Interdependence and the Cost of Uncoordinated Responses to COVID-19

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Social distancing is the core policy response to COVID-19. But as federal, state and local governments begin opening businesses and relaxing shelter-in-place orders worldwide, we lack quantitative evidence on how policies in one region affect mobility and social distancing in other regions and the consequences of uncoordinated regional policies adopted in the presence of such spillovers. We therefore combined daily, county-level data on shelter-in-place and business closure policies with movement data from over 27 million mobile devices, social network connections among over 220 million of Facebook users, daily temperature and precipitation data from 62,000 weather stations and county-level census data on population demographics to estimate the geographic and social network spillovers created by regional policies across the United States. Our analysis showed the contact patterns of people in a given region are significantly influenced by the policies and behaviors of people in other, sometimes distant, regions. When just one third of a state's social and geographic peer states adopt shelter in place policies, it creates a reduction in mobility equal to the state's own policy decisions. These spillovers are mediated by peer travel and distancing behaviors in those states. A simple analytical model calibrated with our empirical estimates demonstrated that the "loss from anarchy" in uncoordinated state policies is increasing in the number of non-cooperating states and the size of social and geographic spillovers. These results suggest a substantial cost of uncoordinated government responses to COVID-19 when people, ideas, and media move across borders.

Keywords: COVID-19 | peer effects | social spillovers | geographic spillovers

J.A., D.E., D.H., and D.G. were previously employees, interns, or contractors of Facebook, J.A. has and until recently D.E. had a significant financial interest in Facebook.

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Pandemics are interdependent phenomena. Viruses and people's adherence to the government policies designed to contain them spill over from region to region. Early on, COVID-19 spread through international and domestic travel (1, 2). It is less well known, however, how behavioral responses to the pandemic and to government mitigation policies spill over from region to region due to social influence. As different regions begin to adopt heterogeneous reopening policies—with some opening businesses and relaxing shelter-in-place orders and others remaining closed and maintaining those orders—it is critical to understand how regional policies affect one another and the cost of adopting uncoordinated policies across regions.

Governments have enacted a variety of non-pharmaceutical interventions to reduce the spread of SARS-CoV-2 including social distancing policies designed to reduce high-density interactions among people in a particular region. Analyses of historical disease spread (3) and COVID-19 (4) indicate adherence to social distancing is crucial to slowing the spread of the pandemic, especially in the absence of a vaccine. But, while social distancing policies have, by and large, been left to individual cities, counties, states, and nations, uncoordinated policy interventions neglect that many geographic borders are porous and that increased social interdependence through communication media could create behavioral social influence across even distant regions.

In cases where coordination has occurred (for instance, in the Northeastern United States), it has often been at the level of the "megaregion" (5). While intuitive, these local coordination efforts neglect the possibility that peoples' behaviors are influenced not just by those in their local communities, but also by those with whom they are geographically distant but socially connected through mobile phones, video conferencing and social media. These social spillovers may be even more relevant to the spread of COVID-19 as shelter-in-place orders have increased our reliance on digital connections, creating record breaking usage of social media and video conferencing to maintain our social ties across geographic distance (6).

Recent studies used population-scale digital trace data (7) to measure the impact of social distancing policies on mobility, interaction intensity and, in some cases, COVID-19 infections and their associated morbidity and mortality (8–11). These studies found adherence to social distancing policies is moderated by demographic attributes such as political affiliation (8, 10), age, gender, educational attainment (12), income and access to high speed internet (13). Unfortunately, our understanding of the impact of social distancing policies on mobility, infection rates, morbidity and mortality is limited because existing research has not credibly accounted for social and geographic spillovers, which, if large, could substantially alter our perceptions of the effectiveness of local policies.

Researchers have causally identified the existence of social contagion in offline behaviors such as exercise (14), product adoption (15) and voting (16), and the potential for local policies to cause geographic spillovers to neighboring communities (17). Given these empirical regularities, it is likely that individuals' mobility and adherence to social distancing are impacted not only by policies in their own regions, but also by the policies of neighboring regions and distant regions in which their social network connections reside. Put differently, a local government's social distancing policy may significantly impact the health outcomes of other communities, including those that are geographically proximate or those that are geographically distant but socially proximate. The existence of such spillovers could imply substantial health and economic consequences to adopting uncoordinated policies across socially and geographically

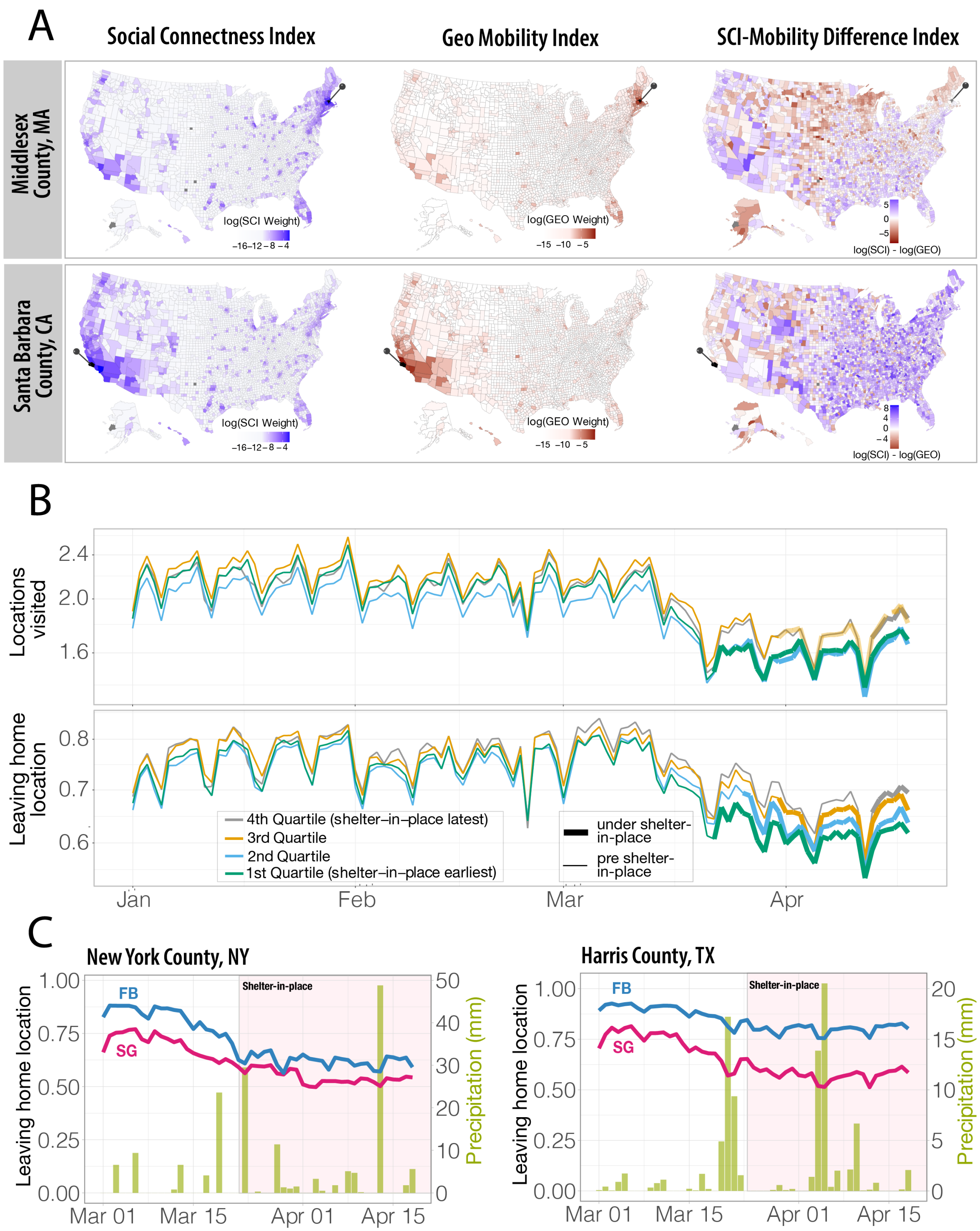

Fig. 1. (A) displays the social and geographic adjacency weights for two counties and the difference between them. For each county, geographic weights are generally stronger for nearby counties, whereas social weights are stronger for geographically distant counties. (B) shows the time series trends for the number of locations visited per device and the fraction of devices leaving home across county quartiles determined by the time at which each county introduced a shelter-in-place policy (if at all). Thicker lines correspond to periods of time where shelter-in-place was in effect. (C) displays the fraction of devices leaving home for two counties, along with the amount of precipitation in each county. Areas of the graph shaded in red correspond to periods during which shelter-in-place was in effect. In general, fewer devices leave home when it is raining, providing visual evidence of the strength of our weather instruments.

connected regions.

Here, we measure mobility across borders, adherence to social distancing and high-density interactions between people in physical space using population-scale digital trace mobility data on the location and movement of over 22 million mobile devices from Safegraph (18), which records the fraction of mobile devices staying home each day in every U.S. county, the average number of locations visited by mobile devices each day in every U.S. county and the number of visits to distinct points of interest each day in every county; and with Facebook mobility data on over 27 million mobile devices (19), which records the fraction of mobile devices staying home each day in every U.S. county and the average number of locations mobile devices visit each day in each U.S. county.

We augmented these mobility data sets with an index of the degree to which different U.S. counties are socially connected on Facebook (20), temperature and precipitation data from the National Oceanic and Atmospheric Administration's (NOAA) global historical climatology network (GHCN) database (21), census counts of each U.S. county's total population and a detailed database of the timing of COVID-related government interventions in every U.S. county. This combination of data allowed us to causally estimate the direct effect of government social distancing policies on local mobility, the indirect effects of other governments' social distancing policies on local mobility, and the mediation of these effects by social influence and geographic proximity across the entire United States. We focus our analysis on the 2,502 U.S. counties appearing in both the Facebook and Safegraph data from March 1, 2020 to April 18, 2020, during which the vast majority of social distancing policies were implemented in the U.S.

We first estimated a difference-in-differences model that considered the direct county-level effect of social distancing policies, but did not account for geographic or social spillovers (Supplementary Information S2.1). Consistent with previous studies (8, 22), we found that implementing a shelter-in-place policy led to a 3.2% ($P < .001$) decrease in the fraction of devices leaving their homes and a 6.0% decrease ($P < .001$) in the number of locations visited.* While this specification suggested that social distancing policies are effective at curbing mobility when enacted by focal states, it fails to account for geographic spillovers and social spillovers, and may therefore overstate the effectiveness of any one county's or state's policy.

We therefore estimated difference-in-differences models that account for geographic spillovers, according to a geographic adjacency matrix, and social spillovers, according to a social adjacency matrix. We constructed the geographic adjacency matrix using the Safegraph data from January and February 2020 to calculate the fraction of Census block group visits to county i from people living in county j (Supplementary Information S1.1.3). We constructed the social adjacency matrix by combining Facebook's Social Connectedness Index with Census data to calculate the fraction of county i's Facebook ties that are to friends in county j (Supplementary Information S1.2.2).

We began by estimating a difference-in-differences model that quantifies geographic spillovers, but not social spillovers (Supplementary Information S2.2). In some sense, this specification accounts for spillovers in the same way mayors and governors who are currently coordinating

*In the text, we report effects on outcomes calculated using Safegraph data. We estimated effects on the same outcomes using the Facebook data, and find similar results. Results based on both Safegraph and Facebook data are shown in the figures throughout the main text and in the SI.

at the "megaregion" level may account for them—by accounting for geographically proximate peer regions. Results from this model, shown in Fig. 2a, suggest that when accounting for geographic spillovers, a focal county implementing a shelter-in-place order reduced the average number of locations visited in that county by 4.0% ($P < .001$). But when half of the county's geographic alters *also* implemented shelter-in-place orders it further reduced the average number of locations visited in the focal county by 2.3% ($P < .001$). A focal county implementing a shelter-in-place order reduced the fraction of devices leaving home in that county by 2.0% ($P < .001$). But when half of the county's geographic alters *also* implemented shelter-in-place orders it further reduced the fraction of devices leaving home in the focal county by 1.4% ($P < .001$).

When we estimated the impact of these geographic spillovers on mobility in a dyadic difference-in-differences model (Supplementary Information S2.5), we found that when only one county in a dyad implemented a shelter-in-place policy, travel from that county to the non-implementing county *increased* by 0.55% ($P = .05$) on average, while travel from the county not implementing the policy to the county implementing the policy decreased by 1.2% ($P < .01$). When both counties implemented shelter-in-place orders, travel between the counties decreased by 0.51% ($P < .001$). The results in Fig. 2a and 2b validate the importance of coordinating geographically connected regions to, for example, reduce travel across boarders from counties in which businesses are closed to neighboring counties in which businesses are open. But, they fail to account for social spillover effects. When we estimated a difference-in-differences model that distinguished between within-state and across-state alters, we found that when considering *both* social and geographic spillovers, the estimated spillover effect from 100% of alter states implementing a shelter-in-place policy was an 13% reduction ($P < .001$) in locations visited and a 9.1% reduction ($P < .001$) in the fraction of devices leaving home (Fig. 2c) (Supplementary Information S2.4). Under this model, policy spillover estimates when accounting for social spillovers are over two times larger than when only considering geographic spillovers. In other words, it is not only the policy decisions of geographically proximate states that affect outcomes in a focal state, but also the communities to which that state is socially connected through communication technology. Results from this model also suggest that 36% of a state's geographic and social peer states implementing shelter in place policies is as effective at reducing mobility as the focal state implementing its own shelter in place policy.

Our analyses thus far establish the importance of two different mechanisms that contribute to spillovers: geographic proximity and social influence. However, although our difference-in-differences estimates show that social spillovers are an important determinant of a focal county's mobility levels, these estimates do not establish the underlying mechanisms that drive these effects. It is unclear if changes in focal county mobility levels are driven by knowledge of peers' counties' policies, changes in the behavior of socially connected peers, or another mechanism. To identify the extent to which this effect is driven by changes in peer behaviors, we employed our IV estimation framework and, while controlling for peers' shelter-in-place policies, instrumented for the behavior of peers in socially connected counties using weather, shifts in industry visit shares, and their interaction with peers' shelter-in-place policies (Supplementary Information S3). We estimated that a 3.0% reduction in the number of peer locations visited leads to a 5.6% reduction in the number of locations visited in a

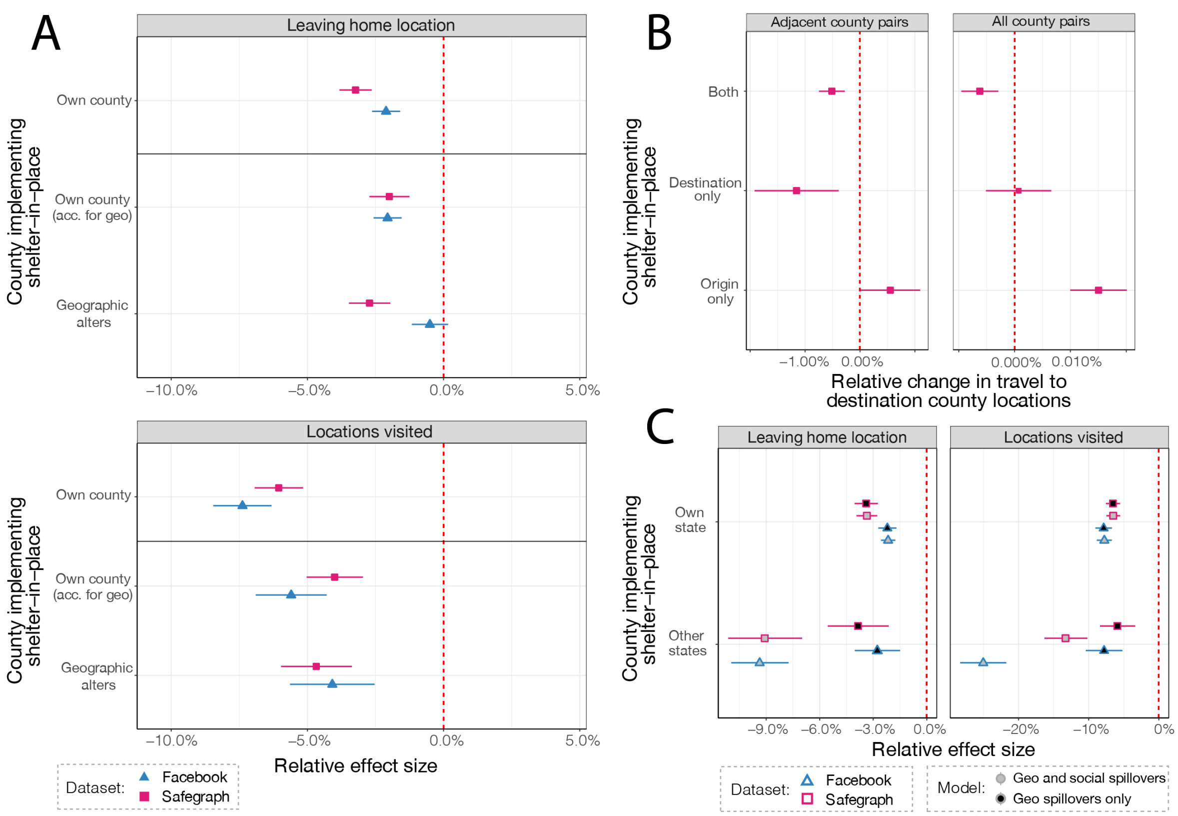

Fig. 2. (A) compares the results of our difference-in-differences (DiD) model that ignores spillovers and estimates the effect of a policy on its "own county" and our DiD model that includes geographic spillovers and separates the effects of a policy on its own county ("own county (acc. for geo)") from the effects of the policies of geographically connected counties ("Geographic alters"). For both the fraction of devices leaving home and the number of locations visited, the geographic spillovers are approximately equal in magnitude to the direct effects of ego county shelter-in-place policies. (B) displays the results of a county-level dyadic difference-in-differences model using either all county pairs or only adjacent county pairs. When only an "origin" county implements a shelter-in-place policy, outbound travel to the destination county increases. Only when either the destination county or both counties implement shelter-in-place does travel to the destination county decrease. (C) compares our estimates of the direct effect of shelter-in-place, as well as the spillover effects of other states' shelter-in-place policies, with and without accounting for social spillovers. When we account for social spillovers, the magnitude of our spillover estimates increases by over a factor of 2.

