

Research

## Do all roads lead to Sapporo? The role of linking and bridging ties in evacuation decisions

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**ABSTRACT.** Why do some communities evacuate long-distances in higher rates than others after disaster? This mixed-methods study uses a new dataset of long-distance evacuation rates after Hokkaido's Eastern Iburi Earthquake in September 2018, aggregated to the city level from geolocated Facebook user movement. We found that communities with stronger linking and bridging social capital tended to see much lower evacuation rates to distant towns. We used statistical models, fieldwork, and content analysis of 12 interviews, finding that despite rumors on social media, communities with stronger linking social networks had greater trust in government and decided to stay in local evacuation shelters. This was especially the case if these communities also had stronger bridging social networks, helping them access key information, especially among vulnerable communities. Meanwhile, residents with weaker linking or bridging networks may have believed rumors of extreme water, food, and power shortages and left town for good. This study highlights the importance of trust in local officials when managing evacuation after disasters.

**Key Words:** *disaster; evacuation; mobility; policy; resilience; social capital*

### INTRODUCTION

When disaster strikes, residents facing new disaster damage in their home or neighborhood often must decide whether to stay in their homes or evacuate to a local shelter to access food, shelter, or medical treatment from local government workers, first responders, and civil society groups. However, some residents may choose to leave town instead (Elliott et al. 2010, Martin et al. 2017, Metaxa-Kakavouli et al. 2018, Yabe and Ukkusuri 2020), choosing to evacuate long-distance for days or weeks (Bowser and Cutter 2015, Metaxa-Kakavouli et al. 2018), or even permanently (Raker and Elliott 2018, Yabe et al. 2020). Past studies suggest residents may leave when facing significant levels of damage (Yabe et al. 2019), when shelters are full or too far away (Chakma and Hokugo 2020), or given sufficient financial resources (Yabe and Ukkusuri 2020). However, many residents stay put because evacuating long-distance is prohibitively expensive (Elliott et al. 2010), full of mobility challenges (Cutter et al. 2003), or exposes residents to discrimination (Raker and Elliott 2018). Local governments in particular typically want residents to remain in town, lest taxpayers leave and never return (Aldrich 2012), and residents are more likely to stay if local governments provide better public goods, investing in local infrastructure, emergency response capacity (Boin and McConnell 2007), and local shelters (Fraser et al. 2021a). Despite these common explanations, evacuation still surges in some localities. This begs a question: Why do some communities see greater rates of long-distance evacuation than others?

In this study we examine the critical effect on community evacuation rates of “social capital,” the social ties between residents in communities that enable trust, reciprocity, and collective action (Putnam 2000, Nakagawa and Shaw 2003). Social capital comes in three types, including bonding, bridging, and linking social capital (Aldrich and Meyer 2015). “Bonding social capital” represents close in-group ties between members of the same social groups in terms of race, age, gender, and socioeconomic status (Hawkins and Maurer 2010, Shoji and

Murata 2021). Meanwhile, “bridging social capital” represents inter-group ties that bridge members of different social groups in terms of race, age, gender, or socioeconomic status (Putnam 2000, Aldrich and Sawada 2015, Smiley et al. 2018). Finally, “linking social capital” describes vertical social ties connecting residents to local, regional, and national authorities, which help residents obtain resources during crisis and foster trust in government (Szreter and Woolcock 2004, Aldrich 2019). Past research suggests that social capital affects evacuation, either by friends and neighbors encouraging and helping each other evacuate (Elliott et al. 2010, Sadri et al. 2017, Collins et al. 2018, Metaxa-Kakavouli et al. 2018, Shoji and Murata 2021), or by spreading confusing messages across diverse, bridging or clustered, bonding networks, thereby reducing essential evacuation to shelters or exacerbating unnecessary evacuation (Fraser et al. 2021a). However, many of these studies focused on hurricane evacuation (Sadri et al. 2017, Collins et al. 2018, Metaxa-Kakavouli et al. 2018). In contrast, during a sudden crisis, like an earthquake, some areas may see greater need for evacuation than others, but blackouts, damage, or misinformation can obscure these details for residents, raising the importance of bridging networks that spread information or linking ties that aid local evacuation orders (Fraser et al. 2021a). This study hypothesizes that linking social capital and the trust in government it imparts might play a greater role in long-distance evacuation too, where stronger linking ties encourage residents to stay while weaker linking ties lead residents to leave town.

We test the effect of each type of social capital on long-distance evacuation using the case of the 2018 Eastern Iburi Earthquake in Japan. After the magnitude 6.7 earthquake struck Japan's northernmost prefecture Hokkaido in September 2018, evacuation behavior varied dramatically. Whereas some residents stayed in local shelters in the rural towns hit by the quake (Fraser et al. 2021a), others, especially around the metropolitan area of Sapporo, evacuated much further afield and traveled extensively throughout the prefecture. This mixed methods study investigates

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this long-distance evacuation using aggregate-level data from Facebook's Data for Good Program and in-person interviews carried out in the disaster region. We combine fixed effects modeling on Facebook and geospatial data with content analysis of interviews and case studies.

This paper adds to the existing literature on evacuations during and after crisis in several ways. First, we find that while social vulnerability traits such as poverty, home ownership, and elderly mobility challenges are frequently discussed as challenges to evacuation and crisis outcomes (Riad et al. 1999, Whitehead et al. 2000, Smith and McCarty 2009, Elliott et al. 2010, Adeola and Picou 2012), this study highlights that social capital can make a critical difference in long-distance evacuation rates, even in vulnerable communities. We find that communities with the strongest linking social capital tend to see the least evacuation, helping residents trust local officials' messages about the scope of the disaster and the kinds of aid and shelter provided locally.

Second, past studies have approximated evacuation behavior using post-hoc surveys (Li et al. 2010, Ahsan et al. 2016, Shoji and Murata 2021) or ad-hoc highway surveys (Collins et al. 2017, 2018), but both of these approaches struggle to capture complete and accurate movements across the population. Using aggregate mobility data from cell phones and other portable electronic devices, this paper avoids the challenges faced by past studies based on retrospective questions and looks instead at actual behavior captured by users' computer geolocation information. This builds on a growing school of thought that uses geolocated cell phone user data to approximate evacuation behavior (Martín et al. 2017, Metaxa-Kakavouli et al. 2018, Yabe et al. 2019). Further, where past studies of behavior have had to either simulate behaviors or ask respondents to select their options from lists of potential targets, we use actual data on the cities to and from which Facebook users traveled, provided by the Facebook Data for Good project.

Finally, many past studies have used only a single method in their investigation of evacuation behavior, highlighting the challenges of collecting evacuation data. Here, we use a mixed methods approach with qualitative and quantitative methods to provide a more holistic view, building on past mixed methods studies of evacuation (Elliott et al. 2010, Fraser et al. 2021a) and recovery (Aldrich 2019). By identifying robustly which cities evacuate when in crisis, policy makers can seek to help residents access the aid and shelter they need when crisis strikes.

## LITERATURE REVIEW

This study examines why people evacuate long-distance away from some cities more than others following disasters. Over the last two decades, scholars have measured wide variation in evacuation rates among communities struck by disaster (Riad et al. 1999, Whitehead et al. 2000, Horney et al. 2010, Li et al. 2010, Ahsan et al. 2016). Past studies frequently used ad-hoc surveys at highway rest stops outside of cities (Collins et al. 2017, 2018) or post-hoc surveys of returned residents (Li et al. 2010) to measure evacuation and infer causal patterns. Recently, researchers have turned to social media to assess evacuation. For example, 54% of Twitter users in the communities affected by Hurricane Matthew evacuated to safer locations before the storm struck (Martín et al. 2017). Recently, though, access to big data has encouraged scholars to measure at scale how much key individual and

community traits affected evacuation patterns over all (Metaxa-Kakavouli et al. 2018). This study examines the effect of different types of social capital on evacuation, while considering three other main explanations for evacuation behavior, drawn from the literature: damage and infrastructure quality, social vulnerability and risk, public goods and services.

### Damage and infrastructure quality

First, some communities may see greater long-distance evacuation than others because of the level of damage and, conversely, the quality of infrastructure in neighborhoods. In this way, some disaster scholars and policy makers view evacuation outcome as a policy implementation problem, where residents would evacuate if these key technocratic policy outcomes were resolved, such as improving post-disaster communication networks, reducing crowding on roads, improving resilience of electrical systems for health care systems, or fortifying broken infrastructure (Boin and McConnell 2007, Petit et al. 2013, Na and Banerjee 2015, Nakai et al. 2016). This perspective prioritizes resolving barriers to implementing these critical infrastructure policies. Policy scholars further argue that technocratic policies, like a Rube Goldberg machine, easily break down if they face opposition from other government actors competing for authority or budget space (Pressman and Wildavsky 1973, Bardach 1977, Lipsky 1980). This infrastructure policy perspective has persisted for decades, with experts highlighting the importance of energy, water, and transportation infrastructure. However, we have good reason to suspect that damage, infrastructure, and transportation were not the main cause of evacuation.

For example, after the Eastern Iwate Earthquake, Hokkaido's main coal-fired power plant in Atsuma City was damaged and the entire prefecture faced intermittent power outages for a month. Similarly, Chitose airport, the prefecture's main conduit to the rest of Japan, lost power and flights were grounded for days. In contrast, Hokkaido's road network was up and running again within 72 hours, because the most severe impacts were landslides in the very rural community of Abira. Further, most rural residents in Hokkaido own cars and do not rely on public transportation as much as residents in other parts of Japan, meaning that mobility was not as affected after this quake as other parts of Japan would have been. As a result, the decision to evacuate became about how distressing it would be to continue living without power for an unknown period of time. Certainly, the extent of damage and quality of public infrastructure might affect this, as some communities might lose potable water while others might not.

However, dozens of studies find that damages and hard infrastructure-focused policy do not explain the majority of variation in disaster outcomes (Cutter and Finch 2008, Edgington 2010, Elliott et al. 2010, Adeola and Picou 2012, Aldrich 2012, Metaxa-Kakavouli et al. 2018). Might some communities be more likely to evacuate for reasons beyond this?

### Risk and social vulnerability

On the other hand, early evacuation studies suggest that the level of social vulnerability of a community can shape long-distance evacuation, in that many do not evacuate for rational reasons because traits of social vulnerability, such as poverty, age, gender, race, and ethnicity, make evacuation more difficult, costly, and

risky. Ethnic minorities evacuate less because of cultural insensitivity and language barriers when interacting with first responders, or information sharing challenges due to housing patterns (Perry and Lindell 1991, Fothergill et al. 1999, Smith and McCarty 2009). Several studies likewise suggest that women are more likely to evacuate than men (Riad et al. 1999, Whitehead et al. 2000), but paradoxically as less likely to evacuate because of family responsibilities and more vulnerable to poverty after disasters (Enarson 1998). Race, socioeconomic status, age, and gender present barriers when disaster strikes to obtaining information, financial, legal, and emotional support, and shelter when disaster strikes (Cutter and Finch 2008, Elliott et al. 2010, Adeola and Picou 2012). After the quake, cities with older, poorer populations on average might have seen less outflow, because it is difficult to uproot one's life and move to another city when you have access to little liquid capital. We might expect more socially vulnerable towns in these ways would experience less evacuation.

#### **Public goods and services**

Alternatively, some communities see less long-distance evacuation, even among wealthier communities, if their city can provide sufficient emergency response and public goods. Strong institutions and norms can greatly affect policy efficacy (March and Olsen 1983), and policy success or failure depends not just on the central government but also local partners in the private and nonprofit sectors who help implement those emergency services (Goggin 1990, Hill and Hupe 2014). As a result, we expect that cities with better balanced budgets and greater institutional capacity, cities that spend more on community oriented resources like emergency services (Bakema et al. 2019), and cities that open up more public shelters for their cities would see many more residents stay local, evacuating just to local shelters instead of leaving town. The provision of these public goods would be vital to evacuation decisions.

#### **Social capital**

Finally, some communities may still see more long-distance evacuation than others, even after accounting for the poor provision of public goods, social vulnerability, or damage and infrastructure quality, because of their level of social capital. Social capital, the social ties in a community that enable collective action, come in at least three types. Bonding social capital refers to homophilous ties among members of the same social group, ethnicity, age-cohort, class, or family (McPherson et al. 2001). Residents from communities with strong bonding social capital might choose not to evacuate, because they support each other and share shelter when hazards strike, as scholars documented after Hurricane Matthew (Collins et al. 2017). Similarly, much research suggests that specific communities use their ethnic, religious, and linguistic ties to band together and recover from shocks (Shoji and Murata 2021), as in the case of Hurricane Katrina (Chamlee-Wright and Storr 2009). However, homophilous ties might limit evacuation for problematic reasons. Homophilous ties limit access to diverse sources of information among evacuees. They may not know where to evacuate to or whether, when, and how to evacuate. Some studies, such as Riad et al. (1999), find that people's social ties affected their decision to evacuate after Hurricanes Hugo and Andrew; others have indicated that bonding ties can help residents evacuate (Shoji and Murata 2021), or sometimes help them shelter-in-place and weather the storm (Collins et al. 2017). For example, studying

evacuation after Hurricane Matthew, Collins et al. (2017) found that non-evacuees tended to have tight-knit communities to rely on during storms.

In contrast, bridging social capital describes relationships between people from different social, ethnic, and class groups. Although the average person can keep only so many strong social ties, individuals can amass dozens or hundreds of "weak" bridging relationships of trust and leverage these at key moments to share information or resources, and civic and political associations like parent-teacher associations and advocacy groups help connect individuals in this way (Granovetter 1973, Putnam 2000, Smiley et al. 2018). Studies have observed these outcomes at the individual, neighborhood, and municipal levels in Japan, the U.S., and many others (Aldrich and Crook 2007, Aldrich and Sawada 2015, Ye and Aldrich 2019). Those from communities with stronger bridging ties might see civic associations work together to help evacuate people during a time of crisis. Similarly, Facebook data from users affected by Hurricanes Harvey, Irma, and Maria added further evidence that individuals with stronger bridging and linking ties are more likely to evacuate (Metaxa-Kakavouli et al. 2018).

Linking social capital refers to vertical relationships between community members and authorities (Hawkins and Maurer 2010, Szreter and Woolcock 2004). Localities where local officials are closely embedded in community groups tend to see improvements in public works, better urban planning, and greater responsiveness to community needs, which improves community resilience and recovery when natural hazards strike (Aldrich and Crook 2007, Tsai 2007, Edgington 2010, Aldrich 2012, 2019). Communities with stronger linking ties might see greater responsiveness from community and regional officials, making them less likely to leave. Those officials might be more likely to set up contingencies and direct evacuees to specific, nearby locations. Further, linking social capital might interact with other types of social capital or social vulnerability: When Hurricane Katrina struck New Orleans, members of the Lower Ninth Ward, a disproportionately poor community, were much less likely to evacuate than members of the nearby wealthy and white neighborhood of Lakeview, whose residents could call on their personal networks in other communities and cities for relief and shelter (Elliott et al. 2010).

#### **Hypotheses**

This study hypothesizes that the social capital of residents, particularly their linking social ties, meaningfully affect evacuation after crisis. We make three main hypotheses about the effect of linking social capital. First, we hypothesize that greater linking social ties lead to lower long-distance evacuation rates in a community; we expect this effect persists even after accounting for damage and infrastructure capacity (Boin and McConnell 2007, Petit et al. 2013, Na and Banerjee 2015, Nakai et al. 2016), based on their social vulnerability before and after the disaster (Perry and Lindell 1991, Fothergill et al. 1999, Smith and McCarty 2009), the amount of public goods and services provided by their local governments after the crisis (Bakema et al. 2019), and the community resources available to them through other types of social capital (Szreter and Woolcock 2004, Elliott et al. 2010, Aldrich 2019). Second, we hypothesize that bridging social ties intervene in the effect of linking social ties, helping to spread information throughout diverse groups in a community, which

can either aid local evacuation advisories or hinder them when rumors spread. Third, we hypothesize that the effect of linking and bridging ties persists even among vulnerable communities. Below, we introduce a methodology to test these hypotheses.

## METHODS

This mixed methods study uses new big data sources and interview data from the field to triangulate why some cities saw more long-distance evacuation than others. Our research pairs quantitative and qualitative methods to answer each of our questions. To examine why some communities evacuate away from town more than others, we combine models of aggregate Facebook data with content analysis of in-person interviews and individual case studies. Below, we introduce our data and methods.

### Data

Our analysis focuses on the case of the Eastern Iburi Earthquake, which struck Hokkaido Prefecture on 6 September 2018. The effects of this disaster were varied, with Atsuma and Abira towns near the epicenter suffering the most direct damage, but dozens of municipalities suffering various damages and complications (Hokkaido Eastern Iburi Earthquake Disaster Verification Committee 2019, Zhou et al. 2021). According to Hokkaido prefectural government data recorded at the end of each week in our study, just nine municipalities saw local evacuees utilize municipal shelters, usually because their homes suffered greatly from landslides after the Eastern Iburi Earthquake (Disaster Prevention Group 2018). These communities' evacuation to local shelters is outlined in Figure A1.1.

However, Hokkaido residents outside of these communities were affected as well, leading to hardships that could certainly motivate evacuation beyond the local community. Thirty-three municipalities in Hokkaido reported homes damaged, 15 reported non-residential buildings damaged (Hokkaido Eastern Iburi Earthquake Disaster Verification Committee 2019), 39 reported water outages, from 1 day to up to 20 days (Cabinet Office 2018), and 66 municipalities were cut off from television service (Cabinet Office 2018), which closely overlaps with phone lines (Fire and Disaster Management Agency 2018). Finally, nearly all of Hokkaido was affected for weeks by power outages caused by loss of power from the Atsuma Coal Fired Power Plant (Fraser et al. 2021b). Although regular service was restored quickly within 45 hours to most communities, Atsuma and Abira towns saw continued power service issues for days after (OCCTO 2018).

