.} \end{cases}$$

For taking the logarithm of the positive values of $\delta_{ij\tau}$, this model is a Tobit model with non-zero cutoff. Following Carson and Sun (2007), in the estimation we should replace the cutoff by the minimum of $\ln \delta_{ij\tau} - \ln E_i + \ln E_j$. Unfortunately, we do not observe $E_i$ and so, in the second stage estimation, we assume that $E_i = E$ for all government $i$.

**Assumption 1** $\alpha_i(\frac{\eta_i}{1-\eta_i} + (1 - \zeta_i))$ *is common for all* $i$*.*

Under Assumption 1, by replacing $\mu$ by $\min\{\ln \hat{\delta_{ij\tau}}\}$ among $ij\tau$ such that $\hat{\delta_{ij\tau}} > 0$, the usual Tobit estimation gives us the consistent result: see the detail in Carson and Sun (2007).

# 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, population moves across prefectures and influences of predicted probability of future earthquakes.

## 5.1 Social Learning Network

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

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

Table 2. Changes in Network After the Catastrophe: Off-diagonal Elements

| Edge Existing | Before 2011 | After 2011 |
|---|---|---|
| Measured by log Expense | | |
| Yes | 105 | 2 |
| No | 2057 | 2160 |
| Measured by Ratio of Expense to Income | | |
| Yes | 32 | 3 |
| No | 2130 | 2159 |

Notes: Before 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of Expense to Income, it has one also with the measure of ln Expense. After 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of ln Expense, it has one also with the measure of Expense to Income.

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 3 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. The order of the prefecture is based on the unique number of prefectures adopted by the Japanese government. The

Table 3. Changes in Network After the Catastrophe: Off-diagonal Elements

| | Tobit Model | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post 2011 | -0.277*** | -0.277*** | -0.111* | -0.176** | -0.156** | -0.222*** |
| | (0.0296) | (0.0295) | (0.0637) | (0.0739) | (0.0629) | (0.0788) |
| Similarity | | | 0.0723 | 0.146 | 0.885** | 0.983** |
| | | | (0.115) | (0.123) | (0.434) | (0.484) |
| log Move Rate (MR) | | | 0.0300** | 0.0183 | 0.0971** | 0.115** |
| | | | (0.0128) | (0.0155) | (0.0448) | (0.0483) |
| log Distance | | | 0.00124 | -0.0236 | 0.0742 | 0.108 |
| | | | (0.0252) | (0.0331) | (0.0971) | (0.102) |
| Risk Preference | | | -0.0658 | -0.0776 | 0.0300 | -0.00109 |
| | | | (0.187) | (0.184) | (0.197) | (0.195) |
| log $P^{in}$ | | | -0.00705 | -0.00841 | -0.241 | -0.198 |
| | | | (0.0196) | (0.0279) | (0.216) | (0.229) |
| Same Area Dummy | | | -0.0136 | -0.0397 | -0.00145 | -0.0307 |
| | | | (0.0642) | (0.0706) | (0.0646) | (0.0714) |
| log Damage$^{in}$ | | | 0.0287** | 0.0282** | 0.0941 | 0.0724 |
| | | | (0.0122) | (0.0130) | (0.0941) | (0.0982) |
| log Human Loss$^{in}$ | | | -0.00318 | 0.0128 | -0.149 | -0.0924 |
| | | | (0.0138) | (0.0152) | (0.135) | (0.140) |
| log MR $\times$ log $P^{in}$ | | | | | 0.0212 | 0.0280* |
| | | | | | (0.0137) | (0.0148) |
| log Distance $\times$ log $P^{in}$ | | | | | 0.0347 | 0.0393 |
| | | | | | (0.0238) | (0.0247) |
| Similarity $\times$ log $P^{in}$ | | | | | 0.270* | 0.268 |
| | | | | | (0.163) | (0.177) |
| log MR $\times$ log Damage$^{in}$ | | | | | 0.0174*** | 0.0190*** |
| | | | | | (0.00613) | (0.00674) |
| log Distance $\times$ log Damage$^{in}$ | | | | | 0.00668 | 0.0131 |
| | | | | | (0.0104) | (0.0111) |
| Similarity $\times$ log Damage$^{in}$ | | | | | 0.0565 | 0.0560 |
| | | | | | (0.0506) | (0.0534) |
| log MR $\times$ log Human Loss$^{in}$ | | | | | 0.0131 | 0.00896 |
| | | | | | (0.0103) | (0.0108) |
| log Distance $\times$ log Human Loss$^{in}$ | | | | | 0.0207 | 0.0137 |
| | | | | | (0.0199) | (0.0206) |
| Similarity $\times$ log Human Loss$^{in}$ | | | | | 0.165** | 0.120 |
| | | | | | (0.0830) | (0.0841) |
| $N$ | 4324 | 4324 | 4324 | 4324 | 4324 | 4324 |
| Other Controls$^a$ | | | x | x | x | x |
| FE | | x | | x | | x |

Notes: Heteroscedasticity-robust standard errors are in parentheses. The superscripts, ***, **, *, denote the statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively. Before 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of Expense to Income, it has one also with the measure of log Expense. After 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of log Expense, it has one also with the measure of Expense to Income.
a: We include an extensive set of controls, such as variables of $from$ prefectures. See Table B2 for the full results. Each column number of this table corresponds to that in Table B2.

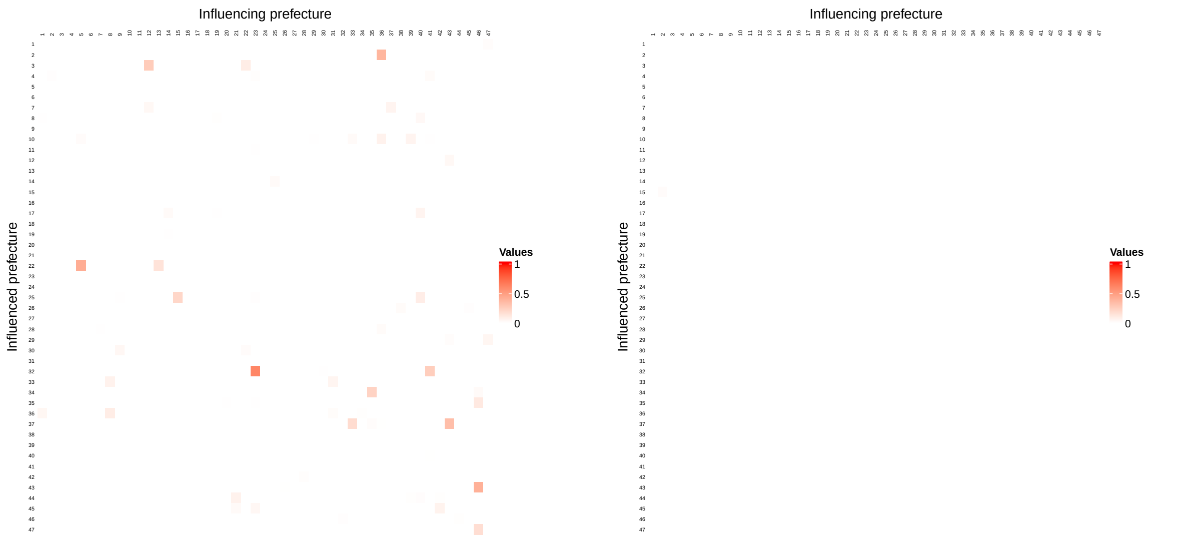
prefectures are numbered basically from the north to the south, so prefectures numbered closely are located close to each other.[27]

