Social Ties, Mobility, and COVID-19 spread in Japan

Timothy Fraser (✉ timothy.fraser.1@gmail.com)

  Northeastern University   https://orcid.org/0000-0002-4509-0244

Daniel P. Aldrich

  Northeastern University   https://orcid.org/0000-0002-4150-995X

Research Article

Abstract

Why are some communities documenting higher case loads of COVID-19 infections than others? Past studies have linked the resilience of communities against crisis to their social vulnerability and to the capacity of local governments to provide public goods and services like health care. Disaster studies, which frequently examine the effect of social ties and mobility, may help illuminate the current spread of COVID-19. We model the occurrence of new cases from February 17 to May 29 using 4841 prefecture-day observations, paired with daily tallies of aggregate Facebook user movement among neighborhoods. This preliminary study of Japanese prefectures finds that communities with strong bridging and linking social ties start out more susceptible to COVID-19 spread, but their rates quickly decrease over time compared to communities with stronger intra-group ties. These results imply that residents' participation in civil society and trust in officials affect their adoption of new health behaviors like physical distancing, improving their capacity to respond and adapt to crisis. Though bridging and linking communities suffered more early on, they adapted better to new conditions, demonstrating greater resilience to the pandemic. We anticipate this study to be a starting point for broader studies of the effect of social ties and mobility on response to COVID-19 worldwide, verifying what kinds of social networks we should invest in to adapt to this pandemic.

Introduction

Why are some communities documenting higher case loads of COVID-19 infections than others? Since the global pandemic started, scholars have looked at the capacity of health care systems, the spread of residents, and the social vulnerability of communities to crisis, but social ties, a key factor in disaster studies, have remained absent from the conversation. This preliminary study of Japanese prefectures finds that communities with stronger bridging and linking social ties start out more susceptible to COVID-19 spread, but quickly see decreasing rates over time compared to communities with stronger intra-group ties. These results imply that residents' participation in civil society and trust in officials affect their adoption of new health behaviors like physical distancing, improving their capacity to respond and adapt to crisis.

This study makes three major contributions to the literature on disaster and pandemic response. First, while past studies have linked social capital and social vulnerability to disaster outcomes (Cutter et al. 2006, Aldrich & Meyer 2015, Fraser et al. 2020), this study applies this to the COVID-19 pandemic. Though social networks are associated with the spread of infection, this only occurs with contact; instead, communities with strong social networks can convince family, friends, and neighbors to adopt vital new behaviors like physical distancing and masks to reduce the spread of the virus.

Second, this study leverages Facebook user mobility data as a key mediating variable to discern the relationships between social ties and COVID-19 case rates, building on a literature on the role of mobility in crises (Yabe 2020, Fraser 2020). While geographic mobility has been linked to the spread of the avian flu and SARS (Bowen & Laroe 2006, Smallman-Raynor & Cliff 2008), as well as COVID-19 (Zhang et al.

2020, Cowling et al. 2020), communities with higher social capital see lower or decreasing associations between mobility and COVID-19 spread, as residents learn about how to protect themselves while moving about.

Third, this study highlights that while health care system capacity is vital to reducing the spread of pandemics (Schoenbaum et al. 2011), individual citizens and communities' participation in public health efforts is vital to ensuring widespread adoption of new health behaviors. This builds on past findings from SARS and Ebola (Tai and Sun, 2007; Funk et al., 2009; Vinck et al 2019), highlights that bridging and linking social ties are especially key, and applies this to Japan. Even after the Japanese government struggled to respond to the Diamond Princess outbreak and subsequent clusters, this study highlights that residents and their social networks have made a difference in Japan's response to COVID-19.

Literature Review

This study examines why some Japanese prefectures saw more new cases of COVID-19 than others. Recent scholarship highlights that COVID-19 spreads through contact with aerosolized droplets from persons carrying the virus, facilitated by coughing and sneezing (WHO 2020). On average, it takes 5 days to develop symptoms, with a range of 1-14 days (Lauer et al. 2020). Tracking infection rates has been problematic, as some states (such as the US and Japan) were slow to begin testing cases and have failed to contact trace(Kingston 2020). Further, many people spread the virus asymptomatically (Lavezzo et al. 2020). Based on infections reported already, we can examine variation in infection rates among communities.

First, some communities might see higher rates of infection because of citizens' behaviors and mobility (Zhang et al. 2020, Cowling et al. 2020). Communities have adopted physical distancing at varying rates; many Japanese prefectures and religious organizations did not close down key institutions until early April (Kingston 2020, McLaughlin 2020). For example, the northern prefecture of Hokkaido saw a high share of cases early on, while Aichi Prefecture in the Chubu Region developed a cluster of infections gradually (See **Figure 1**). Communities where residents still move between neighborhoods frequently might have higher case rates (Bowen & Laroe 2006, Smallman-Raynor & Cliff 2008). Similarly, communities which already have developed cases are more likely to see spread due to exponential rates of infection.

However, some communities see especially high rates of infection and death. In the US, African American neighborhoods with high shares of low-income residents in New York City and the city of Flint, Michigan, have seen disproportionately high infection rates (Mansoor 2020). These communities have greater shares of socially vulnerable populations, such as residents who are elderly, women, single parents, unemployed, in poverty, or racial, religious, or ethnic minorities. These populations tend to see worse outcomes both from initial disasters and long term recovery processes (Cutter et al. 2006, Fussell et al. 2010), because they are financially constrained from seeking help and have faced institutionalized discrimination in the past.

Yet some vulnerable communities manage better outcomes from crisis than others due to the *capacity* of governments to provide better quality response (Bollyky et al. 2019, Hallerod et al. 2013, Farag et al. 2012). In the case of COVID-19, some communities had better funded governments that purchased necessary materials and had more doctors, nurses, hospitals, and clinics available to serve new waves of patients (Schoenbaum et al. 2011). Meanwhile, others struggled to provide similar levels of care for populations.

