

Social connections to COVID-19-affected areas increase compliance with mobility restrictions

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Abstract

We study the role of social connections in households' responses to mobility restrictions imposed amid the COVID-19 epidemic, using aggregated and anonymized Facebook data on social connections and mobile phone data for tracking movement. US counties with a one-standard-deviation more social connections to China and Italy, the first countries with major outbreaks of the virus, roughly double the compliance with mobility restrictions. The effect of social connections on compliance is stronger for Republican counties but exists regardless of political orientation. It is also stronger for counties with older and less educated populations. Groups at higher risk from COVID-19 comply with restrictions better and are less affected by social connections. Our findings are consistent with social networks contributing to households' information acquisition about the pandemic.

Keywords: social networks, non-pharmaceutical interventions, COVID-19

JEL Classification: D83, D85, H75, I12, I18

Short title: social connections and mobility restrictions

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1 Introduction

The COVID-19 pandemic has taken many thousands of lives, strained societies and healthcare systems, and forced a partial shutdown of the global economy [1, 2]. In the United States, the rise of COVID-19 in early March has sparked large-scale mobility restrictions including school closures, social distancing orders, and stay-at-home notices [3]. These interventions are broadly similar to the measures implemented around the world during the ebola and H1N1 epidemics [4, 5, 6, 7, 8, 9] such as school closures [10, 11, 12]. Studies suggest the rigorous, albeit heavy-handed, implementation of such measures in Wuhan, China, was effective in stemming the outbreak [13, 14].

However, interventions related to social distancing face inherent limitations hampering their effectiveness. As local governments may be limited in their capacity to surveil and enforce current laws [15], households must voluntarily comply with social distancing rules for them to be effective [16, 17]. There are several reasons they might not. First, people may choose to not comply with mobility restrictions because they misperceive the risk of the pandemic or believe the benefits of mobility restrictions to be low [18]. Second, people may misinterpret information they receive [19]. For example, a number of recent studies have documented that social distancing appears less common in Republican counties, a proxy for “biased beliefs” [20]. Third, people might simply lack information due to information processing constraints and limited attention [21].

In this paper, we study how social connectedness, as measured by Facebook connections around the world, affects the efficacy of mobility restrictions. Our empirical results suggest the flow of information through social connections is an economically significant driver of social distancing. For our analysis, we use Facebook’s county-level Social Connectedness Index [22] to measure social connectedness between US counties and different foreign countries and combine it with county-level mobility statistics data from SafeGraph. SafeGraph is a company producing anonymized mobile phone location statistics covering 10% of mobile devices in the US population, allowing us to evaluate the local effectiveness of state-wide adoptions of mobility restrictions in response to the COVID-19 pandemic.

Using this novel setting, we study how government-imposed mobility restrictions affect social distancing within different counties depending on how socially connected they are to China and Italy, the first two countries to report major outbreaks of COVID-19.¹ Given they were the two places most severely impacted by COVID-19 outbreaks early on, we expect social connections to these places to be positively linked to the effectiveness of mobility restrictions if such social connections transmit information about the severity of the pandemic. Another benefit of studying the social connections to these two distant countries is that it mitigates the possible concern that social connections proxy for physical movement and thus the local risk of an outbreak [23].

As predicted, we find strong empirical evidence that social connections to these affected regions appear to explain compliance with social distancing guidelines. We also explore alternative interpretations of the relationship between social connections and the effectiveness of regulatory interventions on social distancing. First, social connections may capture both identity [24] and information flows [25, 26]. Therefore, we may misattribute to social connections similarity in beliefs. The two hypotheses are not in conflict, but our central thesis is that at least some portion of the relationship between social connections and compliance with restrictions has to do with the role of social connections in transmitting *information*. While the *biased beliefs* hypothesis suggests households refuse to respond to information, even when it is readily available, the *information friction* hypothesis suggests that households do not respond to social distancing guidelines because they lack information on the severity of a pandemic. Distinguishing the two is crucial to the design of the optimal government interventions, since stricter measures are required if households simply refuse to believe information.

To distinguish the economic channel behind our results, we present three sets of tests examining how the heterogeneity at the county level affects the relationship between social connections and social distancing. First, we test whether the impact of social connections is present among both Republican and Democrat counties. We find the effect to be present, if not stronger, in Republican

¹China was the first country with the COVID-19 virus with over 10,000 publicly reported and confirmed COVID-19 cases and 304 deaths as of February 1, 2020, while Italy has the highest mortality rate as of March 31, 2020 of over 10%.

counties. This suggests social connections do not proxy for political beliefs, as Republican counties socially distance less, not more. Second, comparing social connectedness into Italy versus China, we find evidence of information cross-pollination across racial lines. The effect of social connections to China is stronger for counties with a high fraction of Caucasians, while social connections to Italy matter more for counties with a high fraction of Asians. Under the biased beliefs hypothesis, we might find the converse to be true: communities tend to respond to information within-group rather than across-group. Finally, we find that the effect of social connections on social distancing is stronger in counties with higher median age and lower education level, suggesting that social connections matter more where the population is possibly less sophisticated at information acquisition. Again, this favors the interpretation that social connections interact with mobility restrictions primarily by modulating information flow, rather than proxying for the formation of social connections among those with similar beliefs.

Another potential explanation for our findings is that social connections are a proxy for risk exposure to the pandemic: areas with higher social connectedness to affected areas are also more exposed to travel. It is not clear to us that households would be aware of the demographics of travelers in such manner, but nevertheless, we perform two sets of analyses to address this issue. First, we study whether social connections are more important among high-risk populations, characterized by a high fraction of diabetic or obese or areas with high population density. We find that social connections matter less in high-risk areas, while these areas are generally more compliant with mobility restrictions. This may be because high-risk groups endogenously choose to pay attention to public health risks in any case.

Second, in additional robustness check analysis presented in Appendix Table B.1, we confirm that our findings are robust to excluding various high-risk areas. We begin by excluding New York City and adjacent states, finding very similar results. New York City has the highest number of reported cases in the United States. We also remove all counties with meaningful-sized commercial airports (columns 3 and 4) and their adjacent counties (5 and 6). The coefficient is actually larger in these sub-samples, suggesting counties nearer to airports might have other factors such as urban

density or the widespread awareness of travelers that might substitute for information from social media. We also exclude the 20% of counties with the highest percentage of Asian-Americans, where possibly awareness of the pandemic might be the highest, finding much stronger results in the rest of the sample. Taken together, our findings suggest that stimulating information transmission through social networks could have an economically meaningful effect on the impact of mobility restrictions.

2 Data and methodology

For our analysis, we create a county-day panel of social distancing, exposure of information through social connections at the county level, and county-level local cases. We combine these with standard data on county characteristics from the US Census and American Community Survey.

Our main data on social distancing are provided by SafeGraph Inc. For the purpose of research related to COVID-19, SafeGraph freely provided their data to researchers and government organizations. SafeGraph’s user location data coalesces from users of a variety of smartphone apps in which users opt in to provide their location. The data are anonymized and aggregated to a ‘census block group’, which contains somewhere between 1,500 to 7,500 people. These can be conveniently aggregated to the county level.²

Using its panel data, SafeGraph calculates how long a user spends at home, at work, how far the person has traveled from home, and how long the person stays at a given location away from home. To identify a person’s home, SafeGraph calculates a “common evening location”, a location which an individual typically stays during night time hours. In contrast, those phones staying at a “common daytime location” are classified as “working”. Following [27], we define social distancing as

²Regarding coverage and quality, on an average day from February 1st 2020 to March 31st 2020, SafeGraph observes 18.75 million devices, approximately 5.6% of the US population and about 10% of mobile devices. According to SafeGraph’s analysis of user characteristics, SafeGraph posits that its sample is representative of the US population based on own study of income characteristics, age and demographics of its users.

$$Social\ Distancing_{i,t} = \frac{Completely\ Home_{i,t}}{Total\ Device\ Count_{i,t} - Working_{i,t}}$$

where i indexes a county and t a day. *Completely Home* and *Working* refer to device counts of individuals who appear to stay completely within the vicinity of their home during the day and working either part-time or full-time, respectively. By subtracting out from the denominator those who go to work (presumably out of necessity), we consider the ratio of those mobile devices who remain completely home relative to those with the choice to stay home.

To measure social connections between different counties, we use the Social Connectedness Index [28, 22]. Leveraging Facebook’s 2.1 billion active users globally and 239 million active users in the United States and Canada (as of 2017), Facebook’s SCI calculates the relative frequency of Facebook friendship links between every user in every county-pair in the United States, as well as every county in the United States to every country, defined for pairs of geographical regions i, j as

$$Social\ Connectedness\ Index_{i,j} = \frac{Facebook\ Connections_{i,j}}{Facebook\ Users_i \times Facebook\ Users_j}.$$

This index is a measure of the relative density of Facebook connections between each US county pair, as well as between each US county and each foreign country. It can be interpreted as a relative probability of a Facebook friendship between a given Facebook user location i and j . For each country, the SCI for the county with largest number of friendship links is normalized to 1,000,000. Hence, this allows us to cross-sectionally compare the relative connectedness of each county to China and Italy, respectively.

We obtain data on restrictions imposed in different states from Keystone Strategy. Different regions within the United States have implemented different restrictions, depending on their exposure to the pandemic, institutional capacity, and other local factors. The restrictions fall into five types: school closures, closure of public places, restrictions of gatherings, stay at home orders and closures of all non-essential businesses. Generally, restrictions are state-level, but on occasion (especially when states have not enacted mobility restrictions) there is county-level variation

within a state. Therefore, the variation of the restriction measure is both at the state level and also within-state.

Finally, we gather data related to COVID-19. Daily count of the number of confirmed COVID-19 cases and deaths by each county come from John Hopkins University, accessed through the New York Times.

3 Empirical specification

We use a difference-in-differences specification to study the differential reaction between counties with a high number of social connections with either China or Italy to those with low social connections within the same state and on the same day. We set up this analysis as

$$Social\ Distancing_{i,t} = \alpha_{s,t} + \gamma_i + \beta Restrictions_{i,t} \times \ln(SCI_i) + \psi \ln(Cases_{i,t}) + \varepsilon_{i,t},$$

where i indexes a county, t indexes a day, and SCI is the Social Connectedness Index with either China or Italy. $\alpha_{s,t}$ are state-by-day fixed effects and γ_i are county fixed effects. The outcome variable is the measure of social distancing and the variable of interest is $Restrictions_{i,t} \times Social\ Connectedness\ Index_{i,j}$, which captures the incremental response to mobility restrictions related to social connections.³ The empirical specification includes a control $\ln(Cases_{i,t})$ for the number of cases in that county on that day. Standard errors are double-clustered by county and day, permitting time-series correlation of social distancing and restrictions within a county as well as contemporaneous correlations across states on the same day.

The coefficient of interest, β , is interpreted as the differential effect of one additional mobility restriction for counties with higher social connections to Italy or China versus those with fewer social connections. The empirical specification follows a difference-in-differences design as by the end of our sample on March 30, 2020, none of the restrictions have been lifted. Therefore, econo-

³In the Appendix, Section B.2 studies an alternative measure of social connections using relative friend probabilities, which account for the overall level of social connectivity. We find the same results.

metrically the $Restrictions_{i,t}$ is analogous to an indicator for the “post” period. Our main measure of restrictions is a continuous measure, counting the number of different mobility restrictions that have been introduced. Therefore, the variable ranges from 0 to 5. For a state which implements two measures on the same day, $Restrictions_{i,t}$ jumps from 0 to 2.

For our empirical design to causally identify the effect of social connections on the efficacy of mobility restrictions on the efficacy of mobility restrictions in increasing social distancing, state-wide mobility restrictions must be exogenous to county-level characteristics. Since we control explicitly for the number of cases within a county, we believe the exact timing of restriction introduction is not correlated with our key variables like the amount of social distancing and social connections with China or Italy. Our high-dimensional fixed effects permit correlations of state- and nation-wide policies, and focus on differential responses within states. We include county-level fixed effects to account for any differences in county characteristics, such as personal wealth level, industry composition, age distribution, political leaning, and county-level fiscal conditions.

In additional analyses, we consider interacting our main variables of interest $Restrictions_{i,t} \times Social\ Connection\ Index_{i,j}$ with additional county-level characteristics to disentangle the effect of county-specific bias with an information flow mechanism. Visually, we classify social connection index into deciles, and plot the highest decile and the lowest decile.

4 Results

4.1 Social connections and mobility restrictions

We first document the relationship between social connections and the effectiveness of restrictions and social distancing. Figure B.2 shows the responses of counties in the top decile of social connections around the first mobility restriction event for each state. Panel A suggests that relative to counties with low connections to China, counties with high connections to China socially distance more immediately after the imposition of social restrictions. Panel B repeats the same analysis for Italy.

Social connections increase compliance of mobility restrictions by around 50%, and the effect is 40% to 50% of the effect from more local cases.⁴ Table 1 studies a continuous variable specification in regression form, looking at the impact of social restrictions interacted with social connections we find the relation between social distancing and social connections to China and Italy to be positive. Column 1 runs the analysis for just Chinese social connections alone, and column 2 runs the analysis for just connections to Italy alone. The economic magnitudes across Column 1 and Column 2 are similar. However, Column 3 suggests that when in a horse race, connections to Italy dominate connections to China in importance. The standard deviation and mean of social connection index for Italy is approximately 30% greater, while the coefficient four times as large. This is an economic magnitude roughly five times as large.