First, our estimate shows a lot of darker-coloured cells on the diagonal components, suggesting that social learning concentrates on their own experience. This is intuitive because policymakers may care about the damage they have experienced in the previous period, update their policy, and adjust expenditures for future damage. Second, we see

[27]See Figure A1 and Table A1 for the numbering rule.

Table 4. Changes in Network After the Catastrophe: Off-diagonal Elements

| | Tobit Model | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post 2011 | -0.277*** | -0.277*** | -0.111* | -0.176** | -0.156** | -0.222*** |
| | (0.0296) | (0.0295) | (0.0637) | (0.0739) | (0.0629) | (0.0788) |
| Similarity | | | 0.0723 | 0.146 | 0.885** | 0.983** |
| | | | (0.115) | (0.123) | (0.434) | (0.484) |
| log Move Rate (MR) | | | 0.0300** | 0.0183 | 0.0971** | 0.115** |
| | | | (0.0128) | (0.0155) | (0.0448) | (0.0483) |
| log Distance | | | 0.00124 | -0.0236 | 0.0742 | 0.108 |
| | | | (0.0252) | (0.0331) | (0.0971) | (0.102) |
| Risk Preference | | | -0.0658 | -0.0776 | 0.0300 | -0.00109 |
| | | | (0.187) | (0.184) | (0.197) | (0.195) |
| log $P^{in}$ | | | -0.00705 | -0.00841 | -0.241 | -0.198 |
| | | | (0.0196) | (0.0279) | (0.216) | (0.229) |
| Same Area Dummy | | | -0.0136 | -0.0397 | -0.00145 | -0.0307 |
| | | | (0.0642) | (0.0706) | (0.0646) | (0.0714) |
| $N$ | 4324 | 4324 | 4324 | 4324 | 4324 | 4324 |
| Other Controls[a] | | | x | x | x | x |
| Cross | | | | | x | x |
| FE | | x | | x | | x |




(a) Before 2011

(b) After 2011

Figure 3. 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 $\xi_{ij}$ in Equation (??).

some off-diagonal elements on the network before 2011, i.e. there was social learning. Our interpretation is that before 2011, people did not entirely recognise what damages they would face by a catastrophe and were not fully aware of how they could prepare for it, which induced policymakers to learn from others. On the other hand, after 2011, most off-diagonal elements disappeared. This could be because people became much more aware of the risk of a catastrophe – recall that the 2011 earthquake was the fourth-largest earthquake in human history, and mass media reported it very intensely for the entire years even until now – so they came to focus on their own problem, instead of learning its importance from others (Nishida, 2022; Hara, 2022). We highlighted the change in the number of off-diagonal elements in Table 2. We examine this pattern with different measures of the network, but the decline is robust to our choice of variables. Further, we examine the possibility that other observable factors that simultaneously changed in 2011 altered the network pattern. We run a regression based on the linear probability model and a Probit model, where the dependent variable is an indicator of whether a tie from prefecture $i$ to $j$ exists, i.e., $\mathbb{1}\{\xi_{ij} > 0\}$, while the main independent variable is a dummy variable indicating post-2011. Table B1 in Appendix B supports the previous explanation, regardless of the specifications and the choice outcome variables. The set of results is compatible with the idea 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). Finally, even before 2011, we do not see a clear geographic pattern from whom they learn. As explained above, the prefectures that have a similar number are located closely, so if they had learnt from nearby prefectures, we would see a cluster in the heatmap. However, Figure 3 does not show this pattern, suggesting that the choice of prefectures that they learnt from were selected in different criteria. We will investigate what the drives of network formation are in the following subsection.

## 5.2 Network Mechanism

This subsection presents our analysis of the determinants of the social learning network. In Equation (**??**), $X_{ijT}$ 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 in percentile scale 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 $P_{\text{size},\text{XX}}$ 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

Table 5. Sensitivity Check with respect to Similarity Measures: Off-diagonal Elements

| | Tobit Model | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Similarity Measure | All[a] | Non Geographical[a] | Geographical[a] |
| Post 2011 | -0.222*** | -0.222*** | -0.214*** |
| | (0.0788) | (0.0788) | (0.0797) |
| Similarity | 0.983** | 0.983** | -0.109 |
| | (0.484) | (0.484) | (0.159) |
| log Move Rate (MR) | 0.115** | 0.115** | 0.0879* |
| | (0.0483) | (0.0483) | (0.0494) |
| log Distance | 0.108 | 0.108 | 0.0550 |
| | (0.102) | (0.102) | (0.101) |
| Risk Preference | -0.00109 | -0.00110 | 0.0390 |
| | (0.195) | (0.195) | (0.193) |
| $\log P^{in}$ | -0.198 | -0.198 | 0.0701 |
| | (0.229) | (0.229) | (0.143) |
| Same Area Dummy | -0.0307 | -0.0307 | -0.0420 |
| | (0.0714) | (0.0714) | (0.0718) |
| $\log \text{Damage}^{in}$ | 0.0724 | 0.0724 | 0.123 |
| | (0.0982) | (0.0982) | (0.0777) |
| $\log \text{Human Loss}^{in}$ | -0.0924 | -0.0924 | 0.0280 |
| | (0.140) | (0.140) | (0.105) |
| $\log \text{MR} \times \log P^{in}$ | 0.0280* | 0.0280* | 0.0203 |
| | (0.0148) | (0.0148) | (0.0139) |
| $\log \text{Distance} \times \log P^{in}$ | 0.0393 | 0.0393 | 0.0213 |
| | (0.0247) | (0.0247) | (0.0233) |
| $\text{Similarity} \times \log P^{in}$ | 0.268 | 0.268 | -0.00179 |
| | (0.177) | (0.177) | (0.0407) |
| $\log \text{MR} \times \log \text{Damage}^{in}$ | 0.0190*** | 0.0190*** | 0.0165** |
| | (0.00674) | (0.00674) | (0.00671) |
| $\log \text{Distance} \times \log \text{Damage}^{in}$ | 0.0131 | 0.0131 | 0.00642 |
| | (0.0111) | (0.0111) | (0.0118) |
| $\text{Similarity} \times \log \text{Damage}^{in}$ | 0.0560 | 0.0560 | 0.0131 |
| | (0.0534) | (0.0534) | (0.0214) |
| $\log \text{MR} \times \log \text{Human Loss}^{in}$ | 0.00896 | 0.00896 | 0.00438 |
| | (0.0108) | (0.0108) | (0.00990) |
| $\log \text{Distance} \times \log \text{Human Loss}^{in}$ | 0.0137 | 0.0137 | 0.0000486 |
| | (0.0206) | (0.0206) | (0.0177) |
| $\text{Similarity} \times \log \text{Human Loss}^{in}$ | 0.120 | 0.120 | 0.0413** |
| | (0.0841) | (0.0841) | (0.0206) |
| $N$ | 4324 | 4324 | 4324 |
| Other Controls[b] | x | x | x |
| FE | x | x | x |