Finally, even vulnerable communities with weak government and health care capacity could respond better to crisis if they have strong social networks to rely on. Disaster scholars find that strong social capital - social ties that residents use for physical, financial, and social support in times of crisis - are powerful interventions that boost community resilience (Aldrich & Meyer 2015). Scholars found this after the 1995 Kobe Earthquake, the 1995 Heat Wave in Chicago, the 2011 disaster in Japan, and after Hurricanes Katrina, Sandy, and Harvey in the US (Edgington 2010, Klinenberg 2002, Aldrich 2019, Ye and Aldrich 2019, Aldrich & Crook 2010, Collins et al 2017, Smiley et al. 2018, Metaxa-Kakavouli et al. 2018).

Social capital comes in three forms: bonding, bridging, and linking social ties. Bonding ties connect members of the same social groups, like family members, neighbors, and members of co-ethnic or co-religious groups, and help those groups survive crisis, but can lead to hoarding of resources. Bridging ties connect members of different social groups, like unions, nonprofits, and volunteer organizations, facilitating civic engagement (Putnam 2000), reducing ethnic violence (Varshney 2001), and providing mutual support across different social groups. Finally, linking ties connect residents to local, regional, and national officials, helping them access key public goods they might not otherwise receive (Aldrich 2019, Sretzer & Woolcock 2004, Tsai 2007).

In the case of COVID-19, social networks boost the spread of quality information on how to keep community members from contracting the virus. Past studies of epidemics found that information from trusted personal ties is more effective in changing health behaviors than centralized information campaigns (Tai and Sun, 2007; Funk et al., 2009; Vinck et al 2019). We hypothesize that bonding social ties, like social vulnerability, might backfire, circulating bad information while not providing new, quality information. In contrast, we hypothesize that bridging and linking social ties might facilitate the spread of quality information, since residents who trust their officials and different social groups might trust WHO guidelines on physical distancing more.

Results

This study modeled daily infection rates of prefectures from Japan's Ministry of Health, Labor, and Welfare from February 17 to May 29, compiled by JAG Japan (JAG Japan, 2020). We divided prefecture-day observations into two datasets. First, we modeled why some prefectures encountered their first case using prefectures with 0 or 1 cases. Second, we modeled why some prefectures found additional cases after their first case, using prefectures with 1 or more cases. We tested the effect of social capital, including bonding, bridging, and linking social capital, drawing from new indices (Fraser 2020) and the

cumulative movement of residents among different neighborhoods. We assessed mobility using aggregate level data from Facebook's Data for Good project. Meanwhile, each model controlled for the capacity of health care systems, government finances, and social vulnerability of communities, alongside further demographic controls. Finally, since social processes might change as communities adapt to the new pandemic, we modeled these infection rates using three time chunks, first looking from February 17 to April 5 (to include a surge in cases at the start of April), then from February 17 to May 1, and then from February 17 to May 29. This helps us confirm how long certain trends persist. Our modeling techniques, including proxies used in these models, are discussed in depth in the **Methods** section at the conclusion of this article.

This analysis finds three broad trends, described in **Methods Appendix Tables 1, 2, and 3**. First, the models demonstrate several effects as expected. For example, cumulative inter-neighborhood movement is positively related to increasing case rates, but negatively related to prefectures getting their very first case.

Up until April 5, more inter-neighborhood movement was associated with a higher likelihood of getting a first case of COVID-19 and getting subsequent cases. But by May 29, greater inter-neighborhood movement actually became associated with a lower likelihood of first cases, as cities adapted to the crisis and adopted masks and some social distancing. This is because cumulative movement helps the virus grow, but someone has to catch it first in order to get their first case. Likewise, the likelihood of virus spread increases as time passes, while prefectures that spend more on health and keep a better balanced budget tend to be much less likely to see their first case or subsequent cases of COVID-19.

Second, we find that towns with stronger bridging social capital are more likely to receive their first case and subsequent cases. Meanwhile, towns with strong linking social capital are less likely to receive their first case, but more likely to receive subsequent cases. This is because communities with strong civic participation and frequent meetings of social groups are excellent places for clusters of infection to take root, but communities with stronger linking social capital might be more likely to trust recommendations from local government and health authorities, helping limit the spread of those clusters.

Third, using interaction effects over time, we found that towns with more overall social capital, especially including bridging social capital, tended to see more cases outright, but fewer new cases over time. These effects were strongest from February to May, and were more muted after considering cases from May 1 to May 29. This suggests that social capital had a significant role in shaping resident responses to the virus in its first several months in particular.

As added evidence, we found a similar bivariate trend between social capital predictors and case rates, shown in the top panel of **Figure 2.** We analyzed how the daily correlation between prefectural social capital and vulnerability with case rates changes over time. This shows that in aggregate, towns with stronger bridging and linking social capital tend to see lower new case rates of COVID-19, while those with greater bonding social capital and vulnerability tend to see *higher* case rates.

Then, in the second row of **Figure 2**, we compared our set of prefectures with 0 or 1 cases and our set with 1 or more cases of COVID-19. Then, we used loess regression curves to track the change in these correlations from February to late May. The right panel shows a much clearer (and stronger) relationship between case rates and bridging and linking social capital *after* a prefecture gets its first case than *before*. However, those positive correlations with case rates dropped from February until late April, while bonding social capital and vulnerability developed increasingly less negative relationships with case rates over time. A finding of great concern is that bridging and linking capital's declining relationship with case rates only lasted until mid-April, after which it sharply increased again. Since late April, case rates have shown an increasingly positive relationship with all forms of social capital and social vulnerability. This implies that a tipping point was reached in late April, when some well networked communities began interacting again, creating new clusters of infections.

When we examine the *cumulative* case rates in **Figure 3,** we see that over time, bridging and linking social capital develop strong negative relationships with cumulative total case rates, even though they initially had positive relationships with early case rates. This seems to suggest that these communities with stronger bridging and linking ties are *adapting* over time, shifting from key sources of spread to key mitigators of spread. Even though some communities with strong social capital saw new cases in May, the cumulative pattern suggests that investing in bridging and linking social ties is a powerful grassroots strategy for adaptation to pandemics.

Finally, to triangulate the effect of social ties on COVID-19 rates, we examined *how* social capital shapes COVID-19 spread through mobility patterns. **Figure 4** depicts the changing association over time between case rates and the total cumulative inter-neighborhood mobility of Facebook users, with a line of best fit depicting the overall trend over time. However, each panel displays the relationship between mobility and case rates separately for towns with social capital above vs. below the median. If social capital had no effect, then we would expect the plots with high and low social capital to be nearly identical. However, in several cases, the trend lines are completely reversed, and in others, the correlation differs greatly. This analysis reveals three findings.