4.2 Channels linking social connectedness and mobility restrictions

We think of three reasons why social connections to affected areas such as China or Italy might affect responsiveness to social restrictions:

- *Information flow*: Social media may transmit news [29, 30]. When households are more socially connected to regions such as Italy or China, where households might be likelier to share information related to COVID-19, households may receive information about the severity of the COVID-19 pandemic. This may drive their compliance with social mobility restrictions.
- *Biased beliefs*: Socially connected agents may form connections with people with similar beliefs [31, 32, 33]. Social connections may be highly correlated with the political beliefs, for example, which other studies have argued drive medical decisions such as anti-vaccination or more recently, social distancing in response to mobility restrictions. This might explain the larger coefficient on $\ln(SCI\ Italy)$ relative to $\ln(SCI\ China)$: given demographics of the

⁴Appendix Table A.5 shows unconditional effects of mobility restrictions. One more mobility restriction increases social distancing by 0.11 standard deviations.

American population, news from China about the severity of cases may be discounted relative to news from Italy [34]. Indeed, a self-reinforcing “echo chamber” may deter factual news about the COVID-19 situation from being disseminated [35].

- *COVID-19 riskiness*: Internet social connections between two regions might be correlated with the propensity for transit between the two regions. If households in a region are generally aware of the demographics of households living in that region as well as the demographics of visitors, social connections might proxy for higher risk exposures among households. Thus, the response to mobility restrictions would be higher. Further, the number of Facebook users in China (< 0.1%) as a fraction of the total population is much lower than that in Italy (51% as of September 2018), thus less relevant, timely or useful information might emanate from Chinese users during this period, relative to Italian users.⁵

We first ask whether the relation documented in Table 1 reflects a proxy for biased beliefs. If agents with biased beliefs simply disbelieve the severity of a pandemic, they may be less responsive to social distancing guidelines. If households with certain beliefs associatively match with people with similar beliefs, then social connections to an external region such as Italy or China might indirectly capture similarity in beliefs. In the United States, perhaps the most relevant measure and available of beliefs is political orientation. Political orientation which has been shown to predict differences in public health policies [36, 37].

4.2.1 Alternative: Social connections as a proxy for biased beliefs

In Table 2, we test the effect of social connections on the reaction to social restrictions conditional on whether a county is primarily Democratic or Republican in the 2016 election. It is unlikely social connections capture the effect of political orientation. Column 1 and Column 2 interact with indicators of whether the county is Republican or Democrat. In Republican counties, we find, similar to other studies, Republicans are generally less responsive to mobility restrictions.

⁵<https://www.internetworldstats.com/stats3.htm> as of April 10, 2020. Data for China is as of January 31, 2020 and for Italy is as of December 31, 2018.

However, the coefficient on $\ln(SCI\ China)$ and $\ln(SCI\ Italy)$ are positive, suggesting that Republican counties with high social connections to China or Italy are affected more, not less. A one-standard-deviation increase in social connections to China or Italy increases the effect of mobility restrictions by around 84% in majority Democrat counties and by 105% in majority Republican counties. Given that Democrat counties comply with mobility restrictions more, we would have expected Republican counties to respond less to social connections if social connections captured political orientation.

Under the idea of biased beliefs, we might expect racial homophily to matter, as information emanating from within one's own group might be perceived to be more trustworthy than information outside of it. That is, one might expect connections to China to matter when communities have a large percentage of Asian-Americans, and social connections to Italy to matter more when communities are more so comprised of Caucasian-Americans. However, we find the opposite in Column 3 and Column 4.

On the margin, Asian communities are more responsive to social distancing restrictions when they are more socially connected to people in Italy, and communities with a larger fraction of Caucasian households are more responsive to social distancing restrictions when they are socially connected to people in China. In terms of economic magnitude, social connections to Italy in counties with 10% more Asian people is more than double the average effect from social connections to Italy, and social connections to China in counties with 10% more White people is around 14% larger than the average effect from social connections to China based on the main results in Table 1.

If social media conveys information, on the margin the information that matters is that which is conveyed across racial groups, rather than within groups. One potential explanation is that communities with a larger fraction of Asian-Americans are likelier to pay attention to news related to China, but relatively less likely to be attentive to news related to Europe. In this scenario, social connections and social media could play a role in transmitting information that Asian-American communities may not normally observe.

4.2.2 Alternative: Social connections as a proxy for riskiness in a local population

The above empirical analysis points away from the idea that social connections proxy for biased beliefs, but rather that social connections might instead either capture perceived risk or information flow. We find evidence against the former and evidence in favor of the latter. In Table 3, we study whether social connections impact mobility restrictions more heavily among sophisticated populations. In Table 4, we test whether social connections impact mobility restrictions among high-risk populations.

One may expect less sophisticated individuals to be less responsive to voluntary regulation and rely more on their social connections. Turning to Table 3, we study two measures of sophistication: age and education. First, in columns 1 and 2 show counties with older populations are less compliant with mobility restrictions, the coefficient on $Restr. \times \ln(Age)$ is negative. Since older populations are more susceptible to the COVID-19 virus [38], we would have expected more compliance among counties with older populations. Our coefficient of interest on $Restr. \times \ln(Age) \times \ln(SCI\ China)$ is positive, meaning that the impact of social connections in compliance with mobility restrictions is higher in older populations. Second, columns 3 and 4 show counties with a smaller share college educated residents are less responsive to restrictions, the coefficient on $Restr. \times Education$ being *positive*. Similar to the interaction between restrictions and age, we find less areas with less sophisticated households to be less responsive to restrictions. This is reflected in a negative sign on our coefficient of interest, the interaction between social connections, restrictions and education. However, it is only statistically significant for $Restr. \times \ln(Education) \times \ln(SCI\ China)$, whereas $Restr. \times \ln(Education) \times \ln(SCI\ Italy)$ has a t-statistic of roughly 1. If anything, this evidence suggests that social connections are less relevant in explaining the responsiveness of relatively educated demographics to mobility restrictions. This could be consistent with education and information transmitted through social media to be substitutes, on the margin.

In Table 4, we directly study whether risk factors across counties interact with the mobility restriction compliance effects from social connections by using county-level measures for the in-

cidence of obesity, diabetes and population density. The risk-based hypothesis would predict that high-risk, high-density counties would respond more to mobility restrictions as households endogenously choose to avoid risk. We find the opposite: across all three measures of risk, we find the interaction between social connections and mobility restrictions to be less positively related to social distancing among high-risk populations. These results are consistent with people in higher-risk counties being more attentive to health risk irrespective of social connections, and thus social connections convey marginally less useful information to these counties.

5 Conclusion

Our empirical analyses show the social connections with areas severely affected by COVID-19, namely Italy and China, increase the efficacy of mobility restrictions that local governments impose. Our additional analyses suggest this amplification effect is due to the information flow through social connections, as opposed to social connections proxying for biased beliefs or riskiness through travel.⁶ We believe the findings in this paper can be used to guide public health officials to better monitor or enforce compliance with social distancing measures and hence more effectively reduce the spread of the COVID-19 pandemic.

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⁶Additional empirical analyses in the appendix repeating the main analyses for social connections with New York and accounting for adjacent counties in a short travelling distance, and also study additional cross sectional heterogeneity of social connection effects based on additional county-level characteristics in Section B.

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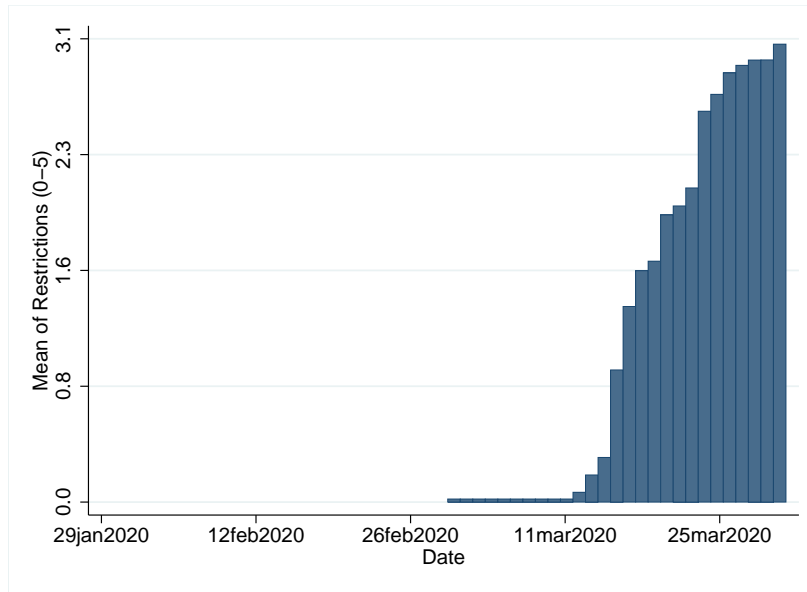
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Tables and Figures

Figure 1: Number of state-level restrictions

County average number of types of restrictions implemented (0-5). As of March 30, 2020, the number of state-level school closing is 52, closures of public places is 43, stay-at-home orders is 36, no-gatherings is 20, and banning non-essential services is 11.

A. Number of restrictions – calendar time



B. Number of restrictions – from first restriction

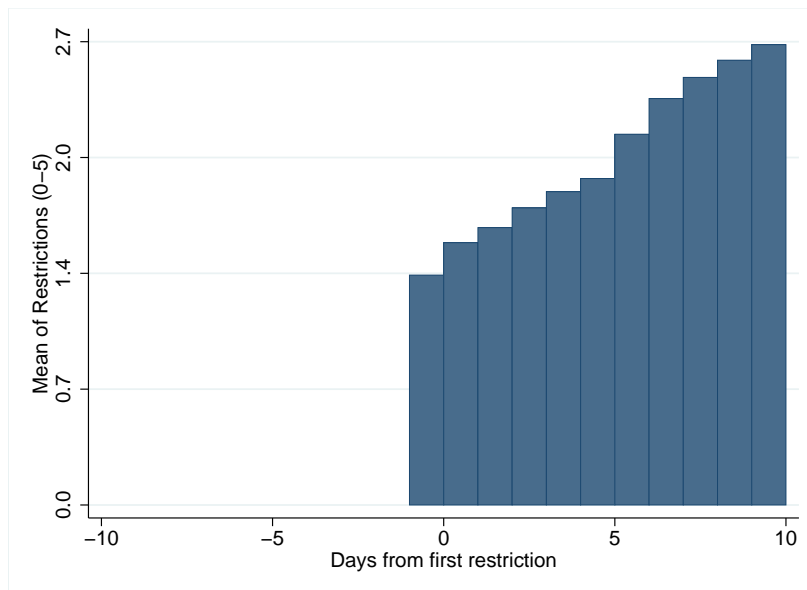
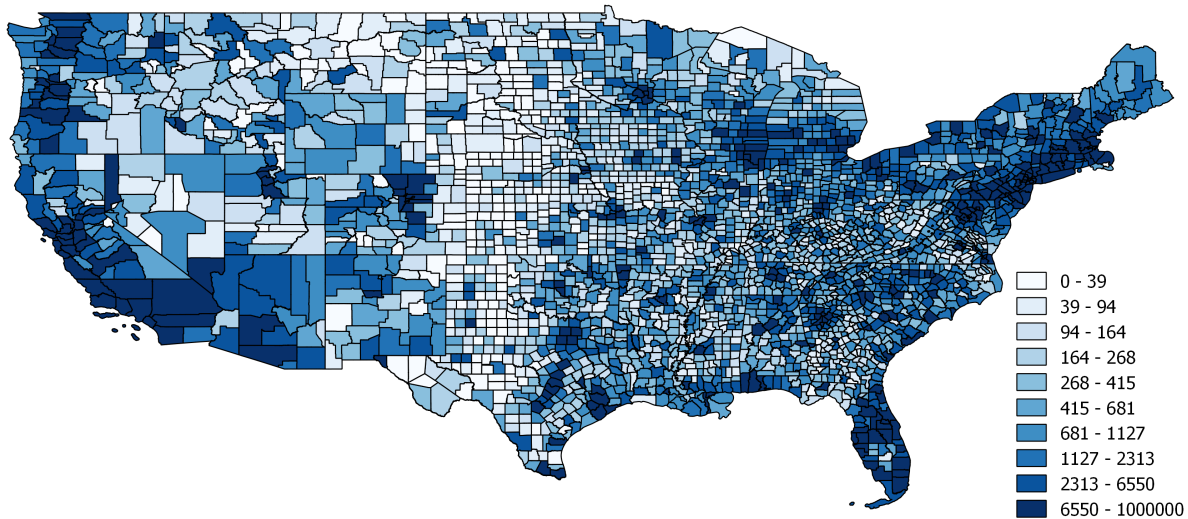


Figure 2: Social Connectedness Index (SCI) with China and Italy

Social Connectedness Index (SCI) between the county and China (*SCI China*) and Italy (*SCI Italy*).