Notes: Heteroscedasticity-robust standard errors are in parentheses. The superscripts, ***, **, *, denote the statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively. The specification is the same as Column (6) of Tables 4 and B2. Before 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of Expense to Income, it also has one with the measure of log Expense. After 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of log Expense, it has one also with the measure of Expense to Income.

a: For *All* similarity measure, we use (i) non-geographical variables, including the predicted probability of having the maximum probability over each prefecture of having an earthquake at the level of Seismic Intensity of 6 Upper or larger in 30 years in the Maximum Case, the average total damage by natural hazards, the average income of a prefecture, average damage ratio (total damage over income), the average number of deaths due to natural hazards, the average number of people found missing due to natural hazards, the average number of people seriously injured due to natural hazards, the average number of people lightly injured due to natural hazards, and (ii) geographic-related variables, such as number of nuclear power plants as of 2018, forest ratio as of 2017, artificial forest ratio as of 2017, and length of the coastal line as of 2016. All averages are taken over each pre or post-2011 period. For *Non-geographical* similarity measure, we use the above category (i), while for *Geographical* similarity measure, we use the above category (ii).

b: We include an extensive set of controls, such as variables of $from$ prefectures. See Table B3 for the full results. Each column number of this table corresponds to that in Table B3.

Table 6. Sensitivity Check with respect to Similarity Measures: Off-diagonal Elements

| | Tobit Model | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Similarity Measure | All[a] | Non Geographical[a] | Geographical[a] |
| Post 2011 | -0.222*** | -0.222*** | -0.214*** |
| | (0.0788) | (0.0788) | (0.0797) |
| Similarity | 0.983** | 0.983** | -0.109 |
| | (0.484) | (0.484) | (0.159) |
| log Move Rate (MR) | 0.115** | 0.115** | 0.0879* |
| | (0.0483) | (0.0483) | (0.0494) |
| log Distance | 0.108 | 0.108 | 0.0550 |
| | (0.102) | (0.102) | (0.101) |
| Risk Preference | -0.00109 | -0.00110 | 0.0390 |
| | (0.195) | (0.195) | (0.193) |
| log $P^{in}$ | -0.198 | -0.198 | 0.0701 |
| | (0.229) | (0.229) | (0.143) |
| Same Area Dummy | -0.0307 | -0.0307 | -0.0420 |
| | (0.0714) | (0.0714) | (0.0718) |
| $N$ | 4324 | 4324 | 4324 |
| Other Controls[b] | x | x | x |
| FE | x | x | x |

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 maximum 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. This is reflected by the mean and the variance of $P_{5-}$ in Table 1. As to the calculating methods, our main motivation is whether a catastrophe alters policymakers' behaviours, so it seems more suitable to use the probability measured by the maximum case method. We show the results using $P_{6+,mm}$ as the predicted probability in the main analysis, while the choice of the prediction methods does not change our results.

To uncover further the drivers of network formation even with the limited number of observations, we create three measures of similarity across prefectures calculated as cosine similarity, based on observed characteristics: *All*, *Non-geographical*, and *Geographical*. For *All* similarity measure, we use (i) non-geographical variables, including the predicted probability of having the maximum probability over each prefecture of having an earthquake at the level of Seismic Intensity of 6 Upper or larger in 30 years in the Maximum Case, the average total damage by natural hazards, the average income of a prefecture, average damage ratio (total damage over income), the average number of deaths due to natural hazards, the average number of people found missing due to natural hazards, the average number of people seriously injured due to natural hazards, the average number of people lightly injured due to natural hazards, and (ii) geographic-related variables, such as number of nuclear power plants as of 2018, forest ratio as of 2017, artificial forest ratio as of 2017, and length of the coastal line as of 2016. All averages are taken over each pre or post-2011 period. For *Non-geographical* similarity measure, we use the above category (i), while for *Geographical* similarity measure, we use the above category (ii).

Table **??** shows the results when we use $P_{6-,aa}$ 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 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

[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.

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 **??**, 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 be reflected by the implemented policy.

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. This kind of non linear increment in the influence of the minority has been found in several situations including politics: for example, Kanter (1977); Dahlerup (1988) found the different ratio of the women politicians leads to the different political outcomes, and recently Centola et al. (2018) experimentally explore the existence of the critical mass in the ratio of the minority group causing a conventional change. Our result can be considered as an additional evidence of this type of non linear increment of the community influence.

Given the estimates in Column (3) of Table **??**, we compute the change in the weights on prefecture $j$ ($\gamma_{ij}$) when the Move Rate for each pair of prefectures increases by 0.1

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

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 coefficient of 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.

Next, we investigate the influence of the size of future earthquakes. Table **??** 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 **??**. 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.