First, prefectures with low social capital, including boning, bridging, and linking social capital, saw much higher positive associations between mobility and infection rates than did prefectures with high social capital. Second, prefectures with high and low social capital both saw the relationship between mobility and case rates decline, indicating residents' adaptation and adoption of new behaviors like physical distancing, staying home, and wearing masks. Third, communities with strong bonding social capital saw a starkly decreasing correlation in mobility and new cases over time, while those with weak bonding social capital saw a starkly increasing association over time. Finally, over time, communities with stronger bridging social ties saw decreasing relationships between mobility and infection, much more so than those with weak bridging social ties. These findings highlight that communities with stronger social networks are adopting new and different mobility patterns and in-so-doing reducing their risk of contracting and spreading COVID-19. **Figure 4's** results are purely descriptive, and do not adjust for social vulnerability, health care capacity, or other factors, but present strong, clear trends.

Discussion

In summary, we see preliminary evidence that social ties and mobility patterns are shaping the spread of COVID-19 among Japanese municipalities. While strong bridging and linking ties trend directly with *more cases of infection,* these same social resources correlate with declining rates of infection over time and fewer cumulative infections. This suggests that communities are leveraging their bridging and linking social ties to adapt to the crisis and helping spread quality information about better health practices. This in turn may be reducing the infection rates of these highly socially active communities.

One challenge of inferring the effect of social ties on infection is that the Japanese government has been widely criticized for testing too few residents over the last three months. Critics might argue that we only observed that bridging and linking ties were related to infection rates *because* prefectures with stronger social ties tend to have better quality governance, and those prefectures used those networks to identify and test more people. However, this explanation is not appropriate. If communities with stronger bridging and linking ties test *more*, we would expect the effect of bridging and linking social ties over time to produce a false *positive.* However, we find the opposite. This lends credence to our hypothesis that, despite limited testing in Japan, bridging and linking social ties are critical to adapting to COVID-19 spread over time.

A second challenge of examining social ties is that communities have changed as COVID-19 unfolded. As residents spent more time with family, commuted less, and companies reduced normally gruelling hours, the monthly suicide rate in Japan dropped precipitously by 20% in April (Blair 2020). As a result, overall models of social behavior during this period eclipse key changing trends over time. However, this study compensated for changing social conditions by modeling three nested time spans, from February 17 to April 5, to May 1, and to May 29. The effect of social networks on reducing COVID-19 spread over time was most pronounced from February 17 to April 5, indicating that communities and local governments should seek to activate these networks as early as possible.

Further, one advantage of this research is that it controls for the tendency of residents to move among different neighborhoods, using aggregate tallies of Facebook user movement. Facebook users are a relatively accurate means of measuring movement, as similar shares of users ages 20 to 59 and male and female use Facebook. See the **Methods** appendix for further information on Facebook demographics. We found that communities with greater cumulative mobility were much more likely to get their first infection, but this effect shrunk greatly thereafter, likely as these communities began to adopt new health practices.

In summary, this study finds that social ties are a vital tool for adapting to and reducing COVID-19 spread, drawing on the case of Japanese prefectures from February 17 to May 29. In Japan, more vulnerable communities have seen fewer infections so far, because high earning urban metropolises have been major vectors for spread instead. Though communities with strong bridging and linking social ties may have facilitated early spread, over time, they are adapting better and reducing the rate of new infections, much more than communities with strong bonding social capital. By investing in residents' ties with their

broader community and with their elected officials, we can improve our capacity to respond not just to disasters but also pandemics.

Methods

This preliminary study examines why some Japanese prefectures saw more new cases of COVID-19 than others. Using data from the Ministry of Health, Labor, and Welfare, this aggregate-level study analyses how social ties shape the spread of COVID-19, while adjusting for the effects of human mobility, cumulative infections, social vulnerability to crisis, health care capacity, governance capacity, and demographics. Because the process that leads a prefecture to develop its first case of infection is likely quite different from the processes that lead a prefecture to develop its third, fourth, and four-hundredth cases, we modeled these processes separately. Drawing from 4841 prefecture-day observations, we used a logit model to explain why in 3683 cases, prefectures either saw zero or one reported new cases of COVID-19. Then, we use a gamma model to explain why in 1632 cases, prefectures saw increasingly positive case rates. In the logit models, the outcome is the count of new cases (0 or 1), controlling for population as a predictor, while in the gamma models, we use the population-controlled case rate. This data stretches from February 17 to May 29.

We repeated our analyses across three time frames to account for changing social processes as the pandemic progresses. First, we analyzed cases from February 17 to April 5, to account for the high spread of cases at the start of April. Second, we analyzed cases from February 17 to May 1, to account for the decreasing rate of cases in late April. Third, we analyzed cases from February 17 to May 29 to account for the stagnation of case rates in May. This three-pronged approach helps contextualize *when* key social processes affect COVID-19 spread the most.

1. *Key Variables*

This analysis employs several key predictors. To model social capital and social vulnerability, we use new indices modeled after the indices by Kyne & Aldrich (2019) & Cutter et al. (2003), aggregated to the prefectural level. As an initial analysis, we model just social capital, while subsequent analyses replace the social capital index with subindices for bonding, bridging, and linking social capital. All indices range from 0 to 1, where 1 denotes the most social capital or vulnerability, and 0 signifies the least. Next, we control for time using the number of days passed in the dataset. Next, to represent mobility, we calculated the total cumulative number of Facebook users who moved between neighborhoods within or between prefectures since the start date of the analysis, lagged by 5 days. This is to account for the fact that it takes on average 5 days for COVID-19 spread to result in symptoms and new cases. This data was provided by Facebook's Data for Good project.

This study never had any contact with individual level Facebook user data, but instead uses aggregated data provided by Facebook. Any user data was collected by Facebook Data for Good according to Facebook's Data Use Policy, then aggregated to the neighborhood level to maintain individuals' privacy, so that researchers never had contact with individual level data. This aggregate level data is regularly

provided to humanitarian NGOs and research teams with data sharing agreements, and does not involve any sensitive data nor user data. This analysis is an observational study of aggregate-level data, so no Institutional Review Board protocol was necessary.

