Natural Hazard Information and Migration across Cities: Evidence from the Nankai Trough Earthquake*

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Abstract

This paper examines the causal effect of the predicted seismic movements and their resulting tsunami on human migration across 251 coastal and their 179 neighboring municipalities in Japan. Using the difference-in-differences method, we find that an increase in predicted tsunami height is significantly associated with a reduction in net migration. We also find that an increase in predicted tsunami height has a persistent negative impact on the in-migration throughout our sample period, whereas it has only a temporal impact on the out-migration. An increase in predicted seismic movement, on the other hand, is significantly associated with a reduction in in-migration only for the year immediately after the dissemination of updated hazard information. Our empirical findings suggest that, after the dissemination of updated tsunami predictions, people are likely to move to less risky areas

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Keywords: Earthquake, Tsunami, Net migration
JEL codes: Q54, Q58, R23

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1 Introduction

The 2011 Great East Japan Earthquake and its subsequent tsunami reminded us that we live in the country of natural disaster. To promote public awareness and prepare for the potential earthquake and its resulting tsunami, Japanese government periodically updates the probability of earthquake occurrence and expected damage estimates from the anticipated megathrust earthquakes. The next Nankai Trough megathrust earthquake, which is anticipated to occur along the fault off the Pacific coast, is one such megathrust earthquake. This earthquake is likely to cause widespread damage and devastation to the Southeast coast of Japan.

In 2012, the Central Disaster Management Council (CDMC), which is a governmental committee for disaster management planning, released the latest report on the estimated damages from the next Nankai Trough earthquake. According to this report, death toll can be as many as 323,000, of which death by tsunami would account for 230,000. Possible economic loss can be approximately 170 trillion yen for assets and 45 trillion yen for degradation of production and services. The report also simulated the maximum possible seismic movements and tsunami height for each municipality, which were updated from the previous ones released in 2003.

How do people react to these updated hazard information? In the literature of urban economics, the impact of hazard information is often investigated in the framework of hedonic pricing approach. For example, Brookshire et al. (1985) examined the effects of the disclosure of a risk hazard map in California on sales prices of single-family houses. They found that their earthquake hazard indices do have a significantly negative impact on sales prices after they are disclosed.[2] There are also several studies investigating the effect of earthquake hazards on property values in the context of Japan (Nakagawa et al., 2007; Naoi et al. 2009; Hidano et al., 2015; Sato et al., 2016; Nakanishi, 2016, 2017).

This paper focuses on the effect on human migration, rather than the housing market response. We exploit the release of the CDMC's updated damage prediction as a natural experiment, and identify the causal effect of updated hazard information on net migration across municipalities. Moving to alternative locations is a form of risk mitigation strategies. People can out-migrate from risky areas or in-migrate into safer areas to protect themselves from the potential risks of disasters.

There is a literature on the relationship between migration and environmental hazards (Hunter, 2005; Gray and Mueller, 2012).[3] This paper improves previous literature in a number of ways. First, this paper focuses on hazard information rather than the actual hazard itself. Second, the paper improves identification strategies used in previous literature. We employ difference-in-differences method to estimate the potential impact of updated hazard prediction.

[2] There are also several studies about the relationship between flood hazards and housing prices primarily in the US (MacDonald et al., 1987; 1990; Bin and Polasky, 2004; Bin et al., 2008).

[3] A slightly different but related topic widely studied in urban economics is that whether urban amenities can foster in-migration and urban growth. See for example Glaeser et al. (2001).

Our preferred specifications show that an increase in predicted tsunami height is significantly associated with a reduction in net migration. Further analysis shows that an increase in predicted tsunami height has a persistent negative impact on the in-migration throughout our sample period, whereas it has only a temporal impact on the increase in out-migration. Moreover, an increase in predicted seismic movement is significantly associated with a reduction in in-migration only for the year immediately after the release of the report. Finally, our analysis shows that young people (aged between 15 and 64) respond to the updated hazard information much more than the old ones (aged 65 and over).

Organization of the rest of the paper is as follows. Section 2 describes the dataset and variables. Section 3 sets out our empirical model and provides empirical results. Finally, section 4 concludes the paper.

2 Data and Empirical Model

2.1 Migration

Our migration measures come from the Report on Internal Migration compiled by the Statistics Bureau of Japan. The report provides information on in- and out-migration for all municipalities, and is derived from the Basic Resident Registry (BRR).

The BRR is a registry of citizens maintained by local governments (municipalities) in Japan. It contains basic information such as name, current address, date of birth and gender for each citizen. A change of address must be declared to the local authorities of the new place of residence. The date of move and the place of past residence are also recorded in the BRR. In Japan, the resident registration is compulsory. As a result, we can track the total number of in- and out-migration across municipalities in Japan.

In the following regression analysis, we use the in- and out-migration rates as our dependent variable. For each municipality, the in-migration rate is defined as the total number of in-migrants during year t divided by the total population at the beginning of year t.[4] The out-migration rate is defined in the same way. We also use the net migration rate, which is simply defined as the in-migration rate minus the out-migration rate.