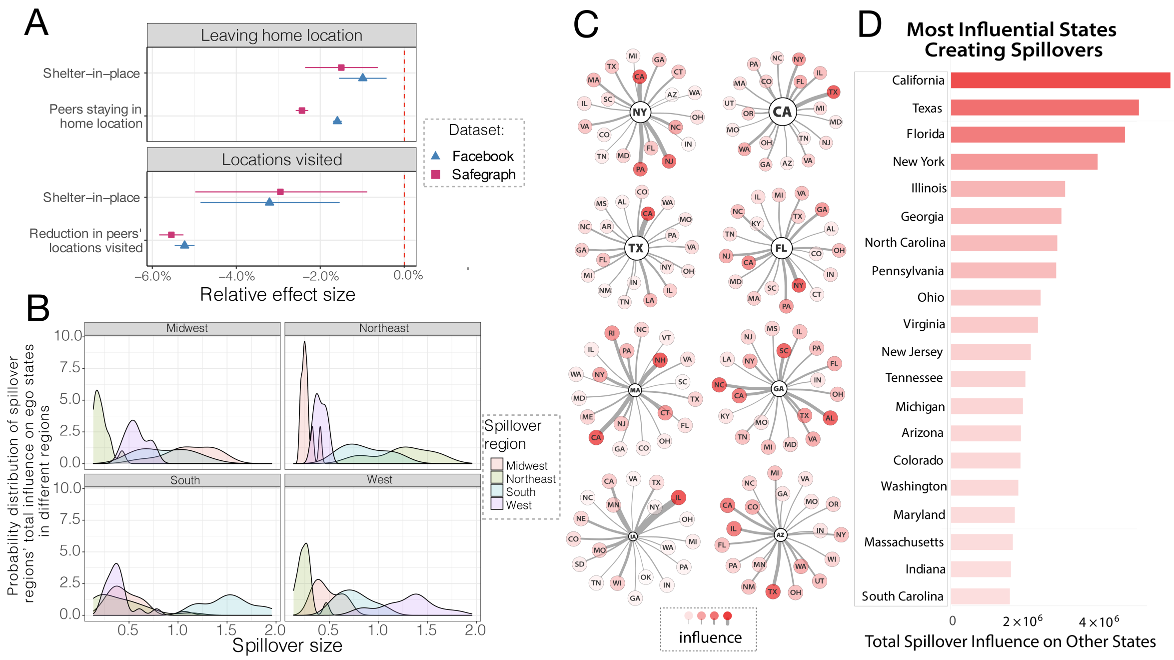

Fig. 3. (A) displays the causal effect of endogenous mobility levels in Facebook-alter counties on mobility levels in focal counties estimated using an instrumental variables framework. The magnitudes of endogenous peer effects are scaled to the direct effect of shelter-in-place orders in their own state. (B) displays the region-level probability distribution functions for the size of the total spillover effect from alter states in each U.S. region, relative to the direct effect of each focal state's own shelter-in-place policy. (C) displays the ego networks for 8 different U.S. states. For each state, we display the 20 alter states whose own shelter-in-place policy causes the largest reductions on mobility levels in the ego state, according to our difference-in-differences model. Both the edge weight and the alter node color correspond to the amount of influence the alter exerts on the ego. (D) displays the 20 states whose shelter in place policies cause the greatest reduction in devices leaving home across the U.S., according to our difference-in-differences model.

focal county ($P < .001$) and that a 1.5% reduction in the number of peers leaving their home location leads to a 2.4% reduction in the number of focal county devices leaving their home location ($P < .001$) (Fig. 3a). These effect sizes suggest that social spillovers are substantially mediated by peer behavior. In other words, people in a focal state are significantly influenced by the behavior of their peers in other states when calibrating their own social distancing behaviors and choices.

We also combined our social and geographic adjacency matrices with the point estimates obtained from our difference-in-differences with spillovers model to estimate the strength of interdependence between each pair of U.S. states to understand, for example, how much mobility would go down in state j if state i implemented a shelter-in-place policy (Supplementary Information S5). Fig. 3c shows the ego networks for eight U.S. states chosen from across the country (we report results for all fifty states in the SI). Generally speaking, each state's mobility outcomes are impacted by the policy decisions of not just geographically proximate states, but also socially connected, distant states. For instance, Florida's mobility is most affected by New York implementing shelter-in-place, presumably through digitally mediated social influence or travel, despite the states being distant. New Hampshire has a strong influence on adjacent Massachusetts, despite being a small state. These interdependence estimates can also be combined with state population levels to estimate the U.S. states whose shelter-in-place policies would lead to the greatest reductions in mobility across the rest of the U.S. (Fig. 3c). A state's total spillover influence is highly correlated, but not equivalent to, that state's population size. This highlights the need for states across the country to coordinate, even if they are not near one another and our results suggest which states should be coordinating with which other states based on the strength of spillovers between them.

Finally, we used our empirical estimates to calibrate an analytical model of the inefficiency created by states failing to coordinate over social and geographic spillovers (Supplementary Information S6). In the model, social distancing is a function of states' (linearly costly) mobility policies and spillovers from the policies of other states. The model's comparative statics measure the difference in aggregate utility achieved under the one-shot Nash equilibrium without transfers, and under optimal coordination by a social planner, for different levels of spillover intensity. States choose their level of restriction balancing their direct cost and a quadratic loss function for missing their target reduction in mobility. The difference between the Nash equilibrium outcome and the socially optimal outcome characterizes losses from uncoordinated policies, while the choices states make in equilibrium characterize the free-riding and compensation for other states' negligence that take place in the absence of coordination.

When spillovers or the cost of implementing policies are low, welfare under coordination through a social planner is not much higher than in a Nash equilibrium. But when spillovers and costs are high, the lack of coordination can be quite costly. Utility can be up to 69% lower when states fail to coordinate in the presence of spillovers as large as those we detect in our empirical analyses (Fig. 4a). When spillovers are high, states' policies diverge, with one state, for example, having to compensate for the neglect of another state's loose restrictions by imposing even stricter, more costly policies than necessary to achieve their desired immobility targets. When states coordinate, however, social and geographic spillovers actually help them achieve their targets more efficiently because they essentially provide "free treatments" as the cooperative behaviors of peer states positively influence social distancing behaviors in focal states.

This work is not without limitations. First, while our estimates of peer influence utilize weather and shift share instruments, our estimates of the interdependence between individual U.S. states rely on our difference-in-differences analysis, which may miss some state- or dyad-level heterogeneity. Furthermore, although our analysis of lags and leads suggests the robustness of our analysis (presented in the Supplementary Information), our difference-in-differences estimates may not capture all anticipatory behavior (e.g., people stocking up on groceries before government policies take effect). In the Supplementary Information, we more carefully examine the robustness of our estimates to these and other challenges, but this work nonetheless relies on assumptions that are not fully testable.

As government officials around the world begin to calculate the costs and benefits associated with lifting social distancing policies, it is crucial we accurately estimate these policies' effects. Our findings indicate that any given government's decision to lift a social distancing policy will likely affect the behavioral and health outcomes of not only their own citizens, but also the citizens of geographically and socially proximate communities. These results suggest there are significant negative welfare repercussions from uncoordinated government social distancing policies, which suffer from a coordination problem resembling the price of anarchy (23). This implies that it is important for federal governing bodies (e.g., the United States federal government, the European Union) to coordinate policy action, even in cases where final policy decisions are in the hands of local governments. We hope our work inspires a greater level of coordination between local government officials when determining policies related to social distancing and future research into the indirect effects of these policies.

Materials and Methods

We first estimated the causal effects of county-level shelter-in-place orders on their own county's population mobility, measured by the fraction of mobile devices leaving home and the mean number of locations visited per device, as well as their effects on mobility in counties to which they are geographically connected through physical proximity or socially connected through social media on Facebook, using the following difference-in-difference model specification

$$Y_{it} = \delta_1 D_{it} + \delta_2 D_{-it}^{geo} + \delta_3 D_{-it}^{social} + f(W_{it}) + \alpha_i + \tau_t + \epsilon_{it}$$

where Y_{it} denotes the social distancing outcome, D_{it} indicates whether shelter-in-place has been enacted in county i in time period t, D_{-it}^{geo} is the geographic adjacency weighted average of peer county policies, D_{-it}^{social} is the social adjacency weighted average of peer county policies, and $f(W_{it})$ is a term that flexibly controls for the potential non-linear impact of weather using a "double machine learning" approach (24). α_i and τ_t represent a set of county and time fixed effects, and ϵ_{it} denotes the error term. Our statistical inference allows for correlations between counties that are socially or geographically connected or located in the same U.S. states using adjacency- and cluster-robust standard errors (25). Although not explicitly indicated in this notation, we estimate DiD models that treat all alter counties equivalently, and also DiD models that distinguish between same state counties and different state counties. We report results for shelter-in-place policies, which typically supersede business closures, in the main text and for business closures in the SI.

While the difference-in-difference analysis allowed us to measure the effect of connected counties' policies on focal counties' population mobility, the effect of connected counties policies could be driven by awareness of the policies of nearby U.S. counties and states, changes in friends' behavior or the amount of inter-county and inter-state travel between regions. We therefore used instrumental variables (IV)

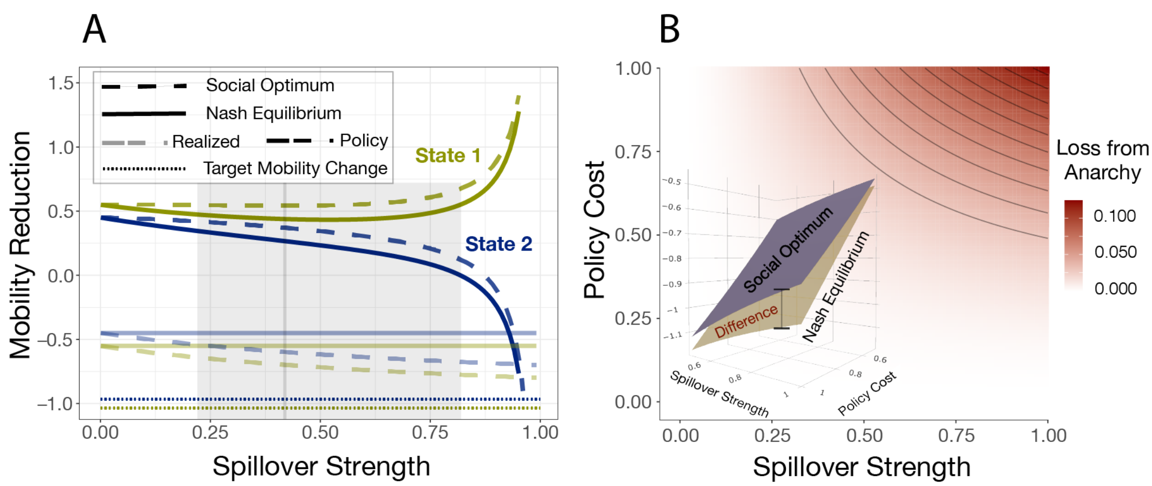

Fig. 4. Displays mobility reduction targets, optimal policy choices, equilibrium mobility reductions, and utility under anarchy (Nash Equilibrium) and coordination (Social Optimum). (A) displays mobility outcomes achieved (faint) under varying levels of spollover strength (x-axis) for a pair of states with similar but not identical reduction targets (dotted) and their resulting policy choices (bold). The grey shading and grey vertical line correspond to the minimum, median, and maximum spillover strengths we observe in our difference-in-differences estimates of between state spillovers (the model producing the grey shaded estimates in Fig 2c). When spillover strength is low, Nash Equilibrium policies for both states are similar, and there is no loss from anarchy compared to coordination (panel B). As spillovers get stronger, policies for two states diverge. Under coordination, this divergence decreases equilibrium mobility toward the target, but under anarchy, the states' actions wastefully offset, leaving outcome mobility unchanged as spillover strength increases. Utility under both equilibria are displayed in the inset figure in (B). Maximum utility is increasing in spillovers because they, in a sense, create "free" reductions in mobility. The loss from anarchy is increasing in both the size of spillovers and the cost of mobility reductions. Spillovers assumed to be symmetrical. In panel A, the cost of implementing policies is set at 1.

analysis to estimate the mechanisms driving geographic and social spillovers by separately measuring the effects of connected county policies and the effects of peer behavior within connected counties on mobility in focal counties. Our IV analysis uses exogenous variation in weather (14, 26, 27) and the extent to which different counties are exposed to national changes in industry visit behavior based on pre-pandemic data (28, 29) as exogenous shocks to peer behaviors in connected counties to identify their causal influence on mobility behavior in focal counties.

We estimate the following main and first-stage model specifications:

$$
\begin{aligned}
Y_{it} =& \beta Y_{-it} + \delta_1 D_{it} + \delta_2 D^{geo}_{-it} + \delta_3 D^{social}_{-it} + \\
& \psi S_{it} + f(W_{it}) + \alpha_i + \tau_t + \epsilon_{it}
\end{aligned}
$$

$$
\begin{aligned}
Y_{-it} =& \gamma_1 D_{it} + \gamma_2 D^{geo}_{-it} + \gamma_3 D^{social}_{-it} + \pi S_{it} + g(W_{it}) + \\
& h(D^{social}_{-it}, S_{-it}, W_{-it}) + \alpha_{-i} + \tau_t + \nu_{-it},
\end{aligned}
$$

where Y_{it}, D_{it}, D^{geo}_{-it}, D^{social}_{-it}, $f(W_{it})$, α_i, τ_t, and ϵ_{it} are as they were in equation 1 above. Y_{-it} denotes the social adjacency weighted average mobility behaviors of individuals in other counties and the main parameter of interest β represents the endogenous peer effect of that behavior. S_{it} is the set of industry shift-shares for county i. In the first-stage, $g(\cdot)$ is also a function that captures the nonlinear effects of W_{it}. D_{-it} and social adjacency weighted averages of alter counties shift-shares and weather, S_{-it} and W_{-it}, form the set of candidate instruments. The associated function $h(\cdot)$ is a post-LASSO (30) that selects a smaller set of instruments. Lastly, ν_{-it} denotes the first stage error term. We report adjacency and cluster-robust standard errors. Further details are provided in the Supplementary Information.

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Supplementary Information

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Materials and Methods

S1 Data

S1.1 Safegraph Data

This paper uses data provided by Safegraph, Inc.[1] which collects location data from approximately 22 million unique devices each month. These data consist of “pings,” which identify the coordinates of a particular smartphone at a given moment in time. Each user of these smartphones has given permission for his or her location to be tracked by a variety of mobile applications. Safegraph in turn partners with many of these mobile application services that obtain affirmative opt-in consent from users to collect their location data. To preserve anonymity, the data is aggregated to the Census block group (CBG) level and all CBGs with fewer than five observations are omitted. We use this data to construct social distancing measures, industry visit shares and shifts, and a geographic adjacency matrix to capture cross-county mobility.

S1.1.1 Social Distancing Measures

We use data from Safegraph’s “Social Distancing Metrics” and “Weekly Patterns” covering the period from January 1, 2020 through April 18, 2020 to construct two measures of social distancing compliance. First we construct “Fraction of Devices Not at Home” (NHDF) as[2] $1 - completely\_home\_device\_count/device\_count$ where $device\_count$ is simply the fraction of devices not detected to be entirely at home on a given day in a Census block group. This data is then aggregated to the county level to conform with the rest of our analysis. To allow us provide results in relative terms, we apply a hyperbolic inverse sin transformation, leading to one of our four main social distancing measures asinh(NHDF). We use the arcsinh transformation because it is defined at zero, and, except for very small values of y, $\sinh^{-1}(y) \approx \log(2y)$. Thus,

[1] https://www.safegraph.com

[2] This transformation is so that it goes in the same direction as our other movement based measure.

arcsinh-transformed variables can be interpreted similarly to log-transformed variables (*1*). The second metric we construct is "Census Block Groups Visited" (dCBGVs), which measures the mean number of census block groups an individual has visited on one day. Specifically, this is formed by summing *non_home_cbg_visits_within_county*, *cbg_visits_outside_county*, and *home_cbg_visits* across all devices and simply dividing by the *device_count*. To allow for a relative interpretation, we apply a log transformation, yielding our second main social distancing measure log(dCBGVs).

S1.1.2 Industry Visits Shares and Shifts

We construct baseline industry visit shares for each county in the pre-COVID period by computing the number of visits by Safegraph users to a particular industry in that county as a proportion of total visits to all industries in that county during the months of January and February 2020 (visits are aggregated from 1/1/20-2/29/20). We construct relative national shifts in industry visits by computing the total number of visits to a particular industry across all of US every day from 3/1/20-4/18/20 and calculating proportional increase from baseline industry visits (i.e. total number of visits to that industry across all of US in January and February 2020). The industry visit shift-share measures S_{it} of a county i on a particular day t are computed by taking a product of the baseline industry visit shares in that county and the relative national level shifts in industry visits on that day. While analyzing ego county's i social distancing outcomes, we instrument for alter county's j social distancing outcomes by a weighted average of alter county's industry visit shift-shares. More formally: $S_{-it} = \sum_j w_{ij} S_{jt}$ where S_{-it} is the weighted average of all alter county's industry visit shares and weights $w_{ij} = \frac{n_j SCI_{ij}}{\sum_k n_k SCI_{ik}} : k \neq i$ and n_j is the population of county j.

S1.1.3 Geographic Adjacency Matrix

In order to better understand how policies can impact cross-county mobility patterns, we compute the number of device visits from an origin county to Census block groups (CBGs) in a destination county, not counting device visits that occur to the same CBG for every pairwise combination of counties (note that this asymmetric). Thus if a device from county A visits two CBGs in county B, the dataset registers two visits to county B. Safegraph does not provide data at the individual device level, so we are unable to determine the number of devices from county A that visit county B; instead, we use the number of device CBG visits to form the edge weights. To get a sense of average mobility patterns pre-crisis, we sum the number of device visits over January and February 2020. To smooth this data, we apply a smoothing procedure to the raw data using an empirical Bayes approach. We use the entire dataset to generate an empirical prior, and then use that prior, along with the observed county-level data, to estimate a Dirichlet multinomial posterior distribution for every individual county. This results in a maximum a posteriori (MAP) estimate of ($\hat{\alpha}_i$) for each county i. For each origin county, we let n_i be the number of device visits from devices with a home in county i excluding own county visits. We then calculate the posterior probability of travel from county i to county j as

$$\hat{\pi}_{ij} = \frac{n_i + \hat{\alpha}_i}{N + K}$$

where N =$\sum_i n_i$ and $K = \sum_i \hat{\alpha}_i$. For more details on this procedure, see (*2*).

S1.2 Facebook Data

Facebook's Data for Good[3] Initiative provides anonymized, aggregate privacy preserving data products for use in humanitarian organizations and universities. For this paper, we specifically make use of two main datasets: US county mobility metrics and the Social Connectedness Index.

[3] `https://dataforgood.fb.com/`

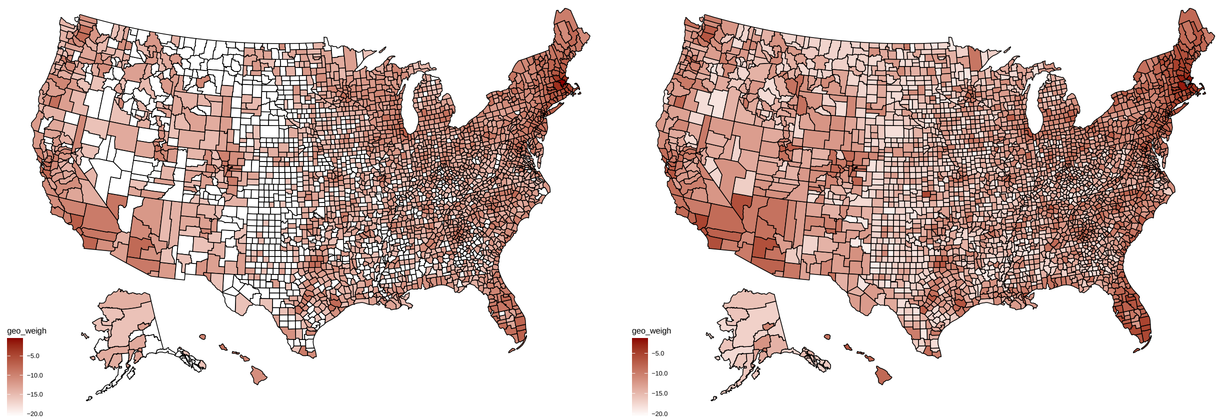


Figure S1: The spatial distribution of the raw (left) and smoothed (right) weighted geographic mobility graph of Middlesex County, MA. Smoothing does not substantially alter the geographic adjacency matrix.