Finally, we also add as a predictor the cumulative case rate of a prefecture five days prior. We might expect that prefectures with greater population movement or more cases five days prior might see more new cases in the present. Facebook users are a decent approximation of movement in the population; similar shares of users across age groups and gender use Facebook. According to a survey by Japan's Ministry of Internal Affairs and Communications (MIAC) in 2019, 32.8% of Japanese reported using Facebook, compared with 17% of teens, 47% of users ages 20-29, 49% of users ages 30-39, 37% of users ages 40-49, 29% of users ages 50-59, and 14% of users ages 60-69. Rates of use among men and women were identical (33%). This gives us a highly detailed glimpse of movement within or between prefectures, helping us assess the effect of this movement on spread rates.

2. *Controls*

This analysis also applied several control variables. First, the logit models use population as a control variable (while population is already incorporated in the gamma model outcome variable, which is the rate of cases per 1000 persons). Next, to represent overall health conditions, we use the life expectancy of a prefecture. If we were modeling death rates, it would be more important to control for additional health conditions, but since we are just modeling spread rates, we do not. Instead, we control for health care capacity, because communities with better health care capacity might identify, quarantine, and treat affected patients faster. This Health Care Capacity Index is a simple index of my own design that combines the proportion of doctors, nurses, hospitals, and clinics per 1000 residents, transforms each into a z-score, and then averages them together to make a single index. It is better to combine these as a single predictor than to apply them as separate predictors, because communities with more nurses but fewer doctors, for example, could still contain the spread of COVID-19 just as fine as communities with more doctors but fewer nurses. Next, we also control for total municipal and prefectural expenditures on health, as well as the health of municipality budgets, represented by the ratio of revenues to expenditures.

Finally, we control for several demographic traits. First, demographic vulnerability has already been represented in this model by the social vulnerability index, which represents overall trends in age, gender, income, education, employment, and health based vulnerability. Even so, we controlled for specific key traits of vulnerability as able, including the median age, unemployment rate, employment in the secondary sector (manufacturing), and population.

Several demographic traits could not be added to the model, because they were highly correlated with other demographic traits. Since there are only 47 prefectures, each demographic trait only has 47 unique values over all prefecture-day observations; adding these variables led to high multicollinearity in models, and so they were removed to ensure accurate estimated effects with no multicollinearity problems. For example, in our dataset, the median age, income per capita, and the college education population are all correlated with a Pearson's r of +/- 0.65 or above. Including any of these causes the variance inflation

factor to spike upwards of 7, which leads us to question the veracity of such a model. Similarly, health conditions like heart disease and hypertension and even traits like population and gender are all strongly correlated with the median age of a prefecture. **Appendix Figure 1** shows a correlation matrix for all variables in both models, shaded blue to signify strong positive correlations and red for strong negative correlations. These reflect a substantial degree of correlation among control variables. To avoid these multicollinearity issues, we employed a social vulnerability index, which already incorporates age, income, occupation, and gender-based vulnerability (Fraser 2020). Similarly, we consider conditions like heart disease and hypertension already controlled for because they are so collinear with age. Since COVID-19 case rates are only available at the prefectural level, this is the highest level of detail available, but future studies may improve on this if municipal level case rates become available.

3. *Models*

For each time frame, we generated eight models in total, including four logit models and four gamma models, resulting in 24 models total (See **Methods Appendix Tables 1-3**). For logit and gamma models, the first model used social capital as a predictor, while the second model included bonding, bridging, and linking social capital instead. The third and four models applied interaction effects with time, testing whether the effect of social capital indices and social vulnerability indices change *over time.* Each model in the period between February 17 and April 5 explained at least 67% of the variation in new cases of COVID-19. As the pandemic progressed, this decreased to 40% by May 1 and 25% by May 29 as prefectures developed new social processes and behaviors in response to the pandemic. Based on chi-squared intercept tests, all models fit better than an intercept model, with a statistically significant fit ($p < 0.001$).

Multicollinearity problems were abated by keeping the average variance inflation factor below 3.5 (except for interaction models, which are naturally collinear). Bridging and linking social capital indices generated the highest VIF scores, at 5.5. This is because bridging and linking social capital are related concepts. While this score is higher than the gold standard of 2.5, it is nowhere near 10, a problematic level of multicollinearity, meaning that it does not affect the validity of the model.

Finally, these models showed considerable heteroskedasticity, as shown by the Breusch-Pagan statistic and p-values in **Methods Appendix Tables 1, 2, and 3.** This is because the same prefectures across days tended to have similar outcomes, and so we used robust standard errors to calculate more conservative estimates of statistical significance. Each model depicts the standardized coefficients, which describe the log-odds of new cases given an increase of one standard deviation in a predictor. As a result, the size of effects can be compared across different variables to show which variable has the largest estimated effect on the outcome.

Declarations

Competing Interests: The authors declare no competing interests.

Correspondence: Correspondence and requests for materials should be addressed to Timothy Fraser at timothy.fraser.1@gmail.com

Ethics Statements: All methods were carried out in accordance with relevant guidelines and regulations. This study never had any contact with individual level Facebook user data, but instead uses aggregated data provided by Facebook. Any user data was collected by Facebook Data for Good according to Facebook's Data Use Policy, then aggregated to the neighborhood level to maintain individuals' privacy, so that researchers never had contact with individual level data. This aggregate level data is regularly provided to humanitarian NGOs and research teams with data sharing agreements, and does not involve any sensitive data nor user data. This analysis is an observational study of aggregate-level data, so no Institutional Review Board protocol was necessary.

References

Aldrich, D. P., & Crook, K. (2008). Strong Civil Society as a Double-Edged Sword: Siting Trailers in Post-Katrina New Orleans. *Political Research Quarterly* 61(3), 379–389. https://doi.org/10.1177/1065912907312983

Aldrich, D. P., & Meyer, M. A. (2015). Social capital and community resilience. *American Behavioral Scientist* 59(2), 254-269.

Aldrich, D.P. (2019). *Black Wave: How Connections and Governance Shaped Recovery from Japan's 3.11 Disasters.* Chicago: University of Chicago Press.