2.2 Estimated Damages from the Next Nankai Trough Earthquake

As mentioned earlier, the CDMC released the latest report on the estimated damages from the next Nankai Trough earthquake in August 2012. The new report estimated the maximum possible seismic movements and their resulting tsunami height for each municipality, which were updated from the previous ones released in 2003. The new report conveys updated information on seismic and tsunami damages to the current and future local residents. We examine the causal impact of updated hazard information on the net migration.

As for the estimated tsunami height, the original analysis of the report simulates the tsunami height for each 10m grid cell all over Japan, and the report provides the maximum

[4] The reference date of the survey was changed in 2014. Prior to 2014, the reference date was April 1 each year, and all in- and out-migrations between April 1 and March 31 next year are documented. In 2014, the reference date was changed to January 1, and all migrations between January 1 and December 31 are documented.

tsunami height in each municipality.[5] In the following regression analysis, we use the changes in the predicted tsunami height between 2012 and 2003 reports as our independent variable.

The report also provides information about the predicted seismic movements measured by the Japan Meteorological Agency (JMA) seismic intensity scale.[6] In the following analysis, we use the dummy variable indicating that the expected seismic intensity is 6^+ or above in the 2012 report but 6^- or below in the 2003 report. There is only one municipality that has lower predicted seismic intensity in the 2012 report than in the 2003 report. Hence this variable can capture the heightening of the perceived seismic risk due to the 2012 report.

2.3 Data

We compiled the municipality-level longitudinal data covering the period 2008-2015. Our original dataset covers the 1741 municipalities as of January 2015.[7] However, since the predicted tsunami damages are highly concentrated along the coastal areas of southeast Japan, we restrict our sample in the following way.

Based on “Act on Special Measures for Promotion of Nankai Trough Earthquake Disaster Management”, the municipalities in 26 prefectures are designated to reinforce the evacuation plan against tsunami triggered by the earthquake. Coastal municipalities in these prefectures are most likely to be affected by the seismic tremor and tsunami caused by the next Nankai Trough Megathrust Earthquake. In comparison, the neighboring inland municipalities are likely to be affected by the seismic tremor, but not by high tsunami. Hence the neighboring municipalities can serve as an ideal comparison group for the coastal municipalities. In the following analysis, we restrict our sample to these coastal and neighboring municipalities. This reduces the sample size up to 430 unique municipalities, of which 251 are coastal and 179 are neighboring inland municipalities. Figure 1 shows the location of municipalities used in the following analysis.

(Figure 1 around here)

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[5] The 2012 report also provides the average (not maximum) tsunami height for each municipality but we decided not to use this figure since the same information is not available in the 2003 report.

[6] The JMA seismic intensity scale, which is measured with a seismic intensity meter, and is graded from 0 to 7, provides a measure of the strength of seismic motion. The typical situations and damages caused by the earthquake with JMA seismic intensity of 6^+ are as follows: It is impossible to move without crawling, people may be thrown through the air, wooden houses occasionally collapse, and walls and pillars may be damaged even in highly earthquake-resistant houses. For full explanation of the JMA scale, see http://www.jma.go.jp/jma/en/Activities/intsummary.pdf. In general, the relationship between the JMA scale and the Richter scale basically depends on the distance from the epicenter. Even an earthquake with a small intensity on the Richter scale can have a large JMA intensity at locations near the epicenter.

[7] There are a number of municipal mergers during our sample period. The data for municipalities involved in mergers are rearranged so that pre- and post-merge data are comparable. For example, if municipalities A and B are consolidated to municipality C, we aggregated the data for municipalities A and B in the pre-merger periods.

In addition to the variables described in previous sections, we also use a number of municipality-level characteristics that can influence the in- and out-migration rates. These control variables include: the predicted probability of earthquakes with JMA seismic intensity of 6^{+} or higher[8], income per capita, population density, the number of airports and railway stations, miles of public road, and the number of manufacturing establishments.[9] Table 1 presents the summary statistics.

(Table 1 around here)

Table 2 shows the distribution of municipalities in terms of the changes in predicted tsunami height between 2003 and 2012. This shows that about half of all municipalities in our sample (N = 195) did not have any changes in their tsunami predictions, most of which are from inland municipalities where no tsunami damages are predicted both in 2003 and 2012 reports.[10] Changes in predicted tsunami height vary substantially among coastal areas. While small number of coastal municipalities (N = 17) did not have any changes in their tsunami predictions, changes in tsunami height are as high as 25m in some municipalities.[11]

Figure 2 compares the net migration rates between coastal and neighboring inland municipalities over our sample period. Levels and trends in net migration are similar between two groups prior to the release of updated hazard information in 2012 (dashed line). After 2012, however, net migration rate becomes substantially smaller in coastal municipality than in inland counterpart.