S1.2.1 Facebook Mobility Metrics

This data provides aggregated county-level mobility metrics built from 27 million Facebook users who have the Facebook app installed on their smartphones and have turned on location history in the United States. These metrics are are provided starting from March 1st, 2020, and continue to be updated daily. We use the data from March 1st until April 18th so that it aligns with our Safegraph data. Our last two social distancing measures come directly from this data.

To start, *ratio single tile users* captures the fraction of users whose location history does not leave a single 0.6km by 0.6km block (a "level 16 Bing tile") during a 24 hour period. We subtract this measure from 1 to construct *not single Bing tile users* (NSBTUs). Similar to NHDF from the Safegraph data, we also apply a inverse hyperbolic sine transformation to form our third main social distancing measure, asinh(NSBTUs). Lastly, *Bing tiles visited relative change* (BTVRC) measures the relative change in the average number of Bing tiles that a Facebook user was present in during a 24-hour period compared to a the pre-crisis baseline. This baseline is computed by averaging across all of February 2020 for each specific day of the week. Since this measure already affords a relative interpretation and we do not directly have access to the

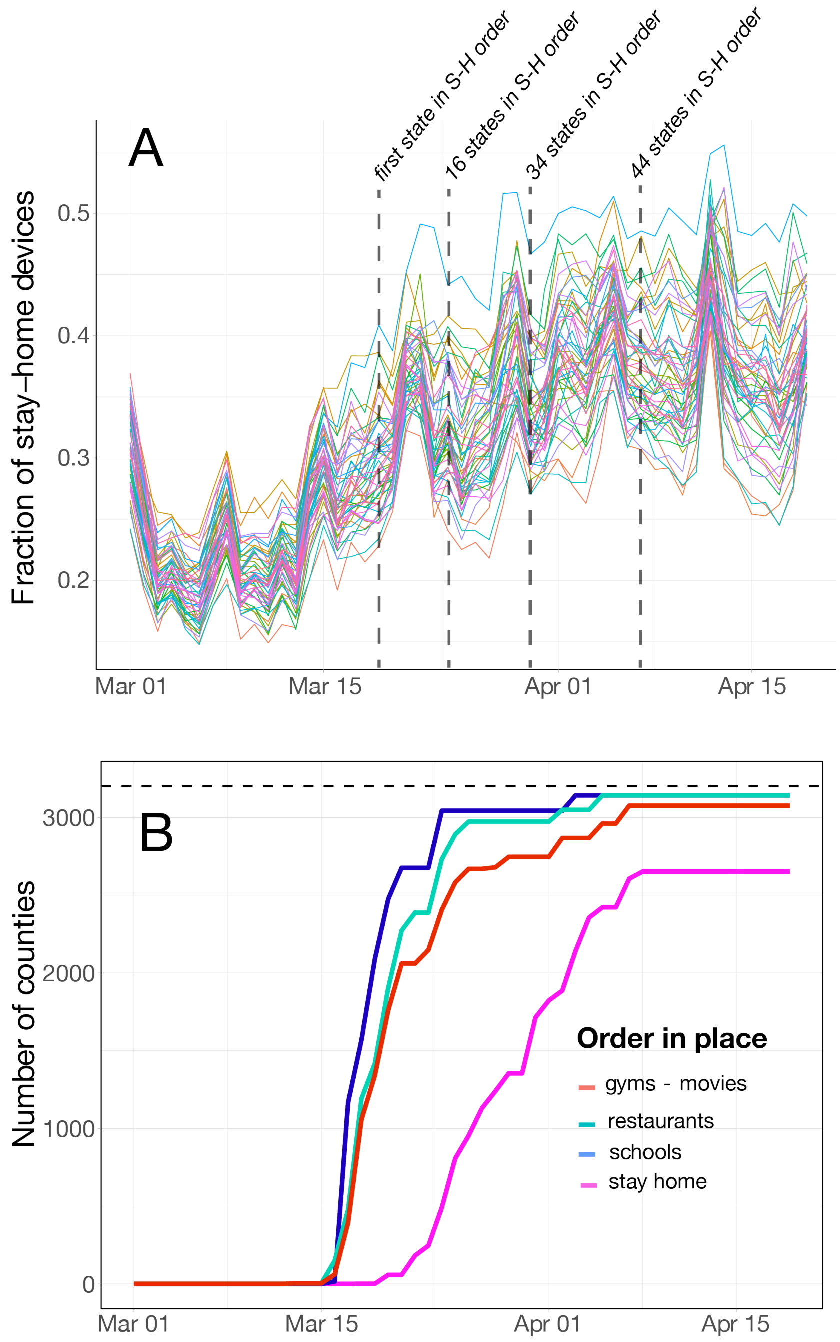


Figure S2: A. The Fraction of Devices at Home for all 50 states in the United States as a function of time. B. The number of counties in different orders-in-place as a function of time.

raw counts, we simply use it as it is.

It is important to note that only counties with at least 300 active users in that county are tracked. Since we want to compare across both Safegraph and Facebook measures, we limit our analysis to the 2,502 counties that have complete data starting March 1st and beyond.

S1.2.2 Facebook Social Connectedness Index

We use the Social Connectedness Index (SCI) dataset which contains a measure of social connectedness at the U.S. county level. The SCI between two counties i and j is defined as:

$$SCI_{ij} = \frac{FBConnections_{ij}}{FBUsers_i \times FBUsers_j} \tag{S1}$$

Here, $FBUsers_i$ and $FBUsers_j$ are the number of Facebook users in locations i and j, and $FBConnections_{ij}$ is the number of Facebook friendship connections between the two. SCI_{ij}, therefore, measures the relative probability of a Facebook friendship link between a given Facebook user in location i and a user in location j. Thus, if this measure is twice as large, a Facebook user in i is about twice as likely to be connected with a given Facebook user in j. The details of the construction of the SCI metric as well as other details of the dataset are provided in (*3*). The SCI index used in this study is drawn from a snapshot of Facebook friendships as of December 31, 2019.

S1.3 Weather Data

Our weather data comes from the Global Historical Climatology Network (GHCN) database maintained by the National Oceanic and Atmospheric Association (NOAA). A detailed description of this data can be found in (*4*). The GHCN data contains daily observations of maximum temperature, minimum temperature, and precipitation for roughly 62,000 weather stations in the United States. We use the geographic coordinates of each weather station in order to derive maximum temperature and precipitation data for each county in our dataset as described below.

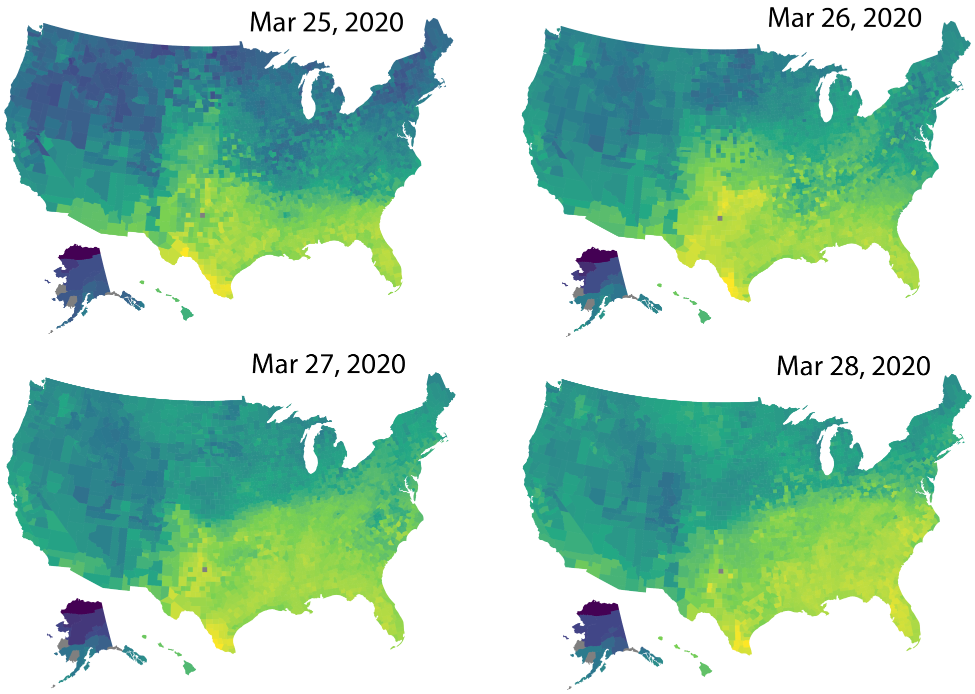


Figure S3: The maximum daily temperature (in degrees Celsius) at county level over four consecutive days. The brighter color indicates higher maximum temperature.

Starting with the daily GHCN data we restrict to weather stations within the United States that contain either maximum temperature or precipitation weather elements. Of the 3,233 counties in the United States, 243 have no weather stations and 967 have fewer than three weather stations. For each of these counties with fewer than three weather stations, we assign the nearest three stations within a 100 kilometer radius of the county centroid to this county. The above procedure assigns weather stations to 97.2% of US counties.

To obtain the weather data for each county-day pair, we average the measurements obtained by the weather stations within each county, including the weather stations assigned to the county if the county has no station within its borders as discussed above. When stations do not have either temperature or precipitation readings, we average the field excluding the missing values. In the sample, 7.3% of station days do not have precipitation readings and 64% do not have temperature readings. After aggregating to the county level, 19.9% and 4.4% of the county-day observations were still missing maximum temperature and precipitation values respectively. To fill in these missing values, we find the three nearest stations within a 100-kilometer radius that contain the missing field and take the average across the 3 measurements. This gives us a precipitation and a maximum temperature reading for 99.9% of county days in our sample. For this study, we use the weather data from January 1, 2020 through April 19, 2020.

We can visualize the precipitation and maximum temperature data across all counties in the United States over time, as shown in Figures S4 and S3, respectively. The histograms of maximum daily county temperature across all counties in the United States over time is depicted in Figure S5, where the histogram color darkens as time progresses. Sample histograms for specific dates are depicted in Figures S6 and S7, where the distributions of average daily county precipitation and temperature throughout the United States are respectively depicted. Interestingly, Figure S7 depicts a bimodal distribution for the distribution of maximum temperature across counties. Sample histograms for a specific county are depicted in Figures S9 and S8, where the distributions of average daily county precipitation and temperature throughout time are respectively depicted.

S1.4 Government Intervention Data

We use the data collected by researchers at Johns Hopkins University that documents various local or federal government interventions that came into effect in various states at various times (*5*). In particular, the data contains information pertaining to 1) school closures, 2) bans on gatherings of large sizes, 3) closing of restaurants, bars, and gyms, and 4) shelter-in-place orders. In the policy space considered in this paper, we use only two of these policy interventions:

- Closing of gyms and cinemas. Restaurant Dine-in bans (GMR).
- Shelter-in-place (SH)

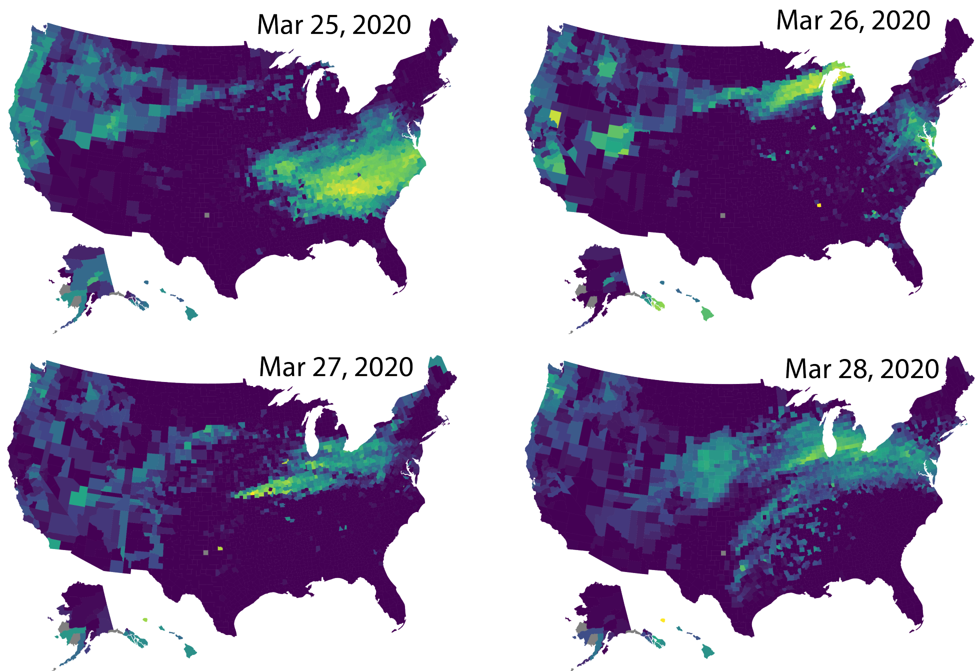


Figure S4: The daily precipitation (in millimeters) at county level over four consecutive days. The brighter color indicates higher precipitation.

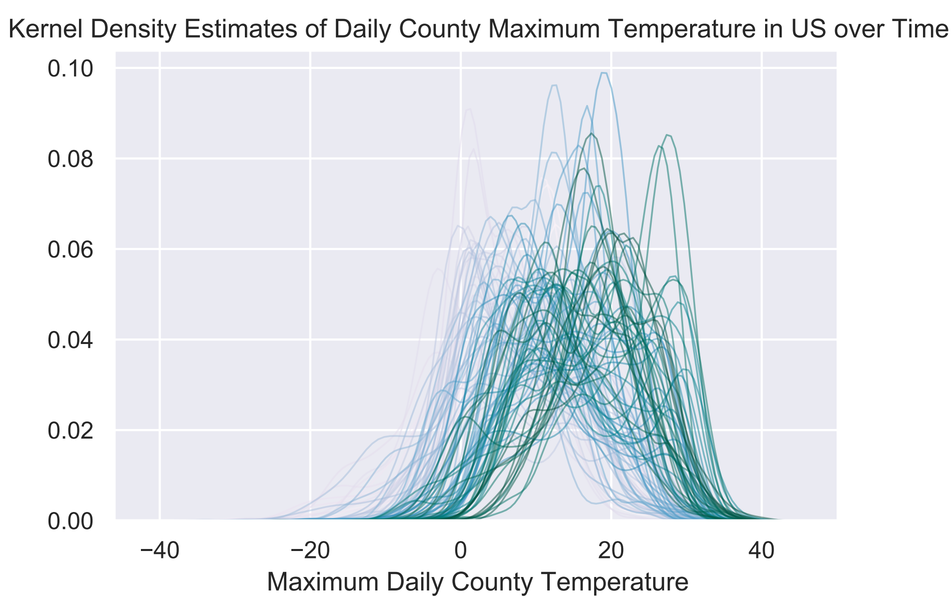


Figure S5: Kernel density estimates of county daily maximum temperature (in degrees Celsius) in the US. Each line represents the distribution of maximum temperature on a specific day, and the color of the lines gets darker as time progresses.

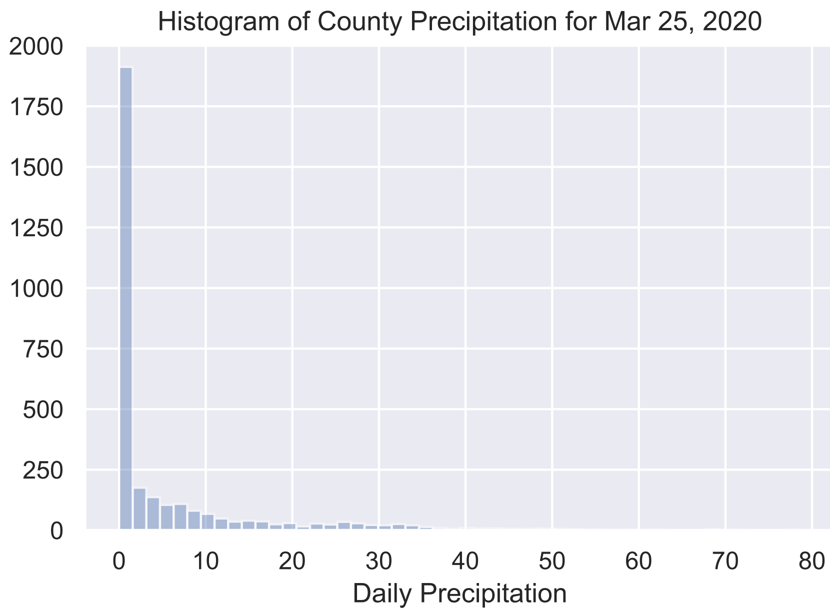


Figure S6: Histogram of precipitation (in millimeters) for one specific day in the US.

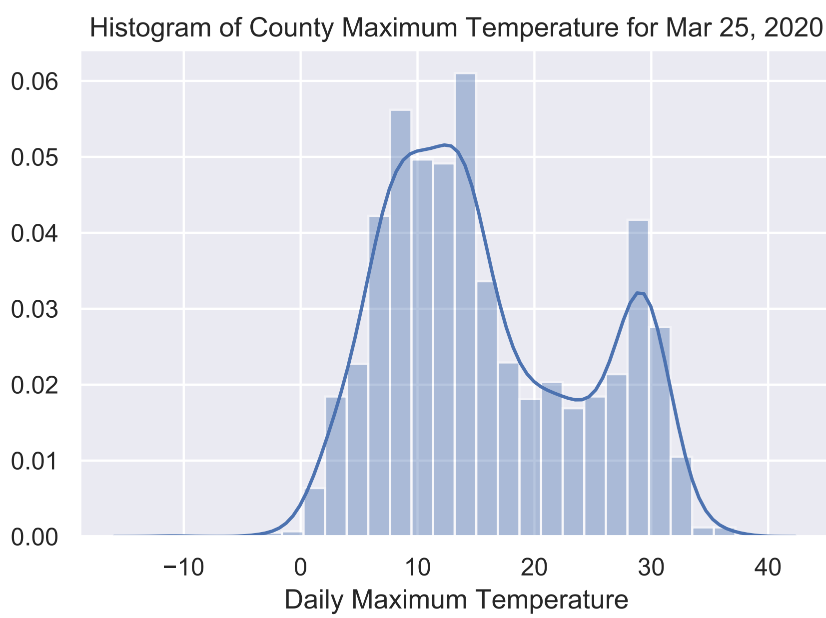


Figure S7: Histogram of daily maximum temperature (in degrees Celsius) for one specific day in the US.