A. Social Connectedness Index with China (SCI China)



B. Social Connectedness Index with Italy (SCI Italy)

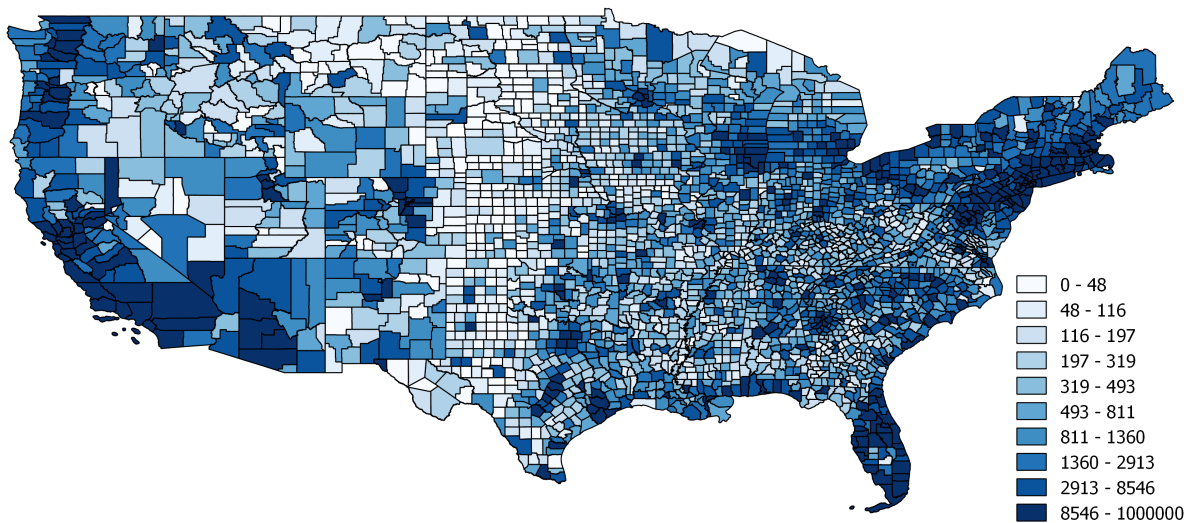
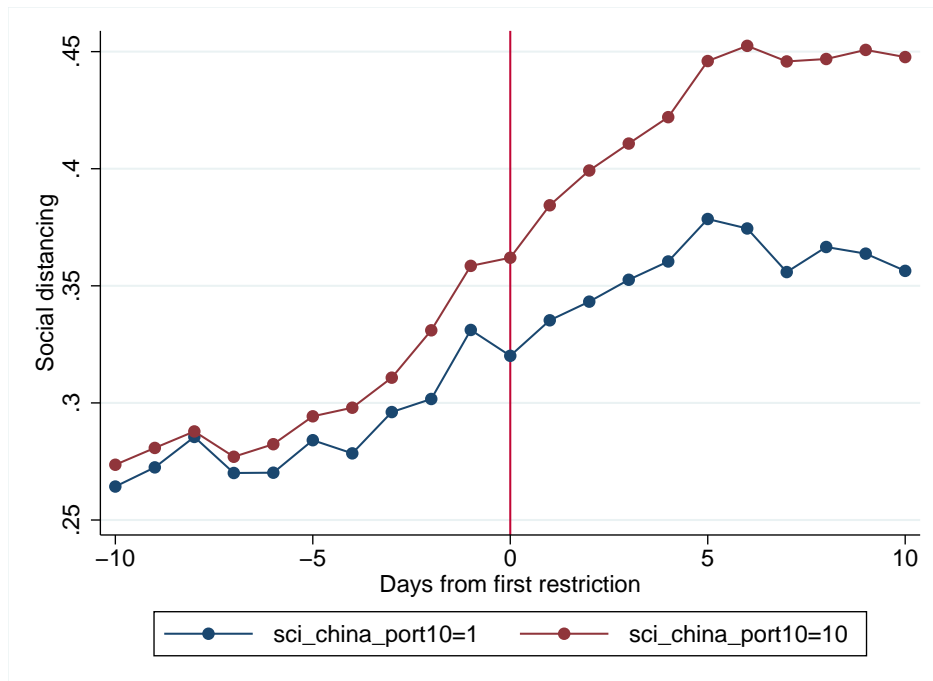


Figure 3: Social connectedness to COVID-affected countries

Average *Social distancing* plotted conditional on the county's social connectedness to China and Italy, the first countries severely affected by COVID-19. Counties are sorted into 10 portfolios by state based on SCI China and SCI Italy, respectively. Portfolio 10 represents the highest social connectedness to these countries, 1 the lowest. Panels A and B plot social distancing measures against the time from the first state-level regulatory restriction, C and D against calendar date.

A. Social distancing vs. SCI China decile - time relative to first restriction in county



B. Social distancing vs. SCI Italy decile - time relative to first restriction in county

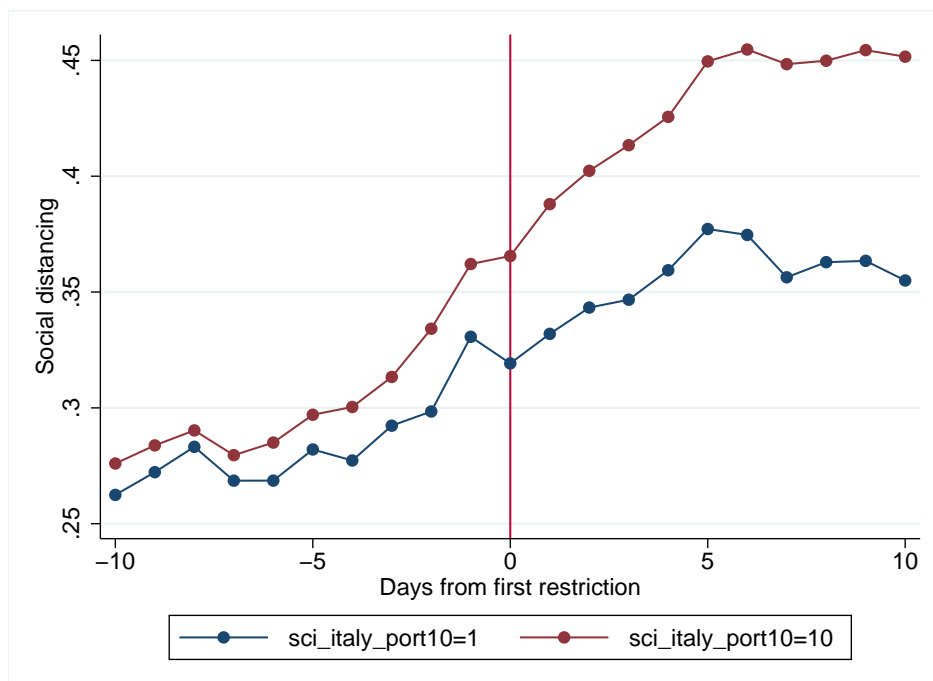


Table 1
Gov't restrictions vs. social connectedness

The dependent variable is *Social distancing*. *Restrictions* is the number of the five restriction types currently adopted in the county. *SCI China* and *SCI Italy* are the Social Connectedness Index values between the county and China and Italy, respectively. *N cases* is the current number of confirmed cases in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	(1)	(2)	(3)
Restr. x ln(SCI China)	0.0048*** (0.0004)		0.0011** (0.0005)
Restr. x ln(SCI Italy)		0.0052*** (0.0004)	0.0042*** (0.0005)
Restrictions (0-5)	-0.0245*** (0.0040)	-0.0280*** (0.0043)	-0.0280*** (0.0042)
ln(N cases)	0.0122*** (0.0009)	0.0114*** (0.0009)	0.0113*** (0.0009)
State-Day FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
N	184,766	184,766	184,766
R ²	0.756	0.756	0.756

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 2
Social connectedness vs. race and political orientation

The dependent variable is *Social distancing*. *Restrictions* is the number of the five restriction types currently adopted in the county. *SCI China* and *SCI Italy* are the Social Connectedness Index values between the county and China and Italy, respectively. *Republican* is a dummy taking the value one if more people voted Republicans than for Democrats in the 2016 presidential election. *Asian* and *White* are the shares of county population classified as Asian and White in the Census, respectively. *N cases* is the current number of confirmed cases in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	Political orientation		Race	
	(1)	(2)	(3)	(4)
Restr. x ln(SCI China) x Rep.	0.0010** (0.0004)			
Restr. x ln(SCI Italy) x Rep.		0.0008* (0.0004)		
Restr. x Republican	-0.0066* (0.0034)	-0.0051 (0.0034)		
Restr. x ln(SCI China) x Asian			-0.0601* (0.0303)	
Restr. x ln(SCI Italy) x Asian			0.0723** (0.0299)	
Restr. x Asian			-0.0824 (0.0896)	
Restr. x ln(SCI China) x White				0.0066** (0.0032)
Restr. x ln(SCI Italy) x White				-0.0048 (0.0034)
Restr. x White				0.0060 (0.0078)
Restr. x ln(SCI China)	0.0040*** (0.0005)		0.0016*** (0.0006)	-0.0043 (0.0027)
Restr. x ln(SCI Italy)		0.0046*** (0.0005)	0.0034*** (0.0006)	0.0083*** (0.0030)
Restrictions (0-5)	-0.0199*** (0.0047)	-0.0245*** (0.0050)	-0.0251*** (0.0043)	-0.0357*** (0.0072)
ln(N cases)	0.0129*** (0.0010)	0.0120*** (0.0010)	0.0106*** (0.0009)	0.0122*** (0.0010)
State-Day FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
N	184,766	184,766	184,766	184,766
R ²	0.756	0.756	0.757	0.757

Significance levels: * 0.1, ** 0.05, *** 0.01.

Table 3
Social connectedness vs. demography

The dependent variable is *Social distancing*. *Restrictions* is the number of the five restriction types currently adopted in the county. *SCI China* and *SCI Italy* are the Social Connectedness Index values between the county and China and Italy, respectively. *Age* is the median age of the county population. *Education* is the share of county population having a bachelor degree or higher. *N cases* is the current number of confirmed cases in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	Age		Education	
	(1)	(2)	(3)	(4)
Restr. x ln(SCI China) x ln(Age)	0.0042*** (0.0014)			
Restr. x ln(SCI Italy) x ln(Age)		0.0041*** (0.0014)		
Restr. x ln(Age)	-0.0242** (0.0097)	-0.0253** (0.0100)		
Restr. x ln(SCI China) x Edu.			-0.0037** (0.0017)	
Restr. x ln(SCI Italy) x Edu.				-0.0018 (0.0018)
Restr. x Education			0.0770*** (0.0150)	0.0624*** (0.0155)
Restr. x ln(SCI China)	-0.0106** (0.0051)		0.0044*** (0.0006)	
Restr. x ln(SCI Italy)		-0.0099* (0.0051)		0.0044*** (0.0006)
Restrictions (0-5)	0.0646* (0.0358)	0.0655* (0.0369)	-0.0335*** (0.0050)	-0.0336*** (0.0053)
ln(N cases)	0.0125*** (0.0009)	0.0117*** (0.0009)	0.0104*** (0.0009)	0.0094*** (0.0010)
State-Day FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
N	184,766	184,766	184,766	184,766
R ²	0.756	0.756	0.758	0.758

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 4
Social connectedness vs. risk groups

The dependent variable is *Social distancing*. *Restrictions* is the number of the five restriction types currently adopted in the county. *SCI China* and *SCI Italy* are the Social Connectedness Index values between the county and China and Italy, respectively. *Age* is the median age of the county population. *Education* is the share of county population having a bachelor degree or higher. *N cases* is the current number of confirmed cases in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	Obesity		Diabetes		Pop. density	
	(1)	(2)	(3)	(4)	(5)	(6)
Restr. x ln(SCI China) x Obesity	-0.0132*** (0.0030)					
Restr. x ln(SCI Italy) x Obesity		-0.0133*** (0.0030)				
Restr. x Obesity	0.0497** (0.0199)	0.0522** (0.0204)				
Restr. x ln(SCI China) x Diabetic			-0.0354*** (0.0057)			
Restr. x ln(SCI Italy) x Diabetic				-0.0374*** (0.0057)		
Restr. x Diabetic			0.1588*** (0.0341)	0.1782*** (0.0360)		
Restr. x ln(SCI China) x Pop. density					-0.0012*** (0.0003)	
Restr. x ln(SCI Italy) x Pop. density						-0.0007*** (0.0003)
Restr. x Pop. density					0.0140*** (0.0038)	0.0085*** (0.0030)
Restr. x ln(SCI China)	0.0088*** (0.0011)		0.0081*** (0.0008)		0.0046*** (0.0004)	
Restr. x ln(SCI Italy)		0.0093*** (0.0011)		0.0088*** (0.0008)		0.0051*** (0.0004)
Restrictions (0-5)	-0.0370*** (0.0076)	-0.0414*** (0.0078)	-0.0384*** (0.0057)	-0.0438*** (0.0061)	-0.0236*** (0.0040)	-0.0273*** (0.0043)
ln(N cases)	0.0107*** (0.0009)	0.0099*** (0.0009)	0.0110*** (0.0009)	0.0101*** (0.0009)	0.0123*** (0.0009)	0.0114*** (0.0009)
State-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
N	184,766	184,766	184,766	184,766	184,766	184,766
R ²	0.756	0.757	0.757	0.757	0.756	0.756

Significance levels: * 0.1, ** 0.05, *** 0.01.