(Figure 2 around here)

3 Empirical Analysis

3.1 Empirical Model

Our benchmark regression model is given as follows:

$$y_{pmt} = \alpha + \beta_0 \Delta s_m + \beta_1 \Delta s_m \times d_t + x'_{pmt}\gamma + \delta_p + \phi_t + \varepsilon_{pmt}, \qquad (1)$$

[8] The variable is taken from the Probabilistic Seismic Hazard Map (PSHM) provided by the National Research Institute for Earth Science and Disaster Prevention (NIED). The PSHM data provides the probability of earthquakes with a given seismic intensity within 30 years. The original data is available at http://www.j-shis.bosai.go.jp/.

[9] Due to data availability, the number of airports and railway stations, miles of public road, and the number of manufacturing establishments have some missing values during our sample period. These missing values are linearly interpolated in order to get a balanced panel.

[10] There is only one inland municipality that have non-zero predicted tsunami height. Excluding this municipality from our sample does not change our empirical results.

[11] There is only one municipality that have lower tsunami prediction in the 2012 report than in 2003 report.

where subscript p, c, and t denote prefecture, municipality, and year, respectively. y_{pmt} is the outcome of interest, i.e., migration rate in municipality m in year t. Δs_m is the differences in predicted seismic movements and their resulting tsunami height between CDMC's reports published in 2003 and 2012. d_t is a dummy variable for the period after the release of the 2012 report. x_{pmt} is a set of municipality-level characteristics that can potentially influence migration. δ_p and ϕ_t are prefecture and year fixed-effects, and ε_{pmt} is random errors.

Equation (1) can be interpreted as a standard Difference-in-Differences (DD) framework, where treatment group in our estimation is municipalities with larger predicted seismic movements or higher tsunami in 2012 report than in 2003 report. Given that Δs_m is the treatment indicator constant across our sample period, it captures possible differences between the treatment and control groups prior to the policy change. The coefficient of interest, β_1, multiplies the interaction term, $\Delta s_m \times d_t$, which captures the impact of updated hazard information released in 2012 on migration rates.

The key assumption for our DD is that the treatment should be independent of the idiosyncratic shocks conditional on observed covariates (x) and a set of fixed effects (δ_p and ϕ_t). This might not be plausible, however, if there are unobserved heterogeneity at the municipality-level and/or location-specific time trends. Exploiting the panel structure of our dataset, we further introduce municipality fixed-effects into Equation (1), and allow prefecture-specific time trend. Our preferred specification becomes:

$$y_{pmt} = \alpha_m + \beta_1 \Delta s_m \times d_t + x'_{pmt}\gamma + \phi_{pt} + \varepsilon_{pmt}, \qquad (2)$$

where α_m is municipality fixed-effects and ϕ_{pt} denotes prefecture$\times$year fixed-effects. Again, the coefficient of interest is β_1.

We also consider a number of alternative specifications to Equation (2). First, we explore the possible nonlinearity of the impact of tsunami height by introducing a set of dummy variables for changes in predicted tsunami height. Second, we test the time-varying post-treatment effects by replacing d_t with a set of year dummies for the post-treatment period. Third, we check whether responses are different between the elderly and younger populations by using age-specific migration rates as our dependent variable.

3.2 Benchmark Results

Our benchmark regression results are presented in Table 3. In the following analysis, we present the robust standard errors clustered by municipality.[12]

(Table 3 around here)

[12] To check the robustness of our results, we also compute the standard errors clustered by prefecture. This, however, does not change our main findings. In addition, we also estimate the model with interaction terms between full set of year dummies and treatment indicators. We could not find any strong evidence of differential pre-trends between treatment and control groups.

Our regression results for the net migration rate are presented in columns [1] and [2], which correspond to Equation (1) and (2), respectively. These results indicate that, regardless of the model specification, increases in predicted tsunami height significantly reduce the net migration. Estimated coefficients show that an additional one meter increase in the predicted tsunami height leads to a reduction of net migration rate by 0.017 and 0.022 p.p., respectively. These numbers seem quite small, but given that sample average of net migration is also small (-0.227%), an additional one meter increase in tsunami height can reduce net migration rate by 7.5-9.7%.

Results for in- and out-migration rates are presented in columns [3]-[6]. These results show that the changes in predicted tsunami height can affect both in- and out-migrations. Higher tsunami prediction can decrease the inflow of people into municipality, and can also increase the outflow of local residents from the municipality. Our results indicate that these two effects are similar in magnitude. Furthermore, if we use levels of predicted tsunami height in the 2012 report instead of its changes from the previous report, they do not have any significant impact for out-migration (results not shown). This suggests that updated information (i.e., changes in predicted tsunami height) is important particularly for existing local residents.

One might think that our results above is not due to updated hazard information but due to the occurrence of the Great East Japan Earthquake and tsunami in March 2011. The massive tsunami of the 2011 earthquake can change people's perception toward tsunami risk elsewhere in Japan. As a result, people might relocate from coastal areas to inland areas, and this can potentially explain our results presented in Table 3. In order to see whether this is the case, we also estimate Equation (2) using sample only from coastal municipalities. As explained before, there are some coastal municipalities which did not experience an increase predicted tsunami height. Also, there is substantial variation in changes in predicted height within coastal municipalities. The regression results from this sample show that net migration rate is significantly negatively associated with the changes in tsunami height within coastal municipalities (results not shown).