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# A Additional Tables and Figures

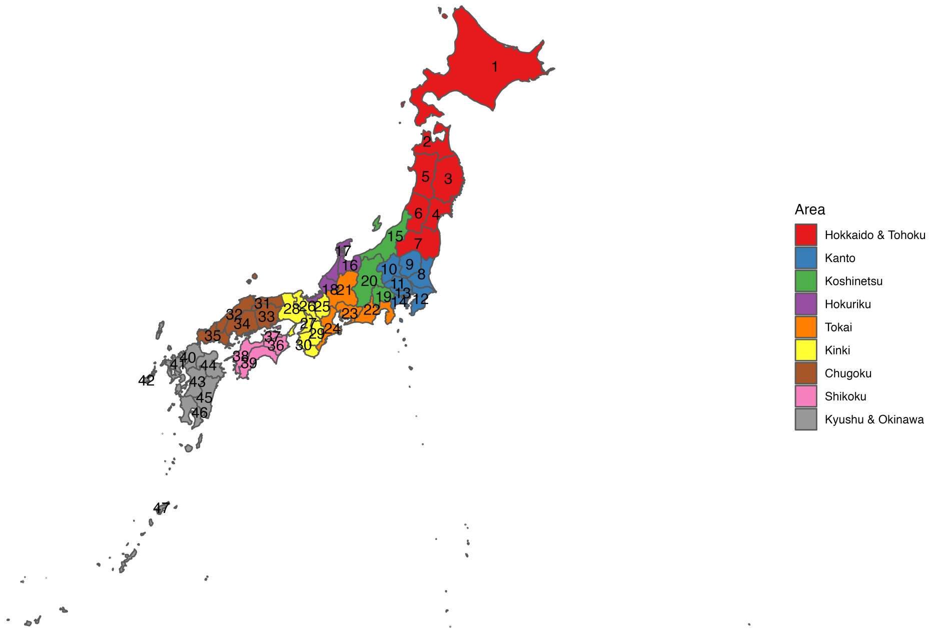


Figure A1. Prefecture Numbers and Regional Division of Japanese Prefectures

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 |
|---|---|---|---|---|---|---|---|---|
| **Prefecture-level Records** | | | | | | | | |
| Risk Preference | | | | | | | | |
| Transformed Reservation Price[a] | | | | | | | | |
| Pre 2011 Disaster[b] | .8115 | .03122 | .7439 | .791 | .8148 | .8305 | .8882 | 1551 |
| Post 2011 Disaster Measure 1 (same in Table 1)[c] | .7524 | .04935 | .6154 | .7231 | .7597 | .7887 | .837 | 1551 |
| Post 2011 Disaster Measure 2[d] | .784 | .03308 | .6771 | .7688 | .7884 | .8027 | .8561 | 1551 |
| Absolute Risk Preference[e] | | | | | | | | |
| Pre 2011 Disaster[b] | 1.858 | .04614 | 1.75 | 1.825 | 1.861 | 1.889 | 1.966 | 1551 |
| Post 2011 Disaster Measure 1[c] | 1.79 | .09732 | 1.447 | 1.733 | 1.822 | 1.862 | 1.943 | 1551 |
| Post 2011 Disaster Measure 2[d] | 1.832 | .05807 | 1.668 | 1.8 | 1.836 | 1.872 | 1.939 | 1551 |
| Predicted Probability of Earthquakes in the Maximum Case[f] | | | | | | | | |
| Average over Each Prefecture | | | | | | | | |
| Seismic Intensity of 6 Upper ($P_{6+,am}$) | | | | | | | | |
| Pre 2011 | .01691 | .03084 | 0 | .0002422 | .006161 | .01736 | .17 | 188 |
| Post 2011 | .03576 | .04486 | .0006055 | .007345 | .01371 | .05617 | .1963 | 423 |
| Seismic Intensity of 6 Lower ($P_{6-,am}$) | | | | | | | | |
| Pre 2011 | .114 | .1336 | .002051 | .01769 | .04346 | .1746 | .6066 | 188 |
| Post 2011 | .154 | .1517 | .004952 | .04144 | .06953 | .3042 | .5723 | 423 |
| Seismic Intensity of 5 Upper ($P_{5+,am}$) | | | | | | | | |
| Pre 2011 | .2343 | .2592 | 0 | .01651 | .116 | .426 | .8707 | 188 |
| Post 2011 | .358 | .2439 | .03319 | .1525 | .2605 | .6025 | .916 | 423 |
| Seismic Intensity of 5 Lower ($P_{5-,am}$) | | | | | | | | |
| Pre 2011 | .5603 | .2572 | .09782 | .3307 | .5251 | .8273 | .9824 | 188 |
| Post 2011 | .6022 | .2164 | .1252 | .4123 | .611 | .7889 | .997 | 423 |
| Predicted Probability of Earthquakes in the Average Case[f] | | | | | | | | |
| Maximum of Each Prefecture | | | | | | | | |
| Seismic Intensity of 6 Upper ($P_{6+,ma}$) | | | | | | | | |
| Pre 2011 | .1835 | .2433 | 0 | .009914 | .07406 | .2374 | .9223 | 188 |
| Post 2011 | .308 | .2411 | .01573 | .0932 | .2577 | .5167 | .9252 | 423 |
| Seismic Intensity of 6 Lower ($P_{6-,ma}$) | | | | | | | | |
| Pre 2011 | .4945 | .2865 | .01766 | .2361 | .4837 | .7273 | .9705 | 188 |
| Post 2011 | .5803 | .2591 | .08173 | .3208 | .6436 | .7726 | .9968 | 423 |
| Seismic Intensity of 5 Upper ($P_{5+,ma}$) | | | | | | | | |
| Pre 2011 | .6117 | .3921 | 0 | .1858 | .7889 | .9413 | .9993 | 188 |
| Post 2011 | .8239 | .158 | .3872 | .7533 | .8556 | .9571 | 1 | 423 |
| Seismic Intensity of 5 Lower ($P_{5-,ma}$) | | | | | | | | |
| Pre 2011 | .9501 | .0769 | .5665 | .9246 | .9858 | .9977 | 1 | 188 |
| Post 2011 | .9572 | .04665 | .8042 | .9274 | .9679 | .9985 | 1 | 423 |
| Average over Each Prefecture | | | | | | | | |
| Seismic Intensity of 6 Upper ($P_{6+,aa}$) | | | | | | | | |
| Pre 2011 | .01487 | .02953 | 0 | .0002411 | .003047 | .01623 | .167 | 188 |
| Post 2011 | .03173 | .04287 | .0006034 | .004998 | .008527 | .05397 | .1949 | 423 |
| Seismic Intensity of 6 Lower ($P_{6-,aa}$) | | | | | | | | |
| Pre 2011 | .1079 | .1323 | .002003 | .01464 | .03422 | .1703 | .6034 | 188 |
| Post 2011 | .1445 | .1501 | .004914 | .02934 | .06251 | .2783 | .5522 | 423 |
| Seismic Intensity of 5 Upper ($P_{5+,aa}$) | | | | | | | | |
| Pre 2011 | .2265 | .258 | 0 | .0149 | .1027 | .4221 | .8669 | 188 |
| Post 2011 | .3428 | .2477 | .02985 | .1269 | .2427 | .5859 | .9102 | 423 |
| Seismic Intensity of 5 Lower ($P_{5-,aa}$) | | | | | | | | |
| Pre 2011 | .548 | .2631 | .08094 | .3214 | .5085 | .8273 | .981 | 188 |
| Post 2011 | .5835 | .2253 | .1056 | .3832 | .5885 | .7784 | .9967 | 423 |