Our analysis approximates long-distance evacuation behavior based on data from the Facebook Data for Good project, which aggregated data from people using Facebook from computer IP addresses in the disaster zone two weeks prior to the disaster, defining those users as disaster-affected users. Facebook tallied how many of these disaster-affected users left their current municipality and where they went, and aggregated this to the city level. Facebook aggregates information to protect user privacy, and then makes this anonymized data available to specific NGOs and academics for studying and responding to crisis. This study follows a continuous population of users in their movement between 116 cities (34 in Hokkaido and 82 in destinations across Japan) for five weeks, including 3–10 September, 11–17 September, 18–24 September, 25 September–1 October 1, and 2–8 October. Although this study cannot claim external validity to

the entire population, our findings apply to the 40% of Japanese who use Facebook, a considerable section of the population.

### Evacuation levels

First, we investigate why some communities experience more evacuation than others, focusing on 34 cities in Hokkaido affected by the disaster about which Facebook collected data. In 34 cities, more disaster zone users left than came to each city; we examined these 34 cities to explain evacuation per city each week, mapped in Figure 1.

We generated a panel dataset of 170 total city-week observations over 5 weeks. For each city per week, we estimated evacuation by counting how many more or fewer users there were in a city compared to the previous week. We visualize this panel dataset in Figure 2, showing the overall right skewed distribution in panel 2A, that distribution broken down by week in panel 2B, and evacuation rates by city each week as tiles in panel 2C.

### Proxies

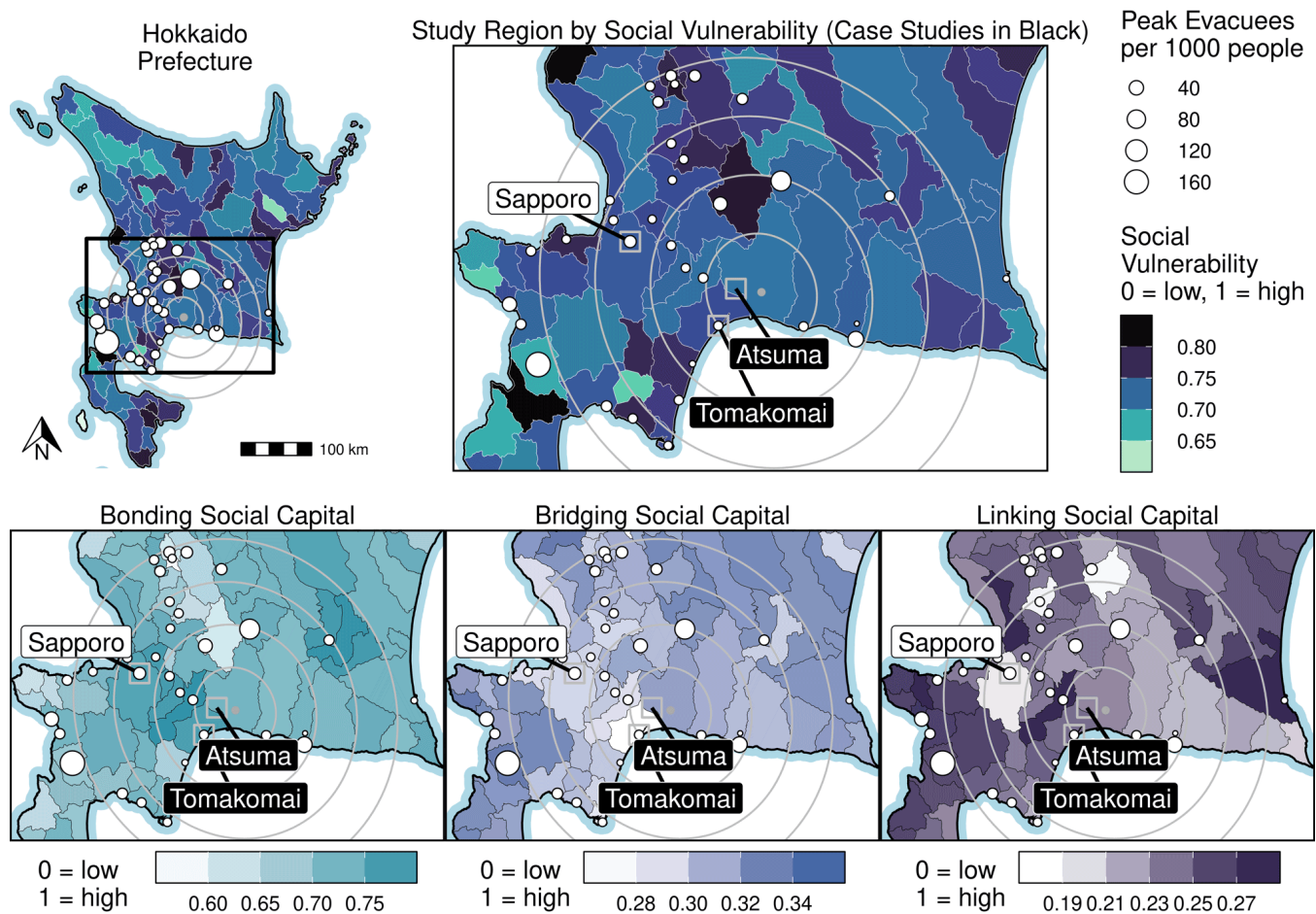
To predict evacuation rates, we used four key variables, followed by several controls. First, to represent social vulnerability and social capital, we use four indices from 2017 constructed from publicly available data at the Japanese municipal level (Fraser 2021) adapted from the Social Vulnerability Index (SoVI; Cutter et al. 2003) and Social Capital Indices (SoCI; Kyne and Aldrich 2020). Each were measured on a scale from 0 (minimum) to 1 (maximum).

The social vulnerability index combines nineteen indicators of vulnerability, measuring how socially vulnerable a town is in terms of 13 key areas, including: (1) race and ethnicity, (2) gender, (3) age, (4) family structure, (5) socioeconomic status, (6) education, (7) mobility, (8) employment loss, (9) employment in vulnerable industries, (10) residential property and rental status, (11) social dependence, (12) medical services and access, and (13) the size of the special-needs population. This index combined indicators using principal component analysis to identify the most salient, important trends of vulnerability in Japanese communities, directly adapting the methods of the oft-used US Social Vulnerability Index (Cutter et al. 2003).

Next, the bonding social capital index measures intra-group connectedness, taking the average of seven proxies that indicate how similar members of a community are in terms of (1) nationality, (2) religion, (3) education levels, (4) employment status, (5) employment levels for men vs. women, (6) age, and (7) communication capacity, drawing on Alesina and colleague's (2003) fractionalization approach to estimating the level of similarity or difference in a community, because bonding social ties are more common among members of the same social strata (McPherson et al. 2001, Lin 2001, Szreter and Woolcock 2004, Dyson 2006, Mouw 2006, Beaudoin 2007, Hawkins and Maurer 2010, Aldrich and Meyer 2015).

The bridging social capital index captures inter-group connectedness, averaging eight measures of cross-cutting associations that build ties across social strata, including rates of (1) community centers, (2) libraries, (3) unions, (4) nonprofits, and (5) religious organizations, supplemented by kinds of civic engagement that build cross-cutting ties, including the (6) volunteer participation rate and voter turnout rates in (7) Prefectural and (8) Lower House elections.

**Fig. 1.** Mapping evacuation and community traits after earthquake. Points depict 34 sites where Facebook recorded evacuation, measured as a net decrease in unique Facebook users from week to week. Rings depict distance from epicenter (25, 50, 75, & 100 km). Polygons depict city and district boundaries, the level at which Facebook data was recorded.



Finally, the linking index captures connections with local and national officials, averaging six measures. Local and prefectural ties were measured with the rate of (1) local and (2) prefectural government employees, (3) prefectural police, and (4) prefectural assembly members per capita. These were supplemented with the share of the vote won by the winning party in the (5) Lower House and (6) prefectural elections, because communities that voted for the winning party are more likely to receive help and support from these officials (Fukui and Fukai 1996, Catalinac et al. 2020).

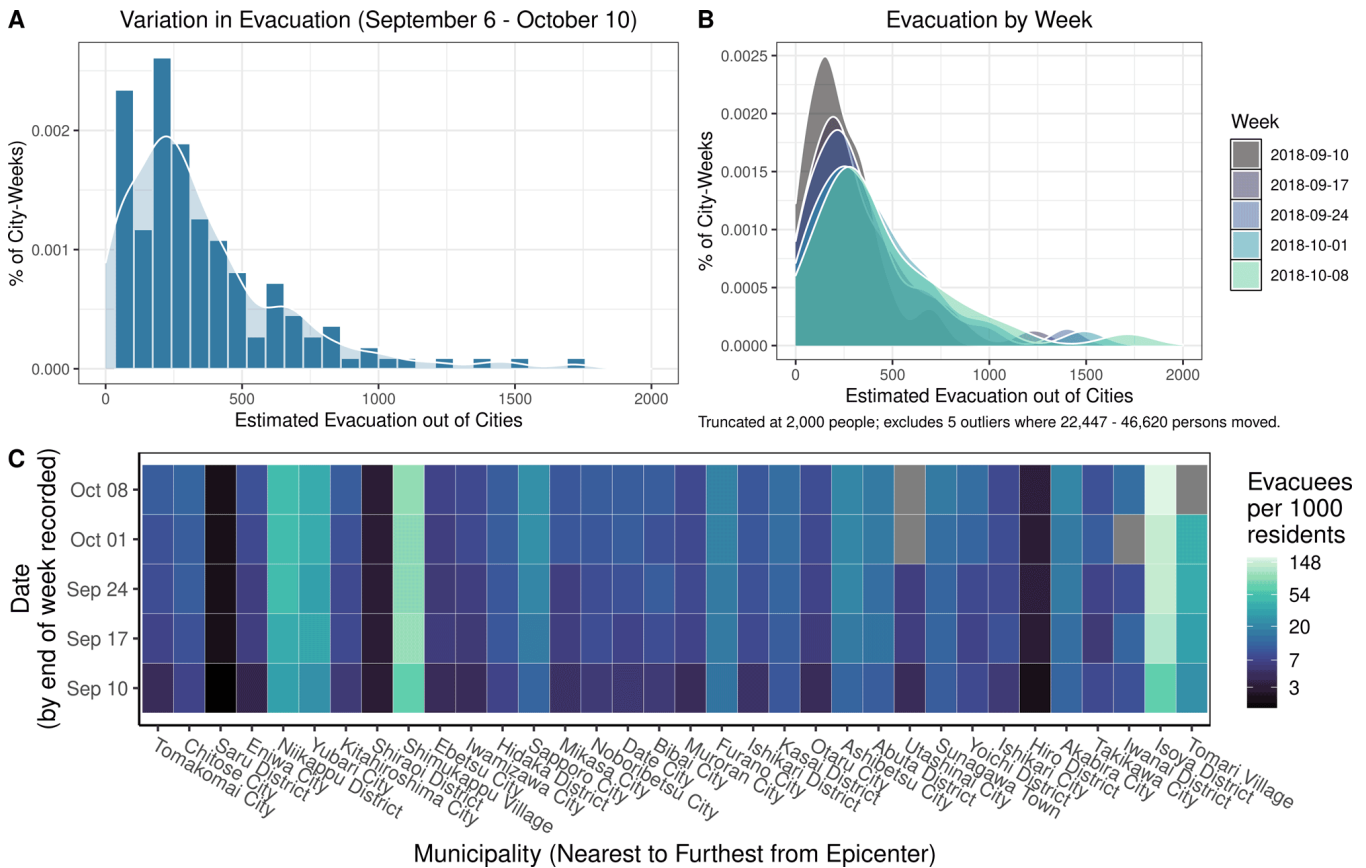
These municipal-level indicators demonstrated high internal and external validity in tests and correctly predicted known correlates including disaster outcomes from Tohoku communities after the 3/11 disaster (see Fraser 2021 for more information). These indices have been applied to study evacuation to location shelters (Fraser et al. 2021a), adaptation to climate change (Fraser et al. 2021b), and community outcomes to the COVID-19 pandemic (Fraser and Aldrich 2021), among other disaster outcomes.

Besides these concepts, we must control for several kinds of public goods and controls for the extent of the earthquake. To represent

the effect of aftershocks on evacuation, we used the Euclidean distance of each city from the epicenter in kilometers (Geospatial Information Authority of Japan 2020). To control for damage, we used the total number of residential and nonresidential buildings per capita damaged or destroyed by the quake (Hokkaido Eastern Iburi Earthquake Disaster Verification Committee 2019). To control for long-term inconveniences posed by the quake, which might motivate population movement, we counted the number of days that water outages caused by the quake persisted in each municipality (Cabinet Office 2018). We also controlled for the number of evacuees who evacuated to shelters within town, instead of leaving town, and stayed there through 20 September (Disaster Prevention Group 2018). This reflects the degree each town relied on local evacuation shelters.

To represent the effect of infrastructure policy, we used the amount of municipal expenditures on public works in thousands of yen per capita in 2016. To represent the effect of disaster-related public goods and services in 2017, we used the amount of municipal spending on fire departments in thousands of yen per capita in 2017, the main source of first responders and emergency

**Fig. 2.** Panel dataset of evacuation rates in 34 recorded municipalities. Four data points shaded grey, because they had zero estimated evacuees; these rates could not be log-transformed.



service providers in each municipality, and the number of public shelters per capita opened to respond to the Eastern Iwate Earthquake. This number includes community centers, public libraries, and elementary schools, middle schools, and high schools. Finally, to account for the effect of government capacity, we used the ratio of revenues to expenditures in 2016. These municipal statistics were derived from the Japanese census (Statistics Bureau 2020). We provide descriptive statistics for all variables in our analysis in Appendix 1, Table A1.1.

**Models**

This study used a series of models to estimate the effect of social capital on evacuation between cities, controlling for damage and infrastructure quality, risk and vulnerability, and quality of public goods provision. First, we ran a basic ordinary least squares (OLS) model of evacuation rates per 1000 residents between cities, log-transforming the outcome to account for its strong right skew common among rates. We tested the effect of bonding, bridging, and linking social capital, with two simple controls, including social vulnerability and distance from the epicenter (Table A1.2, Model 1A). Each model included weekly fixed effects to account for variation in evacuation over time. Then, we added the full battery of controls (Table A1.2, Model 1B). As a robustness check, we focused on effects that reported the same consistent direction of effect when modeled with simple vs. full controls. This model

with full controls explained as high as 63% of the variation in logged long-distance evacuation rates among Facebook users, as indicated by the R<sup>2</sup> statistic. Our basic model found that linking social capital had a strong negative effect on evacuation rates, as discussed further in the results.

Second, to contextualize the negative effect of linking social capital, we applied interaction effects in a subsequent model: We applied one interaction effect between linking and bridging social capital, to identify whether communities with stronger bridging and linking ties see different levels of evacuation than those with simply strong linking ties alone. We added this interaction to our model with simple control (Table A1.2, Model 2A) as well as our fully specified model (Table A1.2, Model 2B). Likelihood ratio tests in Figure A1.3 demonstrate that the inclusion of these terms led to statistically significant improvements in the model's fit, as demonstrated by a statistically significant chi-squared statistic in both cases ( $p < 0.05$ ). Likelihood ratio tests also indicated that the final model fit better than when including supplemental interactions, and that the fully specified model with one interaction (Model 2B in Table A1.2) fit best of all models in Table A1.2. (Other potential configurations of interaction effects, like linking social capital and vulnerability, or three-way interaction effects, did not consistently improve model fit, so we do not discuss them further.) We adopted these limited interactions, rather than

testing the effects of many different types of interactions, so as to create the most parsimonious explanation possible based in theory without overfitting our model, which had just 170 observations.

The data contained two main outliers: The first was Isoya-gun, which experienced the four highest weekly evacuees per capita (118, 129, 140, and 169); the next highest weekly tally was Shimukappu-mura, much lower at 99 evacuees. We repeated our models excluding Isoya-gun and Shimukappu-mura in Table A1.2 Models 3A through 4B, revealing no major differences. Simulations, discussed below, showed the same trends as well, even after excluding outliers (see Figure A1.2).

No models suffered from multicollinearity, as indicated by all variance inflation factor (VIF) scores remaining below 10, the threshold for problematic collinearity, and close to 2.5, the gold standard. The correlation matrices for these variables are highlighted in Figure A1.3, and we provide bivariate scatterplots to support our basic model and interaction model in Figure A1.4. (Our interaction models demonstrated some structural collinearity, which is natural for interaction models, because they literally involve correlated variables). To compare effect sizes across variables, we rescaled all predictors from 1 (minimum) to 10 (maximum).<sup>[1]</sup>

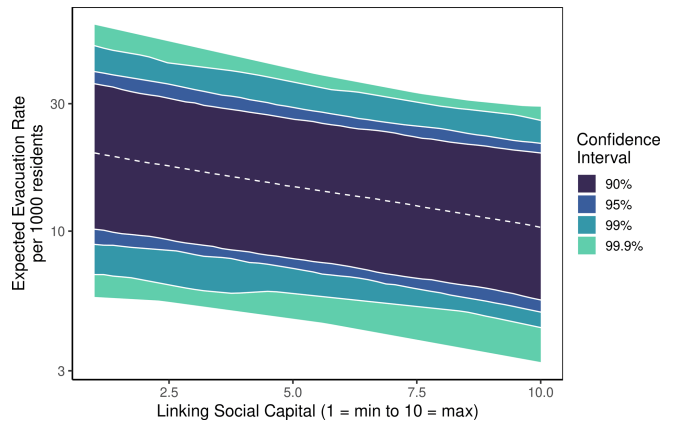
### Statistical simulations

Finally, we relied on statistical simulations in the *Zelig* package in R from our models in Table A1.2 to test our three hypotheses (Choirat et al. 2017). Although past studies used beta coefficients and odds ratios to report results from regression models, these estimated effects tend to be difficult to interpret when using one or more interaction effects or when using a logged outcome variable. Instead, similar to the tradition of predicted probabilities and marginal effects, we estimated median expected evacuation rates simulated from a given model equation at various levels of confidence (90, 95, 99, and 99.9%), based on a set of supplied city traits. These simulations are not *new* models, but instead are direct byproducts from the fully specified models created above in Models 1B and 2B. These expected evacuation rates each rely on 1000 simulations from a multivariate normal distribution in the *Zelig* package to account for estimation uncertainty and fundamental uncertainty. For an in-depth discussion of statistical simulation and related works, see Appendix 2. In the results, we simulate effects for our fully specified Models 1B and 2B from Table A1.2. In Table A1.2, we show that our coefficients for models with just basic controls (Models 1A and 2A in Table A1.2) show nearly identical trends.