As for the updated seismic intensity predictions, we do not find any significant impact on either of three migration measures. However, if we consider the time-varying post-treatment effects, seismic intensity can reduce in-migration shortly after the release of the new report (discussed later).

3.3 Nonlinearity of the Impact of Predicted Tsunami Height

In order to examine the possible nonlinearity of the treatment effect, we categorize the municipalities into thirteen groups depending on the changes in tsunami height, and create a set of dummy variables for these categories.[13] Estimation results are summarized in Figure 3. This presents the marginal effects of the changes in predicted tsunami height at each point relative to the case without any changes (i.e., $\Delta s_w = 0$), where vertical lines show 95% confidence intervals.

[13] Namely, we create a set of dummy variables for each unique value up to 10m. Because there are only a small number of cases with more than 10m changes in predicted tsunami height, those with 11-14m changes and with 15m or more are grouped together.

(Figure 3 around here)

Overall, as the predicted tsunami becomes higher, the net migration rate and in-migration rate tend to be lower, and the out-migration tends to be higher. However, in either case statistically significant effects (as compared to baseline) can be found only in municipalities with extremely large changes in predicted tsunami height (more than 10m).

3.4 Time-Varying Post-Treatment Effects

Migration responses to updated hazard information can vary over time. Time-varying post-treatment effects can be observed, for example, if the relocation decision needs some time to be realized due to transaction costs, or if people get accustomed to the new information quickly. In the former case, the actual migration decisions are influenced by updated hazard information with some time lags. In the latter case, migration responses can be observed only after the release of new information and dissipate over time.

In order to test the time-varying post-treatment effects, we replace d_t in Equation (2) with a set of year dummies for the post-treatment period. Table 4 summarizes the estimation results for this alternative specification, where treatment effects are estimated and presented separately for each year after 2012.

(Table 4 around here)

As a result, the effects of predicted tsunami height on in-migration do not seem to vary over time, whereas the effects on out-migration can be found only in 2012 and 2013, shortly after the dissemination of updated information.

The contrasting results for in- and out-migration can be explained in several ways. First, it is reasonable to assume that in-migrants and out-migrants face different situation in terms of their relocation decisions. In-migrants, on the one hand, are those who have already decided to relocate for the reason perhaps other than potential disaster risks. They can choose their location among several municipalities in the same region. In this case, there may be strong substitution between risky and safe locations: in-migrants are likely to avoid coastal areas and choose nearby safer, probably inland, locations. On the other hand, the relocation of out-migrants can be quite costly due to the existence of certain transaction costs. As a result, updated hazard information can have larger impact on in-migration decisions than on out-migration. Second, even within the same municipality, predicted damage from tsunami can vary substantially depending on the location. There are perhaps only a small number of people who are subject to the large tsunami damages even in the coastal municipalities. In this case, people in the riskiest areas tend to relocate after the dissemination of updated information, whereas those in less risky areas tend to stay in their location over time.

We also find that an increase in seismic intensity predictions is significantly associated with a reduction in in-migration only for the year immediately after the dissemination of updated hazard information. The negative impact on in-migration, however, dissipate quickly over time. Furthermore, we could not find any impact of updated seismic intensity predictions on overall migration or out-migration patterns.

3.5 Age-Specific Migration Rates

Finally, we compare migration response between young and elderly populations. Specifically, we use age-specific migration rates as our dependent variable and run the same regression as Equation (2). Due to data availability, we have only two age categories for this analysis: migration rates for people aged between 15 and 64 and for those aged 65 and older.

Regression results are presented in Table 5. It is found that migration responses are substantially larger for younger population (aged between 15 and 64) than for elderly population (aged 65 and older). Furthermore, migration responses for elderly population are estimated less precisely, resulting in statistically insignificant impacts on in- and out-migrations.

(Table 5 around here)

Our empirical results above have particularly important implications for disaster policy and planning. It is well-known that the elderly population are disproportionately vulnerable to natural disasters (Cutter et al., 2003). In fact, the 2011 earthquake and its subsequent tsunami took the heaviest toll on the elderly, about 65% of the earthquake and tsunami-related deaths were people aged 60 and older, which was far larger than the elderly population share of about 30% in the affected areas (Cabinet Office, 2011). Our results that elderly population are less likely to respond to updated hazard information suggest that the dissemination of hazard information cannot reduce, or might even increase, the social vulnerability at the local level.

4 Conclusion

In this paper, we examined the effect of the dissemination of updated hazard information on inter-municipal human migration. We exploited the CDMC's updated damage predictions and estimated the causal effect of the increase in seismic movement prediction and its resulting tsunami height on migration rate. We used a panel of 430 municipalities (251 coastal and their 179 neighboring municipalities) in our sample for the period 2008-2015.

Using the difference-in-differences method, we found that an increase in predicted tsunami height is significantly associated with a reduction in net migration rate. Our empirical results are robust to the inclusion of additional control variables, such as demographic and socio-economic characteristics, municipality fixed effects, and region-specific time trends.