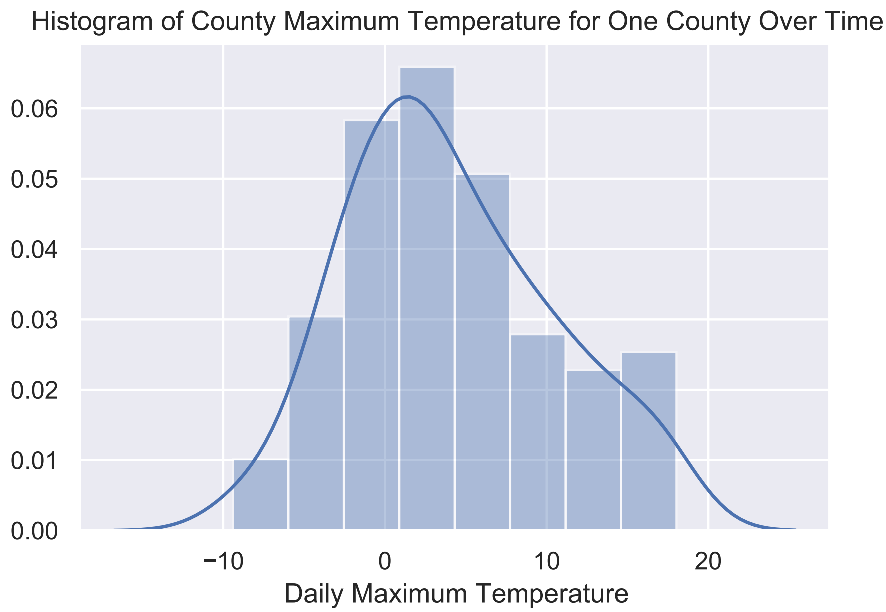


Figure S8: Histogram of daily maximum temperature (in degrees Celsius) for one specific county in the U.S..

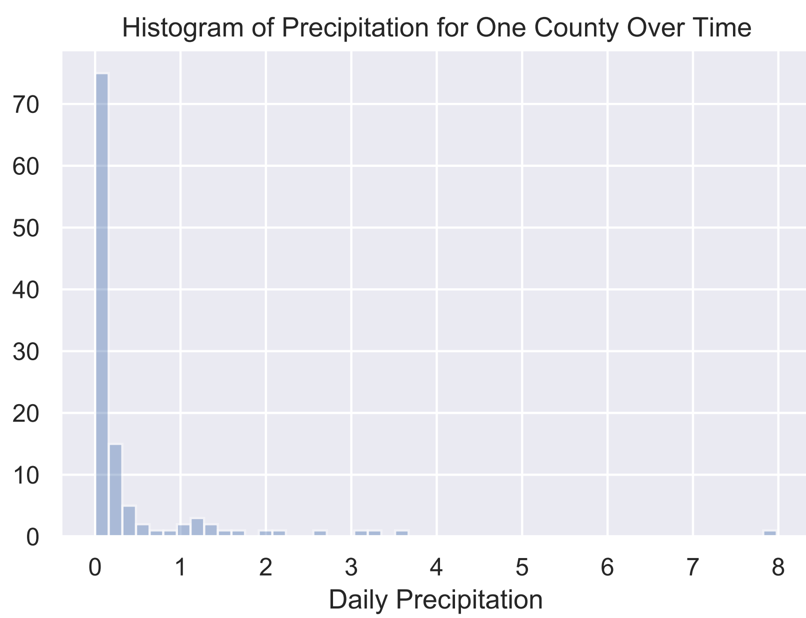


Figure S9: Histogram of precipitation (in millimeters) for one specific county in the US.

In the above, we use shelter-in-place to refer to not only policies explicitly referred to as “shelter-in-place“ by policymakers, but also other similar orders that are named differently (e.g., “stay at home” orders). These policies differ in their level of severity of curbing mobility, with shelter-in-place policy being more severe than the closing of restaurants, movie theaters, and gyms. Note that we do not include the school closure policies in our analyses because of the limitations of the Safegraph data that we use to track movement. Many students in schools in US do not have access to smartphones. Furthermore, relative to other policy interventions enacted across the United States, there is relatively little variation in the enactment of school closure policies. Both of these factors make it difficult to measure the impact of school closure policies on the types of outcomes we measure in this paper. We do not include bans on gatherings since most U.S. states were in this policy state for only a few days before implementing more severe restrictions, and because we suspect that the period of time during which these measures were in place corresponds with high levels of travel as people rushed to stock up on supplies, returned home, or relocated to less urban destinations. Lastly, although our analysis includes both of these policies, in the main text, we focus particularly on shelter-in-place, as both the impact of such policies and our confidence in our inferences are much higher. Figure S2B shows the fraction of counties that had implemented one of the policies of interest as of a particular date.

S1.5 Census Data

We use county-level population estimates for 2018 from the U.S. Census Bureau to weight all county-level analyses by population. We use these same population estimates to re-weight the Facebook Social Connectedness Index, so that each edge corresponds to the fraction of county i's Facebook friendships belonging to Facebook users in county j. Finally, we use this Census data in order to calculate each state's “total influence,“ as reported in Fig. 3c of the main text.

S1.6 Variation in Alter Policies

Figure S10 shows the weighted median percentage of socially connected alter counties and geographically connected alter counties implementing shelter in place polices across our sample over time, as well as the weighted interquartile range for the same measures. Most of the policy variation we observe occurs between mid-March and early April.

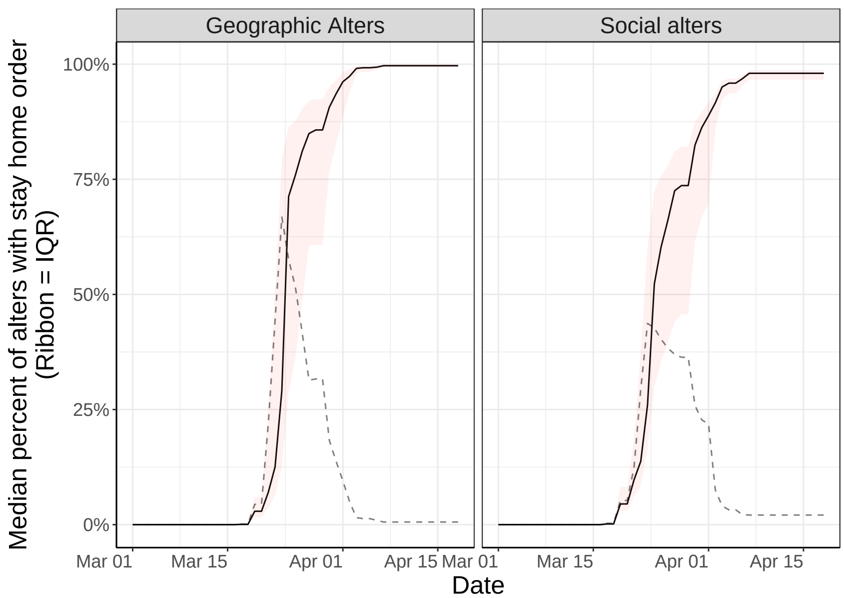


Figure S10: The weighted median percentage of geographic alter counties and social alter counties that have implemented shelter in place policies in our sample over time. Red ribbons correspond to the weighted 25th percentile and the weighted 75th percentile for the same quantities. The dashed line plots the interquartile range over time.

S1.7 Comparison of Outcome Metrics

Figure S11 shows the weighted mean of each of our four outcome variables over time. On average, each of these outcomes begins to decline after mid-March, when social distancing generally begins across the United States. Figure S12 shows the correlation between each of our four outcome variables. In general, all four outcome variables are quite correlated.

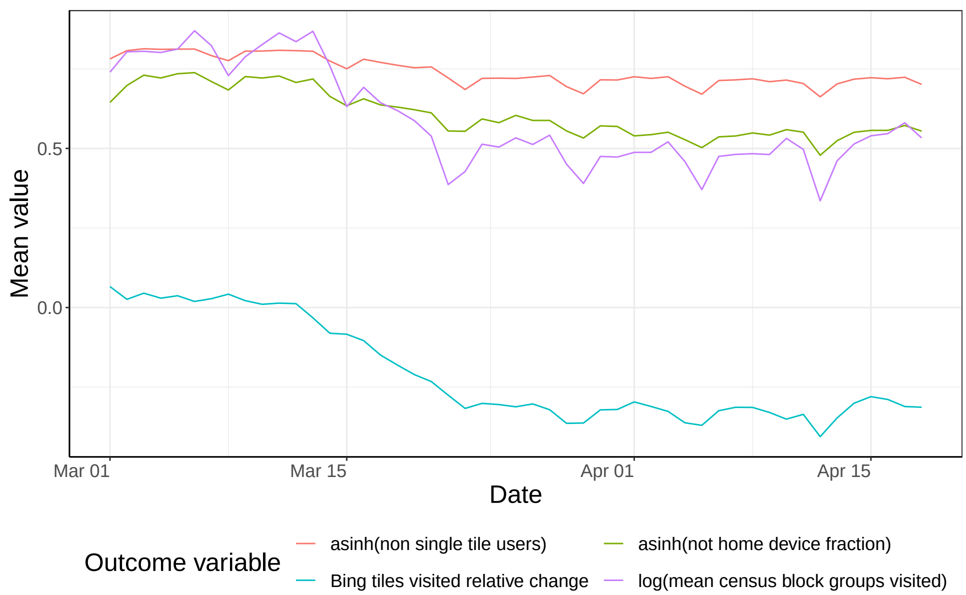


Figure S11: The weighted mean of each outcome variable for our analysis over time.

S2 Difference-in-differences analysis

In this section we present a series of results on the impact of policy interventions on social distancing behaviors. We consider four outcome variables defined in section S1.1.1 and section S1.2.1: asinh(NSBTUs), asinh(NHDF), log(dMCGBVs), and BTVRC. All statistical inference is network-adjacency- and state-cluster-robust; see section S4.

S2.1 Analysis without spillovers

We begin by presenting results which assume that there are no policy spillovers between counties or states in Table S1. Here we estimate the following model specification:

$$Y_{it} = D_{it}\delta_1 + f(W_{it}) + \alpha_i + \tau_t + \epsilon_{it} \tag{S2}$$

where Y_{it} is denotes the social distancing outcome, D_{it} is a 2-dimensional row vector of policies that denotes whether either GMR_{it} (gym, movie, and restaurant ban) or SH_{it} (shelter-in-place order) has been enacted in county i in time period t. The associated parameter, δ_1, is a 2-

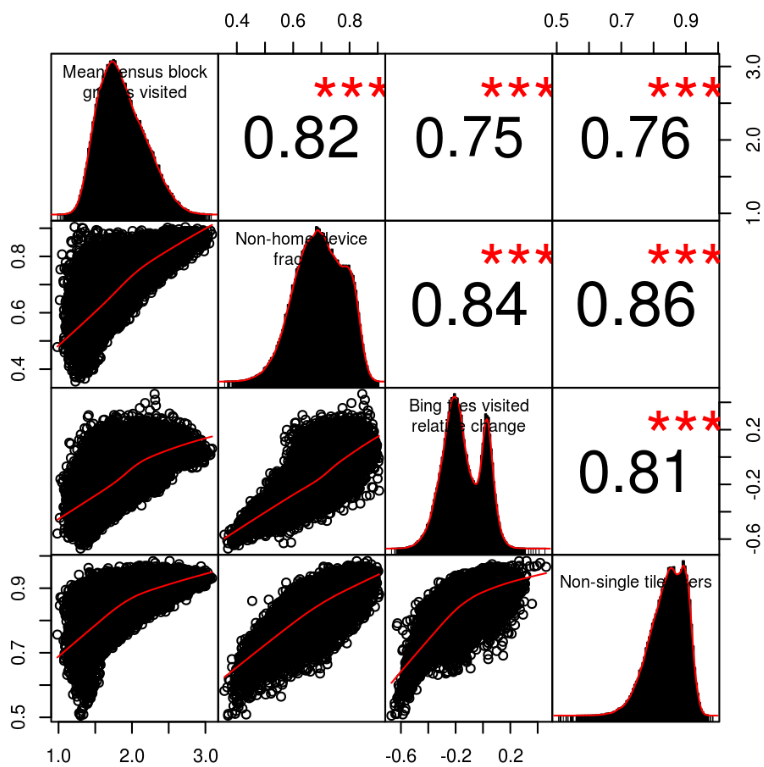


Figure S12: The correlation between different outcome variables. Diagonal tiles show histograms for each outcome. Lower tiles show scatter plots for each pair of outcomes. Upper tiles show the measured correlation between each pair of outcomes, along with p-values.

dimensional column vector of the main parameters of interest δ_1^{GMR} and δ_1^{SH} which capture the effect of each policy on county-level outcomes; that is, $D_{it} = [\text{GMR}_{it}, \text{SH}_{it}]$ and $\delta_1 = \begin{bmatrix} \delta_1^{\text{GMR}} \\ \delta_1^{\text{SH}} \end{bmatrix}$ so that $D_{it}\delta_1 = \delta_1^{\text{GMR}}\text{GMR}_{it} + \delta_1^{\text{SH}}\text{SH}_{it}$. Since we have coded GMR to be zero once a county is under a shelter-in-place order, δ_1^{SH} is interpreted as the total effect of a shelter-in-place order rather than the marginal effect. $f(W_{it})$ is a term that flexibly controls for the potential non-linear impact of weather using a "double machine learning" approach. We describe this in section S3.3.1. α_i and τ_t represent a set of county and time fixed effects, and ϵ_{it} denotes the error term.

These results suggest that both the shelter-in-place and closure policies are associated with increased social distancing exhibited by the individuals covered by those policies. Shelter-in-place orders are associated with a substantially larger reduction in mobility across all outcomes than closing gyms, movies theatres, and restaurants.

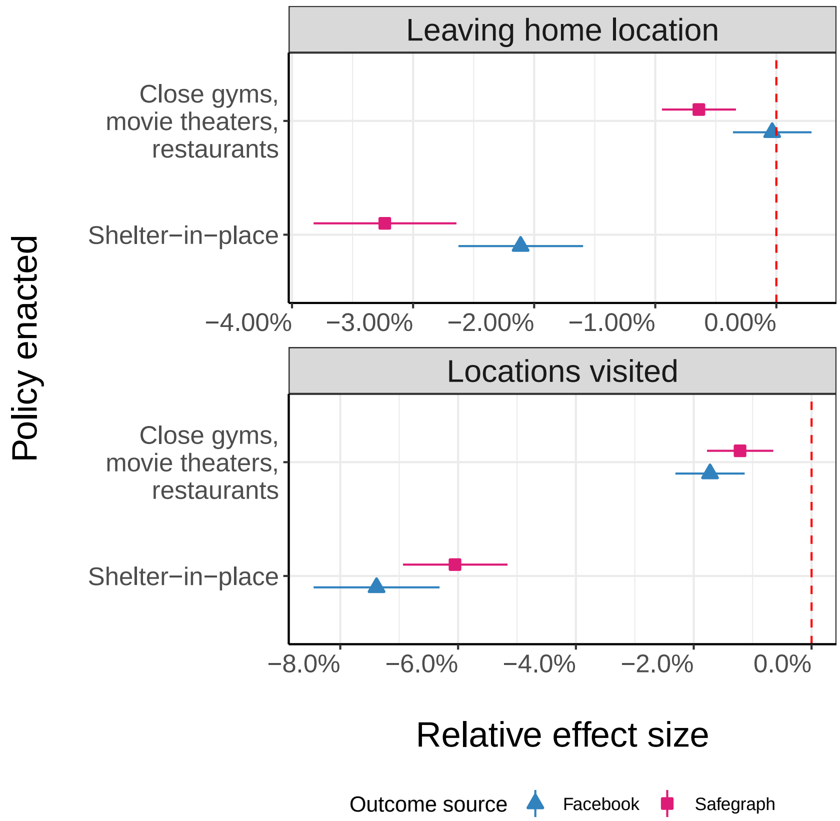


Figure S13: Difference-in-differences analysis of policy effects on mobility, neglecting any spillovers between counties.

S2.2 Analysis with Geographic Spillovers

As we discuss in the main text, it is reasonable to posit that there are effects of one county's policies on the outcomes of other counties; that is, there are spillovers, exogenous peer effects, or interference (*6–11*).

Therefore, our next specification also allows for geographic spillovers by including the policy of neighbors weighted according to their tie strength is the geographic movement adjacency matrix A^g. Details of the construction of this matrix can be found in section S1.1. In particular, we estimate:

$$Y_{it} = D_{it}\delta_1 + D^{geo}_{-it}\delta_2 + f(W_{it}) + \alpha_i + \tau_t + \epsilon_{it} \tag{S3}$$

The main difference with this specification and equation 2 above is the inclusion of D^{geo}_{-it}, a 2-dimensional row vector where each element is the weighted average of peer county policies. Specifically, $D_{-it} = \sum_j \omega_i j * D_{jt}$ where weights $\omega_{ij} = a^{geo}_{ij} / \sum_k a^{geo}_{ik}$ and each a^{geo}_{ij} is the (i, j)th element of the geographic adjacency matrix A^g. Results are presented in table S2. Again we note that, after considering the impact of geographic spillovers, the analysis suggests that both shelter-in-place and closure policies are associated with increased social distancing behaviors, with more pronounced distancing behavior associated with shelter-in-place policies as expected.

S2.3 Analysis with Geographic and Social Spillovers

The model presented in table S3 allows for both geographic spillovers as before in addition to social spillovers. The construction of the social adjacency matrix can be found in section S1.2.2. The specification is similar to above, but we additionally use a weighted average of policies across socially connected counties. We estimate this with the following regression.

$$Y_{it} = D_{it}\delta_1 + D^{geo}_{-it}\delta_2 + D^{social}_{-it}\delta_3 + f(W_{it}) + \alpha_i + \tau_t + \epsilon_{it} \tag{S4}$$

This specification is the same as above, but we also estimate the effects of a weighted average of policies in alter counties weighted by the social adjacency matrix constructed from the Facebook social connectedness index A^s. In particular, $D^{social}_{-it} = \sum_j w_{ij} * D_{jt}$ where weights $w_{it} a^{social}_{ij} / \sum_k a^{social}_{ik}$. When controlling for alter policies, the estimated coefficients on own-county policies are more muted, indicating a shelter in place order is associated with a 1 to

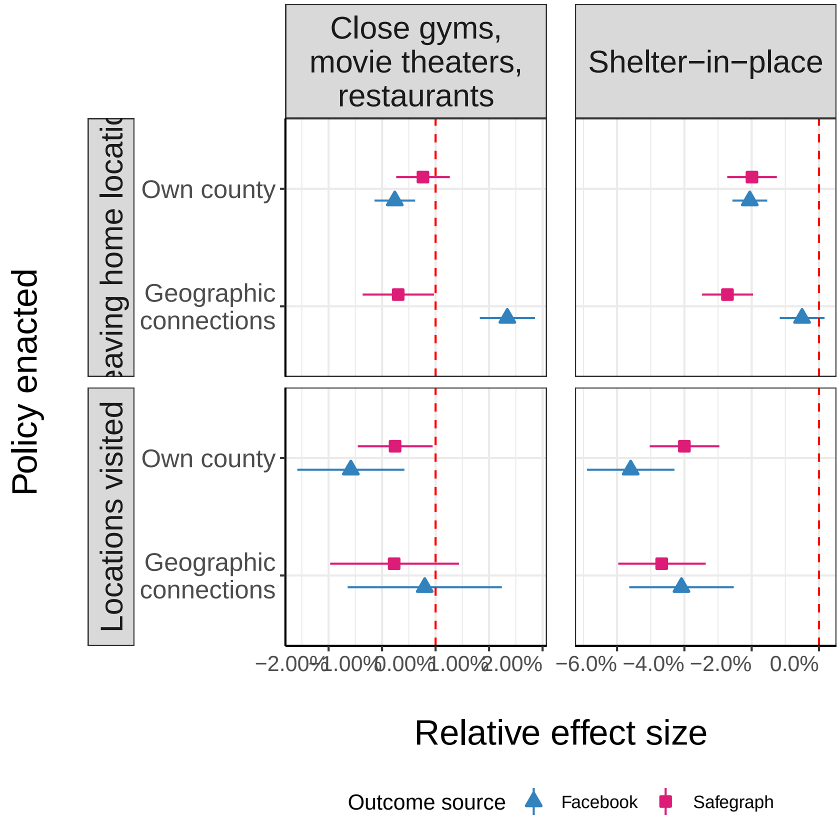


Figure S14: Difference-in-differences analysis of policy effects on mobility, allowing for spillovers via geographic connections.