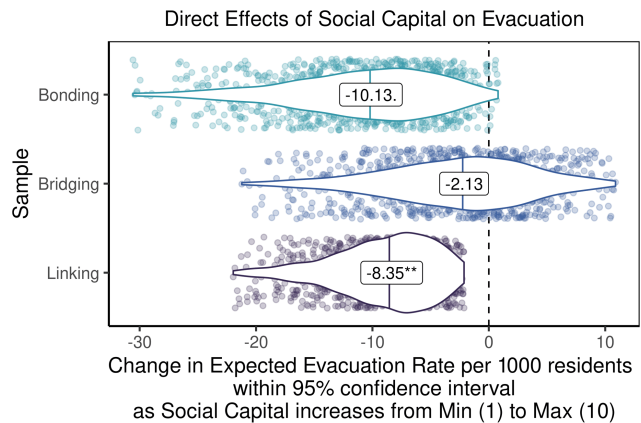
We simulated how much evacuation rates change as one predictor increases, e.g., linking social capital, in an average city, by holding all other predictors constant at their means (or for categorical variables, their modes). To test our first hypothesis, that (H1) linking ties boost evacuation, we simulated expected evacuation rates using our fully specified basic model (Model 1B), varying just linking social capital from min (1) to max (10), while holding all other types of social capital at their minimum (1). We present this simulation in Figure 3. Then, to demonstrate the importance of linking ties over other types of social capital, we compare these against simulations just varying bridging social capital from min (1) to max (10), then just bonding social capital from min (1) to max (10). We present the difference in evacuation in a city with

maximum social capital compared to minimum social capital of each specified type in Figure 4.

**Fig. 3.** Effect of linking social capital on evacuation rates. Depicts confidence intervals at multiple levels composed from 1000 statistical simulations in the *Zelig* package in R. Dashed lined depicts median expected value.



**Fig. 4.** Direct effect of social capital on long-distance evacuation rates. Statistical significance shown by stars: \*\*\* =  $p < 0.001$ , \*\* =  $p < 0.01$ , \* =  $p < 0.05$ , . =  $p < 0.10$ .



To test our second hypothesis, that (H2) cities with strong bridging and linking ties see greater evacuation, we simulated expected evacuation rates using our fully specified interaction model (Model 2B); here, we increased both bridging social capital and linking social capital from min (1) to max (10) at the same time. This shows the interaction effect, where a city with minimum bridging and linking ties has a certain level of evacuation, but a city with maximum bridging and linking ties has a different level of evacuation. These simulations are presented in Figure 4.

To test our third hypothesis, that the (H3) effect of bridging and linking ties persists in both highly vulnerable cities and less vulnerable cities, we used the same fully specified interaction mode (Model 2B). This time, we increased both bridging and linking social capital from min (1) to max (10), but held vulnerability at

its minimum (1) to simulate changing evacuation levels in a less-vulnerable-but-otherwise-average city. Then, in a second panel, we repeated this process but held vulnerability at its maximum (10) to simulate changing evacuation levels in a highly-vulnerable-but-otherwise-average city. We used this approach, rather than creating a three-way-interaction model, because likelihood ratio tests in Appendix 1 found that our bridging and linking interaction model fit best of all possible models.

### Qualitative analysis

Finally, to contextualize these findings, we selected case studies based on the logic of nested analysis, a common technique for mixed methods analysis developed by Evan Lieberman (2005). In nested analysis, researchers test theories using Large-N analysis (our models), and then demonstrate how and why the causal mechanism found in the models leads to the outcome using an “on-the-line” emblematic case well-predicted or emblematic of the trends found in the model. Then, researchers select an “off-the-line” case diverging from the model’s trends to investigate short-comings of the model and build theory for future work. We selected two municipalities, an emblematic case of Tomakomai and an off-the-line case of Atsuma, and conducted interviews in the field in December 2019, collecting 12 interviews from residents and local officials. We then performed qualitative content analysis on interview transcripts, grouping responses into common themes to develop case studies. This process is outlined in the discussion section, where we present case studies. These case studies help illustrate how social capital shaped evacuation between cities.

## RESULTS

### Why some cities evacuate more than others

We modeled whether social capital explained evacuation per capita better than social vulnerability, public goods provision, damages, or time using a logged ordinary least squares regression model on 170 city-week observations of Facebook user movement, giving a high detail approximation of post-earthquake movement.

To test our first hypothesis, that (H1) linking social capital boost evacuation, we examined the direct effects of types of social capital on long-distance evacuation. Because beta coefficients from a logged outcome can be difficult to interpret directly, we used statistical simulation in the *Zelig* package in R (King et al. 2000, Choirat et al. 2017), simulating the change in expected evacuation rates for a community with weak social capital vs. strong social capital. To make meaningful projections for an average city, all simulations below were calculated based on 1000 simulations from the fully specified model for the first week after the disaster (ending in 10 September). All other variables were held at their means.

Figure 3 visualizes the direct effect of linking social capital, simulating evacuation rates for an average city in the first week given the minimum observed levels of bonding, bridging, and linking social capital in our 34 cities. As the level of linking social capital increases from its min (1) to max (10), the average city sees their expected evacuation rate decrease from 2.95 to 2.34 per 1000 residents.

Figure 4 compares the direct simulated effects of each type of social capital in the fully specified model in Table A1.2. Here, the

x-axis shows how many more (+) or fewer (-) evacuees our models projected in an average city, given an increase in the specified type of social capital from their minimum (1) to maximum (10) level. First, we found that towns with more bonding and bridging social capital saw slightly less evacuation, but these effects were not significant at conventional levels, as indicated by how their simulated 95% confidence intervals cross the dashed line at zero. However, linking social capital, a frequent correlate of trust in government, was strongly related to evacuation. We find that towns with more linking social capital saw a median of 8.35 fewer evacuees per 1000 residents leave town. This difference is statistically significant beneath the  $p < 0.01$  level. This effect remains consistent with simple controls (beta = -0.09,  $p < 0.01$ , Model 1A) and the full battery of controls (beta = -0.07,  $p < 0.05$ , Model 1B). After removing outliers, the effect dips slightly, significant just for a one-tailed test (beta = -0.04,  $p < 0.10$ , Model 3B), but still quite meaningfully large. This led us to investigate our interaction models below, which produce consistent significant effects.

However, past literature suggests that bridging ties can help spread information faster through communities and across diverse groups of people (Granovetter 1973), potentially shaping who learns about evacuation shelters or government advisories. In turn, residents who trust in government with stronger linking ties might be more likely to adjust their behavior accordingly.

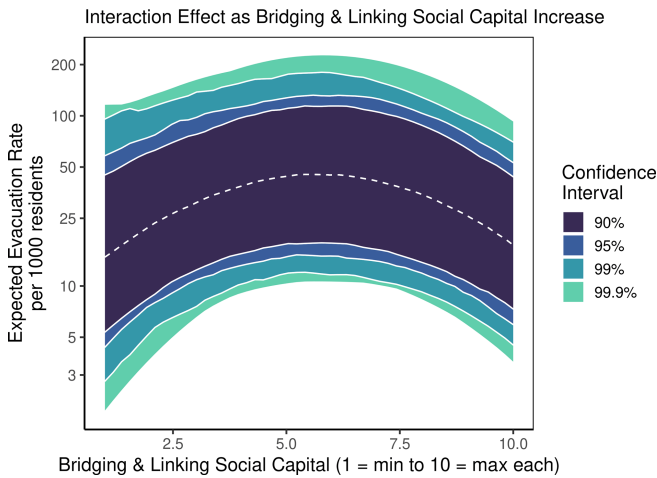
To test our second hypothesis, that (H2) bridging and linking ties together boost evacuation, we tested the effect of communities with stronger linking and bridging social capital using our interaction model. This revealed a negative interaction effect on evacuation (beta = 0.05,  $p < 0.01$ , Model 2B). This was consistent with outliers removed (Model 4B). Our simulations contextualize this effect, revealing a more nuanced story. In Figure 5, we simulated evacuation rates for an average city with the same constraints, assuming weak levels of bonding, bridging, and linking social capital and vulnerability using the minimum levels in our sample, and then varied the levels of bridging and linking social capital from their minimums to their maximums.

Figure 5 reveals a curious trend. Compared to towns with weak bridging and linking social capital (1), towns with middling bridging and linking social capital (5) saw more evacuees. However, as the level of bridging and linking ties increased further, the evacuation rate crested and they tended to see fewer and fewer evacuees. In other words, bridging and linking social ties can have a nonlinear, curvilinear effect.

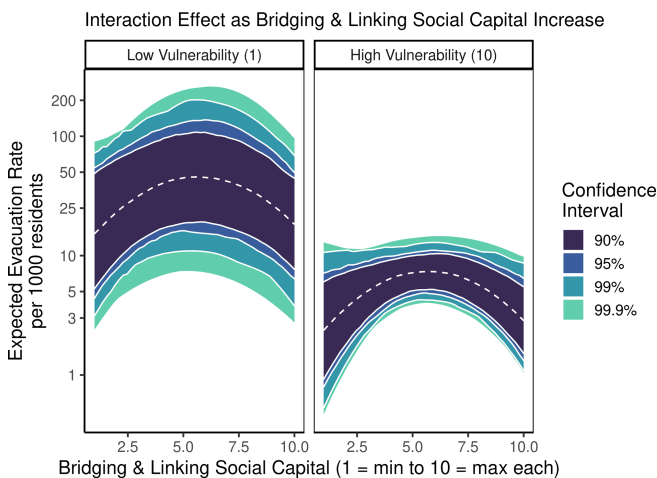
Finally, to test our third hypothesis, that (H3) bridging and linking ties’ effect persists in both highly vulnerable and less vulnerable cities, we repeated our simulation from Figure 5, but for average cities with high vs. low levels of vulnerability, seen in Figure 6. In the left panel, we see that for an average city with low social vulnerability (represented by the minimum value of 1), our model projects the same curvilinear trend, but much higher overall levels of evacuation, reaching as high as 200 evacuees per 1000 residents. In contrast, in the right panel, we see that for an average city with high social vulnerability (represented by a maximum value of 10), our model projects the same curvilinear trend, but much lower overall evacuation rates, reaching just over 10 evacuees per 1000 residents.



**Fig. 5.** Interaction effect of bridging and linking ties on evacuation. Panel depicts confidence intervals at multiple levels composed from 1000 statistical simulations in the Zelig package in R. Dashed line indicates median expected value. Simulation calculated by increasing both bridging and linking social capital together at the same time from minimum (1) to maximum (10), holding all else constant.



**Fig. 6.** Social capital's effect on evacuation consistent in more and less vulnerable cities. Each panel depicts confidence intervals at multiple levels composed from 1000 statistical simulations in the Zelig package in R. Dashed lines depict median expected value. Repeats simulation strategy from Figure 5, increasing bridging and linking social capital from minimum (1) to maximum (10), except for one difference: left panel calculated holding social vulnerability at its minimum (1). Right panel calculated holding social vulnerability at its maximum (10).



**Evacuation pathways**

Our findings above highlight that communities with the greatest linking and bridging ties, especially vulnerable communities,

tended to leave town less, while less vulnerable towns with similarly high social capital tended to leave town more after crisis. To contextualize these findings, we visualized where these residents tended to go by analyzing city-pair data we received from Facebook. In addition to 34 cities in Hokkaido, we also received data on 82 cities outside of Hokkaido which received evacuees from these 34 affected communities, totaling 116 cities. For each of these 116 cities, Facebook reported each week up to three cities that were top sources of new users from the disaster zone during that week. This means, for example, that if Tomakomai, Chitose, and Yubari were the top three sources of disaster-zone users who moved to Sapporo in a given week, that we might know at best that 75% of those users came from Tomakomai, 15% from Chitose, and 10% from Yubari. This data is powerful but limited. We simplified the data into a binary format, describing whether or not (1 vs. 0) a city was among the top three source cities for a destination at any point during the five weeks after the disaster. It describes the diversity of sources and destinations between which a large number of disaster zone users traveled.

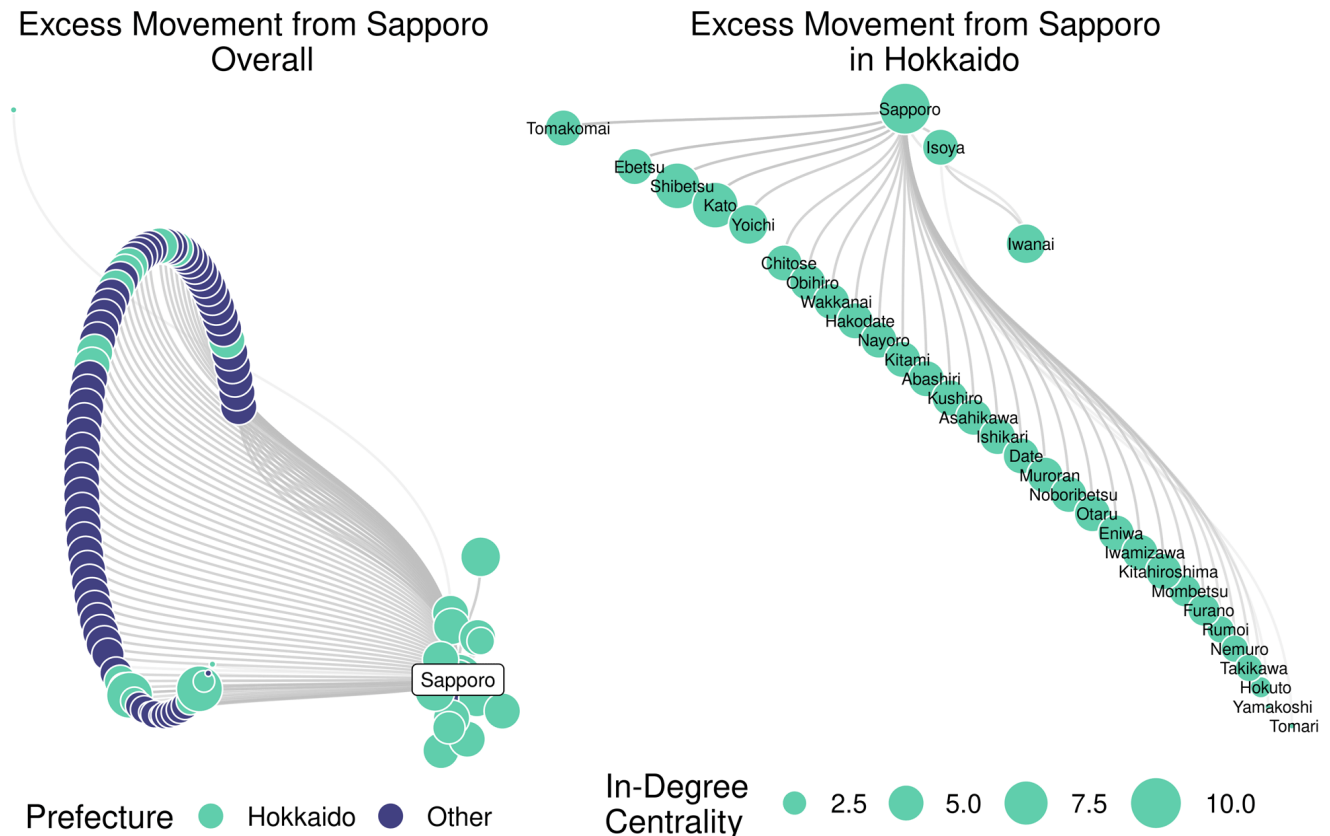
In Figure 7, we visualize which city pairs shared evacuees. In the left panel, we see that the most common source of people exiting the prefecture was Sapporo, the main end destination of the Japan Rail East bullet trains and the major metropolitan area of Hokkaido. This is surprising at first considering that the airport via which most would fly is actually in Chitose, not Sapporo; that airport was temporarily closed after the quake. Notably, Sapporo has a middling social vulnerability index score (5.3 on a scale from 1 to 10 of the 34 communities assessed); the concentration of wealth, transit, and lower levels of damage may have made it easier for residents to leave.

In the right panel, we see that within Hokkaido cities, Sapporo was also the top source city for Hokkaido Facebook users moving between cities after the quake. In other words, nearly all routes passed through Sapporo. We might expect that bridging and linking ties facilitated resident egress in Sapporo and similarly less vulnerable communities, whereas in more vulnerable communities, they helped residents band together, get out the word about local shelter access, and maintain community cohesion after crisis.

**CASE STUDIES**

To better understand why residents chose to stay or leave town after crisis, we applied Lieberman's (2005) model of nested analysis to further investigate two communities that (1) demonstrate or (2) diverge from the trends found in our Large-N analysis. We investigated Tomakomai City, the largest city in Iburi subprefecture, located 25 kilometers from the epicenter, as an emblematic case where social capital and vulnerability shaped evacuation rates. Then, we investigated Atsuma Town, a community located near the epicenter which suffered prolonged blackouts, as a divergent case that our models could not cover where social capital might have triggered different types of evacuation behavior. To investigate these cases, we conducted interviews in the field to learn more about residents' experiences. In December 2019, we conducted 12 interviews with local officials, NGO representatives, first responders, and residents in these two communities. We used neither a random sample nor an exhaustive sample of many types of residents, because this topic remained

**Fig. 7.** Evacuation pathways. (Left Panel) Over five weeks, Sapporo was the top source for users going to 96 unique cities, and a destination for users from two unique cities. Made using a Kamada-Kawai layout. (Right panel) Over five weeks, Hokkaido cities most often nominated Sapporo as their top source city. Made using a fabric layout.