Appendices

A Supplementary Information

Appendix A: Definitions of variables

Variable	Definition
Social distancing	The share of the (not-currently-working) county population that is staying completely at home. Calculated using mobile-phone-based data from Safegraph.
SCI	Social Connectedness Index (Bailey et al., 2018) constructed using aggregated information from all friendship links between all Facebook users as of April 2016. Measures the the normalized total number of friendship links for each geographic pair. Constructed to have a maximum value of 1,000,000, and relative differences in the index correspond to relative differences in the total number of friendship links.
SCI-weighted cases	The total SCI-weighted number of confirmed COVID-19-cases in other US counties. We calculate different versions imposing different minimum distance between the counties.

A.1 Summary Statistics

Over 20 states initiated their first mobility restriction on March 16, 2020. States typically implement various non-pharmaceutical interventions simultaneously, and also appear to follow a ranking in terms of the restrictiveness. On average, states appear to first close schools and public places, then gatherings and stay-at-home orders. The top 5 states have over three mobility restrictions, and throughout our sample from February 1 to March 30, 2020, the average state has 0.629 restrictions. By the end of the sample, the average number of mobility restrictions across states is 3.1.

Appendix Table A.1 show summary statistics for our sample at the county level. There is a large variation across counties and days in social distancing and the fraction of time spent at home. The county in the lowest 10th percentile spends on average 24.8% of flexible time at home while the county in the highest 10th percentile spends on average 44.6% of flexible time at home. The corresponding numbers for the fraction of those staying completely at home is 16.3% for the bottom 10th percentile and 35.1% for the top 10th percentile.

The number of restrictions is positively correlated with social distancing. Table A.5 shows the unconditional effects of mobility restrictions. Column 1 suggests that when restrictions are imposed, social distancing increases. Based on the type of restriction, school closures, closures of public places, and stay-at-home result in greater amounts of social distancing, respectively.

This motivates us to create a restriction index, which counts the number of restrictions of any type. Social connections to China and Italy are highly correlated at 0.948. Whether the percentage of Asians within the county is 0.612 positively correlated with social connections to China and 0.590 positively correlated with social connections to Italy. The incidence of mobility restrictions also does not appear highly correlated with measures of social connections. County-level social connections to China and Italy are only 0.016 to 0.017 correlated with the number of restrictions.

Table A.1
Summary statistics

Summary statistics for the county-day observations in the sample. The sample period is February 1 to March 30, 2020. Variables are defined in Appendix A.

	Mean	Std	p10	p50	p90
Social distancing					
Social distancing	0.337	0.081	0.248	0.326	0.446
Completely home	0.248	0.074	0.163	0.236	0.351
Full-time	0.174	0.045	0.117	0.171	0.232
Part-time	0.100	0.037	0.054	0.096	0.150
Social Connectedness					
SCI - China	3519.549	10634.586	48.000	443.000	6692.000
SCI - Italy	4357.320	13331.747	64.000	539.000	8825.000
Rel. prob. friend Chinese	2.259	1.820	0.835	1.703	4.164
Rel. prob. friend Italian	2.707	1.983	1.081	2.131	4.995
Cases in county					
N cases	4.685	186.139	0.000	0.000	1.000
N deaths	0.068	3.190	0.000	0.000	0.000
Gov't restrictions					
Restrictions (0-5)	0.629	1.152	0.000	0.000	3.000
Schools closed	0.256	0.437	0.000	0.000	1.000
Public places	0.190	0.392	0.000	0.000	1.000
Stay at home	0.065	0.246	0.000	0.000	0.000
Gatherings	0.094	0.292	0.000	0.000	0.000
Non-essential	0.024	0.152	0.000	0.000	0.000
County variables					
Population ('000)	92.632	299.220	4.190	22.300	188.460
Median age	41.305	5.384	34.800	41.200	48.100
Democrat	0.154	0.361	0.000	0.000	1.000
Republican	0.846	0.361	0.000	1.000	1.000
Education	0.216	0.094	0.123	0.192	0.342
Race and ethnicity					
White	0.832	0.167	0.595	0.897	0.969
Black	0.090	0.145	0.003	0.023	0.301
Asian	0.014	0.028	0.001	0.006	0.031
Native American	0.019	0.074	0.001	0.003	0.027
Other race	0.045	0.046	0.013	0.032	0.092
Risk factors					
Obesity rate	0.328	0.057	0.253	0.330	0.397
Diabetes rate	0.104	0.038	0.061	0.099	0.155
Population density ('000/sqm)	0.233	1.522	0.004	0.038	0.359
N	187,965				

Table A.2
Additional summary statistics

Summary statistics for the county-day observations in the sample. The sample period is February 1 to March 30, 2020. Variables are defined in Appendix A.

	Mean	Std	p10	p50	p90
County characteristics					
Avg. household size	2.124	0.387	1.627	2.155	2.563
Personal income (USDbn)	0.006	0.021	0.000	0.001	0.011
PI per capita (USDk)	44.145	12.745	32.620	41.981	57.069
Stock participation	0.162	0.068	0.082	0.158	0.244
Self-employment	0.167	0.039	0.122	0.163	0.217
Unemployment	0.036	0.028	0.013	0.030	0.062
Avg. credit score	698.484	28.313	658.999	701.329	732.419
Social capital	-0.001	0.994	-1.067	-0.163	1.378
Democrat vote	31.606	15.249	15.012	28.382	53.215
Republican vote	63.683	15.546	41.827	66.778	80.907
Healthcare capacity					
Hospitals per 100k	5.981	9.846	0.000	2.742	15.049
ICU beds per 100k	14.681	28.043	0.000	0.000	38.622
No health insurance	0.101	0.051	0.047	0.092	0.168
N	187,965				

Table A.3
Additional summary statistics – logarithmic variables

Summary statistics for the county-day observations in the sample. The sample period is February 1 to March 30, 2020. Variables are defined in Appendix A.

	Mean	Std	p10	p50	p90
ln(SCI - China)	6.255	1.879	3.871	6.094	8.809
ln(SCI - Italy)	6.463	1.866	4.159	6.290	9.085
ln(SCI - New York)	1.785	2.299	-0.904	1.439	5.061
ln(N cases)	0.206	0.730	0.000	0.000	0.693
N	187,965				

Table A.4
Correlations of variables

Variables are defined in Appendix A.

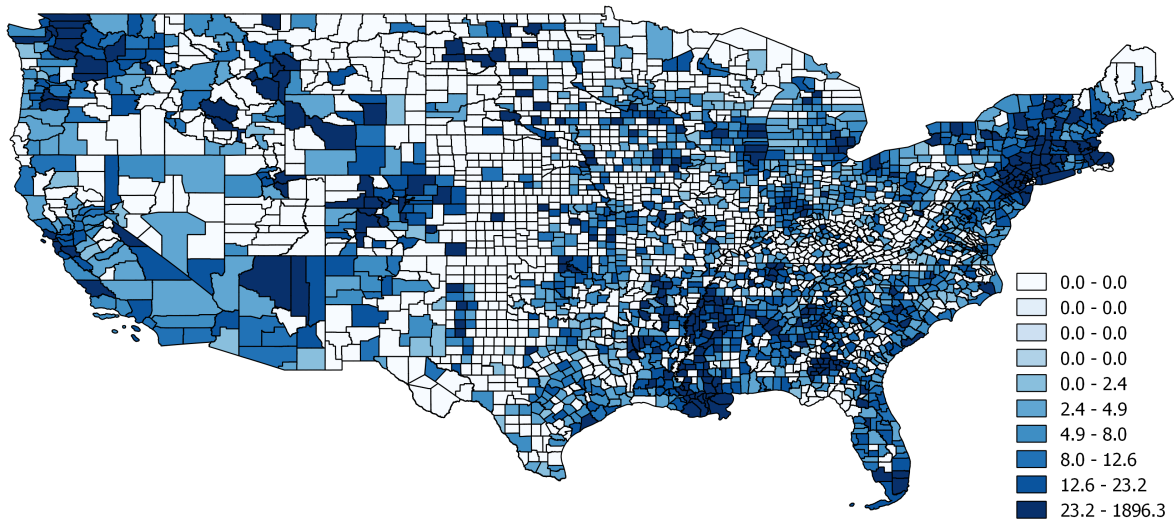
	Social distancing	N cases	Restrictions (0-5)	SCI - China	SCI - Italy	Republican vote	Asian
Social distancing	1.000						
N cases	0.059***	1.000					
Restrictions (0-5)	0.449***	0.052***	1.000				
SCI - China	0.078***	0.110***	0.017***	1.000			
SCI - Italy	0.081***	0.125***	0.016***	0.948***	1.000		
Republican vote	-0.113***	-0.052***	-0.029***	-0.467***	-0.448***	1.000	
Asian	0.087***	0.063***	0.020***	0.612***	0.590***	-0.442***	1.000

A.2 COVID-19 Conditions in the United States

Figure A.1: Confirmed cases of COVID-19 – March 27

Confirmed cases and deaths per 100,000 persons as of March 27, 2020.

A. Confirmed cases and deaths per 100,000



B. Confirmed deaths per 100,000

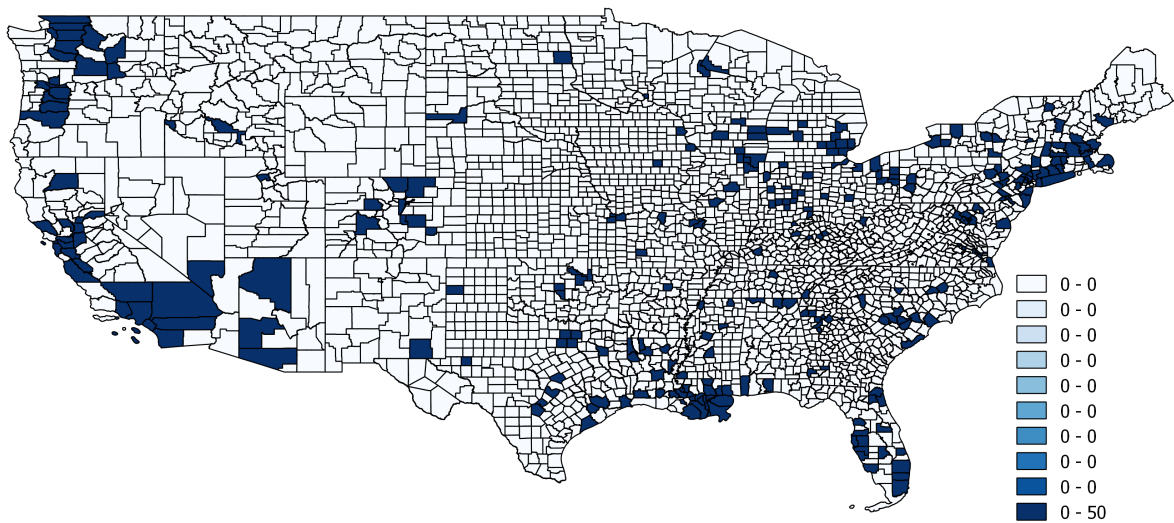
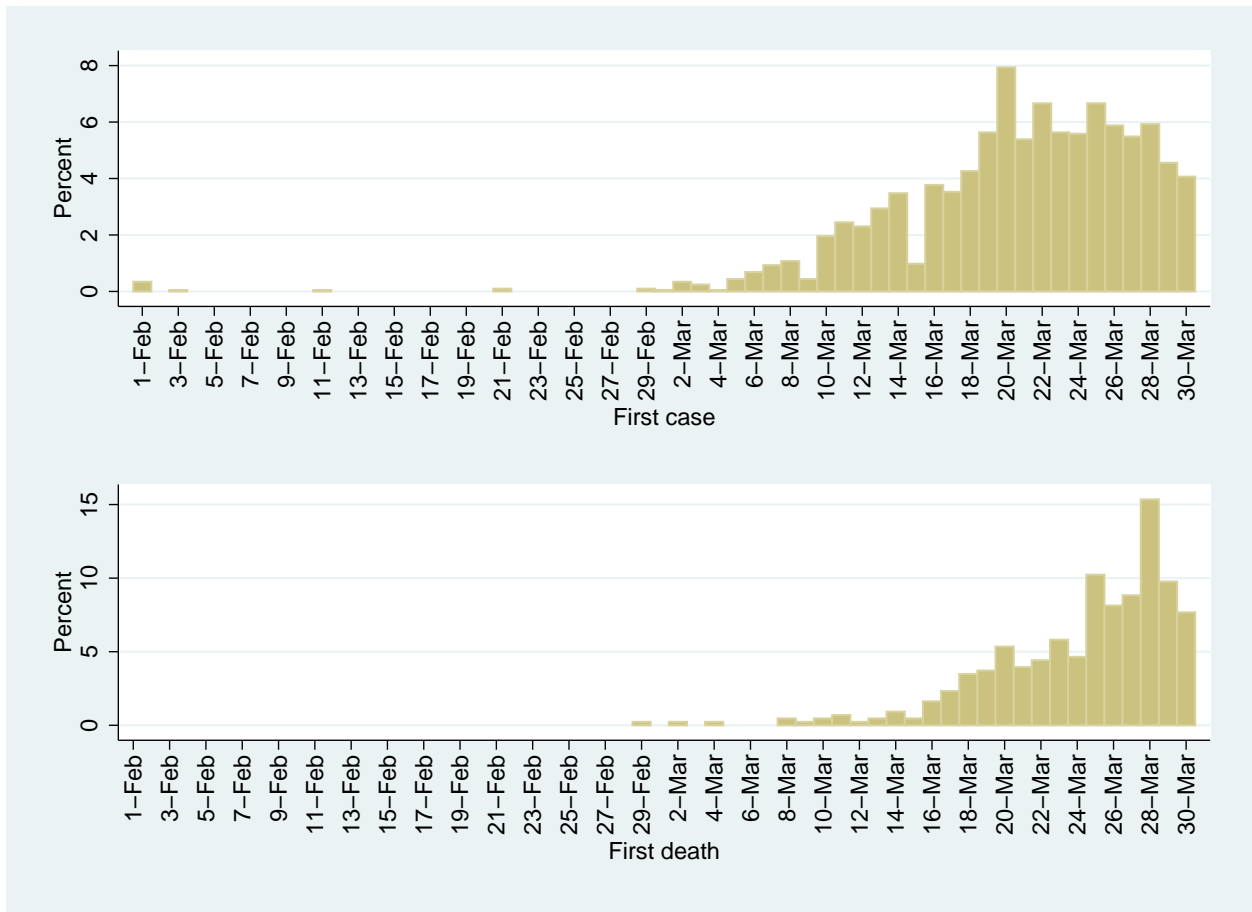