Blair, Gavin. (2020, May 14). Japan suicides decline as Covid-19 lockdown causes shift in stress factors. The Guardian. Accessed May 29, 2020. https://www.theguardian.com/world/2020/may/14/japan-suicides-fall-sharply-as-covid-19-lockdown-causes-shift-in-stress-factors

Bollyky, T. J., Templin, T., Cohen, M., Schoder, D., Dieleman, J. L., & Wigley, S. (2019). The relationships between democratic experience, adult health, and cause-specific mortality in 170 countries between 1980 and 2016: an observational analysis. *The Lancet* 393, 1628–1640. doi: 10.1016/ S0140-6736(19)30235-1.

Bowen, John T., & Laroe, Christian. (2006). Airline Networks and the International Diffusion of Severe Acute Respiratory Syndrome (SARS). The Geographical Journal 172(2), 130-144.

Collins, J., R. Ersing, & A. Polen. (2017). Evacuation Decision-Making during Hurricane Matthew: An Assessment of the Effects of Social Connections. *Weather, Climate, & Society* 9, 769–776.

Cowling, B.J., Ali, S.T., Ng, T.W.Y, Tsand, T.K., Li, J.C.M., Fong, M.W., et al. (2020), April 17. Impact assessment of non-pharmaceutical interventions against coronavirus disease 2019 and influenza in Hong Kong: an observational study. *Lancet Public Health* 5, e279-88. https://doi.org/10.1016/S2468-2667(20)30090-6

Cutter, S. L., Emrich, C. T., Mitchell, J. T., Boruff, B. J., Gall, M., Schmidtlein, M. C., Burton, C. G., & Melton, G. (2006). The long road home: race, class, and recovery from Hurricane Katrina. *Environment* 48(2), 8-20.

Cutter, Susan L., Boruff, Bryan J., and Shirley, Lynn W. 2003. Social Vulnerability to Environmental Hazards. *Social Science Quarterly* 84 (2), 242-261. DOI: 10.1111/j.1539-6924.2009.01341.x

Cyranoski, David. 2020, May 4. Profile of a killer: the complex biology powering the coronavirus pandemic. *Nature*. Accessed 5 May 2020. https://www.nature.com/articles/d41586-020-01315-7

Edgington, David W. (2010). *Reconstructing Kobe: The Geography of Crisis and Opportunity.* Vancouver, CA: University of British Columbia Press.

Fraser, Timothy, Aldrich, Daniel P., & Small, Andrew. (2020). Connecting Social Capital and Vulnerability: A Citation Network Analysis of Disaster Studies. *Northeastern University Global Resilience Institute Working Paper.*

Fraser, Timothy. (2020). Japanese Social Capital and Social Vulnerability Indices: Measuring Drivers of Community Resilience 2000-2017. *Northeastern University Aldrich Resilience Lab Working Paper.*

Fraser, Timothy. (2020). The Road More Traveled: Evacuation Networks from 10 disasters in the US and Japan. *Northeastern University Aldrich Resilience Lab Working Paper.*

Farag, M., Nandakumar, AK, Wallack S., Hodgkin, D, Gaumer G, Erbil C. (2012). Health expenditures, health outcomes and the role of good governance. *Int J Health Care Finance Econ* 13(1):33-52. doi: 10.1007/s10754-012-9120-3. Epub 2012 Dec 25.

Funk, S., Gilad, E., Watkins, C., & Jansen, V. A. (2009). The spread of awareness and its impact on epidemic outbreaks. Proceedings of the National Academy of Sciences, 106(16), 6872-6877.

Fussell, E. Sastry, N., & VanLandingham, M. (2010). Race, socioeconomic status, and return migration to New Orleans after Hurricane Katrina. *Population & Environment* 31(1-3), 20-42.

Halleröd, B., Rothstein, B., Daoud, A., & Nandy, S. (2013). Bad Governance and Poor Children: A Comparative Analysis of Government Efficiency and Severe Child Deprivation in 68 Low- and Middle-income Countries. *World Development* 48, 19−31.

J.A.G. Japan. (2020). Ministry of Health, Labor, and Welfare COVID19 cases for Japanese prefectures. Accessed May 5, 2020. https://gis.jag-japan.com/covid19jp/

Klinenberg, Eric. (2002). Heat Wave: A Social Autopsy of Disaster in Chicago. Chicago: University of Chicago Press.

Kingston, J. (2020, April 1). Abe prioritized Olympics, slowing Japan's pandemic response. *Asia Pacific-Journal Japan Focus* 18, no. 5 (article 5387), 1-9. https://apjjf.org/-Jeff-Kingston/5387/article.pdf

Kyne, D. & Aldrich, D. P. (2019). Capturing Bonding, Bridging, and Linking Social Capital through Publicly Available Data. *Risk, Hazards, & Crisis in Public Policy*. DOI: 10.1002/rhc3.12183

Lauer S.A., Grantz, K.H., Bi, Q, et al. (2020). The Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application. *Ann Intern Med* 172:577–582. [Epub ahead of print 10 March 2020]. doi: https://doi.org/10.7326/M20-0504

Lavezzo, E., Franchin, E., Ciavarella, C., Cuomo-Dannenburg, G., Barzon, L., Del Vecchio, C., et al. (2020). Suppression of COVID-19 outbreak in the municipality of Vo, Italy. *medRxiv* 2020.04.17.20053157; doi: https://doi.org/10.1101/2020.04.17.20053157

Mansoor, S.. (2020, April 5). Data Suggests Many New York City Neighborhoods Hardest Hit by COVID-19 Are Also Low-Income Areas. *Time Magazine.* Accessed 5 May 2020. https://time.com/5815820/data-new-york-low-income-neighborhoods-coronavirus/

Metaxa-Kakavouli, D., Maas, P., & Aldrich, D. P. (2018). How social ties influence Hurricane Evacuation Behavior. *Proceedings of the ACM on Human-Computer Interaction* 2 (122).

Ministry of Internal Affairs and Communications. 2019. Survey on time and information behavior of information and communication media. Accessed 1 May 2020. https://www.soumu.go.jp/main_content/000644166.pdf

McLaughlin, Levi. (2020, May 1). Japanese Religious Responses to COVID-19: A Preliminary Report. *Asia Pacific Journal Japan Focus* 18, no. 3 (article 5394), 1-23. https://apjjf.org/-Levi-McLaughlin/5394/article.pdf

Putnam, Robert D. (2000). *Bowling Alone: The Collapse and Revival of American Community.* Simon & Schuster.