**Table 1.** Interview respondents.

Respondent	Age	Gender	Role	Community
Mr. M	50s	M	Firefighter	Atsuma
Mr. I	50s	M	Firefighter / Paramedic	Mukawa
Mr. K	40s	M	Local Official - Town Development	Atsuma
Mr. A	50s	M	Local Official - Town Development	Atsuma
Mr. T	40s	M	Local Official - Crisis Management Unit	Tomakomai
Mrs. S	40s	F	Fish Market/Restaurant Staff	Tomakomai
Mrs. H	70s	F	Crafts Store Employee	Tomakomai
Mrs. Y	80s	F	Stationary Store Owner	Atsuma
Mrs. U	50s	F	Flower Shop Owner	Atsuma
Mr. O	50s	M	Coffee Shop Owner	Tomakomai
Mr. N	60s	M	Construction Association Officer	Tomakomai
Mr. W	40s	M	Construction Association Employee	Tomakomai

sensitive for residents who had lost much, but our small sample highlighted a diversity of experiences nonetheless. These interviewees' traits are summarized in Table 1, and cover a range of ages, local businesses, local officials, and first responders. Below, we applied content analysis on these interview transcripts, summarized in Table 2.

**Content analysis**

First, we tabulated how often interview respondents discussed certain key themes in their interviews, highlighting distinctions between themes discussed in Atsuma vs. Tomakomai. We transcribed interviews from Japanese and coded how often keywords related to 10 specific themes occurred among our 12 interviews.

Our content analysis highlighted three main themes that played a role in people's decision on whether or not to evacuate: community resources, water, and damage to the home. Six out of 12 people mentioned access to water in their interviews.

Atsuma saw frequent mentions of neighbors and family, indicating the importance of community resources like social ties, as well as concern above water and power outages. Although 67% discussed evacuating, the same proportion reported going to an evacuation shelter, meaning they primarily thought of evacuation to nearby locations.

According to the stories collected through this interview process, some Tomakomai residents evacuated to local shelters as a precautionary measure. However, none of the people interviewed in Tomakomai left town. All respondents responded that they themselves, or someone in their family had started cleaning up fallen items and furniture when they confirmed that there was no

**Table 2.** Content analysis of interviews.

Theme	Keywords	Frequency by Percentage (Respondents)		
		Atsuma Town	Tomakomai City	Total
Evacuation	Evacuation, evacuee, evacuated	67% (4)	17% (2)	50% (6)
Didn't Evacuate	Didn't evacuate, did not evacuate	33% (2)	100% (6)	67% (8)
Shelters	Shelter, housing, temporary	67% (4)	8% (1)	42% (5)
Mobility	Car, train, Japan Railways, road, drive, drove, went	67% (4)	50% (3)	58% (7)
Elderly	Elderly, mother, mom, father, dad, grand-, older	83% (5)	25% (3)	67% (8)
Community Resources	Neighbor, friend, family, kids, father, mother, sibling, sister, brother, daughter, son, wife, husband	100% (6)	83% (5)	92% (11)
Water	Water, faucet	50% (3)	50% (3)	50% (6)
Electricity	Electricity, electric, blackout, light, power	33% (2)	66% (4)	50% (6)
Social Media	Social media, social networking sites, social network, Twitter, Facebook, rumor	17% (1)	25% (3)	33% (4)
Technology	Smartphone, TV, radio, phone	33% (2)	25% (3)	42% (5)
Total		100% (6)	100% (6)	100% (12)

tsunami threat. For most, the earthquake caused more inconveniences than major challenges. The earthquake destroyed 479 and damaged 1736 buildings in Hokkaido but only five damaged homes and 2 out of 44 deaths were in Tomakomai.

Instead, according to Atsuma residents we interviewed, the physical state of the house and lack of water were key reasons that they evacuated. A firefighter from Atsuma recalled how unstable, porous grounds and landslides had caused four families in his neighborhood to evacuate because of their homes being completely destroyed. However, most of the reported cases of evacuees from Tomakomai seemed to be driven by precautionary measures such as fear of aftershocks, rumored and possible water shortages, and power outages. As previously noted, evacuees in evacuation shelters peaked at around 450 people the night after the earthquake and gradually decreased over the next few days.

Finally, respondents from both communities discussed the importance of social media and technology in sharing information after the crisis. Several residents reported hearing sensational reports via social media about the extent of the crisis. These made long-distance evacuation seem necessary even when local evacuation shelters were available. These sensational reports may have also boosted long-distance evacuation in communities less affected by the crisis, even though the crisis was highly localized to Atsuma and Abira towns. These interviews suggest that stronger linking and bridging ties enabled residents to share higher quality information about the crisis and availability of local shelters. Meanwhile, communities with weaker linking and bridging ties struggled to obtain good information, leading their residents to evacuate long-distance to other towns.

**Emblematic vs. divergent case studies**

Below, we turn to two qualitative case studies at the individual level, telling the stories of two residents to demonstrate how social capital and vulnerability altered residents' decisions about evacuation in Atsuma Town and Tomakomai City.

As discussed above, our research design followed an iterative process. We began with qualitative interviews in the field, to build an understanding of what variables mattered and what did not,

and then built models to test our hypotheses. Although the number of interviews collected was small, scholars like Lieberman (2005) and Schatz (2009) have highlighted that even a single interview can shed light on a pattern otherwise invisible from the outside.

That was certainly the case in Tomakomai and Atsuma, respectively. In Tomakomai, Mr. T's observations brought to light how rumors (and correspondingly trust in government messaging) shaped evacuation, emblematic of our large-N findings. Meanwhile, in Atsuma, Mr. K's observations highlighted how this trend was less relevant in the community most affected by the disaster, where close bonding ties played a greater role in reducing evacuation. We then verified whether those patterns occurred using our quantitative models, the most appropriate method for large-N trend detection.

**Emblematic case study: Tomakomai City official: SMS and the spread of rumors**

First, we examine the emblematic case of Tomakomai City, located 25 kilometers from the epicenter, which demonstrates well the trends found in our models about linking social capital and evacuation. We follow the experiences of Mr. T, a Tomakomai City official from the city's Crisis Management Office, to demonstrate how damage, false information, and community resources affected his family's decision to evacuate.

Mr. T, his wife, and two sons were awakened by a sudden, violent shake in the early hours of dawn. "I was sleeping and then felt a 'BOOM' and I woke up immediately ... It came so suddenly! ... I was actually very worried about my house, I didn't know if it could withstand the earthquake." Once the shaking stopped, Mr. T scrambled to turn on the lights to assess the damage, and after two short minutes of brightness, they plunged into the darkness once again.

However, Mr. T had no time to waste. Within 10 minutes of being woken up he drove into the darkness and by 3:40 AM he was at work, at the Tomakomai City Crisis Management Office. "We are the ones who have to collect information regarding the disasters that are happening in Tomakomai and inform our citizens. [As I

was driving] I didn't know anything about the earthquake and I worried about a tsunami." This looming sense of uncertainty was felt throughout Hokkaido, and rumors soon overwhelmed social media. "Rumors started spreading through SNS (social networking sites). There were rumors that there wasn't going to be any running water, [p]ossibilities of aftershocks. Of course, we addressed these concerns but in these kinds of situations, it's easy to believe [rumors] because earthquakes, unlike typhoons, you can't predict." Mr. T indicated that these social media hoaxes about water shortages and aftershocks spread quickly, boosting evacuation to shelters (and, as our models show, to other towns). Although the number of evacuees at shelters nearby peaked at 942 a few hours after the earthquake, it decreased until 8 September at 10:00 PM, when it spiked to 250 people, a jump from 80 people just that afternoon (3:00 PM).

As for Mr. T's family, they stayed home after the earthquake and returned to normalcy fairly quickly. Their close ties to local government gave them trust in local government messages, and assured them that the blackout was only temporary. "Since it was just a blackout, we were able to go about our daily lives. It was also the beginning of September, so the [temperature] wasn't very cold. I don't know what we would have done if it was around [December]."

In summary, Mr. T's experience after the quake highlights how some Tomakomai residents chose not to evacuate because their water and electricity supply was only temporarily affected, and their trust in government messaging helped assure them that the crisis would soon end. However, rumors and false information on social media greatly affected residents' evacuation decisions. Because there was a lack of information, access to TV, or internet, residents turned to various sources for information. This encouraged the spread of false information; respondents mentioned that some residents evacuated when they did not have to because of this false information, helping explain larger long-distance evacuation rates than this kind of localized disaster would usually cause.

In this way, strong linking social ties and the trust in government they impart were critical to avoiding unnecessary long-distance evacuation, while bridging information networks and the rumor mill they enabled proved problematic, encouraging unnecessary evacuation.

#### **Divergent case study: Atsuma Town**

Second, we examine the divergent case of Atsuma Town, located very close to the epicenter and heavily damaged in the quake. Atsuma Town was not modeled in this study, as discussed further in the limitations, because we found no documented Facebook users who evacuated long-distance from here; indeed, the community faced blackouts, damage, and considerable short-distance evacuation to local shelters. Atsuma represents a divergent case, heavily affected by the quake, unlike other communities studied, where other factors might explain the dearth of long-distance evacuation. We follow the experiences of Mr. K, a town official at Atsuma Town Hall, whose account demonstrates how sense of community and shared experience affected his family's decision to evacuate to a local shelter, rather than evacuate away from Atsuma.

Mr. K found out that the violent movements of the earthquake had partially destroyed his home, just three years old since

construction. "We didn't have water ... we didn't have electricity. We couldn't get a lot of information ... We couldn't watch TV ... so I told my family to evacuate," he said. "I only felt anger," he said about the earthquake, and the unfairness of what had transpired. For two weeks, Mr. K's wife and four children, ages ranging from a few months to 12 years old, lived in an evacuation shelter behind Mr. K's workplace, while Mr. K himself slept in his workplace. "The area that I live in didn't have water for around 3 weeks ... Even after we evacuated, his diapers needed to be changed, his bottles needed to be sterilized, and there was no water."

After a week, the family was able to get a camping car-like trailer, but at no stage did they consider leaving Atsuma. This was primarily because of their attachment to the community in Atsuma. Unlike most of Atsuma's residents, neither Mr. K nor his wife are from Atsuma. The family had moved to the town just eight years prior. However, they already had a strong sense of belonging and connection to the town. "My wife's home town is Asahikawa, which is up north ... [I]f we were to evacuate to Asahikawa... [w]e wouldn't know about Atsuma's situation ... I think that if we left it would have been hard to find people to sympathize and empathize with mutually ... especially with this disaster. There aren't that many people who were affected by this earthquake to [the degree that Atsuma] did." Atsuma, a town of 4700 people, lost 36 people, nearly 0.77% of its population.

Furthermore, Mr. K highlighted the close ties that the people of Atsuma have to each other. "Most people in this town know someone who died that day. This is a pretty close-knit town and so we lost people who were close to us. That shock, emotional shock, was pretty big to all of us."

The shock and the novelty of this disaster seemed to lead people to seek understanding, connections and sympathy from those around them. Mr. K responded, "Even though this disaster may not have been like others in Japan, to a small town like us, it was extremely devastating." The highly local impact of this quake actually encouraged residents to stay and evacuate to local shelters, rather than leave town. According to Mr. K, "People outside don't know what truly happened around here. The media can only show some parts of it, so they wouldn't understand. We'd much rather be around friends and people we're close to ... [e]ven though it may be more inconvenient to stay here." Mr. K's experience suggests that bonding ties to friends were more responsible for the dearth of evacuation in Atsuma. This differs from the patterns overserved at large, where we found that linking ties, as shown through trust in government and combating misinformation, encouraged people not to evacuate. Mr. K's story suggests that community cohesion might be especially valuable in heavily affected areas.

In summary, the case of Atsuma shows us that evacuation out of a town occurs as a last resort, not a first resort, even in the communities most heavily damaged and affected by disaster. People generally do not want to leave their homes, communities, and valuables. Only extreme conditions lead individuals to change their patterns of movement between cities, as observed in our models above. Mr. K and his family stayed local because they learned about the evacuation shelters located behind his workplace, and because of the shared support they received from different members of the community. This too points toward the important role of information sharing, which strong bridging

social capital helps facilitate, and the importance of trust in local officials' directives, which linking social ties facilitate. In other words, though a divergent case whose experiences diverge from the rest of our data, the case of Atsuma demonstrates again that, especially for a vulnerable community, bridging and linking social networks are key assets to encouraging residents to stay local rather than evacuate long-distance and leave town.

## DISCUSSION

This mixed methods study has investigated long-distance evacuation, analyzing why some communities see more people leave town when disaster strikes than others. We found three main results. First, we find that the level of social capital in communities greatly impacted the degree to which residents evacuated long-distance to other towns after the Eastern Iburi Earthquake. Although studies of storm evacuation suggest that stronger social capital, especially bridging and linking ties, boost evacuation, our results showed opposite effects for linking capital, and little evidence for bonding or bridging capital (Metaxa-Kakavouli et al. 2018).

Our initial models showed that towns with stronger linking social capital see fewer people leave town after crisis. Past studies help explain why, finding that towns with strong linking social capital tend to evacuate more to local shelters, staying in town (Fraser et al. 2021a). Meanwhile, our two-way interaction models refined that association to reveal that towns with stronger bridging and linking ties experience a curvilinear relationship with evacuation, leading to an early peak followed by successively lower levels of evacuation. This differs from past studies, which primarily found linear trends but did not explore interactions (Collins et al. 2018, Metaxa-Kakavouli et al. 2018). However, this difference is quite explainable. While in storms, residents may rely on help from neighbors or signals from local officials to evacuate; after sudden crises like earthquakes, neighbors who band together or request resources from local officials might be more able to stay than those who cannot access those community resources.

The communities most affected were small, rural towns, and these communities saw large amounts of local, short-distance evacuation to shelters. We can extrapolate that residents from communities with stronger linking social capital learned about the efforts of their local officials and the availability of local shelters, while those with weaker social capital might have had trouble accessing that information and instead chose to leave town.

Second, our three-way interaction models reveal that wealthier, less vulnerable communities like Sapporo see much greater population egress after crisis, perhaps because these resources allow them to do so, while more vulnerable, economically distressed towns like those in Iburi district see a peak in evacuation followed by less and less evacuation given stronger bridging and linking social ties. This may reflect how facing vulnerability after crisis, bridging and linking ties help residents connect, conserve, and share resources (Nakagawa and Shaw 2003, Hawkins and Maurer 2010, Aldrich 2012, 2019), leading them to stay local, whereas in less vulnerable communities, residents may use their bridging and linking ties to identify an exit strategy. This matches with past studies of evacuation after Hurricane Katrina, which found that wealthier communities used their ties to find places to stay out of town (Elliott et al. 2010).

Finally, this study comes with some limitations. Facebook regularly measures the movement of users during crises involving earthquakes, storms, and fires, even including those that lead to blackouts. A blackout, if prolonged, could lead to gaps in data. However, the following conditions give us confidence that our data is unaffected by the blackouts: First, it took just 45 hours to restore power to the Hokkaido Electric service area (OCCTO 2018). Second, Facebook measured movement between municipalities each week; even if someone left Atsuma during this time for Sapporo, as long as they checked Facebook using their cell phone or a computer at some point that week in their new location, then their movement was counted. Third, even during power outages, anecdotal accounts indicate that residents formed lines at city hall buildings and sites with generators to charge their mobile phones (CBS 2018). Finally, if blackouts affected this data, we would expect to see entire gaps in movement data across the whole prefecture. This was not the case.

Additionally, our large-N models examined communities where any evacuation of Facebook users was recorded, but not communities where no evacuation was recorded during this period, because this difference indicated that these were likely qualitatively different cases. This excluded far-flung destinations. For example, in the study region, Soya District, with low vulnerability but high evacuation, was neighbored by Sutttsu District, a highly vulnerable community, but no evacuation was recorded. (Both municipalities are located in the lower left of the study region mapped in Figure 1). Sutttsu District was one such community located far from the epicenter whose evacuation, if there was any, was not picked up by Facebook. This also includes one notable case near the epicenter, Atsuma, our divergent case itself. Atsuma did not show any evacuation of Facebook users, likely because some roads were affected, local shelters absorbed potential evacuees through short-distance evacuation, and blackouts were more frequent there. Further, other studies indicate that Atsuma saw primarily short-distance evacuation (Fraser et al. 2021a). As a result, Atsuma and similar communities showing no evacuees after this major earthquake were qualitatively different, and so this analysis focused only on communities that did demonstrate long-distance evacuation. Future studies should examine triggers of short-distance evacuation in greater detail.

## CONCLUSION

Using a new dataset of long-distance evacuation between towns from geolocated, aggregated Facebook user movement, this mixed-methods study examined why some communities saw higher evacuation rates than others. Modeling 170 city-week observations, we found that communities with stronger linking social capital tended to see much lower evacuation rates than communities with weaker linking ties, even after accounting for vulnerability, public goods provision, damage, and infrastructure quality. This was especially the case for communities with stronger linking and bridging ties, and even those with high vulnerability. We also found that vulnerability impacts this trend, where less vulnerable communities see more evacuation, but more vulnerable communities see less evacuation.

To verify this trend, we conducted 12 interviews in two disaster affected communities. We found that much inter-city user movement occurred from residents leaving Sapporo; we also

learned from interviews that residents faced a barrage of rumors and false information on social media after the quake, which professed upcoming water shortages and prolonged power outages. Residents from wealthier communities in Sapporo may have been more financially able to evacuate long-distance, after encountering rumors of continued blackouts through their bridging networks. In communities with stronger bridging and linking social ties, residents would have more easily received quality information assuring them that their local municipality had evacuation shelters where they could go without having to leave town. In contrast, communities with weaker bridging and linking ties may not have received these key messages, leading them to evacuate further afield.

This study adds to the literature in three key ways. First, it builds on the foundational work of past evacuation studies by using municipal-level census data to control for the effects of half a dozen key intervening variables on evacuation, like income, public goods provision, and shelter availability (Horney et al. 2010, Li et al. 2010, Metaxa-Kakavouli et al. 2018). Second, it leverages big data to analyze complete movement data on the movement of a consistent population, Facebook users, building on the work of past road-side surveys and post-hoc surveys (Riad et al. 1999, Collins et al. 2017). Third, this study incorporates rigorous measurement of social vulnerability, which deeply shapes residents' capacity to evacuate (Cutter et al. 2003, Fraser 2021, Fraser et al. 2021c). We assessed the relationship between all three kinds of social capital and social vulnerability, showing that linking and bridging social capital can serve as important interventions even for communities with high levels of social vulnerability.