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. item 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 **??**, 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 **??**. 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 **??**, we show the same scatter plots as in Figure **??**. 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. Changes in Network with a Regression Specification: Off-diagonal Elements

| | Dependent Variable: $\mathbb{1}\{\xi_{ij} > 0\}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Linear Probability Model | | | | Probit Model | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Network Measured by ln Expense for Disaster Prevention | | | | | | | | |
| Post 2011 | -0.0476*** | -0.0476*** | -0.0392*** | -0.0359*** | -1.454*** | -1.454*** | -1.734*** | -1.612*** |
| | (0.00467) | (0.00467) | (0.0126) | (0.0111) | (0.214) | (0.217) | (0.450) | (0.410) |
| $N$ | 4324 | 4324 | 4324 | 4324 | 4324 | 4324 | 4324 | 4324 |
| FE | | x | x | x | | x | x | x |
| Controls | | | x | x | | | x | x |
| Panel B: Network Measured by Ratio of Expense for Disaster Prevention to Income | | | | | | | | |
| Post 2011 | -0.0134*** | -0.0134*** | -0.00761 | -0.0140** | -0.816*** | -0.830*** | -0.659 | -1.037** |
| | (0.00272) | (0.00272) | (0.00647) | (0.00633) | (0.189) | (0.186) | (0.401) | (0.431) |
| $N$ | 4324 | 4324 | 4324 | 4324 | 4324 | 4048 | 4048 | 4048 |
| FE | | x | x | x | | x | x | x |
| Controls | | | x | x | | | x | x |

Notes: Heteroscedasticity-robust standard errors are in parentheses. The superscripts, ***, **, *, denote the statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively. Columns (3) and (7) use the maximum probability over each prefecture of having an earthquake at the level of Seismic Intensity of 6 Upper or larger in 30 years in the Maximum Case, while Columns (4) and (8) use ones at the level of Seismic Intensity of 5 Lower or larger. See Footnote 19 for the definitions of the Average Case and Maximum Case.

Table B2. Full Results of Changes in Network After the Catastrophe: Off-diagonal Elements

| | Tobit Model | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post 2011 | -0.277*** | -0.277*** | -0.111* | -0.176** | -0.156** | -0.222*** |
| | (0.0296) | (0.0295) | (0.0637) | (0.0739) | (0.0629) | (0.0788) |
| Similarity | | | 0.0723 | 0.146 | 0.885** | 0.983** |
| | | | (0.115) | (0.123) | (0.434) | (0.484) |
| log Move Rate (MR) | | | 0.0300** | 0.0183 | 0.0971** | 0.115** |
| | | | (0.0128) | (0.0155) | (0.0448) | (0.0483) |
| log Distance | | | 0.00124 | -0.0236 | 0.0742 | 0.108 |
| | | | (0.0252) | (0.0331) | (0.0971) | (0.102) |
| Risk Preference | | | -0.0658 | -0.0776 | 0.0300 | -0.00109 |
| | | | (0.187) | (0.184) | (0.197) | (0.195) |
| log $P^{in}$ | | | -0.00705 | -0.00841 | -0.241 | -0.198 |
| | | | (0.0196) | (0.0279) | (0.216) | (0.229) |
| log $P^{from}$ | | | 0.0169 | 0.0226 | -0.205 | -0.241 |
| | | | (0.0189) | (0.0234) | (0.246) | (0.255) |
| Same Area Dummy | | | -0.0136 | -0.0397 | -0.00145 | -0.0307 |
| | | | (0.0642) | (0.0706) | (0.0646) | (0.0714) |
| log $\text{Damage}^{in}$ | | | 0.0287** | 0.0282** | 0.0941 | 0.0724 |
| | | | (0.0122) | (0.0130) | (0.0941) | (0.0982) |
| log $\text{Damage}^{from}$ | | | 0.0295** | 0.00845 | 0.00525 | -0.00242 |
| | | | (0.0132) | (0.0146) | (0.0951) | (0.0970) |
| log $\text{Human Loss}^{in}$ | | | -0.00318 | 0.0128 | -0.149 | -0.0924 |
| | | | (0.0138) | (0.0152) | (0.135) | (0.140) |
| log $\text{Human Loss}^{from}$ | | | -0.0228*** | -0.0173* | 0.00849 | 0.0493 |
| | | | (0.00787) | (0.0101) | (0.0934) | (0.0976) |
| log MR × log $P^{in}$ | | | | | 0.0212 | 0.0280* |
| | | | | | (0.0137) | (0.0148) |
| log MR × log $P^{from}$ | | | | | 0.00355 | 0.00558 |
| | | | | | (0.0124) | (0.0127) |
| log Distance × log $P^{in}$ | | | | | 0.0347 | 0.0393 |
| | | | | | (0.0238) | (0.0247) |
| log Distance × log $P^{from}$ | | | | | 0.0161 | 0.0294 |
| | | | | | (0.0297) | (0.0293) |
| Similarity × log $P^{in}$ | | | | | 0.270* | 0.268 |
| | | | | | (0.163) | (0.177) |
| Similarity × log $P^{from}$ | | | | | 0.171 | 0.147 |
| | | | | | (0.159) | (0.165) |
| log MR × log $\text{Damage}^{in}$ | | | | | 0.0174*** | 0.0190*** |
| | | | | | (0.00613) | (0.00674) |
| log MR × log $\text{Damage}^{from}$ | | | | | -0.00590 | -0.00338 |
| | | | | | (0.00594) | (0.00638) |
| log Distance × log $\text{Damage}^{in}$ | | | | | 0.00668 | 0.0131 |
| | | | | | (0.0104) | (0.0111) |
| log Distance × log $\text{Damage}^{from}$ | | | | | -0.00728 | -0.00566 |
| | | | | | (0.0119) | (0.0119) |
| Similarity × log $\text{Damage}^{in}$ | | | | | 0.0565 | 0.0560 |
| | | | | | (0.0506) | (0.0534) |
| Similarity × log $\text{Damage}^{from}$ | | | | | 0.0142 | 0.0150 |
| | | | | | (0.0508) | (0.0509) |
| log MR × log $\text{Human Loss}^{in}$ | | | | | 0.0131 | 0.00896 |
| | | | | | (0.0103) | (0.0108) |
| log MR × log $\text{Human Loss}^{from}$ | | | | | 0.00309 | 0.00524 |
| | | | | | (0.00494) | (0.00506) |
| log Distance × log $\text{Human Loss}^{in}$ | | | | | 0.0207 | 0.0137 |
| | | | | | (0.0199) | (0.0206) |
| log Distance × log $\text{Human Loss}^{from}$ | | | | | 0.00575 | 0.00655 |
| | | | | | (0.0109) | (0.0106) |
| Similarity × log $\text{Human Loss}^{in}$ | | | | | 0.165** | 0.120 |
| | | | | | (0.0830) | (0.0841) |
| Similarity × log $\text{Human Loss}^{from}$ | | | | | -0.0384 | -0.0581 |
| | | | | | (0.0628) | (0.0657) |
| $N$ | 4324 | 4324 | 4324 | 4324 | 4324 | 4324 |
| FE | | x | | x | | x |