Figure A.2: First cases and first deaths by county

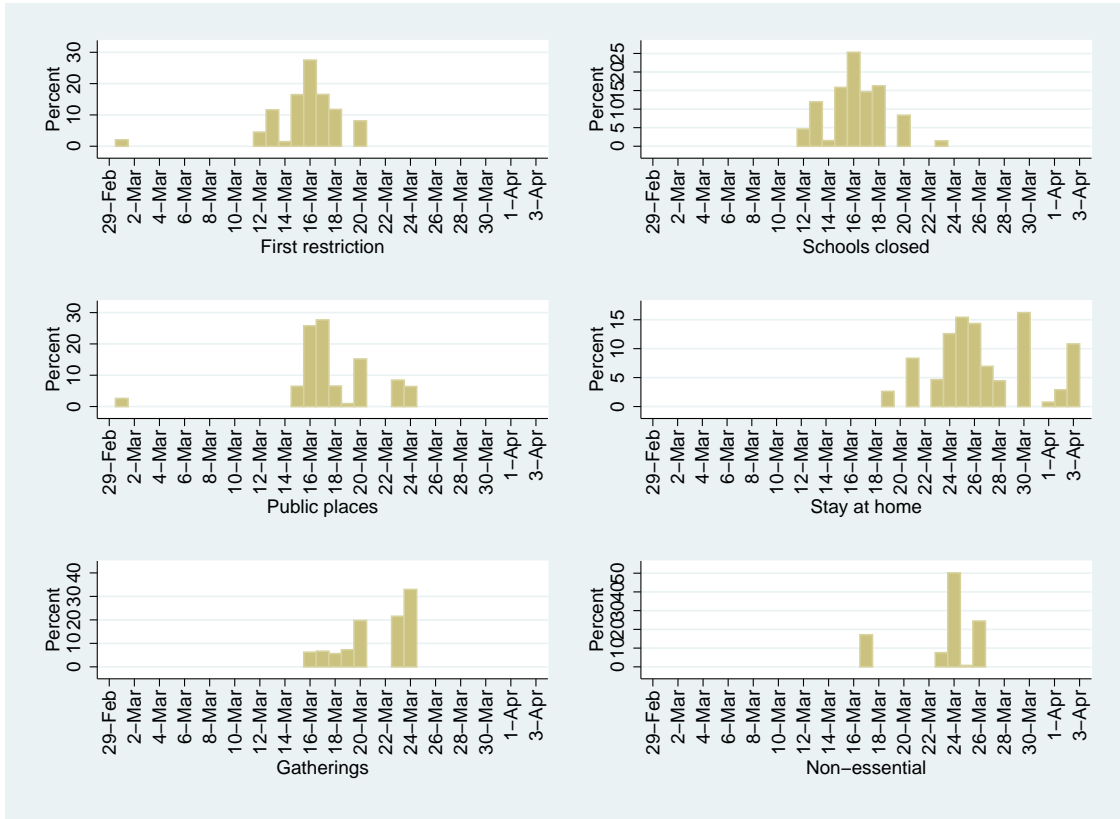
Timing distribution of the first confirmed cases and first deaths in the county.



A.3 Government restrictions timing

Figure A.3: Timing of state-level restrictions

Timing distribution of different state-level restrictions to contain COVID-19. Each distribution shows the percentage of counties that at some point implemented the restriction (i.e., each histogram adds up to 100%).



A.4 Average effects of different types of mobility restrictions

Table A.5
Social distancing vs. gov't restrictions

The dependent variable is *Social distancing*. *Restrictions* is the number of the five restriction types currently adopted in the county. *Schools closed* is a dummy taking the value 1 if a (state-level) school closure has been adopted in the county. *Public places*, *Stay at home*, *Gatherings*, and *Non-essential* similarly indicate whether these types of (state-level) restrictions have been adopted in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Restrictions (0-5)	0.0089*** (0.0014)						
Schools closed		0.0059** (0.0029)					0.0020 (0.0029)
Public places			0.0119*** (0.0029)				0.0079*** (0.0029)
Stay at home				0.0384*** (0.0041)			0.0365*** (0.0043)
Gatherings					-0.0129*** (0.0037)		-0.0072** (0.0032)
Non-essential						0.0101** (0.0040)	0.0183*** (0.0042)
ln(N cases)	0.0275*** (0.0014)	0.0278*** (0.0014)	0.0274*** (0.0014)	0.0264*** (0.0014)	0.0271*** (0.0015)	0.0278*** (0.0014)	0.0256*** (0.0014)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	184,831	184,831	184,831	184,831	184,831	184,831	184,831
R ²	0.674	0.673	0.673	0.679	0.674	0.673	0.680

Significance levels: * 0.1, ** 0.05, *** 0.01.

A.5 Social connections and local threat level

Table A.6
Social distancing and local cases vs. social connections

The dependent variable is *Social distancing*. *SCI China* and *SCI Italy* are the Social Connectedness Index values between the county and China and Italy, respectively. *N cases* is the current number of confirmed cases in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	(1)	(2)	(3)
ln(Cases) x ln(SCI China)	0.0008** (0.0003)		-0.0000 (0.0012)
ln(Cases) x ln(SCI Italy)		0.0008** (0.0004)	0.0008 (0.0013)
ln(N cases)	0.0171*** (0.0035)	0.0167*** (0.0038)	0.0167*** (0.0038)
State-Day FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
N	184,766	184,766	184,766
R ²	0.749	0.749	0.749

Significance levels: * 0.1, ** 0.05, * 0.01.**

B Robustness checks

We run a number of robustness checks. First, we perform a number of sample exclusions. We find qualitatively similar results studying the sub-sample of counties without airports and counties in New York. Removing airports is significant because it mitigates the concern social connections are correlated with travel. Removing New York achieves a similar purpose as New York is has been hardest hit in the United States.

In addition, we consider alternative measures of social connections in Section B.2, and also consider including intra-United States social connections by studying connections to New York in Section B.4.1.

B.1 Sample restrictions

In Table B.1, we perform analyses with different sample restrictions. First, in columns 1 and 2, we exclude all counties based in the state of New York and the adjacent states (Connecticut, Massachusetts, New Jersey, Pennsylvania, Rhode Island, and Vermont). This is because New York has experienced the worst outbreak in the US, and may thus represent the highest levels of perceived risk. Second, we exclude all counties with meaningful commercial airport (columns 3 and 4), as well as adjacent counties.⁷ Finally, we exclude the 20% of US counties with the highest Asian population (columns 7 and 8). With all these subsamples, our main results remain qualitatively unchanged and statistically significant.

⁷For this analysis, an airport is considered relevant if it handles at least 10,000 commercial services per year

Table B.1
Robustness: Sample restrictions

The dependent variable is *Social distancing*. *Restrictions* is the number of the five restriction types currently adopted in the county. *SCI China* and *SCI Italy* are the Social Connectedness Index values between the county and China and Italy, respectively. *N cases* is the current number of confirmed cases in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	Ex. NY and adj. states		Ex. airp. counties		Ex. airp. & adj. counties		Ex. top 20% Asian	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Restr. x ln(SCI China)	0.0048*** (0.0004)		0.0048*** (0.0004)		0.0045*** (0.0006)		0.0052*** (0.0005)	
Restr. x ln(SCI Italy)		0.0052*** (0.0004)		0.0053*** (0.0004)		0.0054*** (0.0006)		0.0056*** (0.0005)
Restrictions (0-5)	-0.0249*** (0.0040)	-0.0280*** (0.0043)	-0.0247*** (0.0040)	-0.0282*** (0.0043)	-0.0159*** (0.0058)	-0.0200*** (0.0059)	-0.0258*** (0.0041)	-0.0295*** (0.0046)
ln(N cases)	0.0126*** (0.0009)	0.0119*** (0.0009)	0.0119*** (0.0009)	0.0111*** (0.0010)	0.0138*** (0.0020)	0.0117*** (0.0019)	0.0100*** (0.0009)	0.0091*** (0.0009)
State-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	168,069	168,069	182,170	182,170	44,405	44,405	147,795	147,795
R ²	0.744	0.745	0.753	0.754	0.713	0.714	0.734	0.735

Significance levels: * 0.1, ** 0.05, *** 0.01.

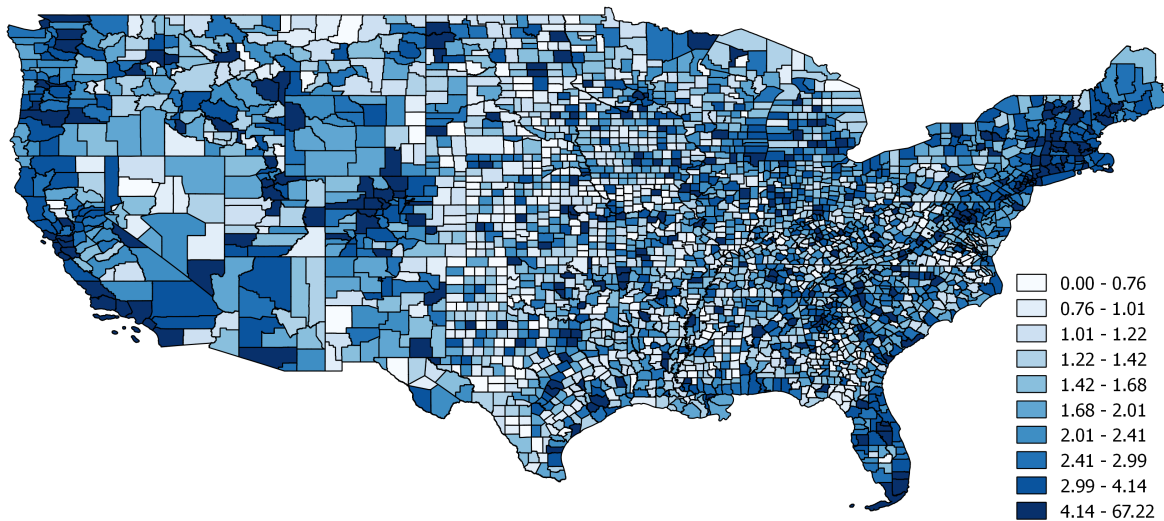
B.2 Relative friend probabilities

Relatedly, one might ask if the social connections index captures friendliness rather than friend composition. To disentangle the composition of friendships from a general level of connectedness in a county, Table B.2 repeats our main analysis with relative friend probabilities rather than the social connection index. Rather than scales by the product of the number of Facebook users in a geography pair, relative friend probabilities (RFP) scaling by populations, defined as $RFP_{i,j} = 10^{12} \times \frac{\text{Social Connection Index}_{i,j}}{\text{Population}_i \times \text{Population}_j}$. We find similar results. A one-standard deviation increase in the relative friend probability in China increases the effect of mobility restrictions on social distancing by 3% of a standard deviation and a one-standard deviation increase in the effect by 4%. As in the main specification, the relative friend probability with Italy exhibits a larger effect. When placing connections to China and Italy in the same specification, the measure for Italy renders the effect of relative friend probability in China statistically insignificant.

Figure B.1: Relative probability of a friend – China and Italy

Relative friend probability between the county and China (*RFP China*) and Italy (*RFP Italy*).