This study presents two directions for future research. More recent releases of data from the Facebook Data for Good program allow scholars to assess how many evacuees moved between each distinct pair of communities. Scholars should therefore assess whether the effect of linking social capital observed in this study appears at this more granular, level of data as well. We might expect that linking and bridging ties affect not only residents' decision to evacuate in general, but also their choice of destinations when they evacuate.

Second, this study distinguished that disasters may cause distinct short-distance and long-distance evacuation patterns, but because our data was municipal and the number of communities affected was so small, we could not model short-distance evacuation. Future studies should look at urban wards or larger scale disasters to verify how the effects of linking and bridging capital differ among short-distance and long-distance evacuation. By clarifying the effects of these key community resources, scholars can provide communities with new tools for local level interventions before and after crises strike.

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[1] Most studies ensure comparable effect sizes by rescaling predictors into Z-scores mean-centered at 0, but this is problematic when using interaction effects, because calculating the product of a number and 0 returns only zero, not a range of values. To fix this, we instead rescale our variables from 1 to 10, so that each coefficient reflects the log-odds of an increase in evacuation rates as the predictor increases by 1 unit on a scale from 1 to 10.

*Responses to this article can be read online at:*  
<https://www.ecologyandsociety.org/issues/responses.php/13097>

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#### Data Availability:

*The data/code that support the findings of this study are openly available in the Harvard Dataverse at <https://doi.org/10.7910/DVN/NKTSMG>, reference number NKTSMG. Ethical approval for this research study was not necessary because all data came from aggregate sources regularly provided to humanitarian NGOs and researchers by Facebook's Data for Good program; researchers had no contact with individual Facebook user data.*

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**Supplementary Information Appendix  
For manuscript:**

**Do All Roads Lead to Sapporo?  
The Role of Linking and Bridging Ties in Evacuation Decisions**

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**Appendix 2: Statistical Simulation Explained**

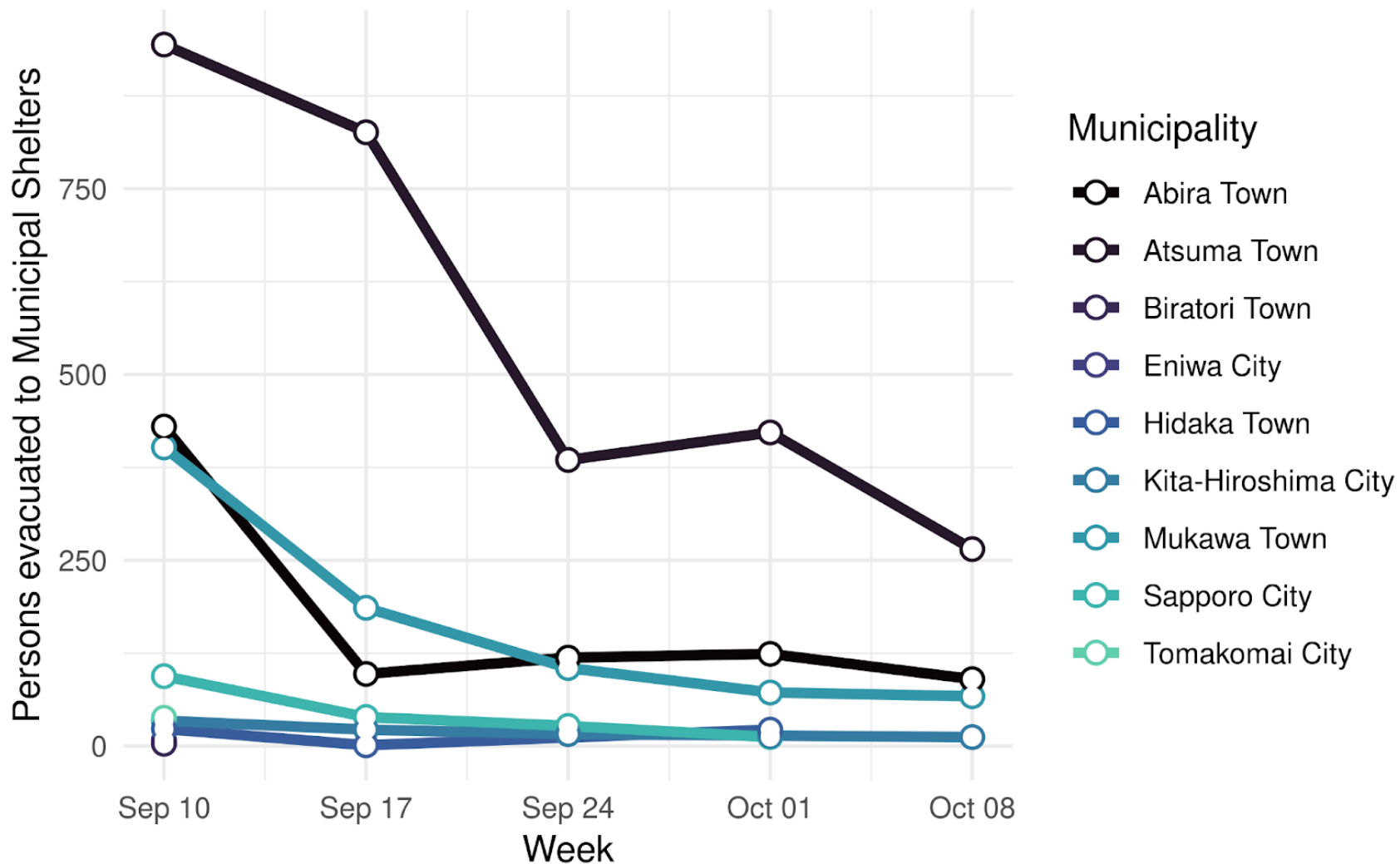
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**Appendix 3: Measuring Social Capital**

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Appendix 1: Descriptive Statistics and Models  
Figure A1.1: Short Distance Evacuation

### Evacuation to Municipal Shelters after Earthquake



**Table A1.1: Descriptive Statistics**

	Descriptive Statistics				
	Mean	Median	Std. Dev.	Min	Max
Rate of Evacuees	16.83	8.87	25.28	0.79	169.52
Bonding Social Capital	0.71	0.72	0.05	0.58	0.78
Bridging Social Capital	0.31	0.3	0.01	0.28	0.33
Linking Social Capital	0.24	0.24	0.02	0.19	0.27
Social Vulnerability	0.74	0.74	0.02	0.68	0.79
Revenues to Expenditures Ratio	4.21	3.58	3.41	0.1	19.6
Emergency Services Spending	35.73	26.71	26.99	9.64	126.5
Public Works Spending	112.23	83.61	66.6	43.52	316.95
Rate of Shelters Opened	0.2	0.1	0.28	0	0.96
Distance from Epicenter	72.51	76.1	23.76	26.27	115.19
Rate of Buildings Damaged	1.74	0.09	6.02	0	35.44
Rate of Evacuees to Local Shelters	0.03	0	0.16	0	1.47
Days of Water Outages	0.86	0	1.48	0	6

Note: Rates calculated per 1000 residents.

**Table A1.2: Models**

OLS Models of logged Evacuees per 1000 residents in Municipalities with any Documented Evacuation Between Cities (n = 34) <sup>1</sup>

Coefficient with Std. Errors in parentheses <sup>2</sup> with Fixed Effects by Week (n = 5)

	Model 1: Model with Direct Effects (All cities)		Model 2: Model with Interaction Effect (All cities)		Model 3: Model with Direct Effects (Excluding Outliers <sup>3</sup> )		Model 4: Model with Interaction Effect (Excluding Outliers)	
	Model 1A: Basic Model	Model 1B: Full Controls	Model 2A: Basic Model	Model 2B: Full Controls	Model 3A: Basic Model	Model 3B: Full Controls	Model 4A: Basic Model	Model 4B: Full Controls
<b>Social Capital</b>								
Bonding	-0.07 (0.05)	<b>-0.08</b> (0.05) <sup>*</sup>	-0.07 (0.05)	<b>-0.12</b> (0.05) <sup>*</sup>	0.04 (0.05)	<b>-0.10</b> (0.05) <sup>*</sup>	0.04 (0.05)	<b>-0.10</b> (0.05) <sup>*</sup>
Bridging	<b>0.09</b> (0.04) <sup>*</sup>	-0.02 (0.04)	<b>0.23</b> (0.12) <sup>*</sup>	<b>0.32</b> (0.12) <sup>**</sup>	0.03 (0.04)	0.02 (0.04)	0.04 (0.11)	<b>0.31</b> (0.11) <sup>**</sup>
Linking	<b>-0.09</b> (0.03) <sup>**</sup>	<b>-0.07</b> (0.03) <sup>*</sup>	0.04 (0.11)	<b>0.25</b> (0.11) <sup>*</sup>	<b>-0.07</b> (0.03) <sup>*</sup>	-0.04 (0.03)	-0.05 (0.10)	<b>0.27</b> (0.11) <sup>*</sup>
<b>Vulnerability</b>								
Social Vulnerability Index	<b>-0.18</b> (0.06) <sup>**</sup>	<b>-0.13</b> (0.05) <sup>*</sup>	<b>-0.19</b> (0.06) <sup>**</sup>	<b>-0.20</b> (0.06) <sup>***</sup>	0.03 (0.04)	-0.07 (0.04)	0.02 (0.04)	<b>-0.10</b> (0.04) <sup>*</sup>
<b>Interactions</b>								
Bridging x Linking			-0.02 (0.02)	<b>-0.05</b> (0.02) <sup>**</sup>			-0.00 (0.02)	<b>-0.05</b> (0.02) <sup>**</sup>
<b>Public Goods</b>								
Revenues to Expenditures Ratio		0.05 (0.04)		0.06 (0.04)		0.01 (0.04)		0.01 (0.04)
Emergency Services Spending		<b>0.22</b> (0.05) <sup>***</sup>		<b>0.18</b> (0.05) <sup>**</sup>		0.01 (0.05)		0.03 (0.05)
Public Works Spending		-0.01 (0.04)		0.03 (0.04)		0.08 (0.05)		<b>0.12</b> (0.05) <sup>*</sup>
Shelters Opened per capita		<b>-0.15</b> (0.03) <sup>***</sup>		<b>-0.16</b> (0.03) <sup>***</sup>		<b>-0.16</b> (0.03) <sup>***</sup>		<b>-0.17</b> (0.03) <sup>***</sup>
<b>Controls</b>								
Distance from Epicenter	0.00 (0.03)	<b>-0.06</b> (0.03) <sup>*</sup>	0.02 (0.04)	-0.04 (0.03)	0.01 (0.03)	<b>-0.09</b> (0.03) <sup>**</sup>	0.02 (0.03)	<b>-0.06</b> (0.03) <sup>*</sup>
Buildings Damaged per capita		<b>-0.15</b> (0.06) <sup>**</sup>		<b>-0.20</b> (0.06) <sup>***</sup>		<b>-0.12</b> (0.06) <sup>*</sup>		<b>-0.19</b> (0.06) <sup>**</sup>
Evacuees to Local Shelters per capita		-0.01 (0.06)		0.01 (0.06)		-0.02 (0.06)		0.00 (0.06)
Days of Water Outages		0.02 (0.03)		<b>0.09</b> (0.04) <sup>*</sup>		0.02 (0.03)		<b>0.09</b> (0.04) <sup>*</sup>
<b>Fixed Effects</b>								
Week 2	0.29 (0.21)	<b>0.29</b> (0.15) <sup>*</sup>	0.29 (0.21)	<b>0.29</b> (0.15) <sup>*</sup>	0.28 (0.19)	<b>0.27</b> (0.16) <sup>*</sup>	0.28 (0.19)	<b>0.28</b> (0.15) <sup>*</sup>
Week 3	<b>0.36</b> (0.21) <sup>*</sup>	<b>0.35</b> (0.15) <sup>*</sup>	<b>0.36</b> (0.21) <sup>*</sup>	<b>0.36</b> (0.15) <sup>*</sup>	<b>0.35</b> (0.19) <sup>*</sup>	<b>0.35</b> (0.16) <sup>*</sup>	<b>0.35</b> (0.19) <sup>*</sup>	<b>0.35</b> (0.15) <sup>*</sup>
Week 4	0.32 (0.21)	<b>0.32</b> (0.15) <sup>*</sup>	0.32 (0.21)	<b>0.32</b> (0.15) <sup>*</sup>	0.31 (0.19)	<b>0.31</b> (0.15) <sup>*</sup>	0.31 (0.19)	<b>0.31</b> (0.15) <sup>*</sup>
Week 5	0.34 (0.21)	<b>0.34</b> (0.15) <sup>*</sup>	0.34 (0.21)	<b>0.34</b> (0.15) <sup>*</sup>	<b>0.32</b> (0.19) <sup>*</sup>	<b>0.31</b> (0.16) <sup>*</sup>	<b>0.32</b> (0.19) <sup>*</sup>	<b>0.32</b> (0.15) <sup>*</sup>
Constant	<b>3.65</b> (0.83) <sup>***</sup>	<b>4.10</b> (0.78) <sup>***</sup>	<b>2.81</b> (1.10) <sup>*</sup>	<b>2.43</b> (0.94) <sup>*</sup>	<b>1.70</b> (0.67) <sup>*</sup>	<b>3.84</b> (0.64) <sup>***</sup>	1.60 (0.97)	<b>1.69</b> (0.98) <sup>*</sup>
Mean VIF	1.69	2.91	10.98	11.73	1.93	3.17	10.64	11.99
R <sup>2</sup>	0.19	0.63	0.20	0.65	0.07	0.44	0.07	0.47
Adj. R <sup>2</sup>	0.15	0.59	0.15	0.61	0.01	0.37	0.01	0.40
Num. obs.	170	170	170	170	160	160	160	160

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05; . p < 0.10.

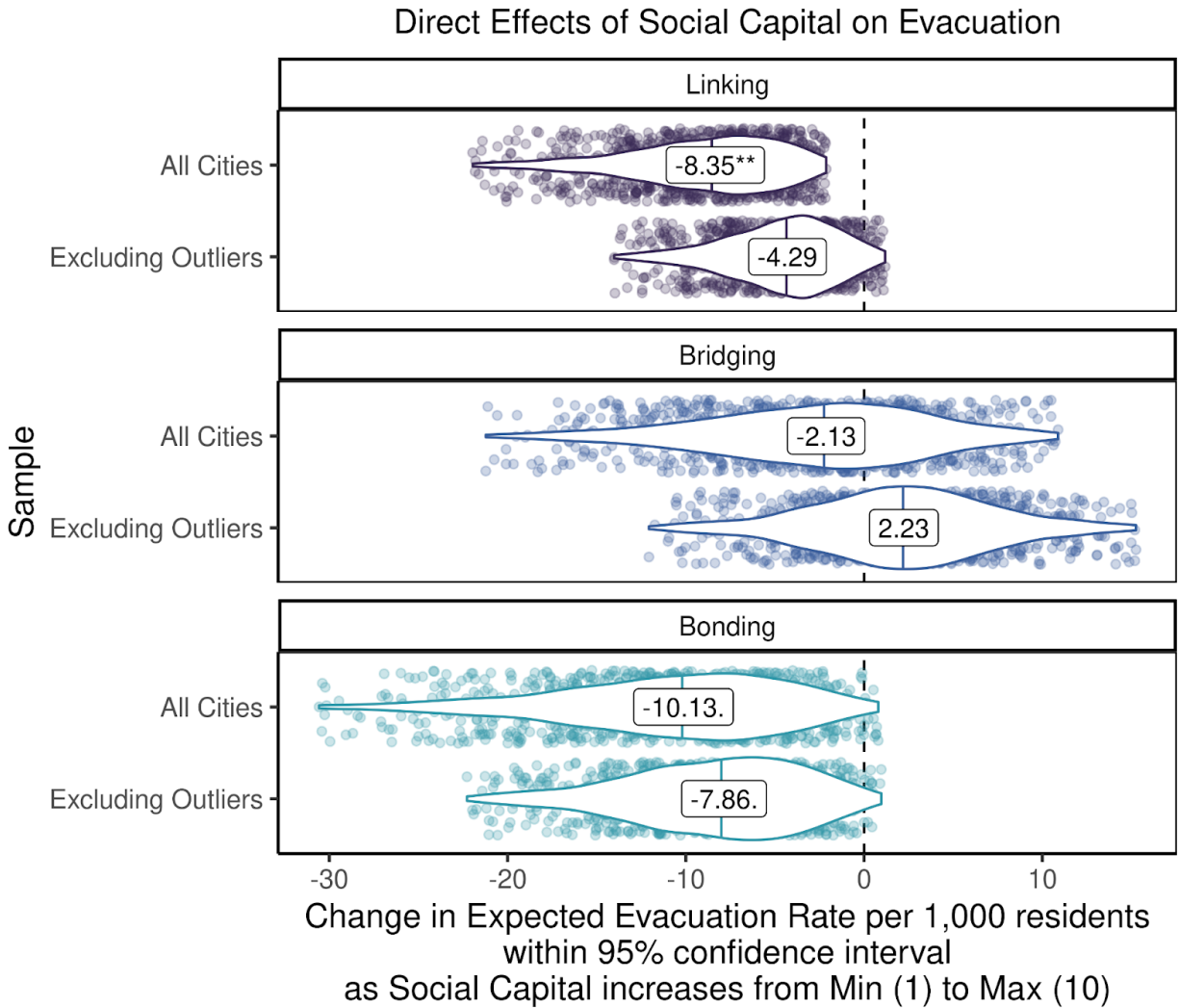
<sup>1</sup>4 city-weeks saw no documented evacuation, but zero could not be log-transformed. To include these cases and respect the original distribution, these cases were assigned a small-but-realistic value: 0.7913, half the size of the smallest non-zero observation. Results were consistent when excluding these cases.

<sup>2</sup> Coefficient depicts log-odds of evacuation given an increase in the predictor by 1 unit on a scale from 1 to 10.

<sup>3</sup> Repeated models excluding 10 observations from outlier cities Isoya-gun and Shimukappu-mura as robustness checks. Models in blue font show best fitting models. Models in grey font show early models.