Further analysis showed that the predicted tsunami height has a persistent negative effect on in-migration throughout our sample period, whereas it has only a temporary effect on out-migration. The predicted seismic movements, on the other hand, is significantly and negatively associated with in-migration only for the year immediately after the release of the report. Our empirical findings suggest that, after the dissemination of tsunami predictions, people tend to choose less risky locations. In addition, it is also found that migration responses to updated hazard information are mainly driven by the relocation of younger population.

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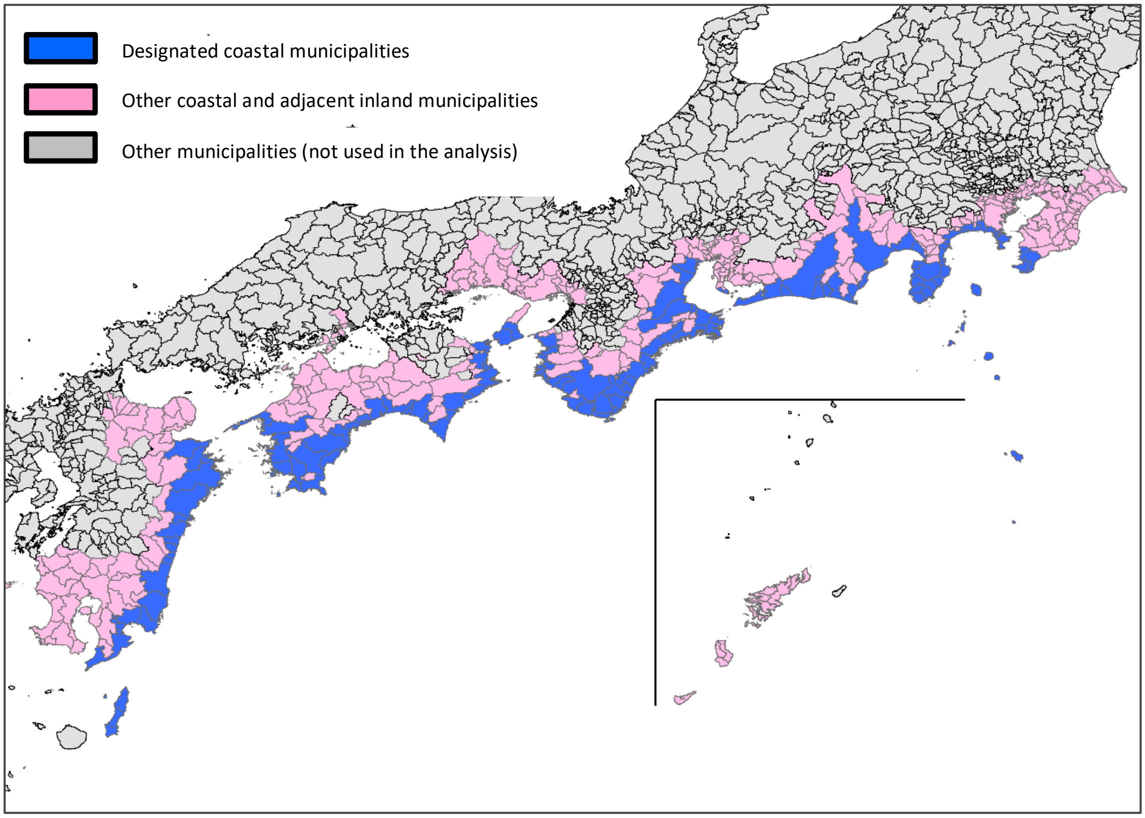
Figure 1: Location of municipalities in the estimation sample



Source: Naoi et al. (2017, Appendix Figure 1)