2 percent reduction in mobility across our outcome measures. Only the estimates using the Facebook mobility data are statistically significant, however.

Spillovers also appear to be important in this context. In particular, social-alter policies, or the average policies enacted in other counties weighted by social connections, are more strongly associated with social distancing behavior than geo-alter policies, or policies in those localities that are geographically closer to the focal location.

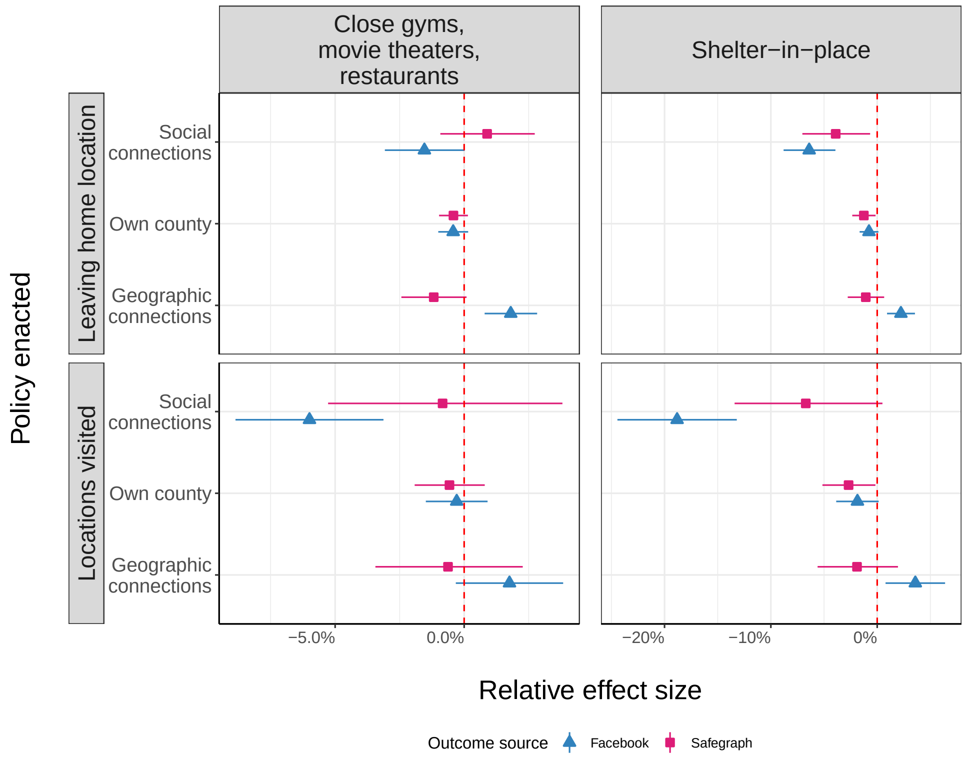


Figure S15: Difference-in-differences analysis of policy effects on mobility, accounting for spillovers via both geographic and social connections.

S2.4 State-Level Policy Contrasts

Our analysis so far has been restricted to the county level. However, in the vast majority of cases, social distancing policy is set at the state level or above. To explore counterfactuals related to different state-level policy contrasts (i.e. one state alone implements a shelter-inplace order vs. one state alone chooses *not* to implement a shelter in place order), we fit the following model specification:

$$Y_{it} = D_{it}\delta_1 + D^{geo,ss}_{-it}\delta^{ss}_2 + D^{geo,ds}_{-it}\delta^{ds}_2 + D^{social,ss}_{-it}\delta^{ss}_3 + D^{social,ds}_{-it}\delta^{ds}_3 + f(W_{it}) + \alpha_i + \tau_t + \epsilon_{it} \quad \text{(S5)}$$

The key differences between this model specification and equation 4, is that the D^{geo}_{-it} and D^{social}_{-it} have been split into the same state (ss) and different state (ds) components. The results from estimating this model can be found in Table S5. Fig. S16 shows this model's estimate of the effects of own state's and alter states' shelter-in-place policies, after combining geo- and social-spillovers. Qualitatively, these results are quite similar to those found in table S3. We also estimate a similar model that considers only geographic spillovers, but differentiates between same state and different state alter counties. The results of that model can be found in Table S5.

Fig. S17 compares the combined own-state and alter state effects of shelter-in-place when considering no spillovers, only geographic spillovers, and both geographic and social spillovers. After account for social spillovers, the estimated magnitude of the effect of alter states' shelter-in-place policies increase by more than a factor of 2.

Table S1: The effect of policy interventions on county-level outcomes

	Dependent variable:			
	asinh(NSBTUs)	asinh(NHDF)	log(dCBGVs)	BTVRC
	(1)	(2)	(3)	(4)
Shelter-in-place	-2.13^{***}	-3.29^{***}	-6.24^{***}	-7.38^{***}
	(0.27)	(0.31)	(0.48)	(0.55)
Close gyms/movies/restaurants	-0.03	-0.64^{***}	-1.22^{***}	-1.72^{***}
	(0.17)	(0.16)	(0.29)	(0.30)
Conley s.e.	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes	Yes
Observations	122,598	122,598	122,598	122,598
R^2	0.43	0.42	0.39	0.38
Adjusted R^2	0.41	0.41	0.38	0.37
Residual Std. Error (df = 120046)	6.36	8.54	14.85	15.81

Notes: NSBTU refers to the fraction of Facebook users in a given county who visit multiple Bing tiles on a given day. NHDF refers to the fraction of devices that are not completely at home, as measured by Safegraph. dCBGVs refers to the mean number of Census block groups devices from a given county visit, as measured by Safegraph. BTVRC refers to the relative change in the number of Bing tiles users visit, as measured by Facebook. All values multiplied by 100. *p<0.1; **p<0.05; ***p<0.01

Table S2: The effect of policy interventions on county-level outcomes, including geo-spillovers.

	Dependent variable:			
	asinh(NSBTUs)	asinh(NHDF)	log(dCBGVs)	BTVRC
	(1)	(2)	(3)	(4)
Ego shelter-in-place	-2.08^{***}	-2.01^{***}	-4.08^{***}	-5.60^{***}
	(0.27)	(0.38)	(0.55)	(0.66)
Geo-alter shelter-in-place	-0.50	-2.76^{***}	-4.79^{***}	-4.09^{***}
	(0.34)	(0.40)	(0.70)	(0.79)
Ego close gyms/movies/restaurants	-0.77^{***}	-0.24	-0.76^{**}	-1.58^{***}
	(0.20)	(0.26)	(0.36)	(0.51)
Geo-alter close gyms/movies/restaurants	1.33^{***}	-0.70^{**}	-0.78	-0.20
	(0.26)	(0.34)	(0.62)	(0.74)
Conley s.e.	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes	Yes
Observations	122,598	122,598	122,598	122,598
R^2	0.43	0.42	0.40	0.38
Adjusted R^2	0.42	0.41	0.39	0.37
Residual Std. Error (df = 120044)	6.33	8.51	14.79	15.76

Notes: NSBTU refers to the fraction of Facebook users in a given county who visit multiple Bing tiles on a given day. NHDF refers to the fraction of devices that are not completely at home, as measured by Safegraph. dCBGVs refers to the mean number of Census block groups devices from a given county visit, as measured by Safegraph. BTVRC refers to the relative change in the number of Bing tiles users visit, as measured by Facebook. All values multiplied by 100. *p<0.1; **p<0.05; ***p<0.01

Table S3: The effect of policy interventions on county-level outcomes, including geo- and social-spillovers.

	Dependent variable:			
	asinh(SBTUs)	asinh(HDF)	log(dCBGVs)	BTVRC
	(1)	(2)	(3)	(4)
Ego shelter-in-place	-0.78^{*}	-1.26^{**}	-2.73^{**}	-1.86^{*}
	(0.46)	(0.57)	(1.31)	(1.02)
Social-alter shelter-in-place	-6.61^{***}	-3.98^{**}	-6.95^{*}	-18.82^{***}
	(1.33)	(1.69)	(3.80)	(2.86)
Geo-alter shelter-in-place	2.21^{***}	-1.08	-1.92	3.58^{**}
	(0.66)	(0.88)	(1.97)	(1.43)
Ego close gyms/movies/restaurants	-0.43	-0.42	-0.57	-0.29
	(0.30)	(0.29)	(0.70)	(0.61)
Social-alter close gyms/movies/restaurants	-1.55^{*}	0.89	-0.84	-5.99^{***}
	(0.80)	(0.93)	(2.34)	(1.46)
Geo-alter close gyms/movies/restaurants	1.79^{***}	-1.19^{*}	-0.63	1.76^{*}
	(0.51)	(0.65)	(1.47)	(1.06)
Conley s.e.	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes	Yes
Observations	122,598	122,598	122,598	122,598
R^2	0.44	0.43	0.40	0.39
Adjusted R^2	0.43	0.41	0.39	0.38
Residual Std. Error (df = 120042)	6.29	8.48	14.76	15.64

Notes: SBTU refers to the fraction of Facebook users in a given county who visit only one Bing tile on a given day. HDF refers to the fraction of devices completely at home, as measured by Safegraph. dCBGVs refers to the mean number of Census block groups devices from a given county visit, as measured by Safegraph. BTVRC refers to the relative change in the number of Bing tiles users visit, as measured by Facebook. All values multiplied by 100. *p$<$0.1; **p$<$0.05; ***p$<$0.01

Table S4: The effect of policy interventions on county-level outcomes, including in-state and out-of-state geo-spillovers.

	Dependent variable:			
	asinh(NSBTUs)	asinh(NHDF)	log(dCBGVs)	BTVRC
	(1)	(2)	(3)	(4)
Ego shelter-in-place	-1.92^{***}	-2.71^{***}	-3.67^{***}	-5.37^{***}
	(0.71)	(0.57)	(0.95)	(1.65)
In-state geo-alter shelter-in-place	-0.32	-0.75	-3.10^{***}	-2.50
	(0.62)	(0.52)	(0.97)	(1.61)
Out-of-state geo-alter shelter-in-place	-2.81^{***}	-3.93^{***}	-6.09^{***}	-7.80^{***}
	(0.67)	(0.90)	(1.36)	(1.33)
Ego close gym/movies/restaurants	-0.53	-0.86	-0.42	-1.72
	(0.69)	(0.53)	(0.86)	(1.60)
In-state geo-alter close gyms/movies/restaurants	0.57	0.26	-0.79	0.08
	(0.63)	(0.51)	(0.91)	(1.57)
Out-of-state geo-alter close gyms/movies/restaurants	1.02^{***}	-0.55	-1.69^{**}	-0.75
	(0.29)	(0.33)	(0.69)	(0.73)
Conley s.e.	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes	Yes
Observations	122,598	122,598	122,598	122,598
R^2	0.44	0.43	0.40	0.39
Adjusted R^2	0.43	0.41	0.39	0.38
Residual Std. Error (df = 120042)	6.29	8.49	14.78	15.69

Notes: SBTU refers to the fraction of Facebook users in a given county who visit only one Bing tile on a given day. HDF refers to the fraction of devices completely at home, as measured by Safegraph. dCBGVs refers to the mean number of Census block groups devices from a given county visit, as measured by Safegraph. BTVRC refers to the relative change in the number of Bing tiles users visit, as measured by Facebook. All values multiplied by 100. *p<0.1; **p<0.05; ***p<0.01

Table S5: The effect of policy interventions on county-level outcomes, including in-state and out-of-state geo- and social-spillovers.

	Dependent variable:			
	asinh(NSBTUs)	asinh(NHDF)	log(dCBGVs)	BTVRC
	(1)	(2)	(3)	(4)
Ego shelter-in-place	−0.32	−1.77***	−2.70**	−1.62
	(0.45)	(0.66)	(1.23)	(1.37)
In-state geo-alter shelter-in-place	1.38**	−0.20	−2.76**	1.74
	(0.62)	(0.78)	(1.23)	(1.31)
Out-of-state geo-alter shelter-in-place	3.43***	0.61	0.82	8.15***
	(0.66)	(1.03)	(1.61)	(1.93)
In-state social-alter shelter-in-place	−3.25***	−1.44	−1.26	−7.89***
	(0.97)	(1.37)	(2.21)	(2.32)
Out-of-state social-alter shelter-in-place	−13.26***	−10.14***	−15.09***	−33.19***
	(1.00)	(1.32)	(2.06)	(2.37)
Ego close gym/movies/restaurants	0.61*	−0.17	0.10	0.83
	(0.32)	(0.50)	(0.80)	(1.18)
In-state geo-alter close gyms/movies/restaurants	1.63***	0.67*	−0.92	2.43***
	(0.29)	(0.41)	(0.71)	(0.69)
Out-of-state geo-alter close gyms/movies/restaurants	1.74***	−1.70***	−2.37**	3.55***
	(0.40)	(0.52)	(0.99)	(1.17)
In-state social-alter close gyms/movies/restaurants	−2.29***	−1.19	−0.53	−5.09***
	(0.51)	(0.82)	(1.15)	(1.47)
Out-of-state social-alter close gyms/movies/restaurants	−2.26***	1.19*	−0.01	−9.96***
	(0.50)	(0.70)	(1.11)	(1.32)
Conley s.e.	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes	Yes
Observations	122,598	122,598	122,598	122,598
R^2	0.46	0.44	0.41	0.41
Adjusted R^2	0.45	0.43	0.39	0.40
Residual Std. Error (df = 120038)	6.16	8.40	14.69	15.46

Notes: SBTU refers to the fraction of Facebook users in a given county who visit only one Bing tile on a given day. HDF refers to the fraction of devices completely at home, as measured by Safegraph. dCBGVs refers to the mean number of Census block groups devices from a given county visit, as measured by Safegraph. BTVRC refers to the relative change in the number of Bing tiles users visit, as measured by Facebook. All values multiplied by 100.
*p<0.1; **p<0.05; ***p<0.01

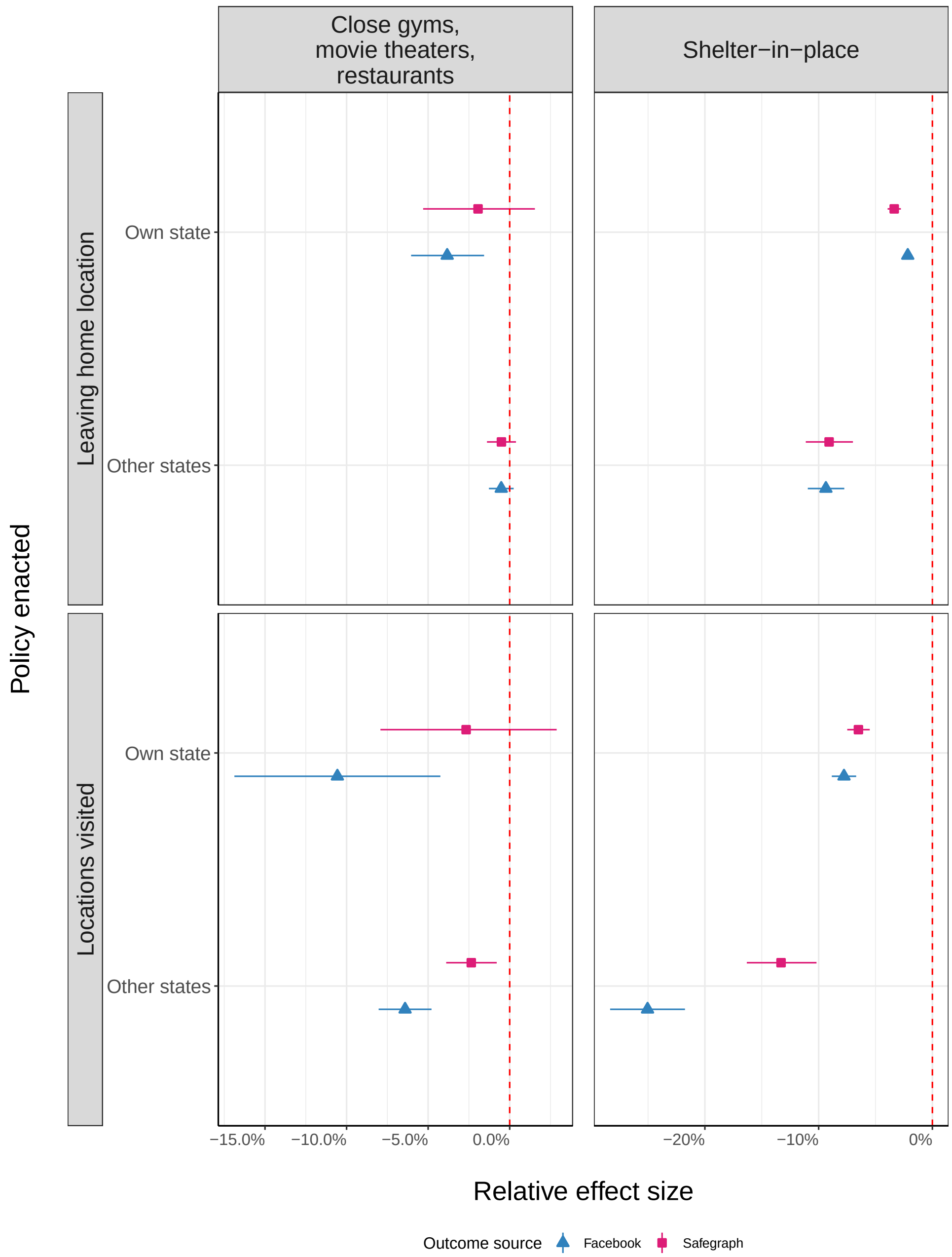


Figure S16: The estimated aggregate effect own-state and other states' shelter-in-place policies after differentiating between same state and different state spillovers. Direct effects, geo-spillovers, and social-spillovers are combined at the ego- and alter-level.