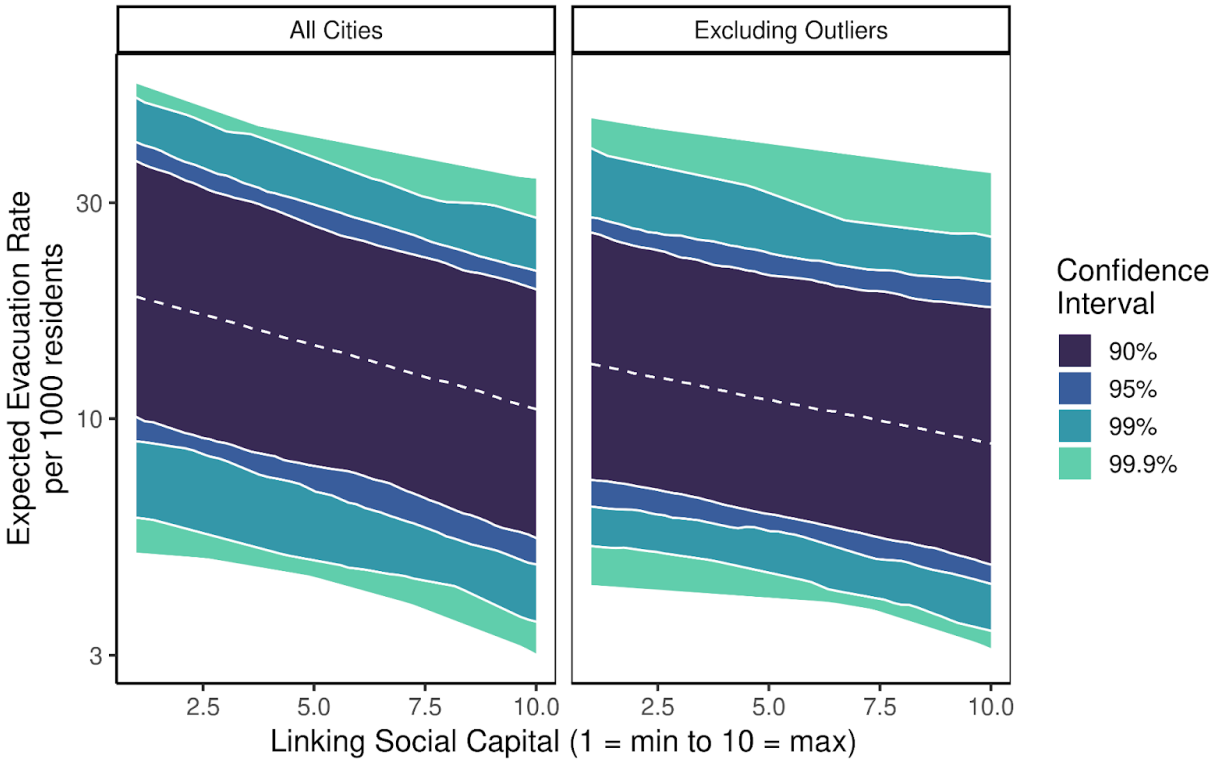
**Figure A1.2: Simulations both including and excluding outliers**

**Figure A1.2-1: Simulated Direct Effects on Evacuation,**  
*Repeating Figure 4 while including Outliers (Model 1B) and Excluding Outliers (Model 3B)*



As described in the main text, we see in the top panel under “Excluding Outliers” that when excluding 10 observations from outlier cities Isoya-gun and Shimukappu-mura, the 95% confidence interval for the significant effect of linking social capital dips ever so slightly below 0. This reflects how though the effect of linking social capital was statistically significant with all observations (and when removing just Isoya-gun), removing Shimukappu-mura as well deflates the effect just slightly. Linking social capital’s effect is still somewhat statistically significant when performing a one-tailed hypothesis test, since 93% of expected changes are still greater than zero ( $p < 0.07$ ). However, this study uses two-tailed hypothesis tests.

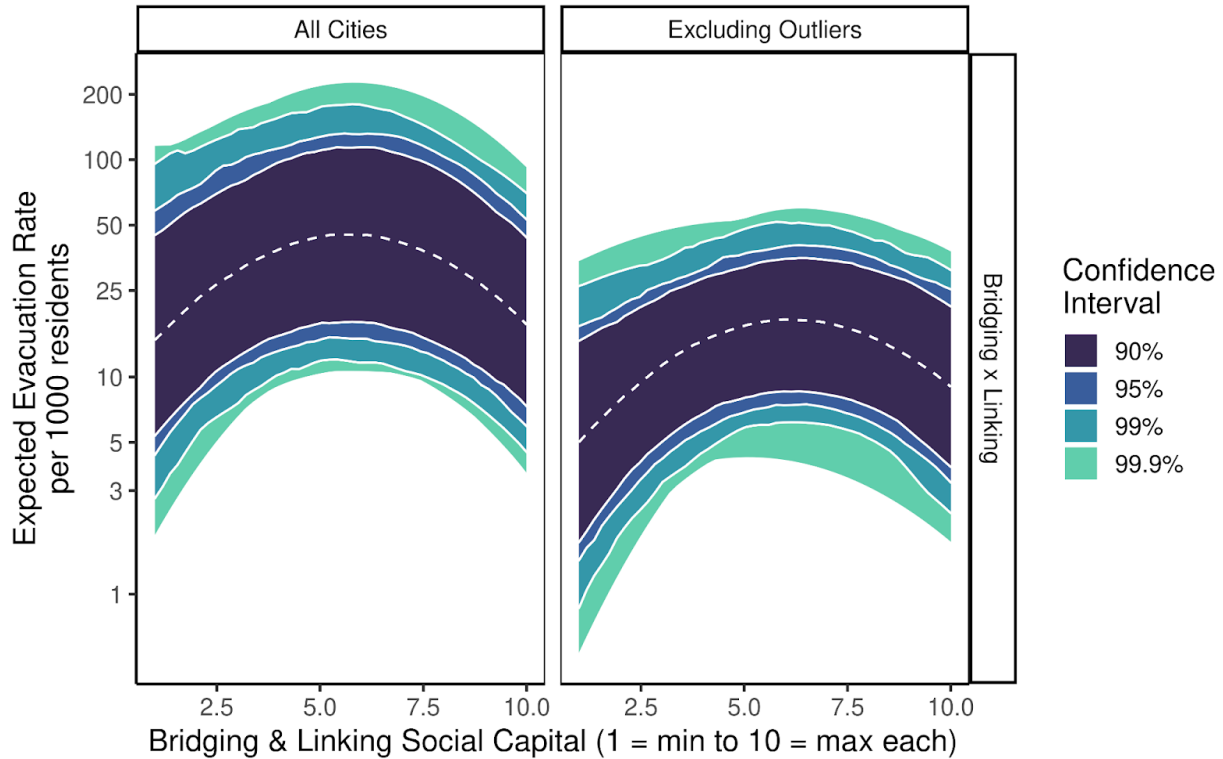
**Figure A1.2-2: Simulated Direct Effects on Evacuation,**  
*Repeating Figure 3 while including Outliers (Model 1B) and Excluding Outliers (Model 3B)*



**Figure A1.2-2** shows this effect directly, repeating the analysis from **Figure 3** in the main text for a model of all cities (Model 1B), in the left panel, vs. the model excluding outliers (Model 3B), represented by the right panel. This reveals that though the level of statistical significance differs officially, substantively, the effect of linking social capital is still quite considerable.

To summarize, this minor difference in statistical significance means that the effect of linking social capital remains quite large even when removing outliers, but every outlier removed decreases the significance of the effect somewhat. This suggested to the authors that perhaps we should investigate interactions as well; indeed, our interaction models produce statistically significant beta coefficients both when including and excluding outliers.

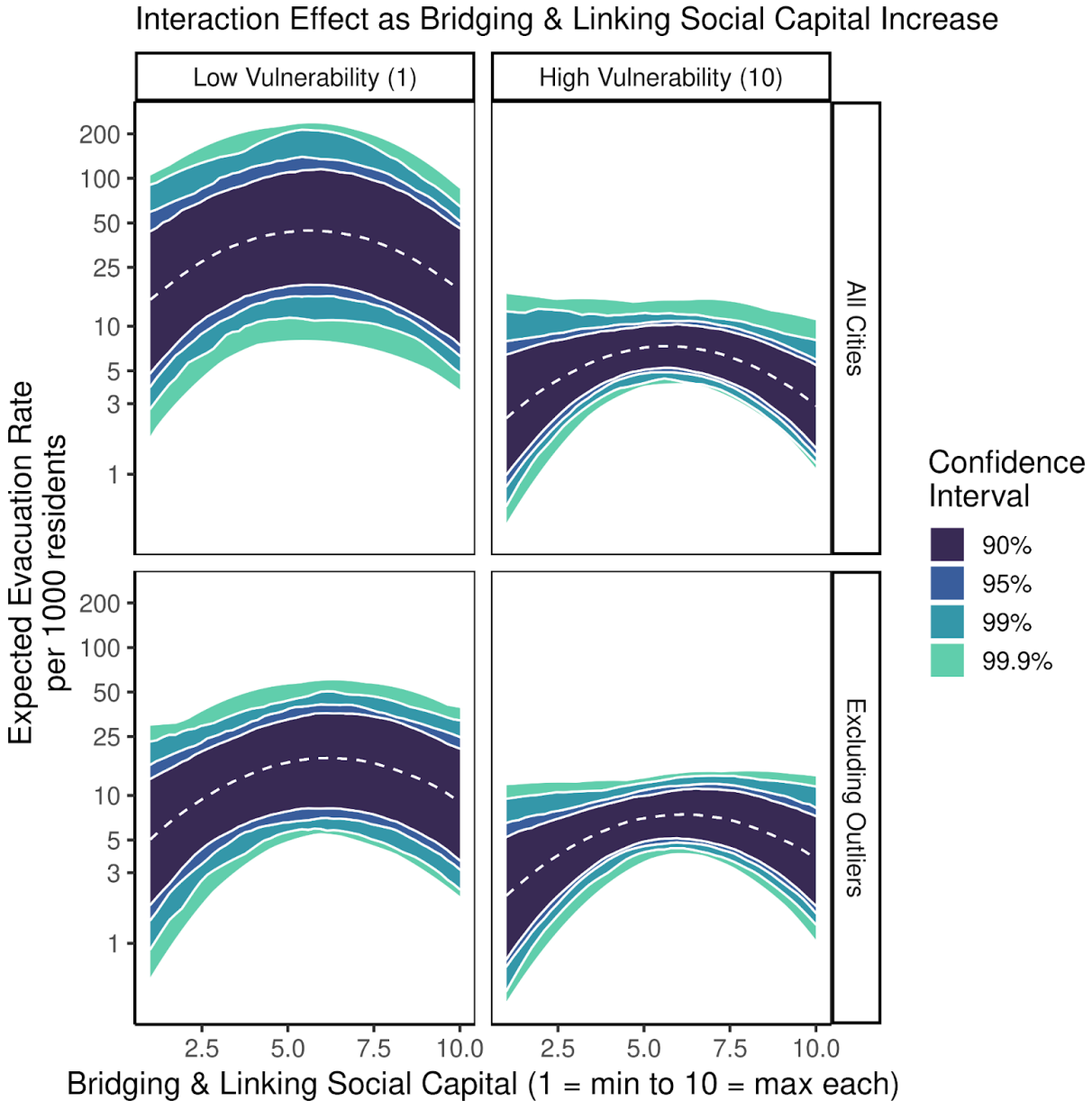
**Figure A1.2-3: Simulated Interaction Effects on Evacuation,**  
*Repeating Figure 5 while including Outliers (Model 2B) and Excluding Outliers (Model 4B)*



As seen above, the general curvilinear trend of our interaction effect in Figure 5 remains the same both when including outliers (left panel, same as Figure 5 in main text) and when removing outliers (right panel, based on Model 4B). The trend deflates somewhat, which makes sense, because we have removed outlier observations, but it shows the same pattern as before.



**Figure A1.2-4: Simulated Interaction Effects on Evacuation,**  
*Repeating Figure 6 while including Outliers (Model 2B) and Excluding Outliers (Model 4B)*

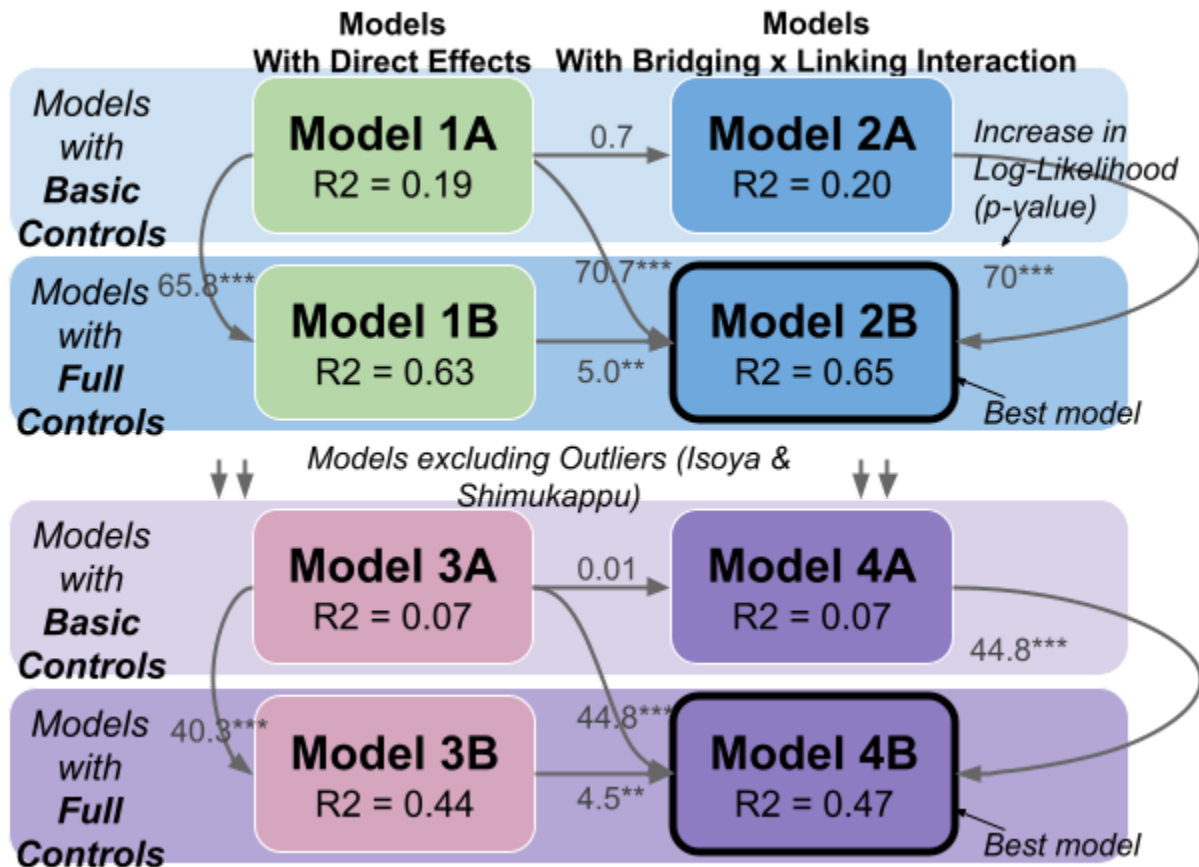


Finally, we replicated our findings from **Figure 6** from the main text above in **Figure A1.2-4**. This shows in the top two panels the interaction effect between bridging and linking social capital for our models of all cities (Model 2B), split by level of social vulnerability, as shown in the main text. Then, in the bottom two panels, we compare this against same visuals, but produced from Model 4B, our fully specified models of cities excluding outliers Isoya-gun and Shimukappu-mura. This shows similarly that the curvilinear trend persists in both. Similar to in the overall sample of cities, we project lower overall evacuation curves for highly vulnerable cities (right lower panel), and greater overall evacuation curves for less vulnerable cities (left lower panel). This shows that excluding outliers does not affect the veracity of our results.

## Likelihood Ratio Tests

We used a series of likelihood ratio tests in the *lmtest* package in R to analyze which of our models from **Table A1.2** fit best. Likelihood ratio tests are a common technique for comparing ordinary least squares regression models. Likelihood ratio tests allow us to analyze whether a model with an extra term (eg. additional controls or an interaction effect) sees an improvement in log-likelihood, compared to a model without that extra term. The value added of likelihood ratio tests is that it produces a chi-squared statistic and p-value we can use to identify whether the improvement in log-likelihood from our second model was statistically significant enough to know that increase was definitely not due to chance. Likelihood ratio tests are a more robust test than comparing R2 statistics alone, because it takes into consideration the number of covariates and quantifies how statistically significant that improvement in model fit is - how confident we are that this improvement was not just due to chance.

**Figure A1.3: Visual Summary of Likelihood Ratio Tests**



Note: Lines depict likelihood ratio tests between two models, where the direction of the arrow depicts the model that fit better according to the likelihood ratio test. Each arrow is accompanied by the difference in log-likelihood, with the statistical significance of that statistic marked by asterisks. Statistical significance is represented where \*\*\* =  $p < 0.001$ , \*\* =  $p < 0.01$ , and \* =  $p < 0.05$ .

In **Figure A1.3** (above), we visualize likelihood ratio tests pertaining to our 8 models. The first 4 models (in **blue**) are our main models 1A to 2B from **Table A1.2**; the second 4 models (in **purple**) represent our models with outliers removed, from **Table A1.2 Models 3A to 4B**. Each model displays its name and R2 statistic (percentage of variation in log-evacuation explained). In each case, we performed 5 likelihood ratio tests (represented by the 5 arrows between our 4 squares above in **Figure A1.3**).

As described below, we used these tests to measure the value added of 1) control variables and 2) interaction effects, and 3) confirm that excluding outliers did not impact these tests. Please see the visual above, followed by a description of this visual below.

### **1. Value of Controls?**

To test the value of adding controls, we compared our basic model Model 1A to our fully specified model Model 1B; the arrow connecting them indicates that Model 1B fit better, seeing an improvement in log-likelihood of 65.8 ( $p < 0.001$ ) compared to Model 1A. Similarly, Model 2B fit better than 2A, seeing an improvement in log-likelihood of 70.0 ( $p < 0.001$ ).