A. Relative probability of a friend – China



B. Relative probability of a friend – Italy

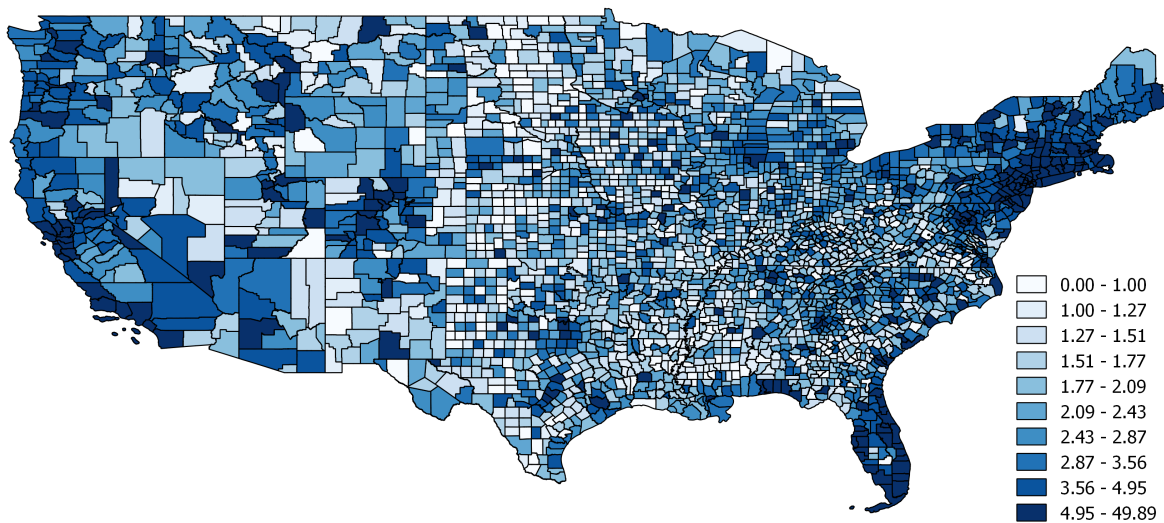
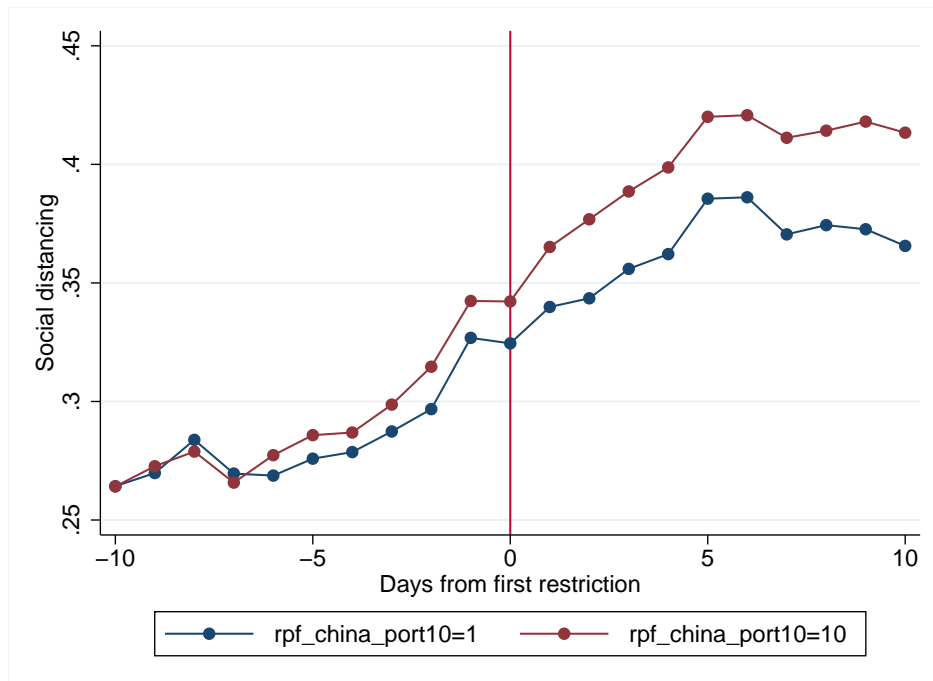


Figure B.2: Social connectedness to COVID-affected countries

Average *Social distancing* plotted conditional on the county's social connectedness to China and Italy, the first countries severely affected by COVID-19. Counties are sorted into 10 portfolios by state based on *Relative friend probability - China* and *Relative friend probability - Italy*, respectively. Portfolio 10 represents the highest social connectedness to these countries, 1 the lowest. Panels A and B plot social distancing measures against calendar date, C and D against the time from the first state-level regulatory restriction.

A. Social distancing vs. RFP China decile - time relative to first restriction in county



B. Social distancing vs. RFP Italy decile - time relative to first restriction in county

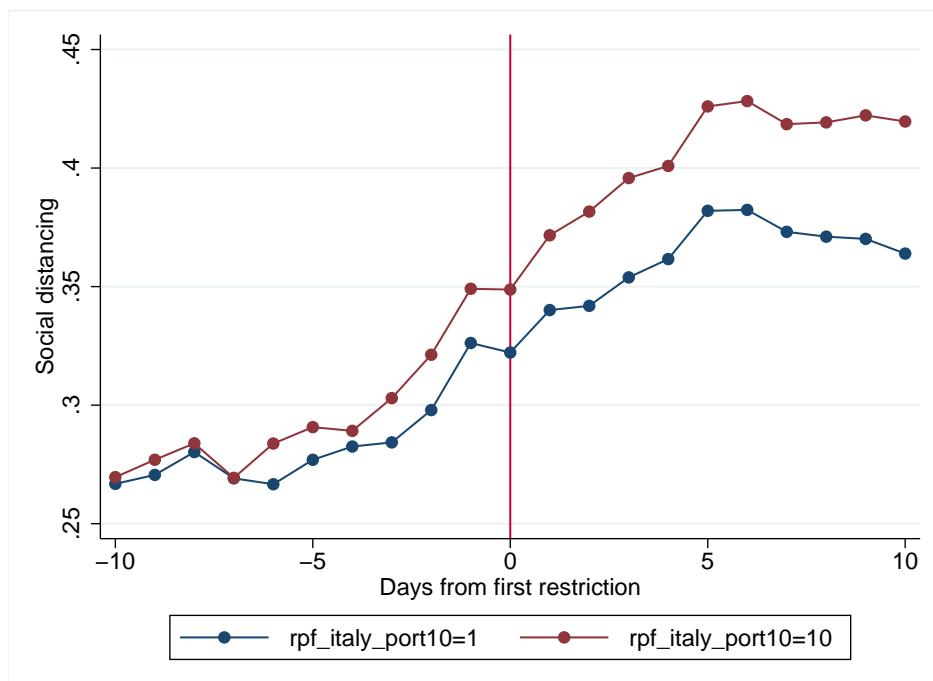


Table B.2
Gov't restrictions vs. social connectedness

The dependent variable is *Social distancing*. *Restrictions* is the number of the five restriction types currently adopted in the county. *RFP China* and *RFP Italy* are the relative friend probabilities of the county for China and Italy, respectively. *N cases* is the current number of confirmed cases in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	(1)	(2)	(3)
Restr. x RPF China	0.0012*** (0.0002)		0.0002 (0.0002)
Restr. x RPF Italy		0.0017*** (0.0003)	0.0016*** (0.0003)
Restrictions (0-5)	0.0040 (0.0046)	0.0036 (0.0048)	0.0034 (0.0047)
ln(N cases)	0.0224*** (0.0012)	0.0213*** (0.0012)	0.0212*** (0.0012)
State-Day FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
N	184,766	184,766	184,766
R ²	0.750	0.750	0.750

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table B.3
Local cases vs. social connections

The dependent variable is *Social distancing*. *RFP China* and *RFP Italy* are the relative friend probabilities of the county for China and Italy, respectively. *N cases* is the current number of confirmed cases in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	(1)	(2)	(3)
ln(Cases) x RPF China	0.0000 (0.0002)		-0.0001 (0.0003)
ln(Cases) x RPF Italy		0.0001 (0.0002)	0.0001 (0.0002)
ln(N cases)	0.0244*** (0.0016)	0.0240*** (0.0019)	0.0241*** (0.0019)
State-Day FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
N	184,766	184,766	184,766
R ²	0.749	0.749	0.749

Significance levels: * 0.1, ** 0.05, * 0.01.**

B.3 Social connectedness and additional county-level characteristics

Table B.4
Social connectedness vs. healthcare capacity

The dependent variable is *Social distancing*. *Restrictions* is the number of the five restriction types currently adopted in the county. *SCI China* and *SCI Italy* are the Social Connectedness Index values between the county and China and Italy, respectively. *Age* is the median age of the county population. *Education* is the share of county population having a bachelor degree or higher. *N cases* is the current number of confirmed cases in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Restr. x ln(SCI China) x Hospitals	-0.0002*** (0.0000)					
Restr. x ln(SCI Italy) x Hospitals		-0.0002*** (0.0000)				
Restr. x Hospitals per 100k	0.0005*** (0.0002)	0.0006*** (0.0002)				
Restr. x ln(SCI China) x ICU beds			-0.0000*** (0.0000)			
Restr. x ln(SCI Italy) x ICU beds				-0.0000*** (0.0000)		
Restr. x ICU beds per 100k			0.0002*** (0.0000)	0.0002*** (0.0000)		
Restr. x ln(SCI China) x Uninsured					-0.0092** (0.0041)	
Restr. x ln(SCI Italy) x Uninsured						-0.0129*** (0.0042)
Restr. x Uninsured					-0.0117 (0.0243)	0.0130 (0.0253)
Restr. x ln(SCI China)	0.0048*** (0.0004)		0.0059*** (0.0005)		0.0056*** (0.0007)	
Restr. x ln(SCI Italy)		0.0053*** (0.0004)		0.0063*** (0.0005)		0.0065*** (0.0007)
Restrictions (0-5)	-0.0225*** (0.0038)	-0.0256*** (0.0040)	-0.0298*** (0.0039)	-0.0336*** (0.0043)	-0.0228*** (0.0048)	-0.0288*** (0.0051)
ln(N cases)	0.0112*** (0.0010)	0.0104*** (0.0010)	0.0129*** (0.0009)	0.0122*** (0.0009)	0.0117*** (0.0009)	0.0108*** (0.0009)
State-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
N	184,766	184,766	184,766	184,766	184,766	184,766
R ²	0.757	0.757	0.757	0.757	0.757	0.757

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table B.5
Social connectedness vs. wealth level

The dependent variable is *Social distancing*. *Restrictions* is the number of the five restriction types currently adopted in the county. *SCI China* and *SCI Italy* are the Social Connectedness Index values between the county and China and Italy, respectively. *Age* is the median age of the county population. *Education* is the share of county population having a bachelor degree or higher. *N cases* is the current number of confirmed cases in the county. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Restr. x ln(SCI China) x ln(PI pc.)	0.0015** (0.0007)					
Restr. x ln(SCI Italy) x ln(PI pc.)		0.0018** (0.0007)				
Restr. x ln(PI per capita)	0.0064 (0.0049)	0.0033 (0.0049)				
Restr. x ln(SCI China) x Credit score			0.0001*** (0.0000)			
Restr. x ln(SCI Italy) x Credit score				0.0001*** (0.0000)		
Restr. x Credit score			-0.0002*** (0.0000)	-0.0002*** (0.0000)		
Restr. x ln(SCI China) x Unemployment					0.0064 (0.0095)	
Restr. x ln(SCI Italy) x Unemployment						0.0074 (0.0090)
Restr. x Unemployment					-0.0454 (0.0587)	-0.0512 (0.0585)
Restr. x ln(SCI China)	-0.0111 (0.0078)		-0.0307*** (0.0049)		0.0046*** (0.0005)	
Restr. x ln(SCI Italy)		-0.0141* (0.0076)		-0.0320*** (0.0049)		0.0050*** (0.0005)
Restrictions (0-5)	-0.0909* (0.0531)	-0.0600 (0.0522)	0.0833** (0.0325)	0.0975*** (0.0331)	-0.0228*** (0.0044)	-0.0261*** (0.0047)
ln(N cases)	0.0092*** (0.0009)	0.0085*** (0.0010)	0.0112*** (0.0009)	0.0104*** (0.0009)	0.0122*** (0.0009)	0.0114*** (0.0009)
State-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
N	182,052	182,052	184,294	184,294	184,766	184,766
R ²	0.757	0.757	0.764	0.764	0.756	0.756

Significance levels: * 0.1, ** 0.05, * 0.01.**

B.4 Do social connections proxy for risk?

B.4.1 New York and US counties

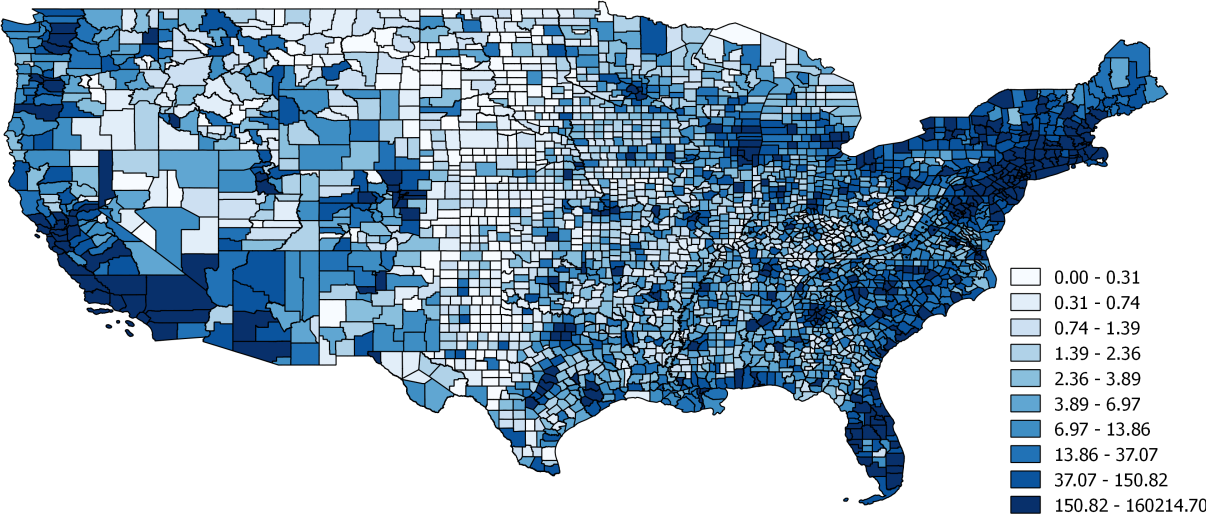
In addition, to disentangle social connections from risk exposures due potentially to more intra-United States travel, Table B.6 studies whether social connections to New York affect the responses to mobility restrictions. To distinguish the information effect from social connections predicting travelling, we exclude all counties located in the state of New York, as well as the adjacent states, including Connecticut, Massachusetts, New Jersey, Pennsylvania, Rhode Island, and Vermont.