S2.5 Dyad-level Difference-in-differences

To establish the existence and relevance of geographic spillovers when enacting social distancing policies, we estimate the following two-way fixed effects difference-in-differences model,

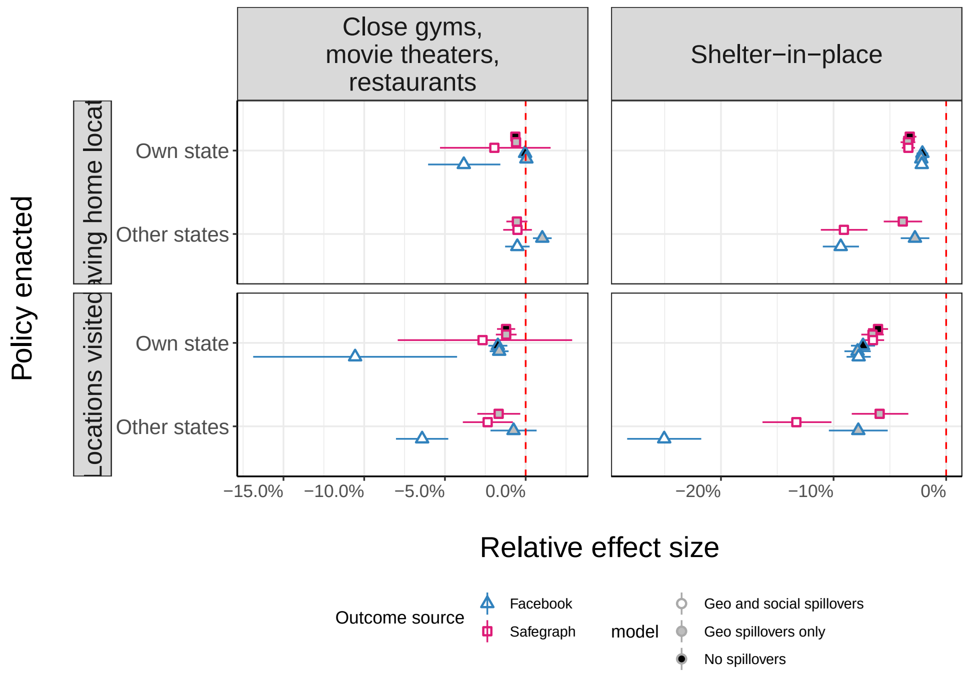


Figure S17: A comparison of the estimated impact of own-state and other states' shelter-in-place policy under three different specifications: a model with no spillovers, a model that includes only geographic spillovers (and distinguishes between within state and out of state counties), and a model that includes both geographic and social spillovers (and distinguishes between within state and out of state counties).

which relies on directed, dyad-level data. We create our directed, dyadic dataset by first looking at the movement from every county i to every alter county $j \neq i$ from January 1, 2020 to April 18, 2020. We proceed to analyze data for every ij pair for which there was at least one device moving from i to j on at least one day in January, February, March, and April, and for which movement from i to j occurred on at least 30 distinct days. This produces a set of 548,450 ij pairs. We then use data from March 1, 2020 to April 18, 2020 to estimate the following model

$$m_{i \to j,t} = \sum_{p_{ij}} \delta_{p_{ij}} p_{ijt} + \alpha_{ij} + \gamma_t + \epsilon_{ijt}, \tag{S6}$$

where $m_{i \to j,t}$ is a measure of the extent to which residents of county i are traveling into county j on day t, p_{ijt} is a measure of whether county i and county j have both enacted a given policy as of day t, α_{ij} is a dyad-level fixed effect, and τ_t is a day-level fixed effect. We estimate twelve different $\delta_{p_{ij}}$'s. First, we group all possible policy interventions into three groups: bans on gatherings; closing of restaurants, movie theaters, and gyms; and shelter-in-place. We then estimate a coefficient for each possible combination of dyadic policy states, i.e., $i = 0$ and $j = 0$, $i = 0$ and $j = 1$, $i = 1$ and $j = 0$, and $i = 1$ and $j = 1$. When a given county has enacted shelter-in-place, we also set the policy states for bans on gatherings and closing of restaurants, movie theaters, and gyms to 1, since by definition, if people are sheltered in place, they cannot hold large gatherings or visit non-essential business establishments. Observations are weighted by the number of devices observed in county i on day t, and we report cluster-robust standard errors that are clustered at the level of county i's U.S. state and county j's U.S. state.

Column 1 of Table S6 reports our estimates, where $m_{i \to j,t}$ is the arcsinh transform of the average number of Census block groups in county j devices from county i visit on day t. Column 1 of Table S7 repeats this analysis after restricting our sample to county dyads that are physically adjacent. Our results are qualitatively similar.

S2.6 Robustness Checks

S2.6.1 Leading and Lagging Policy Effects

As a supplement to the parallel pre-trends plot of Figure 1B in the main text, we consider other evidence about the parallel trends assumption for difference-in-differences that counties with different times of introduction of policies have parallel potential outcomes (*12, 13*).

In particular, given that one may reasonably posit that, e.g., shelter-in-place policies may be anticipated by the public, such that some effects could precede the policy introduction, we analyze leads and lags of the policy variable as a test of anticipation effects and other dynamics. Figures S19, S20 and S21 display marginal effects of leads and lags of the policies we analyze.

Table S6: The effect of policy interventions on dyadic movement patterns (all connected counties)

	Dependent variable:		
	asinh(dCBGs/device)	log(dCBGs/device + 1)	dCBGs/device
	(1)	(2)	(3)
Or. = 0, Dest. = 1 (G/M/R)	-5.38^{***}	-5.21^{***}	-5.35^{***}
	(1.71)	(1.62)	(1.73)
Or. = 1, Dest. = 0 (G/M/R)	-0.04	-0.32	0.08
	(3.21)	(2.97)	(3.27)
Or. = 1, Dest. = 1 (G/M/R)	-3.43^{***}	-3.34^{***}	-3.37^{***}
	(1.11)	(1.10)	(1.13)
Or. = 0, Dest. = 1 (shelter-in-place)	0.73	0.41	0.85
	(2.99)	(2.70)	(3.05)
Or. = 1, Dest. = 0 (shelter-in-place)	15.03^{***}	13.64^{***}	15.38^{***}
	(2.58)	(2.35)	(2.67)
Or. = 1, Dest. = 1 (shelter-in-place)	-6.23^{***}	-6.44^{***}	-5.96^{***}
	(1.68)	(1.58)	(1.75)
Clustered s.e.	Yes	Yes	Yes
Dyad fixed effect	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes
Observations	26,874,050	26,874,050	26,874,050
R^2	0.89	0.90	0.89
Adjusted R^2	0.89	0.90	0.88
Residual Std. Error (df = 26325546)	0.36	0.31	0.37

Notes: Or. refers to the origin county, Dest. refers to the destination county. 1 indicates that a given policy is in place, whereas 0 indicates it is not. G/M/R refers to closing gyms, movie theaters, and/or restaurants, and shelter-in-place refers to a shelter in place order. dCBGs/device refers to the average number of Census block groups in the destination county that devices from the origin county visited on a given day. All coefficients and standard errors are multiplied by 10,000. *p<0.1; **p<0.05; ***p<0.01

Table S7: The effect of policy interventions on dyadic movement patterns (adjacent counties)

	Dependent variable:		
	asinh(dCBGs/device)	log(dCBGs/device + 1)	dCBGs/device
	(1)	(2)	(3)
Or. = 0, Dest. = 1 (G/M/R)	−3.60	−2.90	−3.84
	(2.67)	(2.13)	(2.89)
Or. = 1, Dest. = 0 (G/M/R)	0.42	0.33	0.48
	(1.34)	(1.15)	(1.40)
Or. = 1, Dest. = 1 (G/M/R)	-0.98^{*}	-0.91^{*}	-0.94^{*}
	(0.50)	(0.47)	(0.51)
Or. = 0, Dest. = 1 (shelter-in-place)	-11.63^{***}	-9.91^{***}	-11.99^{***}
	(3.95)	(3.31)	(4.10)
Or. = 1, Dest. = 0 (shelter-in-place)	5.51^{**}	4.25^{**}	5.97^{**}
	(2.74)	(2.13)	(3.01)
Or. = 1, Dest. = 1 (shelter-in-place)	-5.13^{***}	-4.97^{***}	-5.00^{***}
	(1.20)	(1.08)	(1.23)
Clustered s.e.	Yes	Yes	Yes
Dyad fixed effect	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes
Observations	878,472	878,472	878,472
R^2	0.89	0.90	0.88
Adjusted R^2	0.89	0.90	0.88
Residual Std. Error (df = 860490)	1.67	1.41	1.74

Notes: Or. refers to the origin county, Dest. refers to the destination county. 1 indicates that a given policy is in place, whereas 0 indicates it is not. G/M/R refers to closing gyms, movie theaters, and/or restaurants, and shelter-in-place refers to a shelter in place order. dCBGs/device refers to the average number of Census block groups in the destination county that devices from the origin county visited on a given day. All coefficients and standard errors are multiplied by 1,000. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

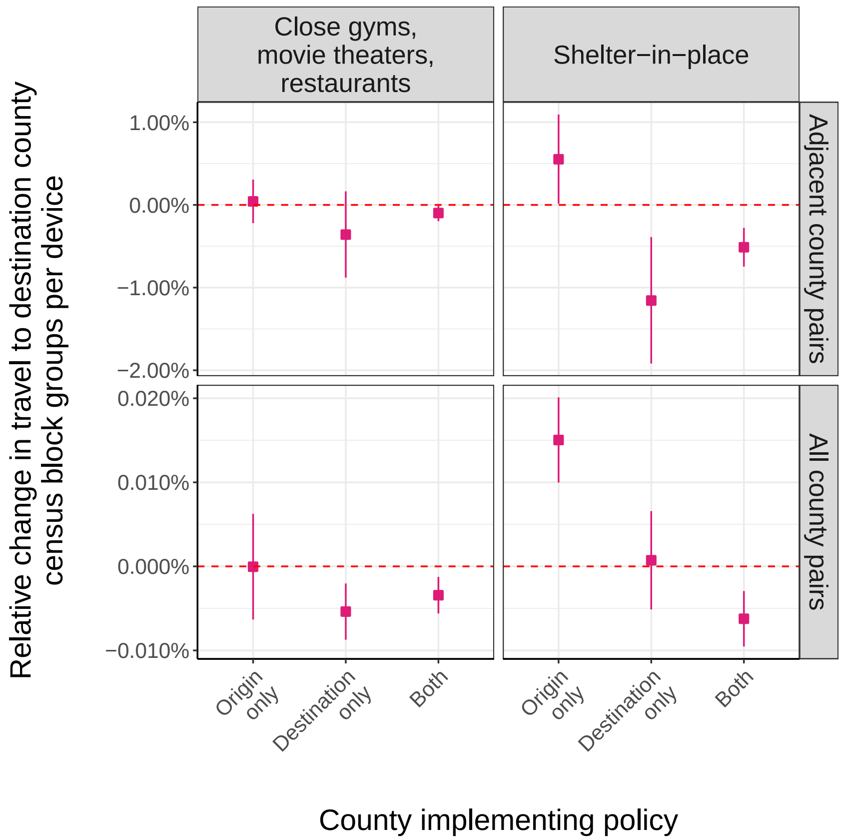


Figure S18: Difference-in-differences analysis of the geographic spillovers arising from different dyad-level policy vectors in response to COVID-19.

Note that each estimate is of the marginal effect of the leaded (or lagged) policy, so the increases after the introduction of the policy need not indicate a reversal of effects.

S2.6.2 Randomization Inference

As a robustness check, we use a Fisherian randomization inference (FRI) procedure to estimate the null distributions of the spillover effects (*14–17*). In a simple experimental context, this is accomplished by either re-drawing (typically, permuting) the treatment assignment vector R times and then estimating the treatment effect under the permuted treatment assignment vectors. However, in our context, there is an important structure to the policy assignment vectors that our re-sampling procedure needs to account for. Specifically, the main concern is that county-level

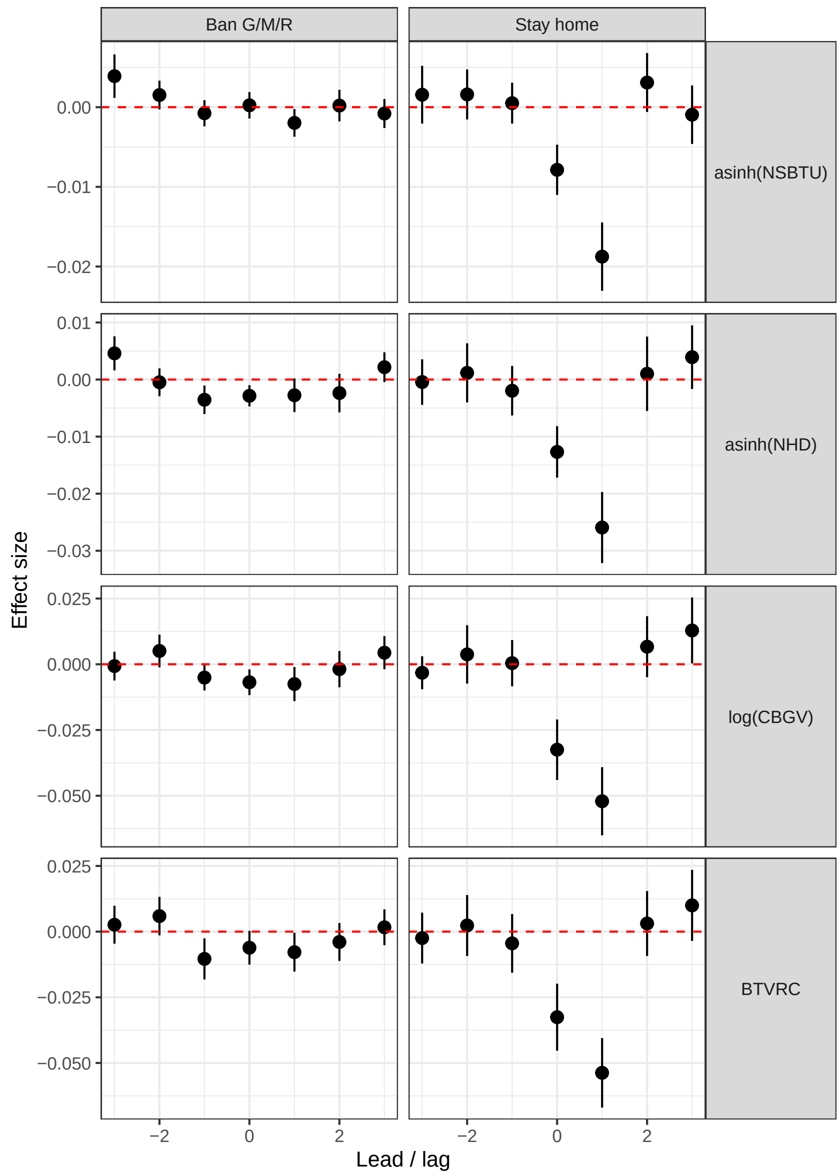


Figure S19: The leads and lags of the own-state policy decisions to close gyms, movie theaters, and restaurants and implement shelter-in-place. For shelter-in-place / "stay home" policies, there is no evidence of anticipatory effects. Note that each estimate is of the marginal effect of that lead or lag policy, so an estimate of zero after the policy corresponds to a constant effect, not a reversal.

policy is often set at the state level. though there are some exceptions. Furthermore, we need to make sure that once a county is "treated" it remains "treated."

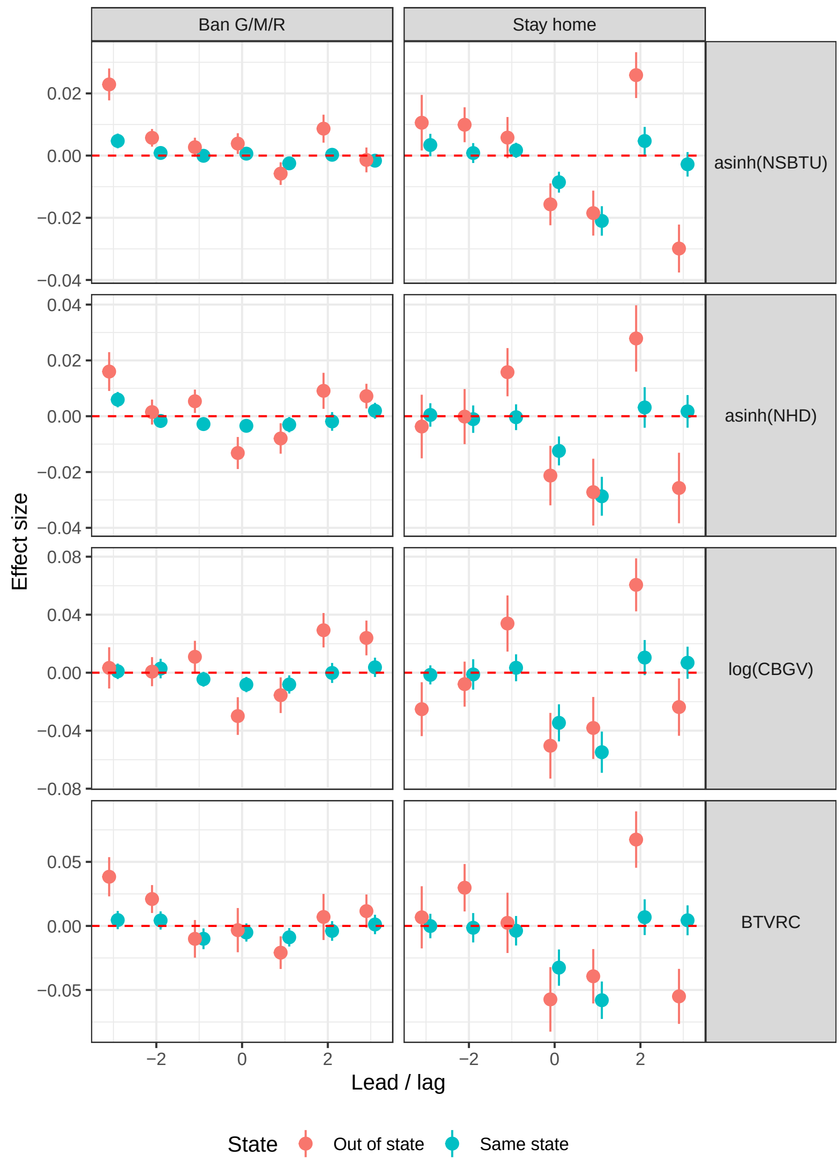


Figure S20: The leads and lags of the own-state, as well as alter-state policy decisions to close gyms, movie theaters, and restaurants and implement shelter-in-place / "stay home" (geographic alters only). Note that each estimate is of the marginal effect of that lead or lag policy, so an estimate of zero after the policy corresponds to a constant effect, not a reversal.