Schoenbaum, Stephen C., Schoen, Cathy, Nicholson, Jennifer L, & Cantor, Joel C. 2011. Mortality amenable to health care in the United States: The roles of demographics and health systems performance. Journals of Public Health Policy 32 (4), 407-429.

Smallman-Raynor, Matthew, & Cliff, Andrew D. 2008. The Geographical Spread of Avian Influenza A (H5N1): Panzootic Transmission (December 2003-May 2006), Pandemic Potential, and Implications. Annals of the Association of American Geographers, Vol. 98, No. 3, pp. 553-582.

Smiley, K., Howell, J., & Elliot, J. (2018). Disasters, Local Organizations, and Poverty in the USA, 1998 to 2015. *Population and Environment* 40 (2): 115–35.

Szreter, S, & Woolcock, M. (2004) Health by association? Social capital, social theory, and the political economy of public health. *International Journal of Epidemiology* 33 (4), 650–667, https://doi.org/10.1093/ije/dyh013

Tai, Z., & Sun, T. (2007). Media dependencies in a changing media environment: The case of the 2003 SARS epidemic in China. *New Media & Society* 9(6), 987-1009.

Tsai, L. (2007). Solidary Groups, Informal Accountability, and Local Public Goods Provision in Rural China. *American Political Science Review* 101(2), 355-372.

Varshney, A. (2001). *Ethnic Conflict and Civil Society: India and Beyond.* New Haven, CT: Yale University Press.

Vinck, Patrick, Phuong N Pham, Kenedy K Bindu, Juliet Bedford, and Eric J Nilles (2019). Institutional trust in misinformation in the response to the 2018-19 Ebola outbreak in North Kivu, DR Congo: A population-based survey. *The Lancet Infectious Diseases*.

World Health Organization. (2020, April 17). Q&A on Coronaviruses (COVID-19). Accessed 5 May 2020. https://www.who.int/news-room/q-a-detail/q-a-coronaviruses

Yabe, T, Tsubouchi, K, Fujiwara, N, Sekimoto, Y, Ukkusuri, SV. (2020). Understanding post-disaster population recovery patterns. *Journal of Royal Society Interface* 17(163), doi: 10.1098/rsif.2019.0532.

Ye, Maoxin, and Aldrich, Daniel P. (2019). Substitute or complement? How social capital, age and socioeconomic status interacted to impact mortality in Japan's 3/11 tsunami. Social Science and Medicine: Population Health. Vol 7 https://doi.org/10.1016/j.ssmph.2019.100403

Zhang, J., Litvinova, M., Liang, Y., Wang, Y., Wang, W., Zhao S., Wu, Q., Merler, S., Viboud, C., Vespignani, A., Ajelli, M., & Yu, H. (2020, April 29). Changes in contact patterns shape the dynamics of the COVID-19 outbreak in China. *Science*. eabb8001 DOI: 10.1126/science.abb8001