Table B.7 repeats the social connection with counties at different distances. Column 1 studies the interaction of mobility restrictions on all SCI-weighted cases, column 2 only studies SCI with counties at least 100, and column 3 at least 200 miles. In all cases, we find statistically significant results consistent with our main results: higher SCI-weighted cases, which we interpret as a proxy for the information flow from a county's social connections, increases the impact of mobility restrictions on social distancing.

Figure B.3: SCI and relative probability of a friend – New York

SCI and relative friend probability between the county and New York County.

A. SCI New York



B. Relative probability of a friend – New York

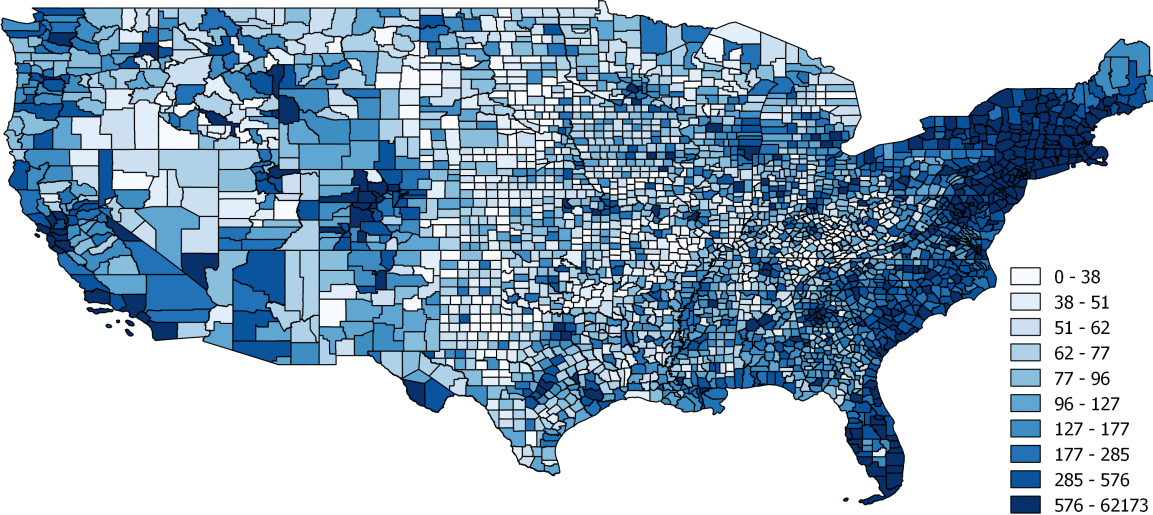


Figure B.4: Social connectedness to New York

Average *Social distancing* plotted conditional on the county's social connectedness to New York, the US county most severely affected by COVID-19 during the sample period. Counties are sorted into 10 portfolios by state based on SCI New York. Portfolio 10 represents the highest social connectedness to New York, 1 the lowest. This analysis excludes all counties located in the state of New York, as well as the adjacent states (Connecticut, Massachusetts, New Jersey, Pennsylvania, Rhode Island, and Vermont).

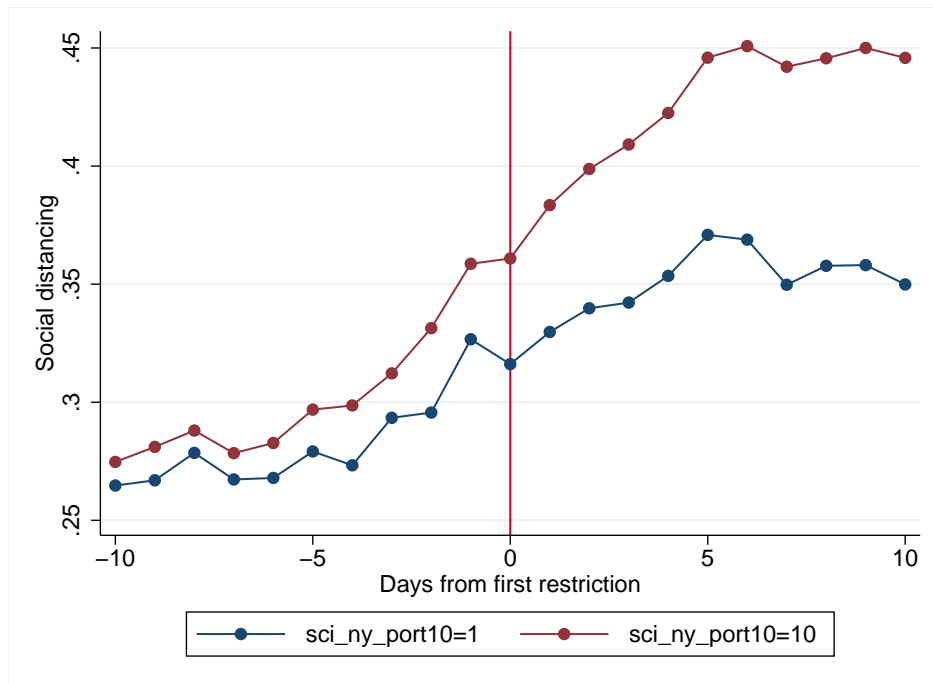


Table B.6
Gov't restrictions and local cases vs. social connectedness

The dependent variable is *Social distancing*. The analysis using *SCI New York* excludes all counties located in the state of New York, as well as the adjacent states (Connecticut, Massachusetts, New Jersey, Pennsylvania, Rhode Island, and Vermont). Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	(1)	(2)	(3)	(4)
Restr. x ln(SCI New York)	0.0046*** (0.0004)	0.0027*** (0.0005)		
Restr. x ln(SCI China)		-0.0005 (0.0005)		
Restr. x ln(SCI Italy)		0.0010 (0.0006)		
Restrictions (0-5)	-0.0011 (0.0036)	-0.0047 (0.0042)		
ln(Cases) x ln(SCI New York)			0.0013*** (0.0002)	-0.0001 (0.0010)
ln(Cases) x ln(SCI China)				-0.0015 (0.0013)
ln(Cases) x ln(SCI Italy)				0.0032** (0.0013)
ln(N cases)	0.0106*** (0.0009)	0.0100*** (0.0009)	0.0133*** (0.0020)	0.0041 (0.0060)
State-Day FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
N	168,069	85,459	85,459	85,459
R ²	0.745	0.820	0.817	0.817

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table B.7
Gov't restrictions vs. New York

The dependent variable is *Social distancing*. This analysis excludes all counties located in the state of New York, as well as the adjacent states (Connecticut, Massachusetts, New Jersey, Pennsylvania, Rhode Island, and Vermont). Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

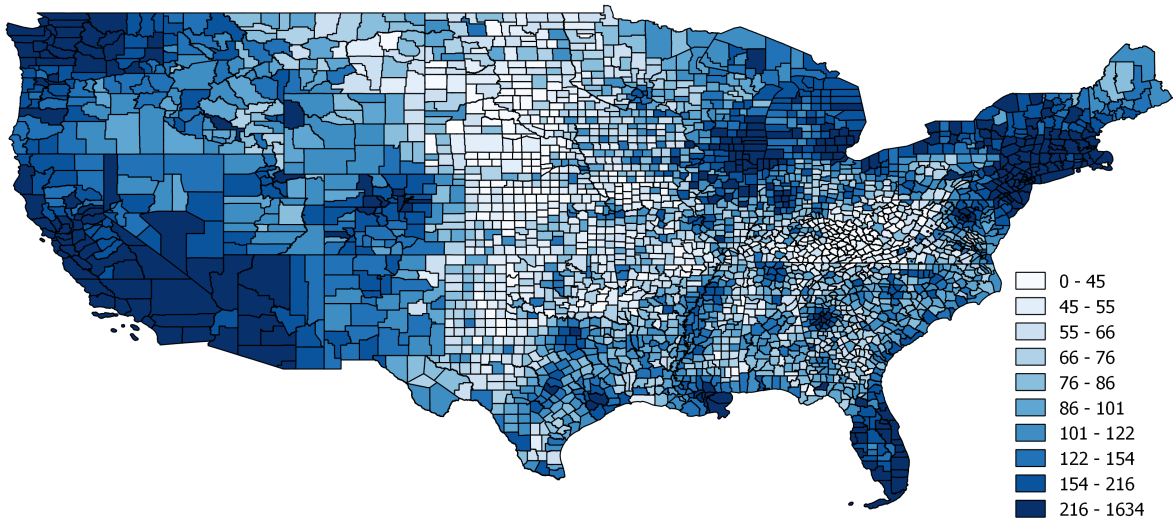
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Restr. x ln(SCI New York)	0.0046*** (0.0004)						
Restrictions (0-5)	-0.0011 (0.0036)						
Schools closed x ln(SCI New York)		0.0125*** (0.0010)					0.0099*** (0.0010)
Schools closed		0.0069 (0.0096)					-0.0163 (0.0145)
Public places x ln(SCI New York)			0.0109*** (0.0009)				0.0030*** (0.0007)
Public places			0.0053 (0.0085)				0.0192 (0.0121)
Stay at home x ln(SCI New York)				0.0050*** (0.0011)			0.0003 (0.0008)
Stay at home				-0.0236*** (0.0077)			0.0122** (0.0059)
Gatherings x ln(SCI New York)					0.0089*** (0.0010)		0.0020** (0.0009)
Gatherings					0.0000 (.)		0.0000 (0.0000)
Non-essential x ln(SCI New York)						0.0062*** (0.0013)	0.0010 (0.0012)
Non-essential						-0.0246*** (0.0070)	-0.0087 (0.0066)
ln(N cases)	0.0106*** (0.0009)	0.0110*** (0.0012)	0.0147*** (0.0011)	0.0234*** (0.0016)	0.0213*** (0.0013)	0.0251*** (0.0013)	0.0097*** (0.0010)
State-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	168,069	168,069	168,069	168,069	168,069	168,069	168,069
R ²	0.745	0.746	0.743	0.738	0.740	0.738	0.746

Significance levels: * 0.1, ** 0.05, *** 0.01.

Figure B.5: SCI-weighted US cases of COVID-19 – March 27

Social Connectedness Index-weighted number of US cases, based on the SCI between each county pair and the current number of confirmed COVID-19-cases, calculated on a daily basis. We construct these measures imposing different minimum distances between the counties, ranging from zero to 200 km.

A. SCI-weighted US cases - minimum county distance zero



B. SCI-weighted US cases - minimum county distance 100 km

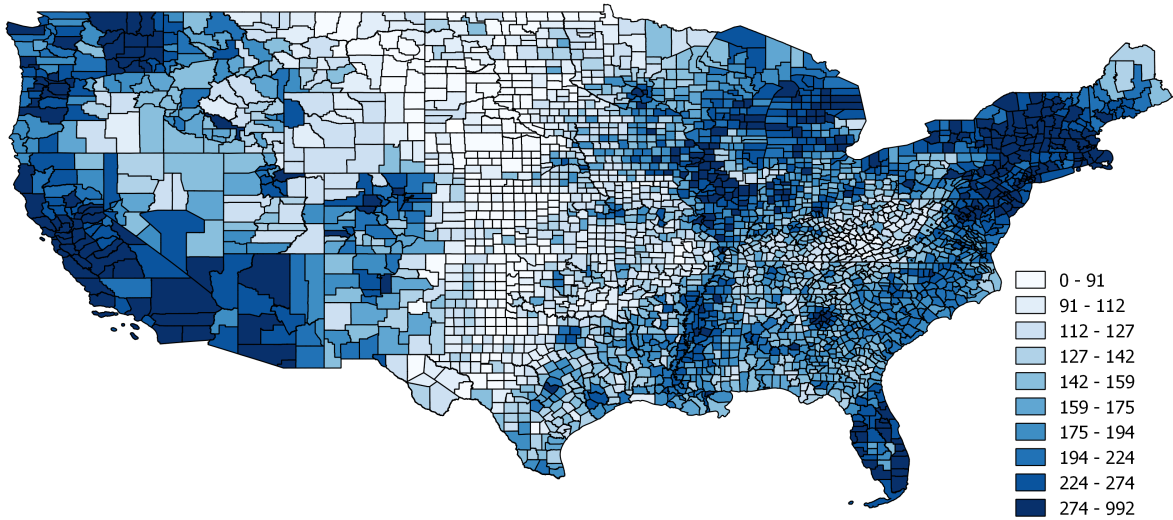


Figure B.5: SCI-weighted US cases of COVID-19 – March 27 (cont'd)