We record the the fraction of counties that have implemented a gym/movie theater/restaurant ban or a shelter-in-place order for each state–date pair. To create a re-sampled policy draw, we start by randomly assigning each state a "replacement" state whose policy assignments take the

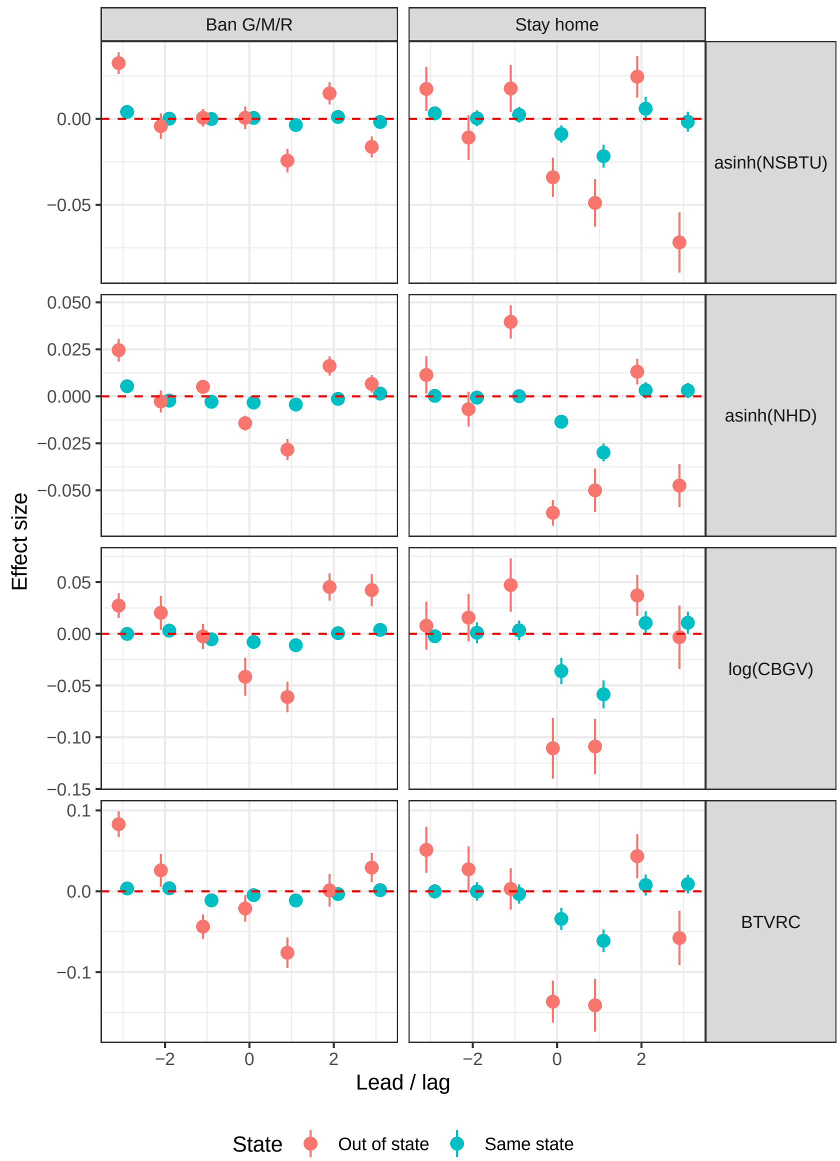


Figure S21: The leads and lags of the own-state, as well as alter-state policy decisions to close gyms, movie theaters, and restaurants and implement shelter-in-place / "stay home" (geographic and social alters). Note that each estimate is of the marginal effect of that lead or lag policy, so an estimate of zero after the policy corresponds to a constant effect, not a reversal.

place of the "original" state. For example, suppose that Oklahoma (a state without a shelter-in-place order) was assigned the replacement state of California. The re-sampled data would then include a policy vector for Oklahoma in which a shelter-in-place order was applied across all counties starting on March 19, 2020.

Since there is some deviation between county-level policy and state-level policy, and the number of counties varies from state to state, we ensure that the fraction of "treated" counties in the original state approximately matches the expected fraction of "treated" counties in the replacement state on each day. Specifically, for each original state, we randomly create an order in which that state's counties implement a policy. This is done to insure consistency in policy assignment at the county level (i.e. if county 10 is treated on date 1, then we would want it to stay treated since our data does not cover lifting of policies). For example, suppose that a state has 41 counties and the replacement state has 50% of its counties treated on date 1 and all of its counties treated on date 2. In this case, our procedure would have the first 50% (rounded up to the nearest whole county) of counties in the original state treated on date 1 according to the randomly drawn order, and 100% of counties treated on date 2.

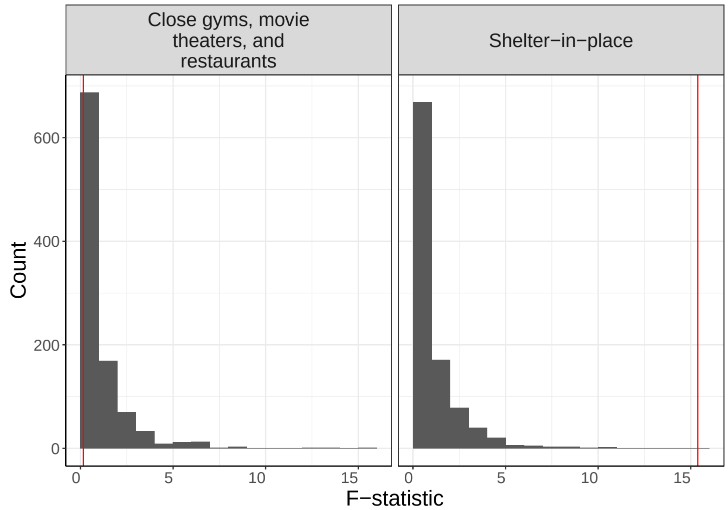
We repeat this policy replacement procedure for every single state to form a single resampled policy draw. We then perform the DML residualization procedure on the the resampled policy vector and then re-estimate Equation 4. We then run a Wald test of the full unrestricted model against restricted models where the social and geographic spillovers sum to 0 for each policy and record the resulting state-cluster-robust F-statistics. This test statistic is selected based on the expectation that it will be approximately pivotal and result in valid tests of a weak (non-sharp) null hypothesis (*16, 18, 19*). Overall, we repeat the policy resampling procedure $R =$ 1,000 times to form the Fisherian null distributions.

Figure S22 shows the null distribution of spillover F-statistics for our model specification obtained through random permutation, as well as our observed F-statistic values, for both closing gyms/movies theaters/restaurants and implementing shelter-in-place for the Safegraph outcomes asinh(NDHF). The p-values for spillovers from closing gyms, movie theaters, and restaurants are 0.763 (for leaving home, asinh(NDHF)) and 0.706 (for locations visited, log(dCBGVs)), whereas the p-values for spillovers from implementing shelter-in-place are $< .001$. Figure S23 shows the policy spillover F-statistic null distributions and observed F-statistic values for the Facebook outcomes. We find that the p-values for spillovers from closing gyms, movie theaters, and restaurants are 0.346 (for leaving home, asinh(NSTUs)) and $< .001$ (for locations visited, BTVRC), whereas the p-values for spillovers from implementing shelter-in-place are $< .001$. These results are generally qualitatively consistent with the results presented in table S5 using the adjacency and clustering-robust standard errors.

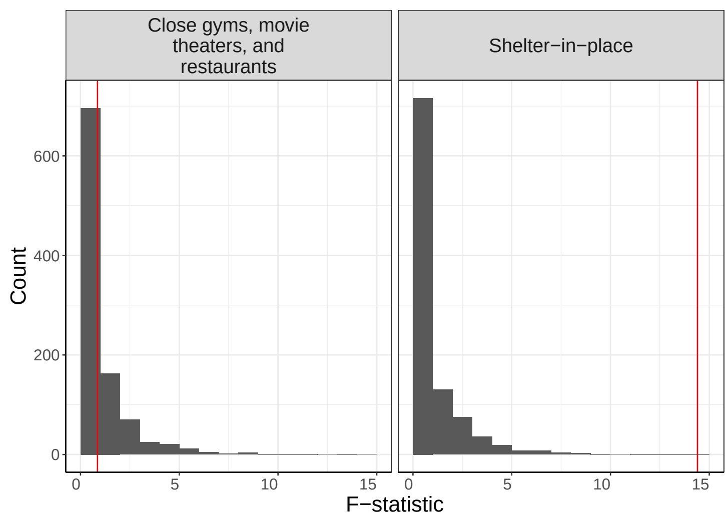
S3 Identifying Endogenous Social Effects

In prior sections, we had primarily focused on measuring the effect of alter county policy spillovers on a focal county's social distancing behavior. In this section we focus directly on measuring the endogenous peer (or social) effects in social distancing behavior amongst peers. However, inference for endogenous peer effects must overcome issues of simultaneity (i.e., reflection (*20*)), confounding with homophily, and other processes that produce correlations in behaviors among connected units. We address this problem through an instrumental variable[4] (IV) approach that leverages fluctuations in peer weather and geographic variation in shares of industries that are deferentially affected during this period as shocks to peer behavior. The rest of this section is organized as follows: section S3.1 and S3.2 describe and motivate our 2 sets of instruments, section S3.3 details our model specifications, section S3.4 reports our estimation results, and S3.5 presents a series of robustness checks.

[4] As long as the standard IV assumptions (relevancy and exclusion) are met, (*21, 22*) prove that IV approaches are able to consistently estimate endogenous peer effects.



(a) asinh(NHD)



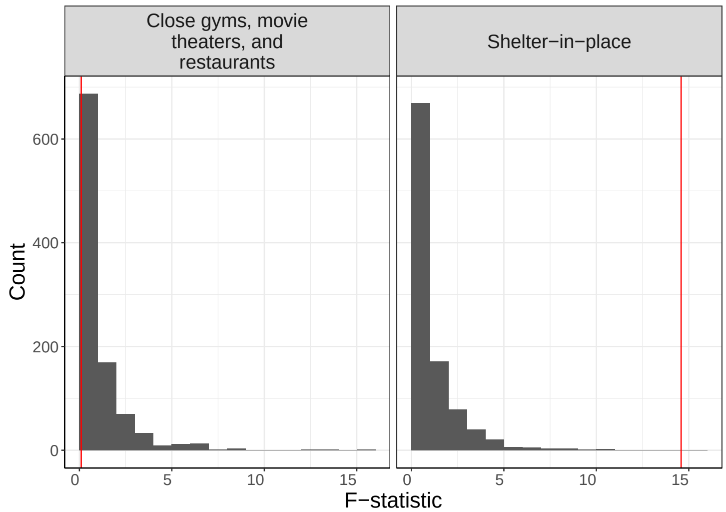
(b) log(dCBGVs)

Figure S22: Null distribution (grey) and observed value (red line) of the test statistic (F-statistic) for spillovers of alter county policies on the Safegraph outcomes.

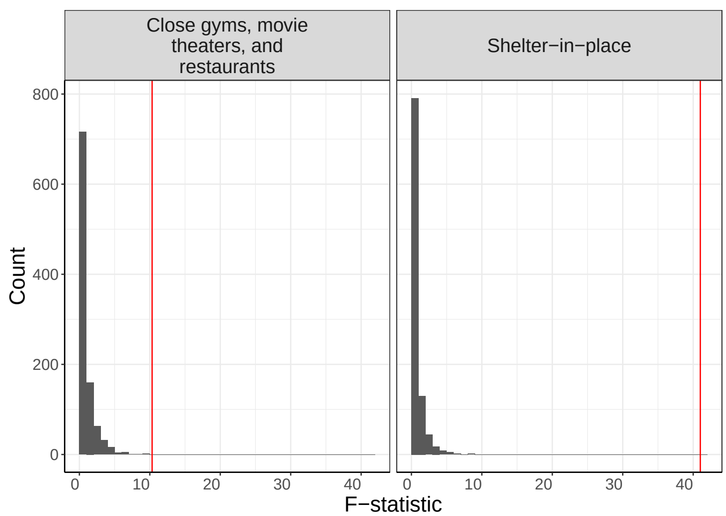
S3.1 Weather Instruments

One set of the instrumental variables we use is constructed from the weather,[5] which has been used to identify social spillovers across a variety of different contexts (*23–25*). The intuition

[5]These instruments are built from the county-level precipitation and max temperature measures computed via a procedure described in section S1.3. The exact details on how the specific weather instruments are constructed are detailed in section S3.3.2 below.



(a) asinh(NSTU)



(b) BTVRC

Figure S23: Null distribution (grey) and observed value (red line) of the test statistic (F-statistic) for spillovers of alter county policies on the Facebook outcomes.

is that while the variations in my weather will have a meaningful impact on my behavior, they shouldn't directly affect the behavior of a friend who lives in a different area. This relationship between weather and movement seems to be true for social distancing behaviors: even if a shelter-in-place order is in effect, there are considerably more people out and about when the

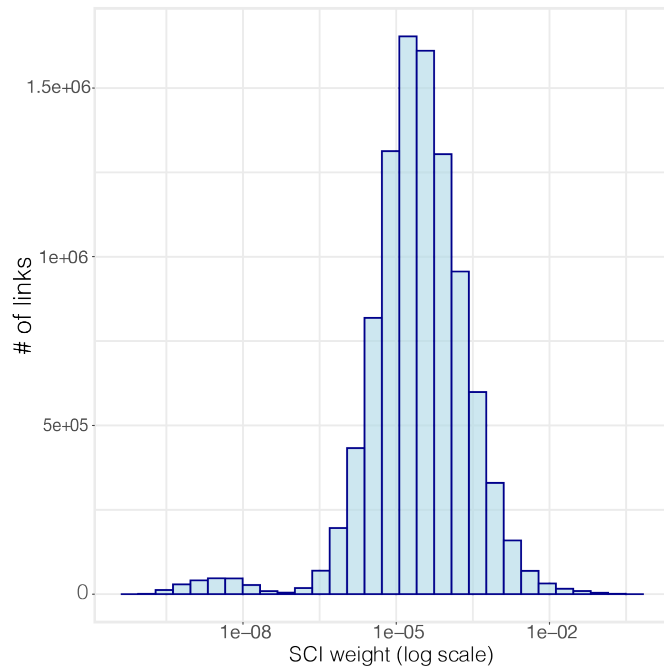


Figure S24: The distribution of the SCI weights between counties.

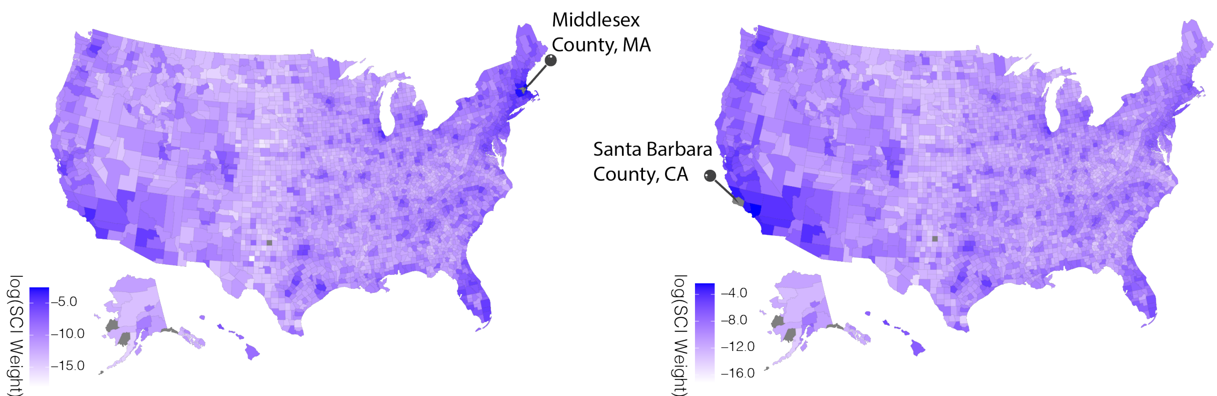


Figure S25: The spatial distribution of the weighted social graph ofMiddlesex County, MA (left) and Santa Barbara County, CA (Right) as extracted by the SCI.

weather is nice. We observe this effect in our data as shown in Figure 1C in the main text of the paper.

As such, we should be able to use peer weather to instrument for peer behavior, thereby allowing us obtain a consistent estimate of endogenous peer effects. However, one major concern with weather instruments is the fact that geographically proximate locations tend to have similar weather. Theoretically, this should not create an identification issue: even if "peer weather" is highly correlated with "own weather," it should be conditionally ignorable so long as the effects of "own weather" are properly accounted for. However, this can be difficult as the impact of weather can be very nonlinear. For example, the going from 0mm to 1mm of rain is going to elicit a much larger behavioral response than going from 20mm to 21mm. Furthermore, there are likely significant interactions between different weather measures to consider: the effect of rain when it is a comfortable 22C outside is going to be very different than the effect of rain when it is a frigid 2C outside. These complexities may result in a "practical" violation of conditional ignorability since peer weather may be providing additional information about own weather that is not fully captured by a linear model specification. To address this potential concern, we adopt an modeling approach that can flexibly account for these issues that we detail in section S3.3.1.

S3.2 Industry Visits Shift-Share Instrument

Our second set of instruments are Bartik-like (*26*) industry shift-share variables that measure the industry visit composition of alter counties[6]. At a high level, these instruments average national employment growth across industries using local industry employment shares as weights to produce a measure of local labor demand that is unrelated to changes in local labor supply. Bartik popularized the application of the variable of interest in empirical regression analyses as a shift-share, whereby the variable of interest comprises a regression of related variables weighted by their relative importance (where, in Bartik's case, labor market outcomes were predicted based on regional sectoral shocks).

Industries have been impacted differently by governmental policies depending on whether

[6]These instruments are constructed from the Safegraph visits data, in a process described in section S1.1.2 above.

they are deemed essential or non-essential. Moreover, some industries have more jobs that can be done at home than other industries (*27*). Industries with more jobs that can be done at home are more likely to close their physical locations and ask their employees to work from home either on their own volition or due to government regulations. Furthermore, counties have different industry compositions. Figure S26 plots the total visits in the Safegraph data in the US for a sample of 8 industries. There is substantial heterogeneity in changes in number of visits across industries. The exact construction of these variables is described above in section S1.1.2.