Appendices

Appendix Table 1: Daily New Cases among Japanese Prefectures, Feb 17 - April 5

Appendix Table 2: Daily New Cases among Japanese Prefectures, Feb 17 - May 1

Appendix Table 3: Daily New Cases among Japanese Prefectures, Feb 17 - May 29

Appendix Figure 1: Correlation Matrix for Logit and Gamma Models
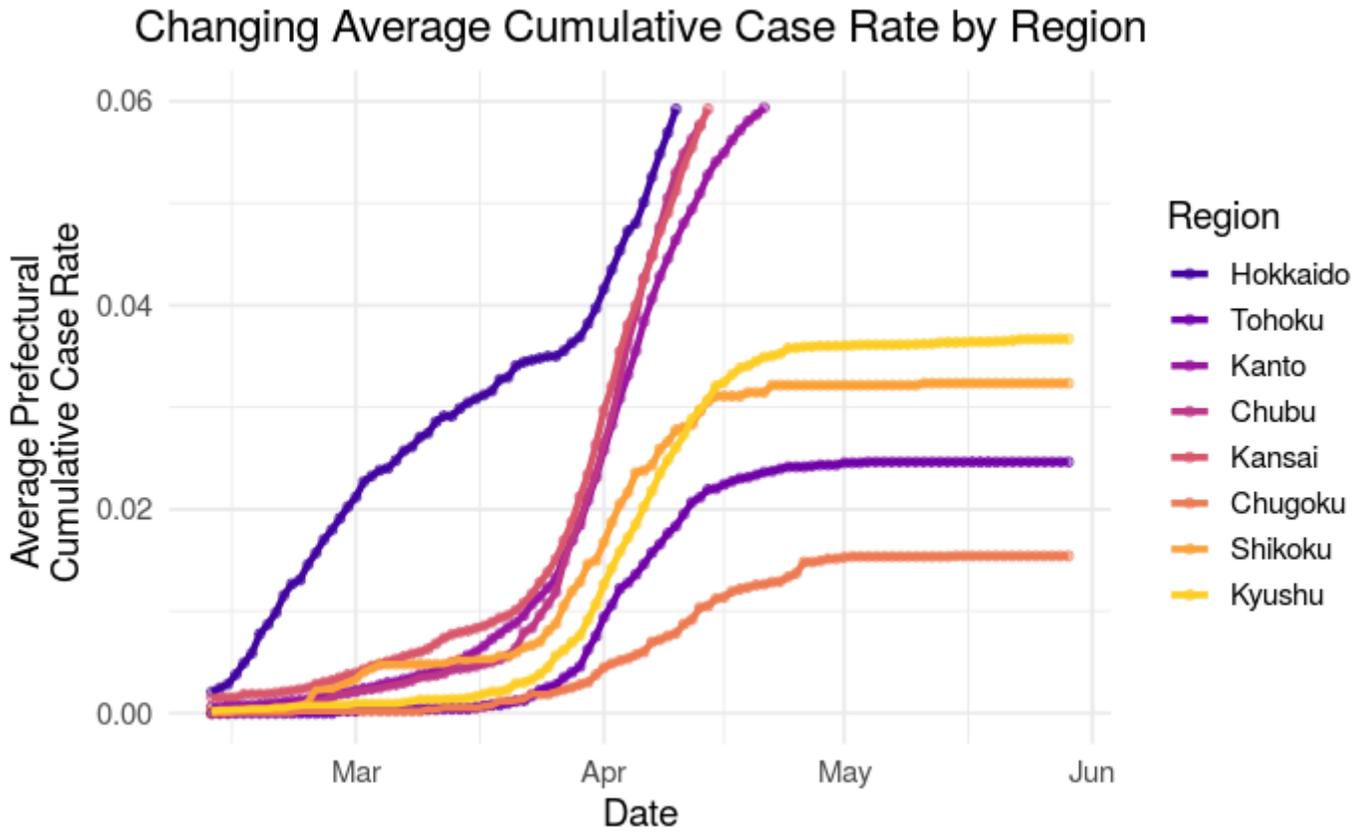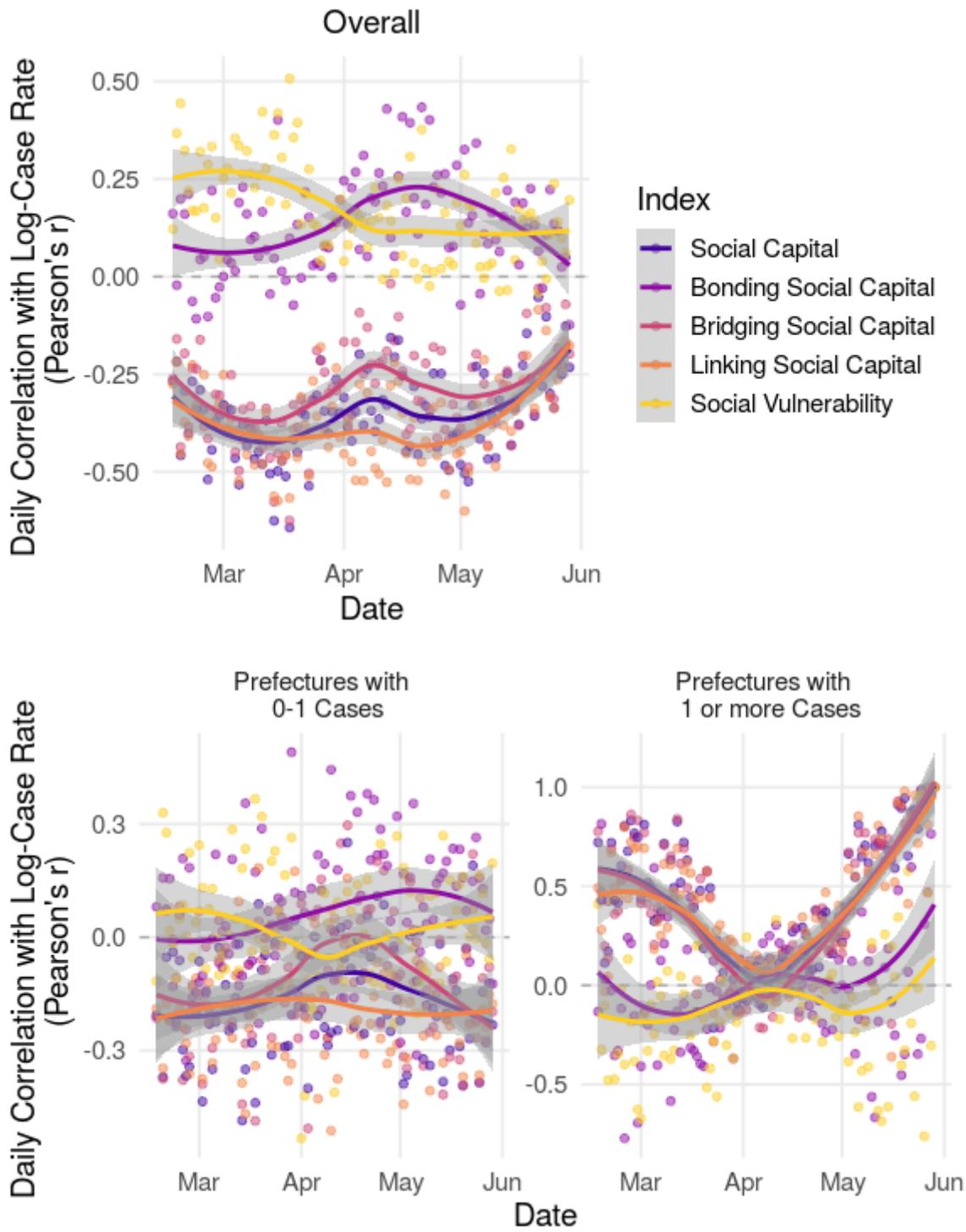
Figures