Figure 2: Net Migration Rates in Coastal and Adjacent Municipalities

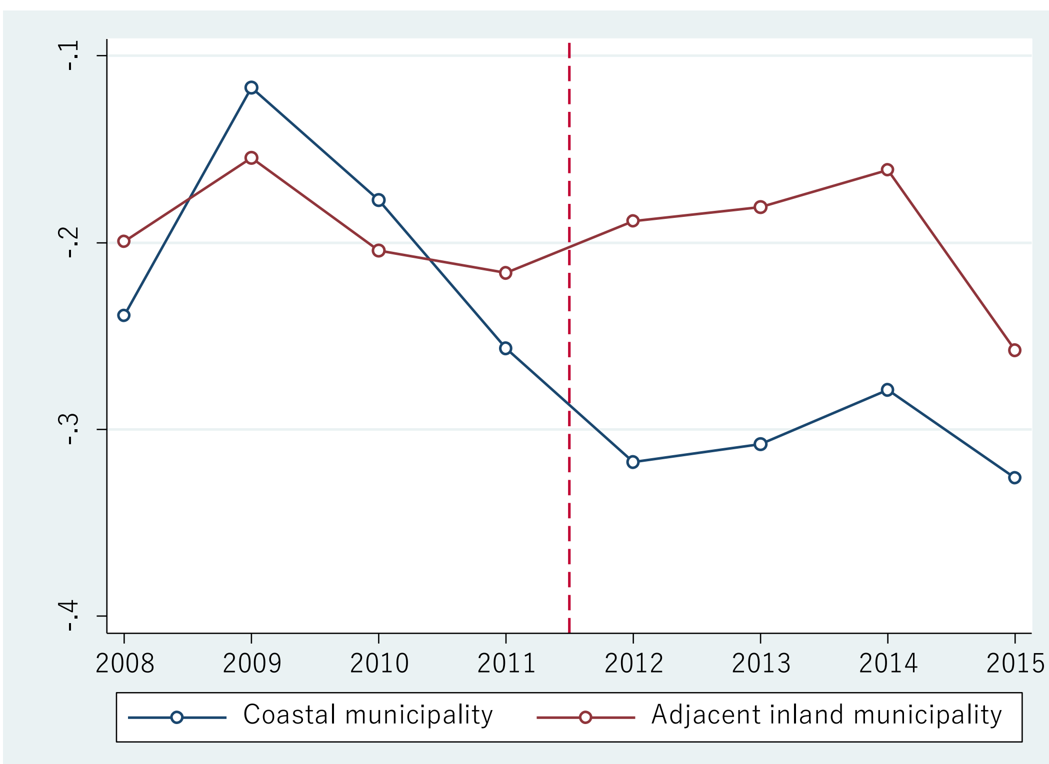
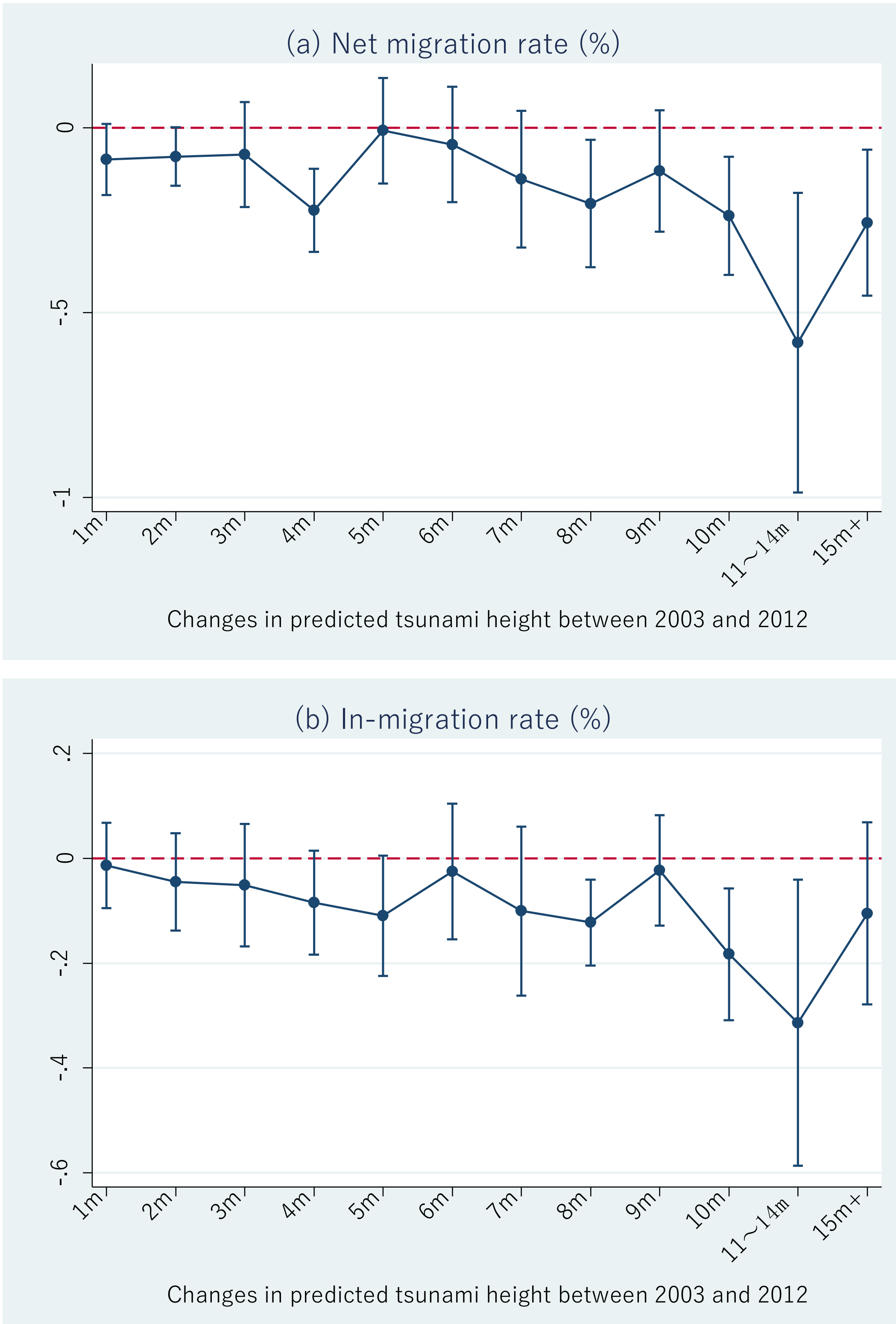