Notes: Heteroscedasticity-robust standard errors are in parentheses. The superscripts, ***, **, *, denote the statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively. Before 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of Expense to Income, it has one also with the measure of log Expense. After 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of log Expense, it has one also with the measure of Expense to Income.

Table B3. Full Results of Sensitivity Check with respect to Similarity Measures: Off-diagonal Elements

| | Tobit Model | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Similarity Measure: | All[a] | Non Geographical[a] | Geographical[a] |
| Post 2011 | -0.222*** | -0.222*** | -0.214*** |
| | (0.0788) | (0.0788) | (0.0797) |
| Similarity | 0.983** | 0.983** | -0.109 |
| | (0.484) | (0.484) | (0.159) |
| log Move Rate (MR) | 0.115** | 0.115** | 0.0879* |
| | (0.0483) | (0.0483) | (0.0494) |
| log Distance | 0.108 | 0.108 | 0.0550 |
| | (0.102) | (0.102) | (0.101) |
| Risk Preference | -0.00109 | -0.00110 | 0.0390 |
| | (0.195) | (0.195) | (0.193) |
| log $P^{in}$ | -0.198 | -0.198 | 0.0701 |
| | (0.229) | (0.229) | (0.143) |
| log $P^{from}$ | -0.241 | -0.241 | -0.0805 |
| | (0.255) | (0.255) | (0.166) |
| Same Area Dummy | -0.0307 | -0.0307 | -0.0420 |
| | (0.0714) | (0.0714) | (0.0718) |
| log Damage$^{in}$ | 0.0724 | 0.0724 | 0.123 |
| | (0.0982) | (0.0982) | (0.0777) |
| log Damage$^{from}$ | -0.00242 | -0.00242 | 0.0106 |
| | (0.0970) | (0.0970) | (0.0735) |
| log Human Loss$^{in}$ | -0.0924 | -0.0924 | 0.0280 |
| | (0.140) | (0.140) | (0.105) |
| log Human Loss$^{from}$ | 0.0493 | 0.0493 | -0.0168 |
| | (0.0976) | (0.0976) | (0.0600) |
| log MR × log $P^{in}$ | 0.0280* | 0.0280* | 0.0203 |
| | (0.0148) | (0.0148) | (0.0139) |
| log MR × log $P^{from}$ | 0.00558 | 0.00558 | 0.00318 |
| | (0.0127) | (0.0127) | (0.0122) |
| log Distance × log $P^{in}$ | 0.0393 | 0.0393 | 0.0213 |
| | (0.0247) | (0.0247) | (0.0233) |
| log Distance × log $P^{from}$ | 0.0294 | 0.0294 | 0.0257 |
| | (0.0293) | (0.0293) | (0.0278) |
| Similarity × log $P^{in}$ | 0.268 | 0.268 | -0.00179 |
| | (0.177) | (0.177) | (0.0407) |
| Similarity × log $P^{from}$ | 0.147 | 0.147 | -0.0454 |
| | (0.165) | (0.165) | (0.0427) |
| log MR × log Damage$^{in}$ | 0.0190*** | 0.0190*** | 0.0165** |
| | (0.00674) | (0.00674) | (0.00671) |
| log MR × log Damage$^{from}$ | -0.00338 | -0.00338 | -0.00279 |
| | (0.00638) | (0.00638) | (0.00623) |
| log Distance × log Damage$^{in}$ | 0.0131 | 0.0131 | 0.00642 |
| | (0.0111) | (0.0111) | (0.0118) |
| log Distance × log Damage$^{from}$ | -0.00566 | -0.00566 | -0.00228 |
| | (0.0119) | (0.0119) | (0.0122) |
| Similarity × log Damage$^{in}$ | 0.0560 | 0.0560 | 0.0131 |
| | (0.0534) | (0.0534) | (0.0214) |
| Similarity × log Damage$^{from}$ | 0.0150 | 0.0150 | -0.0146 |
| | (0.0509) | (0.0509) | (0.0234) |
| log MR × log Human Loss$^{in}$ | 0.00896 | 0.00896 | 0.00438 |
| | (0.0108) | (0.0108) | (0.00990) |
| log MR × log Human Loss$^{from}$ | 0.00524 | 0.00524 | 0.00477 |
| | (0.00506) | (0.00506) | (0.00530) |
| log Distance × log Human Loss$^{in}$ | 0.0137 | 0.0137 | 0.0000486 |
| | (0.0206) | (0.0206) | (0.0177) |
| log Distance × log Human Loss$^{from}$ | 0.00655 | 0.00655 | 0.00689 |
| | (0.0106) | (0.0106) | (0.0110) |
| Similarity × log Human Loss$^{in}$ | 0.120 | 0.120 | 0.0413** |
| | (0.0841) | (0.0841) | (0.0206) |
| Similarity × log Human Loss$^{from}$ | -0.0581 | -0.0581 | 0.00801 |
| | (0.0657) | (0.0657) | (0.0183) |
| $N$ | 4324 | 4324 | 4324 |
| FE | x | x | x |

Notes: Heteroscedasticity-robust standard errors are in parentheses. The superscripts, ***, **, *, denote the statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively. The specification is the same as Column (6) of Tables 4 and B2. Before 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of Expense to Income, it also has one with the measure of log Expense. After 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of log Expense, it has one also with the measure of Expense to Income.

a: For *All* similarity measure, we use (i) non-geographical variables, including the predicted probability of having the maximum probability over each prefecture of having an earthquake at the level of Seismic Intensity of 6 Upper or larger in 30 years in the Maximum Case, the average total damage by natural hazards, the average income of a prefecture, the average damage ratio (total damage over income), the average number of deaths due to natural hazards, the average number of people found missing due to natural hazards, the average number of people seriously injured due to natural hazards, the average number of people lightly injured due to natural hazards, and (ii) geographic-related variables, such as number of nuclear power plants as of 2018, forest ratio as of 2017, artificial forest ratio as of 2017, and length of the coastal line as of 2016. All averages are taken over each pre or post-2011 period. For *Non-geographical* similarity measure, we use the above category (i), while for *Geographical* similarity measure, we use the above category (ii).