Changing Average Cumulative Case Rate by Region

Figure 1

Changing Average Cumulative Case Rates by Region

Figure 2

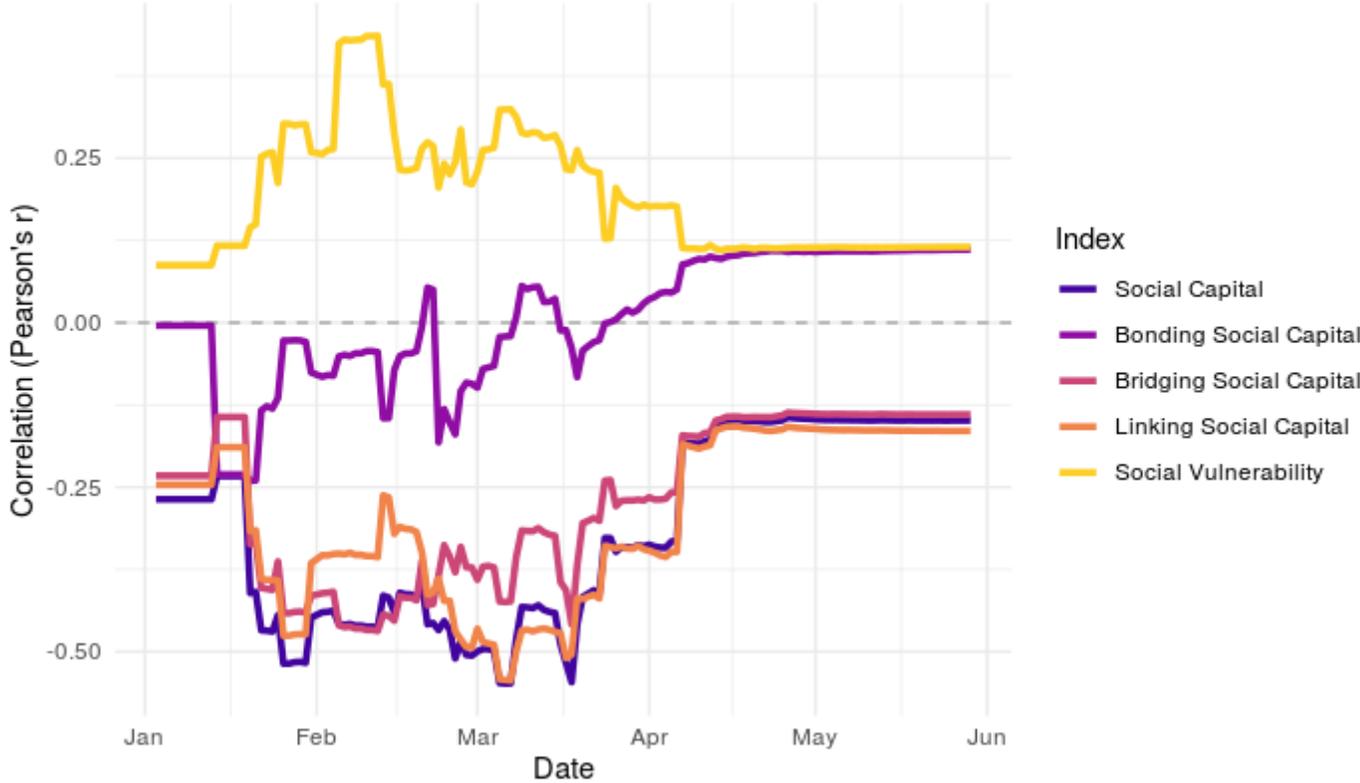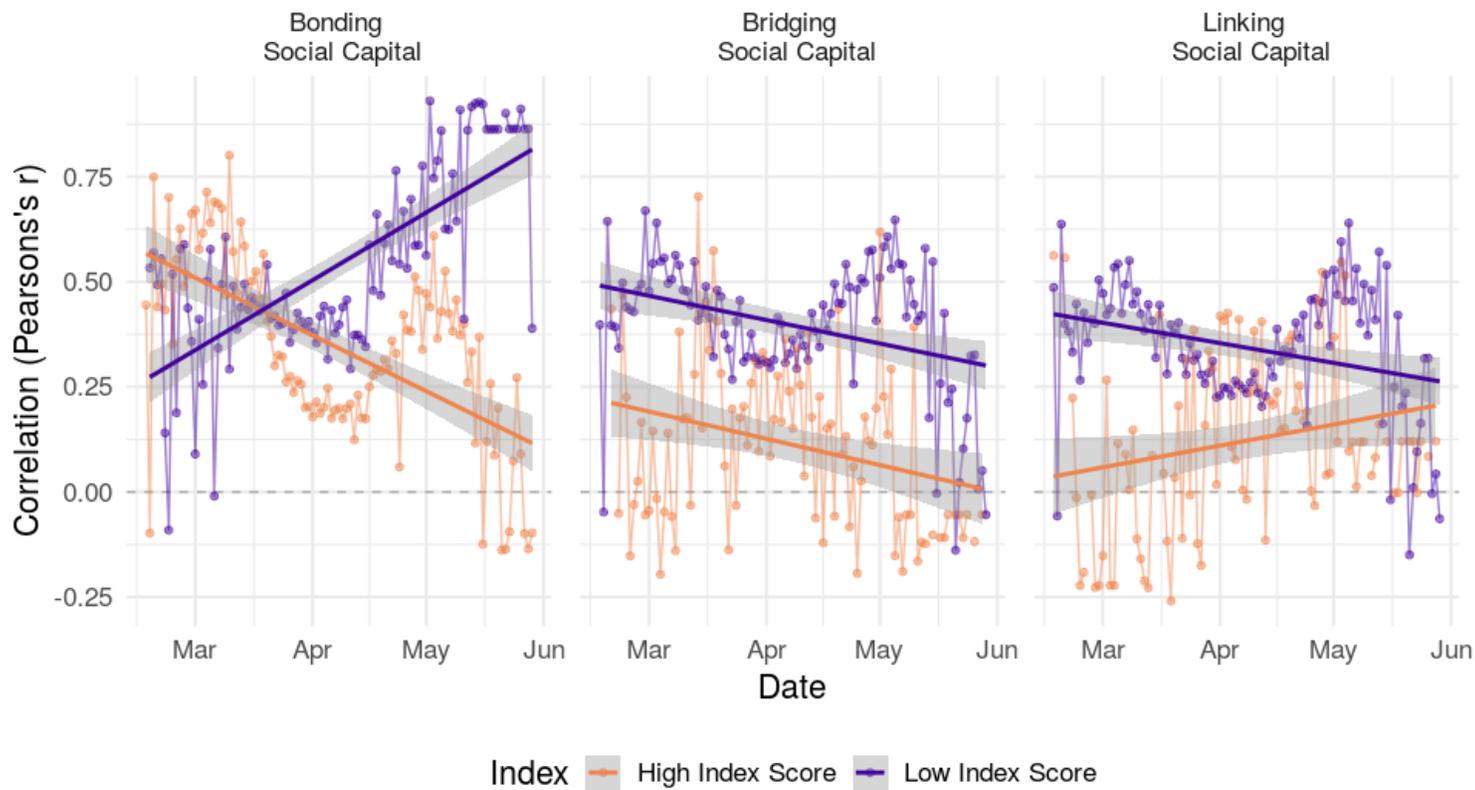Bridging and Linking Social Ties Associated with Lower Case Rates

Figure 3

Cumulative Case Rate, Social Capital & Vulnerability

Dotted line depicts daily change in actual correlation between cumulative inter-neighborhood mobility and log case rate.
Trend line and band depict overall linear trend with 95% confidence interval.

Figure 4

Social Capital's Intervening Effect on Mobility and COVID-19 Spread

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- appendixtable1.png
- appendixtable2.png
- appendixtable3.png
- appendixfigure1.png