Figure 3: Nonlinear Effect of the Changes in Predicted Tsunami Height



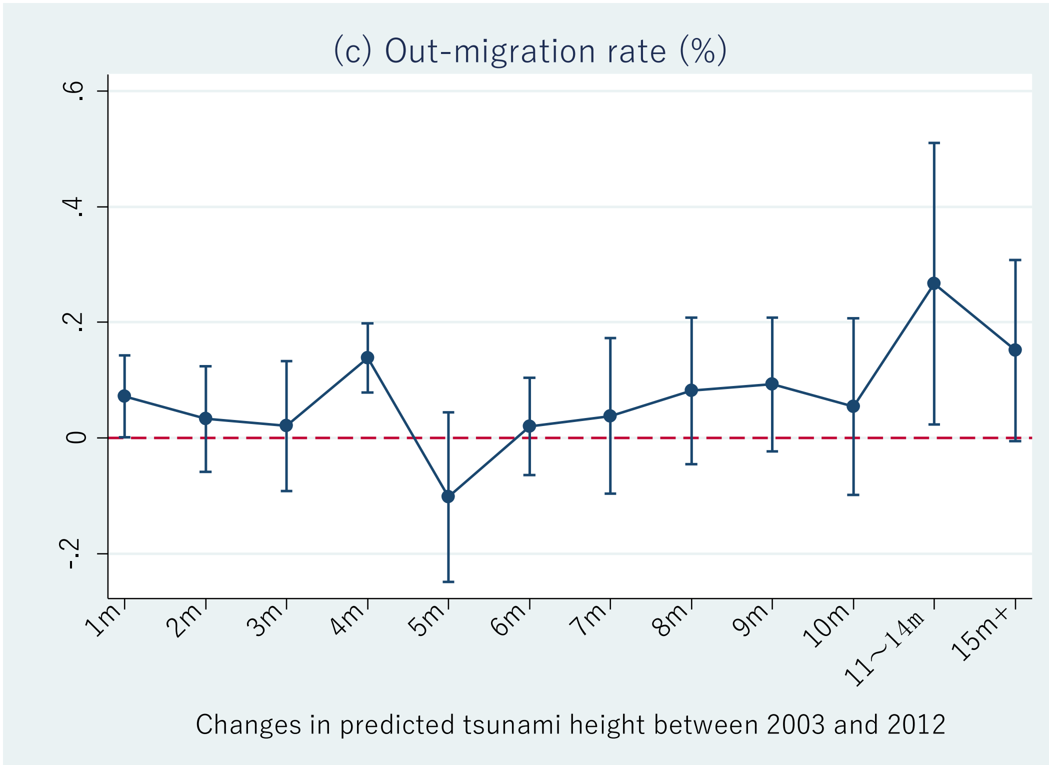

(c) Out-migration rate (%)
.6
.4
.2
0
-.2
1m
2m
3m
4m
5m
6m
7m
8m
9m
10m
11～14m
15m+
Changes in predicted tsunami height between 2003 and 2012

Table 1: Summary Statistics

Variables	Mean	(S.D.)	Min.	Max.
Net migration rate (annual, %)	-0.227	(0.684)	-8.092	5.096
In-migration rate (annual, %)	3.593	(1.753)	1.240	21.019
Out-migration rate (annual, %)	3.820	(1.511)	1.800	20.833
Changes in predicted tsunami height (m)	2.984	(4.395)	-1.000	25.000
Predicted seismic intensity (1 if 6+ or above in the 2012 report and 6- or below in the 2003 report)	0.307	(0.461)	0.000	1.000
Predicted probability of earthquakes with JMA seismic intensity of 6+ or higher	0.088	(0.110)	0.000	0.614
Log of per capita income (10 thousand JPY)	4.732	(0.355)	3.790	6.628
Population density (per sq. km)	1459.9	(2922.4)	2.157	18062.0
Number of major airports (per sq. km)	0.001	(0.010)	0.000	0.161
Number of railway stations (per sq. km)	0.125	(0.426)	0.000	5.886
Miles of public road (per sq. km)	6.953	(5.505)	0.491	26.175
Number of manufacturing establishments (per sq. km)	2.491	(6.085)	-0.013	96.938
Sample size		3,440		

Table 2: Changes in Predicted Tsunami Height

Δpredicted tsunami height	# of muni.	(%)	Δpredicted tsunami height	# of muni.	(%)
0m	195	(45.3)	7m	14	(3.3)
1m	46	(10.7)	8m	12	(2.8)
2m	32	(7.4)	9m	11	(2.6)
3m	23	(5.3)	10m	11	(2.6)
4m	28	(6.5)	11-14m	16	(3.7)
5m	14	(3.3)	15m+	11	(2.6)
6m	17	(4.0)	Total	430	(100.0)

Note : "0m" includes one municipality with lower prediction in 2012 than in 2003.