### **2. Value of Interaction Effect?**

Then, to compare the value added from our interaction effect *and* fully specified controls, we compared Model 2B to previous models. It turns out Model 2B fitted better than models 1A (+70.7,  $p < 0.001$ ), 1B (+5.0,  $p < 0.01$ ), or 2A (+70,  $p < 0.001$ ). This Figure indicates that the model which fit best was **Model 2B**, as it was preferred to all other models when compared systematically. It also had the highest R2 statistic, at 0.65.

### **3. Not due to Outliers?**

In the bottom of Figure A1.6, we repeated this same process for models 3A, 3B, 4A, and 4B, namely our models with outliers removed. We found the same consistent improvements in log-likelihood, with similar levels of statistical significance. Model 4B, our fully specified interaction model, saw significant improvements in model fit compared to all other models. This shows that our results are consistent even after excluding outliers. This Figure indicates that the model (excluding outliers) which fit best was **Model 4B**, as it was preferred to all other models when compared systematically. It also had the highest R2 statistic, at 0.47.

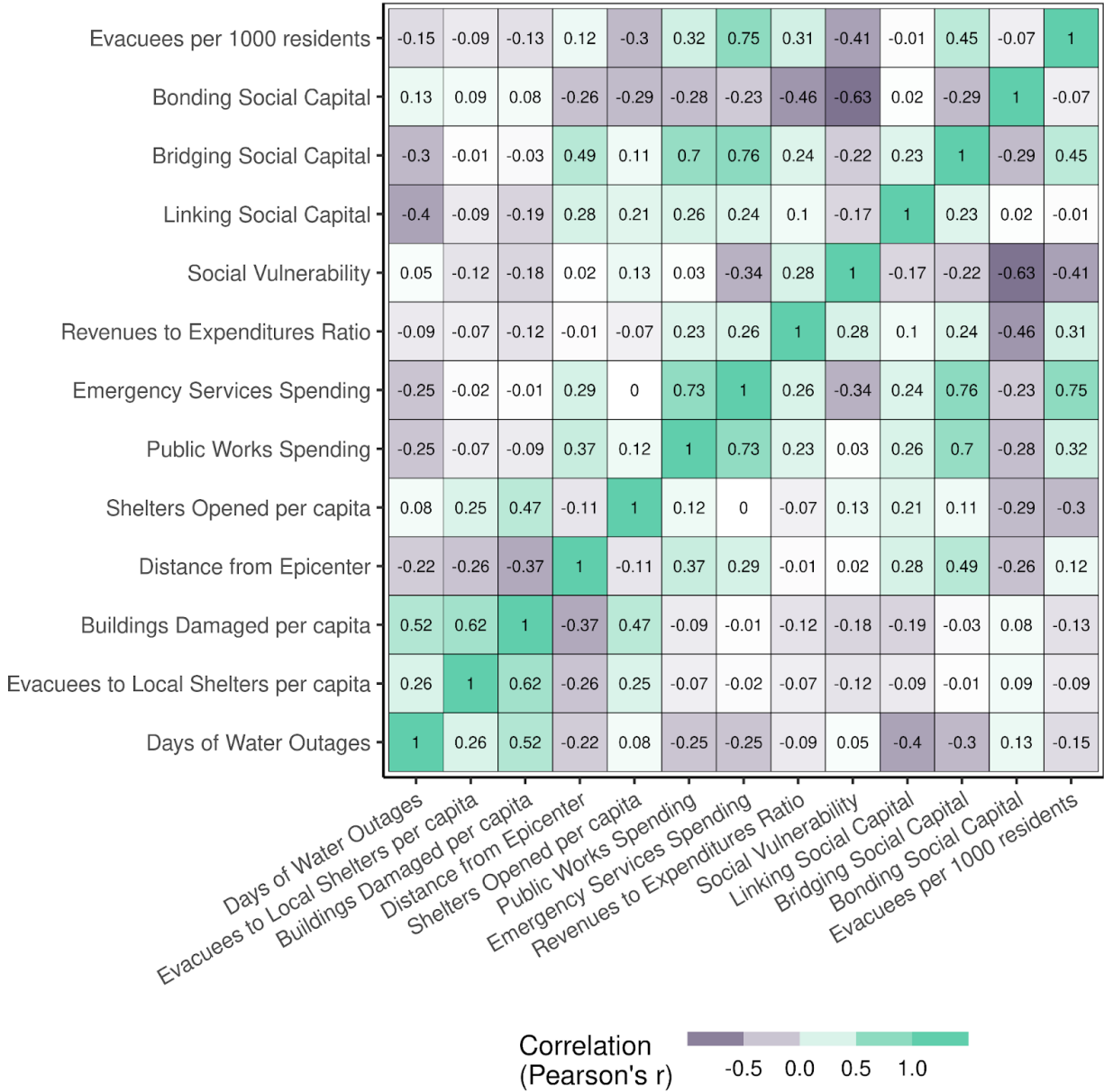
### **4. Choosing the right Interaction Effect**

Finally, we selected the interaction effect between bridging and linking social capital from Models 2B and 4B, because it consistently improved the log-likelihood of the models. Separate from **Figure A1.3**, we also compared other specifications instead, including an interaction effect between linking social capital and vulnerability, or an interaction between linking social capital, bridging social capital, and vulnerability, but neither of these interactions produced statistically significant improvements in the log-likelihood for both the original model and the models with outliers removed. This means neither of these interactions consistently improved the explanatory

power of the model to a significant degree. (See our replication code for demonstrations of these alternative specifications and their lack of explanatory power.)

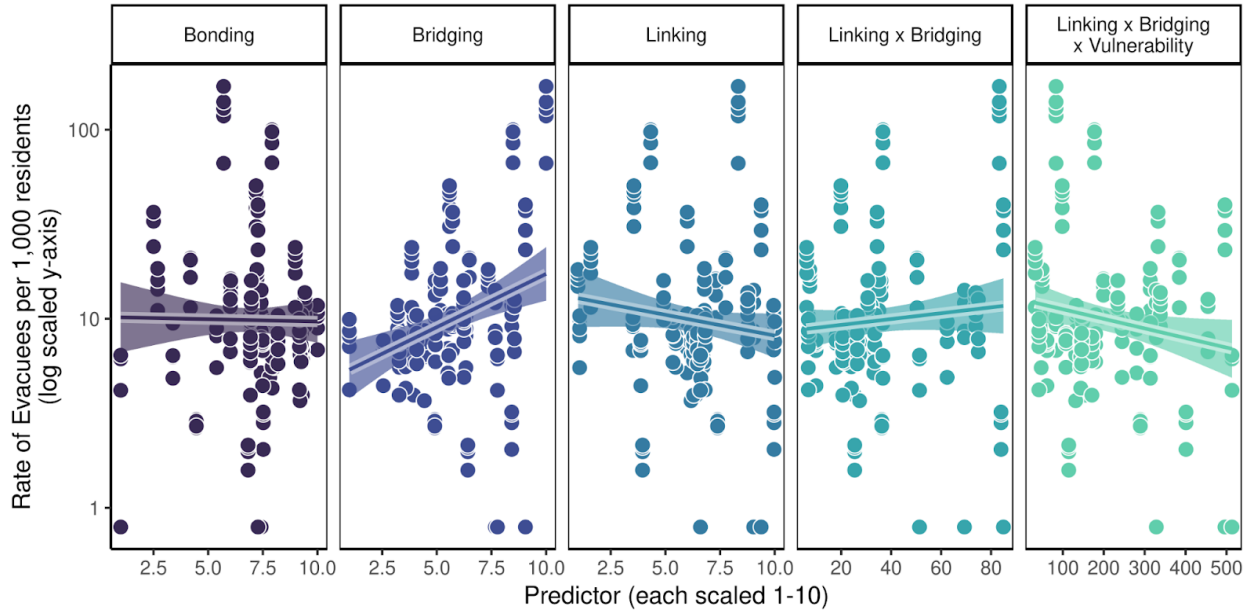
As a result, we present results in this manuscript for just the direct effect of linking social capital (Models 1A-B) and the interaction effect between bridging and linking social capital (Models 2A-B) in this paper.

**Figure A1.4: Correlation Matrix**



*Caption: Cell labels and shading reflect the strength of association between each pair of variables based on the Pearson's r correlation coefficient, where -1 indicates strong negative association, 0 indicates no association, and 1 indicates strong positive association.*

**Figure A1.5: Bivariate Scatterplots of Evacuation, Social Capital, and Key Interactions**



Caption: Points depict raw data, jittered for effect, with simple bivariate OLS regression lines of best fit to approximate the association between each predictor and the outcome.

Bonding social capital displays no particular association, as expected, while bridging ties are positively associated with evacuation. In keeping with our models, linking ties are *negatively* associated with evacuation, as expected. The furthest right panels multiple two or more predictors together, to approximate the interactions studied in our models.

Cities with stronger linking *and* bridging ties descriptively see more evacuees. This matches the left and right panels in **Figure 5**, and may be strongly influenced by the strong bivariate effect of bridging ties described above in **Figure A1.5**. However, the bivariate trend for the interaction between linking and bridging ties with evacuation rates contrasts somewhat with the center panel of Figure 5. According to that panel, after adjusting for covariates, our interaction model (**Table A1.2**, column 4) projected *fewer* evacuees given more bridging *and* linking ties (with an interesting curvilinear trend in **Figure 5**). In contrast, the furthest right panel in **Figure A1.5** descriptively reflects the trends of our model better, showing that vulnerable cities with stronger linking and bridging social capital tended to see fewer evacuees. We found in **Figure 6** and our interaction model the same trend (albeit with an interesting curvilinear shape). It is compelling that this general negative trend appears descriptively in **Figure A1.5**.

## Appendix 2: Statistical Simulation Explained

### Statistical Simulation

#### What is statistical simulation?

‘Statistical simulation’ refers to estimating specific quantities of interest about a researcher’s dependent variable, by applying simulation techniques to a statistical model. For example, how many evacuees per capita does a city experience given high linking social capital, but otherwise average traits? This technique was developed in the early 2000s (King et al. 2000), implemented in the Clarify package in Stata (Tomz et al. 2001), implemented in R in the *Zelig* package (Imai et al. 2008), and given improved functionality in 2017 (Choirat et al. 2017). Simulation has been applied to hundreds of different social science studies, used to visualize models of political behavior (Klofstad et al. 2013), diffusion of institutions (Bush 2011), and electoral outcomes (Panagopoulos 2021), as well as the topics of this study, disaster outcomes (Aldrich 2019) and evacuation outcomes (Fraser et al. 2021b), among others.

#### How does simulation work?

What does statistical simulation entail? In **Figure A2.1**, we visually summarize the stages of statistical simulation, we describe them below, referencing each part of the figure. Statistical simulation takes a **model equation (eg. Models 1A through 2B in Table A1.2, or the example model shown at the top of Figure A2.1)**. Then, as shown in **Step 1 in Figure A2.1**, we create 1000 versions of that model equation that are each just slightly different, approximating *estimation uncertainty*, as in the error term in the model equation. It does so by drawing model terms from a multivariate normal distribution (for precise technical details, see King et al. 2000).

Then, in **Step 2 in Figure A2.1**, we feed those 1000 model equations the same observed data, such as the traits of an average city (eg. mean distance from epicenter, mean buildings damaged per capita). This produces 1000 simulated predicted outcomes.

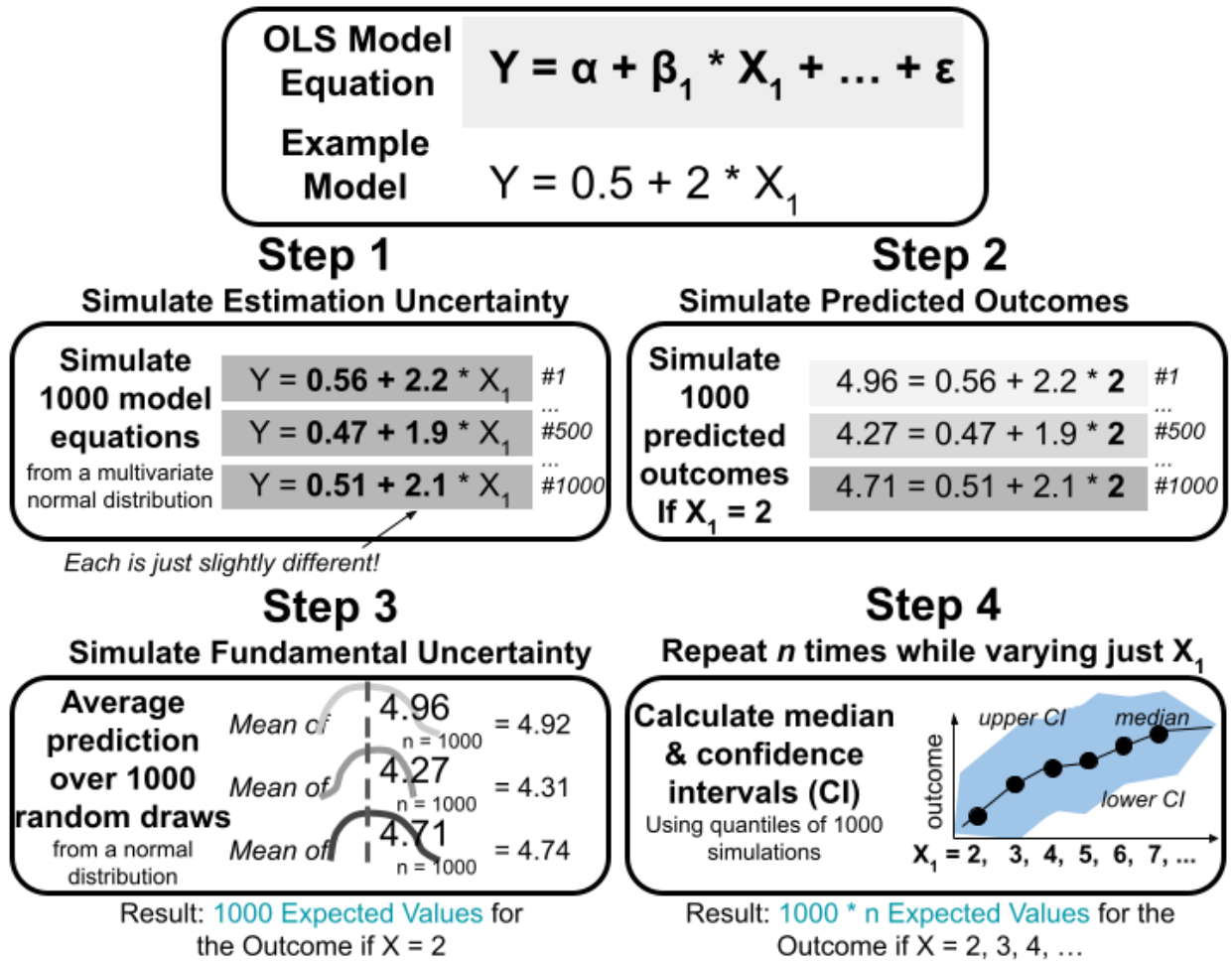
In **Step 3 in Figure A2.1**, for each prediction, we take the average of 1000 random draws from a normal distribution, producing 1 expected value that accounts for *fundamental uncertainty*. Applying this strategy to each of the 1000 simulated predictions produces 1000 simulated expected values, given the set of city traits fed into the model.

Finally, we can then take those 1000 simulated values and calculate various quantities of interest using them, such as the median or confidence intervals. These 1000 expected values for our models with logged outcome variables can be exponentiated to provide expected values in the original observed units of evacuation rates. This is the standard process for generating expected values in the *Zelig* package in R. The *Zelig* package in R does this entire process automatically, after feeding the model a set of average traits.

The main power of simulation comes from showing *how much the expected outcome changes* when the researcher alters a single trait of a city, holding all else constant. This is depicted in **Step 4 in Figure A2.1**, where we visualized simulated expected effects when the trait  $X_1 = 2, 3, 4, 5$ , etc. For example, we show the same process in **Figure 4**, simulating changes in evacuation

when the level of linking social capital is increased from its minimum to maximum observed value, holding all else constant at their means or modes. In **Figures 5 and 6**, we take this a step further, adjusting two or more variables at the same time to demonstrate interaction effects.

**Figure A2.1: Visual Summary of Statistical Simulation**



**What is the value added from simulation?**

There are two main kinds of value added from statistical simulation:

*First*, while other studies in the past used beta coefficients or odds ratios to express the effects of their models, these can be unintuitive. This is especially the case for this study’s models, where the outcome has been log-transformed, meaning that beta coefficients represent log-odds, and when interaction effects are involved. For years, scholars have recommended marginal effects or simulated effects in order to show the precise results of an interaction effect (Kam and Franzese 2007). Simulation allows us to visualize these interaction effects on the outcome, in its original units. Identifying whether an effect is positive, negative, or meaningfully large, can be challenging



using just beta coefficients or odds ratios in this circumstance. Instead, techniques like simulation (and its close cousin, marginal effects) provide precise estimates of the outcome of interest, with confidence intervals.

*Second*, simulation allows us to visualize effects with many different levels of confidence (90%, 95%, 99%, etc.), without relying on standard errors or p-values, which have numerous assumptions that are not always true (Ziliak and McCloskey). Because simulation relies on prediction and approximates uncertainty via simulating from a multivariate normal distribution, standard error and the assumption of independence of observations is not involved. As a result, simulation is unaffected by heteroskedasticity, making it more robust than evaluating the statistical significance of a beta coefficient's p-values, which can be suspect in the face of correlated residuals (King et al. 2000). For more information on statistical simulation, please consult the original paper (King et al. 2000) and later applications (Imai et al. 2008, Choirat et al. 2017).