C. SCI-weighted US cases - minimum county distance 200km

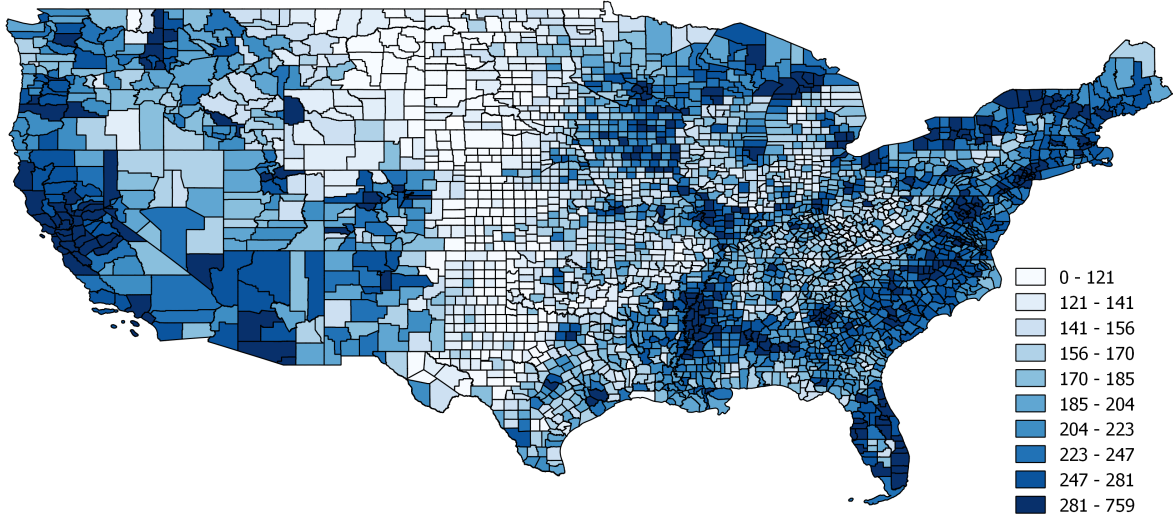
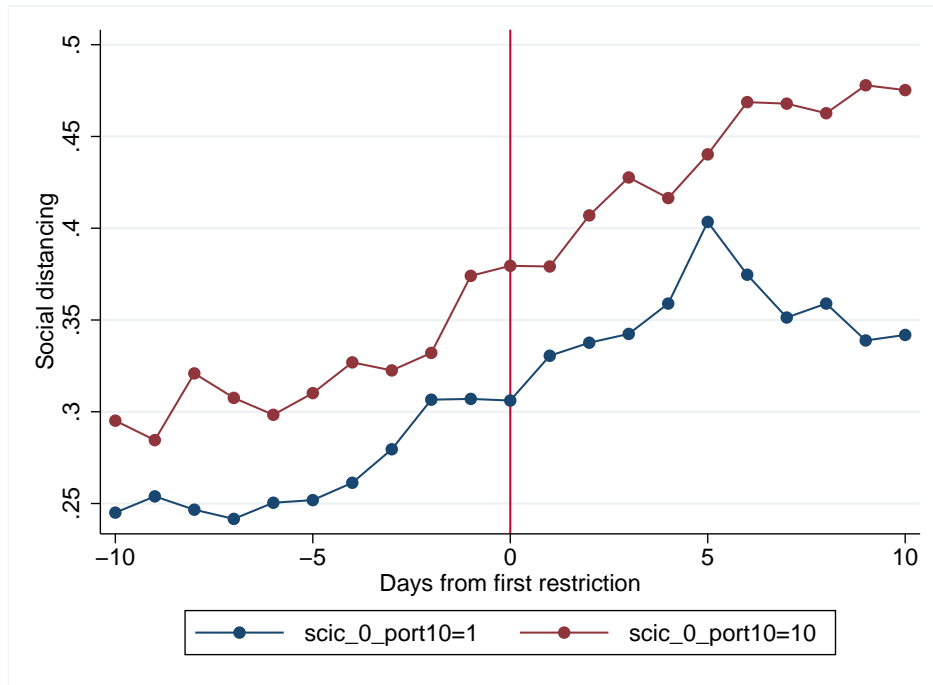


Figure B.6: Social connectedness to COVID-affected US counties

Average *Social distancing* plotted conditional on SCI-weighted US cases. Each day, counties are sorted into 10 portfolios based on SCI-weighted number of cases in socially connected US counties. Portfolio 10 represents the highest number of socially connected cases, 1 the lowest. We construct these measures imposing different minimum distances between the counties, ranging from zero to 200 km.

A. Social distancing vs. SCI-weighted US cases - minimum county distance zero



B. Social distancing vs. SCI-weighted US cases - minimum county distance 100 km

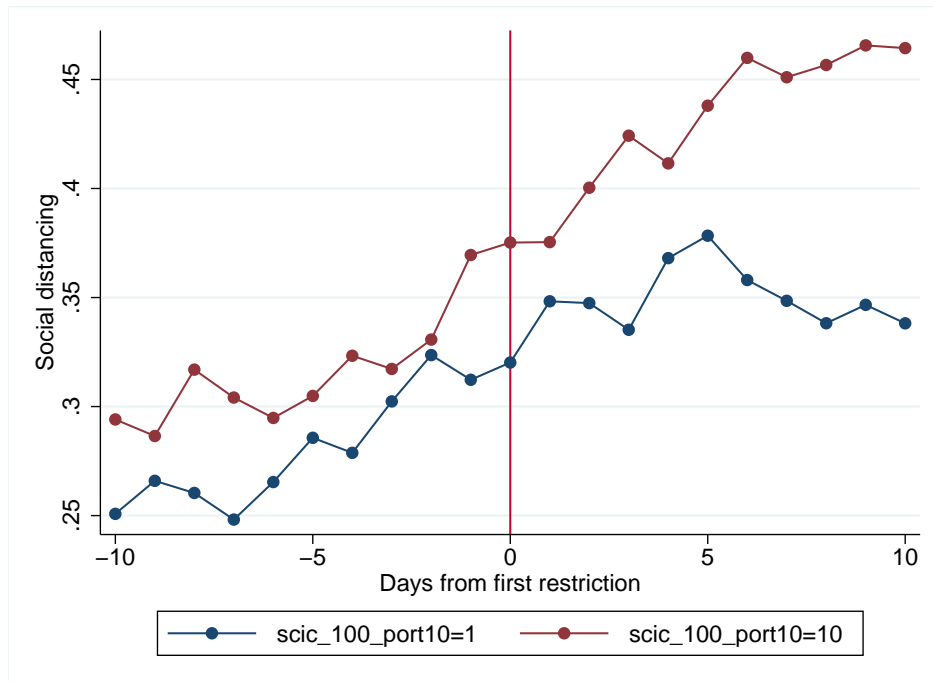


Figure B.6: Social connectedness to COVID-affected US counties (cont'd)

C. Social distancing vs. SCI-weighted US cases - minimum county distance 200 km

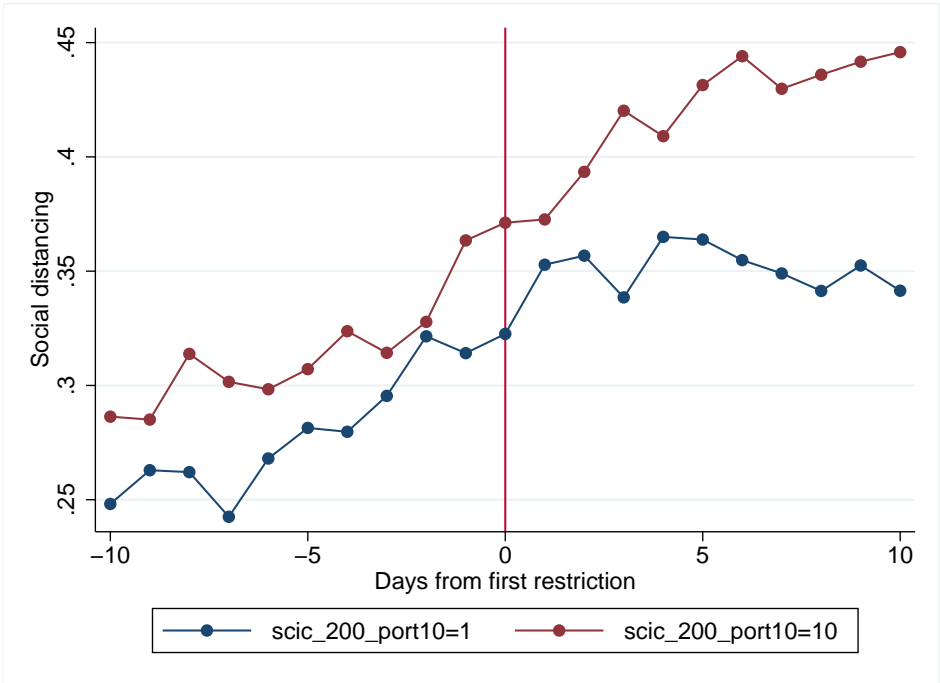


Table B.8
Gov't restrictions vs. SCI-weighted US cases

The dependent variable is *Social distancing*. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	(1)	(2)	(3)
Restr. x ln(SCI-w. US cases)	0.0044*** (0.0011)		
ln(SCI-w. cases - min dist. 0)	0.0357*** (0.0035)		
Restr. x ln(SCI-w. US cases) (100)		0.0075*** (0.0015)	
ln(SCI-w. cases - min dist. 100)		0.0307*** (0.0044)	
Restr. x ln(SCI-w. US cases) (200)			0.0070*** (0.0018)
ln(SCI-w. cases - min dist. 200)			0.0287*** (0.0054)
Restrictions (0-5)	-0.0102 (0.0061)	-0.0320*** (0.0080)	-0.0308*** (0.0095)
ln(N cases)	0.0153*** (0.0011)	0.0200*** (0.0011)	0.0207*** (0.0010)
State-Day FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
N	184,766	184,766	184,766
R ²	0.755	0.753	0.752

Significance levels: * 0.1, ** 0.05, * 0.01.**

B.5 Informative and uninformative social connections

We study the role of social connections with China and Italy, as they were the first countries to experience major outbreaks of COVID-19 and hence substantially ahead of the United States in terms of the spread of the epidemic. Therefore social connections in these countries are likely to be useful for Americans for obtaining information about the seriousness of the threat. Using a similar logic, connections with countries that are *behind* America in terms of the spread of the virus are likely to be less useful for obtaining information. To test this prediction, we perform a similar analysis using the social connectedness with a number of large countries that US citizens are likely to have significant social ties with, but which have experienced later and/or less severe COVID-19 outbreaks than the US.⁸

The results, shown in Table B.9, are consistent with the prediction. Social connections with countries with less experience of COVID-19 than the US are generally not associated with higher compliance rates with government restrictions. When including all countries in the same regression, the estimated coefficients for China and Italy remain significantly positive and larger in magnitude than those for other countries. In particular, connections with Italy appear associated with significantly higher compliance rates than those with other countries.

⁸We classify countries as less severe than the US if the date when they reached a daily death rate of 0.1 deaths per million was after the US, and if their daily death rate as of March 31, 2020, was lower than that of the US.

Table B.9
Robustness check: Social connectedness to informative vs. uninformative countries

The dependent variable is *Social distancing*. Heteroscedasticity-consistent standard errors, double-clustered by county and day, are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Restr. x ln(SCI China)	0.0011** (0.0005)	0.0009 (0.0005)	0.0008 (0.0005)	0.0010* (0.0006)	0.0010* (0.0006)	0.0011* (0.0006)	0.0011* (0.0006)
Restr. x ln(SCI Italy)	0.0042*** (0.0005)	0.0037*** (0.0008)	0.0036*** (0.0008)	0.0037*** (0.0008)	0.0036*** (0.0008)	0.0038*** (0.0008)	0.0039*** (0.0009)
Restr. x ln(SCI Canada)		0.0008 (0.0009)	0.0006 (0.0009)	0.0009 (0.0009)	0.0008 (0.0010)	0.0009 (0.0010)	0.0011 (0.0010)
Restr. x ln(SCI Mexico)			0.0004 (0.0003)	0.0005 (0.0003)	0.0005 (0.0003)	0.0005 (0.0003)	0.0006* (0.0004)
Restr. x ln(SCI India)				-0.0007 (0.0005)	-0.0007 (0.0005)	-0.0006 (0.0005)	-0.0005 (0.0006)
Restr. x ln(SCI Philippines)					0.0002 (0.0006)	0.0003 (0.0006)	0.0004 (0.0006)
Restr. x ln(SCI Vietnam)						-0.0005 (0.0004)	-0.0005 (0.0004)
Restr. x ln(SCI Brazil)							-0.0007 (0.0008)
Restrictions (0-5)	-0.0280*** (0.0042)	-0.0288*** (0.0043)	-0.0284*** (0.0043)	-0.0293*** (0.0043)	-0.0291*** (0.0044)	-0.0300*** (0.0044)	-0.0297*** (0.0044)
ln(N cases)	0.0113*** (0.0009)	0.0112*** (0.0009)	0.0112*** (0.0009)	0.0113*** (0.0009)	0.0113*** (0.0009)	0.0113*** (0.0009)	0.0113*** (0.0009)
State-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	184,766	184,766	184,766	184,766	184,766	184,766	184,766
R ²	0.756	0.756	0.756	0.756	0.756	0.756	0.756

Significance levels: * 0.1, ** 0.05, *** 0.01.