Table B4. Robustness Check: Different Measures of Predicted Probability of Earthquakes

| | Tobit Model | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Measure of $P$: | $P_{6+,mm}$ | $P_{6+,ma}$ | $P_{6+,am}$ | $P_{6+,aa}$ |
| Post 2011 | -0.222*** | -0.222*** | -0.217*** | -0.223*** |
| | (0.0788) | (0.0763) | (0.0744) | (0.0743) |
| Similarity | 0.983** | 0.802* | 1.343** | 1.178* |
| | (0.484) | (0.469) | (0.658) | (0.674) |
| log Move Rate (MR) | 0.115** | 0.0939* | 0.119 | 0.104 |
| | (0.0483) | (0.0480) | (0.0736) | (0.0750) |
| log Distance | 0.108 | 0.0779 | 0.177 | 0.173 |
| | (0.102) | (0.100) | (0.161) | (0.159) |
| Risk Preference | -0.00109 | -0.00114 | -0.0271 | -0.0170 |
| | (0.195) | (0.191) | (0.189) | (0.189) |
| log $P^{in}$ | -0.198 | -0.161 | -0.160 | -0.155 |
| | (0.229) | (0.192) | (0.190) | (0.176) |
| log $P^{from}$ | -0.241 | -0.172 | -0.144 | -0.119 |
| | (0.255) | (0.228) | (0.171) | (0.168) |
| Same Area Dummy | -0.0307 | -0.0345 | -0.0258 | -0.0288 |
| | (0.0714) | (0.0713) | (0.0710) | (0.0707) |
| log $Damage^{in}$ | 0.0724 | 0.0764 | 0.0695 | 0.0717 |
| | (0.0982) | (0.0975) | (0.105) | (0.104) |
| log $Damage^{from}$ | -0.00242 | 0.00534 | -0.0101 | -0.00895 |
| | (0.0970) | (0.0974) | (0.107) | (0.106) |
| log Human Loss$^{in}$ | -0.0924 | -0.0954 | -0.105 | -0.111 |
| | (0.140) | (0.141) | (0.148) | (0.148) |
| log Human Loss$^{from}$ | 0.0493 | 0.0581 | 0.0188 | 0.0233 |
| | (0.0976) | (0.0970) | (0.107) | (0.108) |
| log MR × log $P^{in}$ | 0.0280* | 0.0203* | 0.0134 | 0.0125 |
| | (0.0148) | (0.0120) | (0.0128) | (0.0119) |
| log MR × log $P^{from}$ | 0.00558 | 0.00302 | 0.00279 | 0.000752 |
| | (0.0127) | (0.0116) | (0.00865) | (0.00870) |
| log Distance × log $P^{in}$ | 0.0393 | 0.0325 | 0.0184 | 0.0217 |
| | (0.0247) | (0.0214) | (0.0202) | (0.0188) |
| log Distance × log $P^{from}$ | 0.0294 | 0.0190 | 0.0250 | 0.0198 |
| | (0.0293) | (0.0260) | (0.0209) | (0.0200) |
| Similarity × log $P^{in}$ | 0.268 | 0.198 | 0.194 | 0.166 |
| | (0.177) | (0.134) | (0.129) | (0.112) |
| Similarity × log $P^{from}$ | 0.147 | 0.105 | 0.0523 | 0.0384 |
| | (0.165) | (0.146) | (0.108) | (0.106) |
| log MR × log $Damage^{in}$ | 0.0190*** | 0.0189*** | 0.0176** | 0.0178** |
| | (0.00674) | (0.00678) | (0.00716) | (0.00721) |
| log MR × log $Damage^{from}$ | -0.00338 | -0.00492 | -0.00299 | -0.00401 |
| | (0.00638) | (0.00652) | (0.00691) | (0.00697) |
| log Distance × log $Damage^{in}$ | 0.0131 | 0.0129 | 0.0104 | 0.0116 |
| | (0.0111) | (0.0110) | (0.0118) | (0.0115) |
| log Distance × log $Damage^{from}$ | -0.00566 | -0.00760 | -0.00193 | -0.00325 |
| | (0.0119) | (0.0119) | (0.0126) | (0.0126) |
| Similarity × log $Damage^{in}$ | 0.0560 | 0.0501 | 0.0598 | 0.0526 |
| | (0.0534) | (0.0526) | (0.0500) | (0.0496) |
| Similarity × log $Damage^{from}$ | 0.0150 | 0.00355 | 0.00853 | 0.00521 |
| | (0.0509) | (0.0522) | (0.0570) | (0.0566) |
| log MR × log Human Loss$^{in}$ | 0.00896 | 0.00845 | 0.0111 | 0.0109 |
| | (0.0108) | (0.0107) | (0.0110) | (0.0111) |
| log MR × log Human Loss$^{from}$ | 0.00524 | 0.00561 | 0.00476 | 0.00446 |
| | (0.00506) | (0.00502) | (0.00547) | (0.00556) |
| log Distance × log Human Loss$^{in}$ | 0.0137 | 0.0132 | 0.0162 | 0.0170 |
| | (0.0206) | (0.0206) | (0.0208) | (0.0210) |
| log Distance × log Human Loss$^{from}$ | 0.00655 | 0.00696 | 0.00975 | 0.00948 |
| | (0.0106) | (0.0106) | (0.0113) | (0.0114) |
| Similarity × log Human Loss$^{in}$ | 0.120 | 0.121 | 0.143 | 0.143 |
| | (0.0841) | (0.0852) | (0.0956) | (0.0957) |
| Similarity × log Human Loss$^{from}$ | -0.0581 | -0.0654 | -0.0470 | -0.0518 |
| | (0.0657) | (0.0656) | (0.0690) | (0.0692) |
| $N$ | 4324 | 4324 | 4324 | 4324 |
| FE | x | x | x | x |

Notes: Heteroscedasticity-robust standard errors are in parentheses. The superscripts, ***, **, *, denote the statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively. Before 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of Expense to Income, it has one also with the measure of log Expense. After 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of log Expense, it has one also with the measure of Expense to Income.