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### Appendix 3: Measuring Social Capital

This study employed three indices measuring social capital, developed and validated in a separate study by Fraser (2021). The original study measured several types of social capital, ranging from 0 (low) to 1 (high), describing the strength of each type of social capital in Japan's 1741 municipalities from 2000 to 2017, based on publicly available data. This framework is based on Kyne & Aldrich's (2020) framework, which measured social capital for every US county using publicly available data. These indices (Kyne & Aldrich 2020; Fraser 2021) synthesize a variety of proxies drawn from other studies of measuring and conceptualizing social capital and community resilience (Tierney 2001, McPherson et al. 2003, Mouw 2006, Murphy 2007, Norris et al. 2008, Morrow 2008, Chamlee-Wright 2010, Cutter et al. 2016). Their framework developed three subindices for (1) bonding (in-group ties), (2) bridging (inter-group) ties, and (3) linking social capital (verticale ties), a common way of delineating social capital (Szreter & Woolcock 2004; Aldrich & Meyer 2015). Together, these measures were used to approximate social capital in each county. In Fraser's (2021) Japanese framework, these measures can be used together to approximate social capital for each municipality. While national context does matter for social capital, scholars have examined and found considerable variation in social capital in communities and countries across the world, adding credence to the idea that we can successfully evaluate it in different country contexts (see for example Putnam 1993; Uekusa 2020; Roque 2020; Alcorta 2020; Fraser, Page-Tan, & Aldrich 2021).

Below, I briefly describe (1) the indicators involved in each index and (2) examples of validation in past studies. For further information, please consult the original articles introducing these indices, including Kyne & Aldrich (2020), Fraser (2021), and Fraser, Page-Tan, & Aldrich (2021).

#### **Building the Indices**

These indices relied on several indicators, which each measure different aspects of social capital. Fraser (2021) then averaged these indicators together into bonding, bridging, and linking subindices. I describe each below.

#### ***Bonding Social Capital***

To represent bonding social capital in the US, this study used several indicators describing how similar members of each municipality are in terms of key salient demographics, including, for example, race and ethnicity (Alesina et al. 1999), income, education (Morrow 2008), gender (Norris et al. 2008), employment (Tierney et al. 2001), age (Cutter et al. 2010), and more.

Because most censuses do not ask about trust, instead, bonding, in-group ties were measured by proxy, measuring how similar members of a community are in terms of 7 commonly measured traits: These traits 7 include similarity in terms of (1) nationality, (2) religion, (3) education, (4) employment levels by gender, (5) employment status, (6) communication capacity, and (7) age. These are *not* sheer demographics, but rather several different representations measuring how similar (or, conversely, fractionalized) that community is. The key rationale here is that homophilous communities tend to have strong bonding social ties (Mouw 2006; Pretty 2003), and taking into account *similarity* better captures the strong in-group focus of bonding social capital (McPherson et al. 2003). Homophily has been linked to stronger bonding social ties in numerous studies (Lin, 2001; Dyson, 2006; Mouw 2006; Beaudoin, 2007; Hawkins & Maurer, 2010). By definition, bonding ties are between members of the same social strata (Szreter & Woolcock 2004; Aldrich & Meyer 2015; Mouw 2006; McPherson et al. 2003). For example, if

there are higher rates of young people, for example, there can be more ties between them, but if there are fewer residents of that background, the total number of potential in-group, bonding ties ultimately decreases.

In Japan, Fraser (2021) averaged the following 7 rescaled indicators to create a bonding social capital index for each municipality (*shikuchoson*), specified in **Table 1**:

1. *Similarity by nationality* (Japanese vs. foreign population).
  - The bonding social capital index relies heavily on Alesina and colleagues' (1999) method of assessing divisions in a community using fractionalization measures. Fractionalization measures how fractionalized a community is into different categories (eg. religion, nationality/ethnicity, etc.); Fraser (2021) and Kyne & Aldrich (2020) reverse scale this measure so that 1 = complete homogeneity and 0 = complete heterogeneity.
  - Japan's census does not collect data on race. This is because most Japanese communities are relatively ethnically homophilous, at least compared to other countries like the US. However, Japanese communities still contain more ethnic diversity than is commonly known (Lie 2001). This helps approximate similarity among immigrants including Korean, Chinese, and Indian immigrants, among others.
2. *similarity by religion* (religious minorities vs. Non-religious minorities).
  - Japan's census records the share of residents who identify as Christian or part of an other religious minority (eg. Soka Gakkai); meanwhile, many Japanese identify as Buddhist, Shinto, both, or neither, at various points in their lives. As a result, Fraser (2021) measured religion in terms of Non-minority religions (the latter), Christian, or other minority religions, to capture potential in-group ties within religious identity.
3. *similarity by education levels* (college educated vs. Elementary school graduates).
  - Large inequalities in education levels, especially the most and least educated members of society, may make residents less likely to interact, while smaller inequalities in education provide more opportunity for interaction among residents with similar levels of education (Morrow, 2008; Norris et al., 2008).
4. *similarity in employment rates by gender* (women's vs. men's employment).
  - Differences in gender roles and access to the workplace shape opportunities for cohesion and trust. If levels of employment are similar, men and women have more equal access to make ties among peers at home and at work. Meanwhile, if levels of employment are greatly different by gender, men and women have unequal opportunities to make these ties with others, especially members of their own gender, both at home and at work. This captures a decreased total potential for making in-group social ties (Morrow 2008).
5. *employment equality* (whether the labor force is mostly employed, or not).
  - Employment inequality has been linked to less cohesion and trust (Tierney et al., 2001).
6. *communication capacity* (NHK television broadcast reception contracts per capita).
  - Communities with greater communication infrastructure have a higher potential for building and supporting strong ties between friends and family, while those lacking such infrastructure may have difficulty making these connections electronically.

(Morrow, 2008). The Japanese census does not measure telephone connectivity, but it does report NHK broadcast reception, a close proxy for access to phone lines.

7. *age similarity* (share of residents below age 65).

- Many aging individuals live in nursing homes, living assistance homes, or have limited mobility, reducing levels of interaction with other community members (Morrow, 2008). Meanwhile, given more residents under age 65, this majority section of the population has more total people in their age groups to interact with. For these reasons, past studies used the percentage of non-elders as a measure of bonding social capital (Kyne & Aldrich 2020; Fraser 2021).

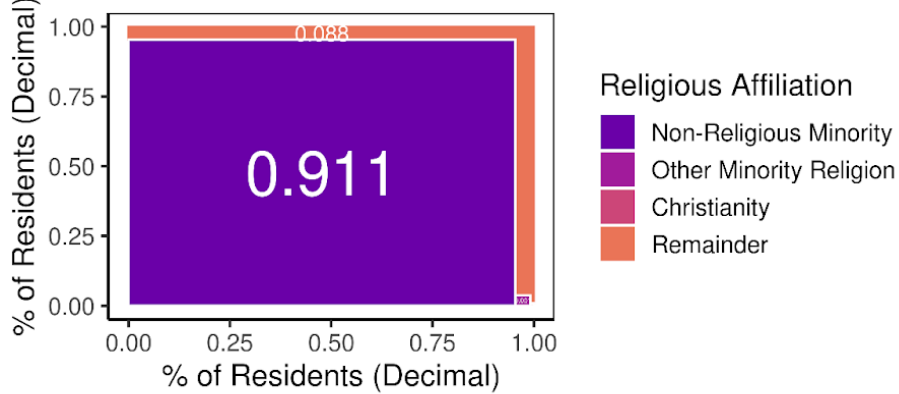
Finally, in **Figure A3.1** below, I visualize three examples of measures used in the bonding social capital index. The first (**Figure A3.1 panel A**) is a visual representation of religious similarity in the city of Sapporo, using Alesina and colleagues' (1999) fractionalization method. This panel visualizes the squared percentages of each religious grouping in the population as a literal square, then calculates fractionalization as the remainder of the total area of the square (0.088) after subtracting the sum of squared percentages (0.912). In a heterophilous society, where these three categories would be evenly sized, the squares would be equally sized, leaving a very large remainder (thus high fractionalization/heterophily). But in a very homophilous society, where most people are not part of a religious minority, like in Sapporo, these three categories are very unevenly sized, leaving a very small remainder. Thus, we calculated religious similarity as 1 minus the remainder (fractionalization), giving us a religious similarity score of 0.912, very close to the max of 1. This same technique is used to measure *similarity by nationality*.

Next, the second (**Figure A3.1 panel B**) is a visual representation of educational equality in the city of Sapporo, using Kyne and Aldrich's (2020) formulation. This panel visualizes the difference in the percentage of the population that is college educated (representing high educational attainment) vs. the percentage of the population that completed elementary school, but not high school. This gap of 4% is then multiplied by -1 to produce an education equality score of -0.04, where educational equality equals 0 while inequality equals -1. The greater the gap, the more unequal levels of education are and the more stratified the population is into groups that have less interaction with each other, reducing bonding social ties. The same general approach of comparing two percentages is used to measure *similarity in employment rates by gender* (but reverse coded), and *employment equality* (but reverse coded).

Finally, the third (**Figure A3.1 panel C**) is a visual representation of age similarity in Sapporo, measured at 0.712, using Kyne and Aldrich's (2020) formulation based off of Morrow's observations about age and social cohesion (2008). This stacked bar chart shows the breakdown of the population by three age groups, including youth, adults, and elders. The share of residents who are non-elders (under age 65) is depicted via a black line, at 71.2%, to show the share of the population who tend to be especially active in social interactions, and who do not face as many barriers to social interaction compared to elders (25% in Sapporo), who face many challenges due to mobility and institutionalization. Age similarity is measured as a simple percentage or rate. The remaining measures of social capital are all either percentages or population controlled rates, like this measure.

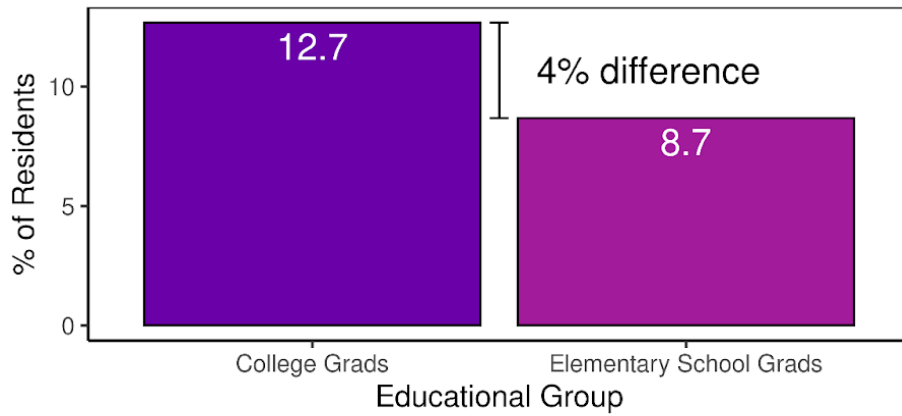
**Figure A3.1: Three Measurement Techniques used in Bonding Social Capital Index**

**A** Religious Similarity \* (0.912) in Sapporo



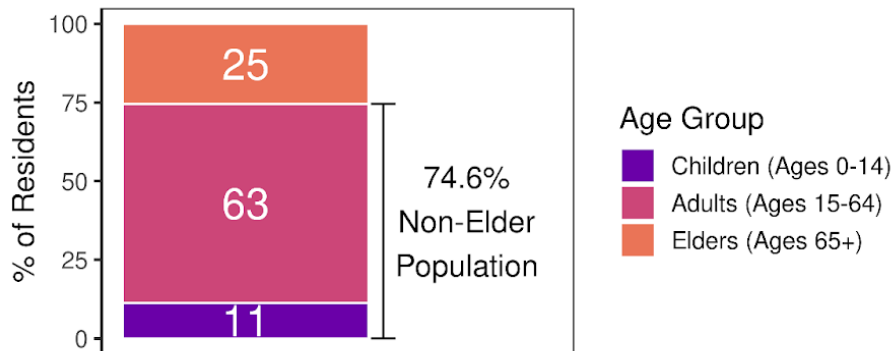
\* Values depict percentage squared (area) of each group in the community. Religious Similarity = 1 - Fractionalization (Remainder), so 0.912, where 1 = homophily and 0 = heterophily.

**B** Educational Equality \* (-0.04) in Sapporo



\* Measured by absolute difference in share of college vs. elementary school graduates. Then, multiplied by -1 so that equality = 0 and inequality = -1.

**C** Age Similarity\* (0.746) in Sapporo



\* Values depict percentage of each age group in the community. Age Similarity = relative size of non-elder residents (largest chunk of society), providing opportunities to build relationships within these age groups, where 1 = max potential and 0 = min potential.

### ***Bridging Social Capital***

Next, to represent bridging social capital, this study used several indicators of associational membership and civil society participation (Pekkanen et al. 2014; Small 2009; Taniguchi 2016; LeBlanc 1999). This is because associations are reported to frequently build ties across different racial, ethnic, income, and age groups (Putnam 2000). These inter-group ties help *bridge* divides and reduce inter-ethnic conflict (Varshney 2001), share information about evacuation (Fraser, Morikawa, & Aldrich 2021), and recover from crisis (Aldrich 2012).

In the US, Kyne & Aldrich (2020) and Fraser, Page-Tan, & Aldrich (2021) averaged rates of several different types of community organizations to create a bridging social capital index for each county and county subdivision, using different types of associations (religious, civic, advocacy, charitable, unions, fraternal), based on the work of Chamlee-Wright (2010), Norris et al. (2008), and Cutter et al. (2016). In the Japanese indices, Fraser (2021) used 8 indicators, including associational measures, supplemented by civil society participation to replace US indicators not available in Japan. Libraries and community centers, for example, are key places in communities that foster social capital and connectedness across different group lines (Klinenberg 2018). Similarly, voter turnout is a common approximation of civic engagement, a by-product of bridging ties that help build a sense of shared stake in one's community among residents from different backgrounds. Voter turnout has been used to measure bridging social ties in several studies (Fraser 2019; Aldrich 2021).

1. *Volunteer participation rate*
2. *Unions per capita*
3. *Nonprofit organizations per capita*
4. *Religious organizations per capita*
5. *Rate of community centers per capita*
6. *Rate of libraries per capita.*
7. *Voter turnout in prefectural elections (as measures of civic engagement)*
8. *Voter turnout in lower house elections (as measures of civic engagement)*

### ***Linking Social Capital***

Finally, to represent linking social capital, Fraser (2021) used several indicators of political linkages and representation to signify vertical ties to government officials and authorities, matching the approach of Kyne & Aldrich (2020), Fraser, Page-Tan, & Aldrich (2021), and past literature (Tierney 2001; Murphy 2007; Morrow 2008). For Japan, Fraser (2021) used 6 measures of linking ties. These approximated linkages between residents and local, prefectural, and central government, as well as political linkages through support for the party in power.

The logic here is that in communities with more government employees, policy, assembly members, etc. per capita, residents literally have more decision-makers available to connect with, petition, and build relationships and experiences with (Murphy 2007; Morrow 2008). Further, support for the ruling party has been used in several past studies (Fraser 2021b; Fraser 2019; Aldrich 2019) to measure linking ties.

Particularly in Japan, parties frequently form clientelist relationships with constituencies, providing communities with valuable construction and infrastructure jobs and new economic development projects to reward them for their support, cater to their constituents' needs, and ensure their votes in future elections (Fukui & Fukai 1996; Aldrich 2008; Tsai 2007; Catalinac et al. 2020). Communities which supported the party in power in the most recent election therefore often

have greater pull on those officials, able to make their needs heard to local, prefectural, and central government bodies (Aldrich 2019; Fraser et al. 2021).

1. *Local government employees per capita*
2. *Prefectural government employees per capita*
3. *Prefectural assembly members per capita*
4. *Prefectural police per capita*
5. *% of vote for ruling party in Lower House elections*
6. *% of vote for ruling party in prefectural elections*

**Past Indices**

In Japan, the author is unaware of other past indices available for every municipality; previous measurements of social capital have often been by single proxy (Aldrich 2011; Ramseyer 2015; Fraser 2019) or in-depth surveys of specific neighborhoods (Hikichi et al. 2020, for example). While the US has several alternative social capital datasets (United States Joint Economic Committee’s Social Capital Index 2018; Rupasinga et al. 2006), the Fraser (2021) indices are the first main measure of social capital closely engaged with the literature that are available in Japan.

There are two major types of value added by the Kyne & Aldrich framework. First, it captures bonding social capital especially well in terms of the propensity of homophilous communities to form strong in-group ties, which are effective at helping members of the same racial, ethnic, religious, age, income, or gender groups, but not as effective at extending help and resources across different social lines. (Alternative measures, like overall trust, are really too general to capture this in-group nature; additionally, trust measures are not available for Japanese municipalities.) The second major value added is that by sourcing from publicly available data sources, these indices can be easily redesigned at lower-levels of analysis, like the city level (as done by Fraser (2021) in Japan and Fraser, Page-Tan, & Aldrich (2021) in the US).

**Validation in past studies**

Both sets of indices were validated in their original studies by Kyne & Aldrich (2020) and Fraser (2021), where the authors showed that index components had strong conceptual and internal validity, correlating in expected ways with each other and with original indicators. The studies also validated these indices by showing that they appropriately correlated with known correlates, including disaster recovery outcomes.

Further, these indices have been repeatedly applied to multiple disaster scenarios, consistently demonstrating the associations expected by the literature, even in spite of different national contexts. These outcomes are listed in Table A3.1 below:

**Table A3.1: Expected Associations with Indices Found Consistently in 10 Studies**

#	Outcomes associated with these Indices, as expected	Source(s)
1	Presidential disaster declarations, disaster-related fatalities, and disaster damage in the US	Kyne & Aldrich 2020
2	Post-disaster death rates, outmigration rates, and public works spending in Japan after the 2011 triple disaster	Fraser 2021

3	Long-term migration and financial recovery among Tohoku and Miyagi communities affected by the 2011 triple disaster	Fraser, Small, & Aldrich 2021
4	Preemptive evacuation and long-term evacuation after the 2018 Eastern Iburu Earthquake in Hokkaido, Japan	Fraser, Morikawa, & Aldrich 2021
5	Building back better through climate change adaptation after Hurricane Sandy in 2012 and the 2011 triple disaster in Japan	Fraser, Cunningham, & Nasongo 2021
6	Reduction in greenhouse emissions in Japanese municipalities between 2005-2017	Fraser et al. 2020
7	Excess death rates during the COVID-19 pandemic among US counties	Fraser, Aldrich, & Page-Tan 2021
8	COVID test positivity rates during the COVID-19 pandemic among US census tracts and zipcodes	Fraser, Page-Tan, & Aldrich 2021
9	COVID-19 case rates and death rates during the pandemic among Japanese prefectures	Fraser & Aldrich 2021
10	Improvements in Health in US Counties	Panagopoulos et al. 2021

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