Table 3: Migration Responses to Updated Hazard Information

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent variables:	Net migration rate (%)		In-migration rate (%)		Out-migration rate (%)	
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)
Changes in predicted tsunami height	-0.0059		0.0196		0.0255	
	(0.0041)		(0.0161)		(0.0157)	
Changes in predicted tsunami height	-0.0170 ***	-0.0220 ***	-0.0085 *	-0.0115 ***	0.0085 ***	0.0104 ***
× After the dissemination of updated information	(0.0046)	(0.0059)	(0.0044)	(0.0041)	(0.0032)	(0.0037)
Predicted seismic intensity (1 if 6+ or above in the	0.0226		0.1457		0.1231	
2012 report but 6- or below in the 2003 report)	(0.0550)		(0.1144)		(0.0993)	
Predicted seismic intensity	0.0061	-0.0350	-0.0096	-0.0452	-0.0157	-0.0101
× After the dissemination of updated information	(0.0356)	(0.0570)	(0.0347)	(0.0374)	(0.0328)	(0.0416)
Fixed-effects						
Year	Yes	No	Yes	No	Yes	No
Municipality	No	Yes	No	Yes	No	Yes
Prefecture	Yes	No	Yes	No	Yes	No
Prefecture × Year	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.3857	0.1040	0.6576	0.2084	0.5599	0.1584
Sample size	3,440	3,440	3,440	3,440	3,440	3,440

Notes: ***, **, and * indicate that estimated coefficients are significant at 1, 5, and 10% levels, respectively. Robust standard errors clustered by municipality are presented in the parentheses. Following control variables are included in all estimation but results are omitted from the table: predicted probability of earthquakes with JMA seismic intensity of 6+ or higher , income per capita, population density, the number of airports and railway stations, miles of public road, and the number of manufacturing establishments.

Table 4: Time-Varying Treatment Effects

Dependent variables:	Net migration rate (%)	In-migration rate (%)	Out-migration rate (%)
	Coef. (S.E.)	Coef. (S.E.)	Coef. (S.E.)
Changes in predicted tsunami height			
× Year = 2012	-0.0266 **	-0.0122 *	0.0144 **
	(0.0105)	(0.0074)	(0.0061)
× Year = 2013	-0.0238 ***	-0.0132 **	0.0106 *
	(0.0076)	(0.0055)	(0.0056)
× Year = 2014	-0.0193 ***	-0.0081	0.0112
	(0.0056)	(0.0060)	(0.0068)
× Year = 2015	-0.0177 ***	-0.0130 **	0.0048
	(0.0058)	(0.0060)	(0.0064)
Predicted seismic intensity			
× Year = 2012	-0.0378	-0.1053 **	-0.0675
	(0.0735)	(0.0504)	(0.0723)
× Year = 2013	-0.0883	-0.0949 *	-0.0066
	(0.0773)	(0.0501)	(0.0584)
× Year = 2014	-0.1329 **	-0.0476	0.0853
	(0.0635)	(0.0530)	(0.0593)
× Year = 2015	0.1174	0.0689	-0.0485
	(0.1053)	(0.0531)	(0.0838)
Fixed-effects			
Municipality	Yes	Yes	Yes
Prefecture × Year	Yes	Yes	Yes
Adjusted R^2	0.1074	0.2110	0.1612
Sample size	3,440	3,440	3,440

Notes: ***, **, and * indicate that estimated coefficients are significant at 1, 5, and 10% levels, respectively. Robust standard errors clustered by municipality are presented in the parentheses. Following control variables are included in all estimation but results are omitted from the table: predicted probability of earthquakes with JMA seismic intensity of 6+ or higher , income per capita, population density, the number of airports and railway stations, miles of public road, and the number of manufacturing establishments.

Table 5: Age-Specific Migration Responses to Updated Hazard Information

Dependent variable:	Net migration rate (%)		In-migration rate (%)		Out-migration rate (%)	
	Age 15-64	Age 65+	Age 15-64	Age 65+	Age 15-64	Age 65+
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)	(S.E.)
Changes in predicted tsunami height	-0.0182 ***	-0.0071 *	-0.0102 **	-0.0028	0.0080 *	0.0043
× After the dissemination of updated information	(0.0068)	(0.0041)	(0.0048)	(0.0026)	(0.0047)	(0.0029)
Predicted seismic intensity	-0.0078	-0.0130	0.0571	0.0153	0.0649	0.0284
× After the dissemination of updated information	(0.0824)	(0.0354)	(0.0936)	(0.0287)	(0.0465)	(0.0235)
Fixed-effects						
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture × Year	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0731	0.0677	0.0939	0.0588	0.0893	0.0907
Sample size	3,008	3,008	3,008	3,008	3,008	3,008

Notes: ***, **, and * indicate that estimated coefficients are significant at 1, 5, and 10% levels, respectively. Robust standard errors clustered by municipality are presented in the parentheses. Following control variables are included in all estimation but results are omitted from the table: predicted probability of earthquakes with JMA seismic intensity of 6+ or higher , income per capita, population density, the number of airports and railway stations, miles of public road, and the number of manufacturing establishments.