Table B5. Sensitivity Analysis: Different Measures of Predicted Probability of Earthquakes

| | Tobit Model | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Measure of $P$: | $P_{6+,mm}$ | $P_{6-,mm}$ | $P_{5+,mm}$ | $P_{5-,mm}$ |
| Post 2011 | -0.222*** | -0.222*** | -0.262*** | -0.231*** |
| | (0.0788) | (0.0723) | (0.0928) | (0.0715) |
| Similarity | 0.983** | 0.570 | 0.473 | 0.250 |
| | (0.484) | (0.450) | (0.660) | (0.449) |
| log Move Rate (MR) | 0.115** | 0.0549 | 0.0542 | 0.0198 |
| | (0.0483) | (0.0462) | (0.0618) | (0.0461) |
| log Distance | 0.108 | 0.0474 | 0.135 | 0.0136 |
| | (0.102) | (0.0890) | (0.111) | (0.0798) |
| Risk Preference | -0.00109 | 0.00342 | 0.0390 | 0.0223 |
| | (0.195) | (0.191) | (0.191) | (0.192) |
| log $P^{in}$ | -0.198 | -0.224 | -0.219 | -0.594 |
| | (0.229) | (0.329) | (0.748) | (3.374) |
| log $P^{from}$ | -0.241 | -0.493 | -1.476 | -6.518 |
| | (0.255) | (0.443) | (1.228) | (5.543) |
| Same Area Dummy | -0.0307 | -0.0325 | -0.0335 | -0.0286 |
| | (0.0714) | (0.0719) | (0.0720) | (0.0722) |
| log $Damage^{in}$ | 0.0724 | 0.0548 | 0.00492 | 0.0527 |
| | (0.0982) | (0.0969) | (0.107) | (0.0959) |
| log $Damage^{from}$ | -0.00242 | 0.0125 | -0.0377 | 0.0126 |
| | (0.0970) | (0.0992) | (0.121) | (0.0992) |
| log Human Loss$^{in}$ | -0.0924 | -0.0847 | -0.0713 | -0.0648 |
| | (0.140) | (0.141) | (0.142) | (0.144) |
| log Human Loss$^{from}$ | 0.0493 | 0.0912 | 0.112 | 0.122 |
| | (0.0976) | (0.0950) | (0.0925) | (0.0922) |
| log MR × log $P^{in}$ | 0.0280* | 0.0294 | 0.0547 | 0.0974 |
| | (0.0148) | (0.0207) | (0.0543) | (0.250) |
| log MR × log $P^{from}$ | 0.00558 | -0.00503 | -0.00683 | -0.113 |
| | (0.0127) | (0.0223) | (0.0625) | (0.283) |
| log Distance × log $P^{in}$ | 0.0393 | 0.0624 | 0.146 | 0.414 |
| | (0.0247) | (0.0416) | (0.103) | (0.424) |
| log Distance × log $P^{from}$ | 0.0294 | 0.0330 | 0.157 | 0.635 |
| | (0.0293) | (0.0552) | (0.159) | (0.713) |
| Similarity × log $P^{in}$ | 0.268 | 0.230 | 0.153 | 0.264 |
| | (0.177) | (0.205) | (0.537) | (2.547) |
| Similarity × log $P^{from}$ | 0.147 | 0.248 | 0.377 | 1.066 |
| | (0.165) | (0.299) | (0.778) | (3.508) |
| log MR × log $Damage^{in}$ | 0.0190*** | 0.0188*** | 0.0177** | 0.0154** |
| | (0.00674) | (0.00689) | (0.00761) | (0.00651) |
| log MR × log $Damage^{from}$ | -0.00338 | -0.00778 | -0.00537 | -0.00776 |
| | (0.00638) | (0.00687) | (0.00775) | (0.00711) |
| log Distance × log $Damage^{in}$ | 0.0131 | 0.0156 | 0.0221* | 0.0124 |
| | (0.0111) | (0.0112) | (0.0121) | (0.0107) |
| log Distance × log $Damage^{from}$ | -0.00566 | -0.0107 | -0.000138 | -0.00955 |
| | (0.0119) | (0.0122) | (0.0139) | (0.0122) |
| Similarity × log $Damage^{in}$ | 0.0560 | 0.0567 | 0.0543 | 0.0394 |
| | (0.0534) | (0.0487) | (0.0579) | (0.0487) |
| Similarity × log $Damage^{from}$ | 0.0150 | -0.0165 | -0.00712 | -0.0251 |
| | (0.0509) | (0.0557) | (0.0733) | (0.0560) |
| log MR × log Human Loss$^{in}$ | 0.00896 | 0.00683 | 0.00727 | 0.00869 |
| | (0.0108) | (0.0105) | (0.0105) | (0.0107) |
| log MR × log Human Loss$^{from}$ | 0.00524 | 0.00607 | 0.00600 | 0.00626 |
| | (0.00506) | (0.00485) | (0.00489) | (0.00487) |
| log Distance × log Human Loss$^{in}$ | 0.0137 | 0.00971 | 0.00819 | 0.0100 |
| | (0.0206) | (0.0204) | (0.0204) | (0.0204) |
| log Distance × log Human Loss$^{from}$ | 0.00655 | 0.00613 | 0.00323 | 0.00236 |
| | (0.0106) | (0.0102) | (0.00984) | (0.00996) |
| Similarity × log Human Loss$^{in}$ | 0.120 | 0.111 | 0.108 | 0.103 |
| | (0.0841) | (0.0847) | (0.0875) | (0.0893) |
| Similarity × log Human Loss$^{from}$ | -0.0581 | -0.0879 | -0.0883 | -0.0895 |
| | (0.0657) | (0.0657) | (0.0650) | (0.0656) |
| $N$ | 4324 | 4324 | 4324 | 4324 |
| FE | x | x | x | x |

Notes: Heteroscedasticity-robust standard errors are in parentheses. The superscripts, ***, **, *, denote the statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively. Before 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of Expense to Income, it has one also with the measure of log Expense. After 2011, if prefecture $i$ has a node from prefecture $j$ with the measure of Ratio of log Expense, it has one also with the measure of Expense to Income.