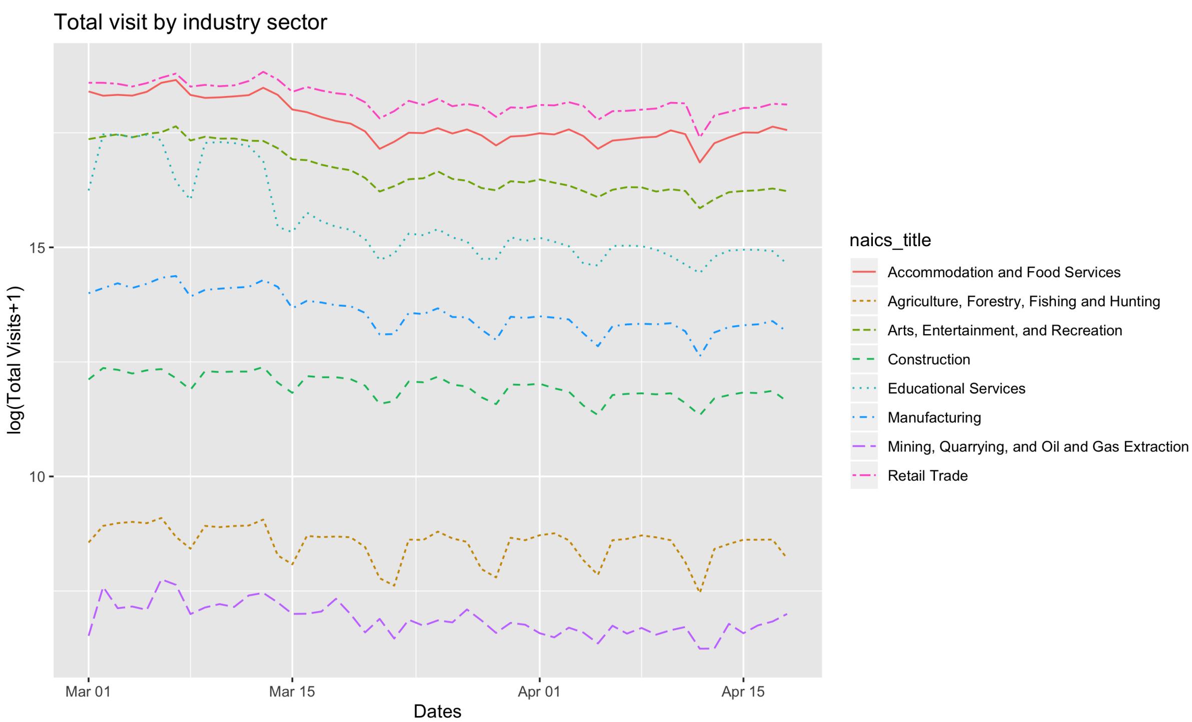


Figure S26: Total visits to a sample of 8 industries from 3/1/20-4/18/20 across the US

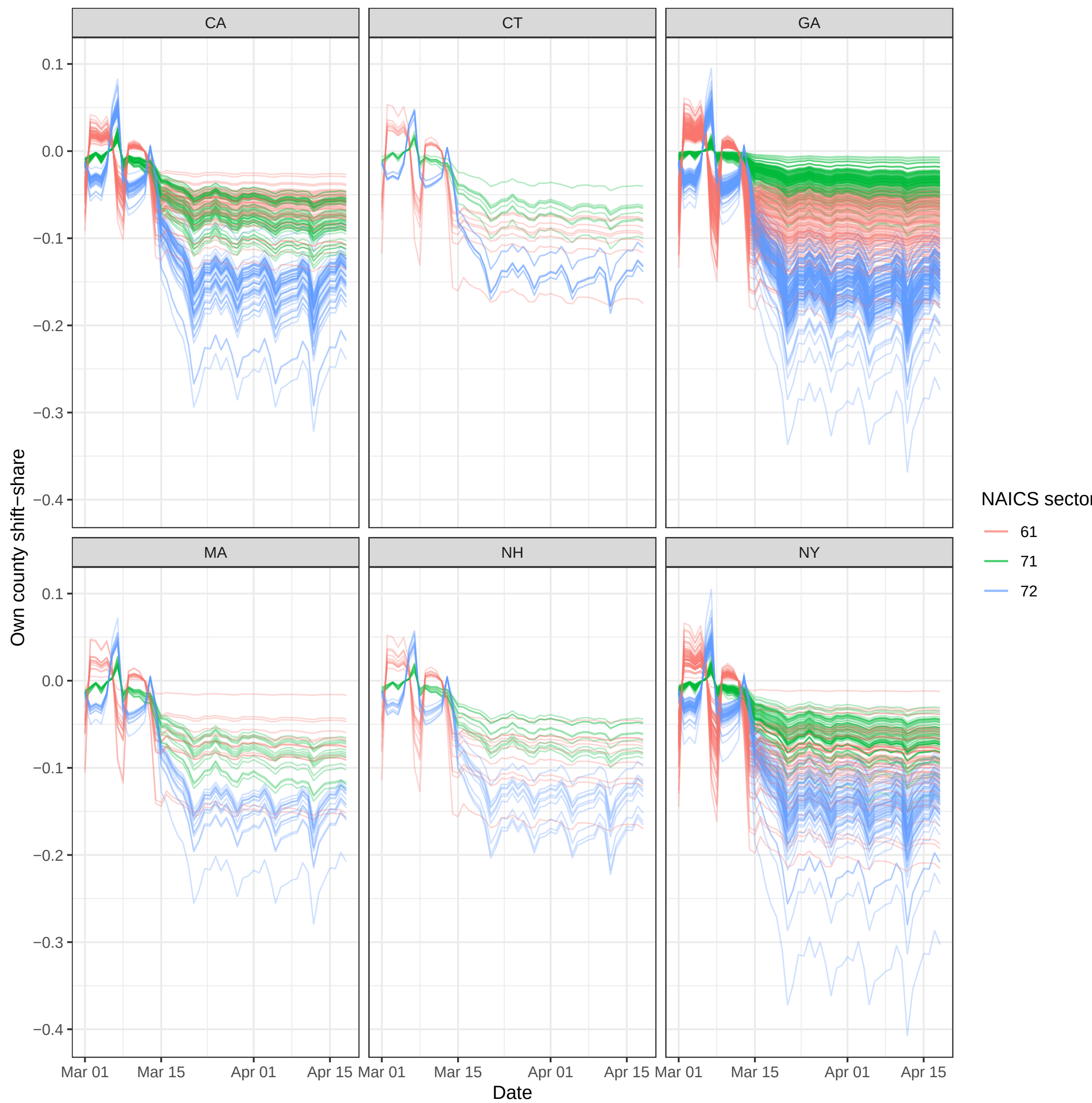


Figure S27: Illustration of county-level shift-shares for three NAICS sectors — 61 (Educational Services), 71 (Arts, Entertainment, and Recreation), and 72 (Accommodation and Food Services) — for six states. For a given NAICS sector, the curves for different counties differ only in scale due to baseline differences in visits to those locations, as all are multiplied by the common, national changes in visitation.

S3.3 Model Specification

We estimate the following set of semi-parametric model specifications:

$$Y_{it} = Y_{-it}\beta + D_{it}\delta_1 + D^{geo}_{-it}\delta_2 + D^{social}_{-it}\delta_3 + S_{it}\psi + f(W_{it}) + \alpha_i + \tau_t + \epsilon_{it} \tag{S7}$$

$$Y_{-it} = D_{it}\gamma_1 + D^{geo}_{-it}\gamma_2 + D^{social}_{-it}\gamma_3 + S_{it}\pi + g(W_{it}) + h(W_{-it}, S_{-it}, D^{social}_{-it}) + \alpha_{-i} + \tau_t + \nu_{-it} \tag{S8}$$

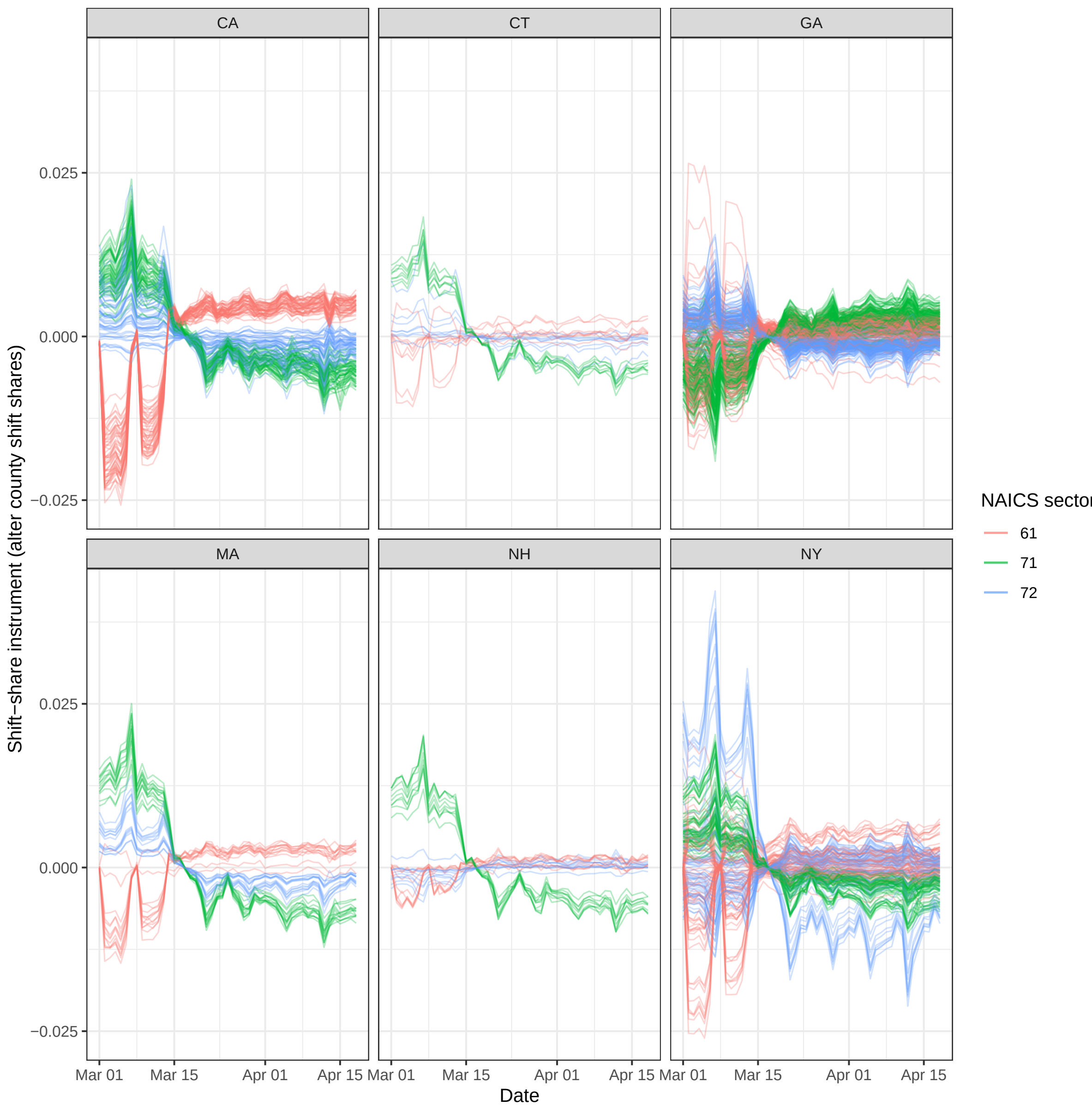


Figure S28: Illustration of shift-share instruments for three NAICS sectors — 61 (Educational Services), 71 (Arts, Entertainment, and Recreation), and 72 (Accommodation and Food Services) — for six states. For a given NAICS sector, the curve for a focal county is a weighted combination of the shift-shares of its alter counties as determined by SCI.

Equation 7 refers to our main model specification. Our dependent variable Y_{it} denotes the social distancing behavior of individuals in county i on date t (as measured by our 4 main social distance outcomes: asinh(NSBTUs), asinh(NHDF), log(dCBGVs), and BTVRC). Y_{-it}, denotes the weighted average of social distancing behaviors of individuals in other counties where weights are determined by the social connectedness between county i and other counties j. More formally: $Y_{-it} = \sum_j w_{ij} * Y_{jt}$ where $w_{ij} = \frac{n_j * a_{ij}^{social}}{\sum_k n_k * a_{ik}^{social}} : k \neq i$ and n_j is the population of county j[7]. β is the main parameter of interest, representing the endogenous peer effect of social distancing behavior. D_{it} denotes whether any county-level[8] social distancing policies are in effect in county i on date t, while δ_1 captures the effects of policy on social distancing behavior. Both D_{-it}^{social} and D_{-it}^{geo} are weighted averages of other counties' social distancing policies on date t, where the weights used to construct D_{-it}^{social} are identical to the weights used to construct Y_{-it} while the weights used to construct D_{-it}^{geo} are constructed using the pre-crisis county-to-county movement as discussed in section S1.1. The associated parameters, δ_2 and δ_3 capture the potential spillover effects of other counties' policies that may not be mediated by endogenous peer behavior. As mentioned above, each of D_{it}, D_{it}^{geo}, and D_{it}^{social} are 2-dimensional row vectors to both account for both gym, movies, and restaurant bans and shelter-in-place orders. Likewise, δ_1, δ_2, and δ_3 are 2-dimensional column vectors. S_{it} is a

W_{it} reflects the weather (measured as precipitation and maximum temperature) in county i and date t and $f(.)$ is a non parametric function that can capture nonlinear responses of Y_{it} to fluctuations in W_{it}. We will more formally describe how $f(.)$ is estimated below in section S3.3.1. α_i and τ_t denote a set of county and date fixed effects respectively. Lastly, the ϵ_{it} represents the error term.

In the first-stage (equation 8), Y_{-it} takes its place as the dependent variable. γ_1, γ_2, γ_3, and $g(.)$[9] capture the effects D_{it}, D_{it}^{geo}, and W_{it} on Y_{-it} respectively. W_{-it} and I_{-it} are weighted averages of weather and industry shares of other counties (not i), again weighted by social

[7]Since 3 of our outcomes have been nonlinearly transformed, we first compute the weighted average of the untransformed variable and then apply the appropriate transformation on the weighted average.

[8]State-wide policies are automatically propagated down to the county level.

[9]Like $f(.)$, $g(.)$ is a function that can capture the nonlinear effects of W_{it}.

connectedness. These variables and their interactions with D_{-it} will form the set of potential candidates for our instruments. The associated function $h(.)$ will select a much smaller subset that we will actually use in our estimation. We will describe this selection procedure in section S3.3.2 below. Again, α_i and τ_t represent fixed effects for county and day, and ν_{-it} denotes the first stage error term.

S3.3.1 Flexibly Controlling for the Effect of Weather

To flexibly control for the impact of weather, we employ a "double machine learning" (DML) procedure (*28*). This approach is designed to estimate and draw inferences on a low-dimensional parameter in the presence of high-dimensional nuisance parameters. Consider the following "canonical example" from (*28*) which we reproduce here:

$$
\begin{aligned}
Y &= D\theta_0 + g_0(Z) + U, \quad \mathbb{E}[U|D, Z] = 0 \\
D &= m_0(Z) + V, \quad \mathbb{E}[V|Z] = 0
\end{aligned}
$$

Y denotes the outcome, D is a policy or treatment variable, θ_0 is the low-dimensional parameter of interest, Z is a high-dimensional vector of covariates ($g_0(Z)$ can be considered to be the high-dimensional nuisance parameter), and U and V are the errors. The basic intuition behind DML is that $g_0(.)$ and $m_0(.)$ can be estimated using non-parametric statistical methods (aka machine learning) and then "partialed out" (*29*) from both Y and D. Then one simply regresses the residuals of the dependent variable on the residuals of the treatment variable in order to estimate θ_0. In order to provide guarantees that key moment conditions are satisfied, the machine learning predictions needs to be orthogonalized which can be achieved via sample splitting. As such, the general double ML algorithm is as follows:

1. Split the dataset into K equal size partitions or "folds." Let $F_k, F_k^c : k \in 1, ..., K$ denote each fold and its complement.[10]

[10] Suppose a dataset has 100 observations and is split into 5 block. B_1 consists of observations 1-20 and $F_1^c :=$

2. Estimate g_0 and m_0 with some non-parametric statistical model of choice using only the observations in B_1^c

3. Form residuals $\tilde{Y} := Y - \hat{g}_0(Z)$ and $\tilde{D} := D - \hat{m}_0(Z)$ only on observations in F_1.

4. Regress $\tilde{Y}$ on $\tilde{D}$ to obtain an estimate of θ_0. Overall, this estimate can be thought of as function of F_1 and F_1^c: $\hat{\theta}_0(F_1, F_1^c)$.

5. Repeat steps 2-4 for the the remaining $K-1$ folds

6. Form the final estimate of θ_0 by averaging across all estimates: $\hat{\theta}_0^* = \frac{1}{K}\sum_k \hat{\theta}_0(F_k, F_k^c)$

In our case, we consider a county's own weather to be the high-dimensional nuisance parameter, as we are not principally interested in identifying the effect of own weather on social distancing behavior. We use gradient boosted decision trees via XGBoost (*30*), a state-of-art machine learning algorithm, to estimate $f(.)$ in equation 7, $g(.)$ in equation 8, as well as the effect of weather on any of the other variables included in our models. XGBoost is an ensemble method that works by fitting a series of forward stage-wise decision trees aimed to minimizing a specified loss function. To give a general idea of the basic procedure:

1. Fit an initial decision tree T_1 that minimizes $E\left[(Y - T_1(X))^2\right]$, where Y is the outcome and X are the covariates or features.

2. Each successive tree is then fitted on the residuals of the previous state[11]:
   $T_n = \arg\min_T \mathbb{E}[(Y - \sum_{n-1}^{i=1} T_i(X) - T(X))^2]$

In order to prevent overfitting, this iterative process is stopped once out-of-sample predictive performance starts to decline.

F_2, F_3, F_4, F_5 consists of the remaining observations 21-80.

[11]To be more precise, the degree to which each successive tree contributes to the ensemble can be controlled via tuning hyperparameter called a learning rate. We provide a little bit more detail on this below.

As with many other machine learning algorithms, there are a number of hyperparameters that control this estimation procedure of XGBoost. In particular, we adjust:

- `tree_depth`: Controls the depth that each tree-based model is allowed to grow to. The deeper the tree, the more complex the model.
- `eta`: Controls the "learning rate" or step size of each model. One way to think of this parameter is as a form of regularization on each model step in order to prevent overfitting.
- `nrounds`: The maximum number of stages the fitting process is allowed to continue on for.

We fix `tree_depth` to 2 and `eta` = 0.5, but allow `nrounds` to run up to a maximum of 100. Then, for each individual variable, the optimal number of rounds (given our choice of `tree_depth` and `eta`) is determined via a cross-validation procedure for each variable individually[12]. Once the optimal `nrounds` is determined, we form the residuals for all our dependent variables and covariates by first partialing out the set of fixed effects and then following the DML approach described above. This then leads to the following set of partialed out specifications:

$$\tilde{Y}_{it} = \tilde{Y}_{-it}\beta + \tilde{D}_{it}\delta_1 + \tilde{D}^{geo}_{-it}\delta_2 + \tilde{D}^{social}_{-it}\delta_3 + \tilde{S}_{it}\psi + \epsilon_{it} \tag{S9}$$

$$\tilde{Y}_{-it} = \tilde{D}_{it}\gamma_1 + \tilde{D}^{geo}_{-it}\gamma_2 + \tilde{D}^{social}_{-it}\gamma_3 + \tilde{S}_{it}\pi h(\tilde{W}_{-it}, \tilde{S}_{-it}, \tilde{D}^{social}_{-it}) + \nu_{-it} \tag{S10}$$

S3.3.2 Sparse Instrumental Variable Selection Procedure

We use sparse linear model (*31, 32*) to estimate $h(.)$. In order to try to maximize the power of our first stage, we opt to include a large set of instruments formed by interacting W_{-it}, S_{-it}, and D^{social}_{-it}.

[12] We note that it would be more optimal to do an exhaustive grid search across the entire hyperparameter space for each individual variable that needs to have the effect of weather partialed out. However, such a grid search would be extremely computationally expensive and would only yield very minor improvements in predictive accuracy.

To allow for nonlinearity in the impact of weather, we first construct a sequence of county-level indicator variables that take a value of 1 if the amount of rainfall in county i on date t falls within or exceeds a specific precipitation ventile [13] (20-quantiles). We generate a similar sequence of indicator variables for maximum temperature as well. To avoid perfect multi-colinearity, we remove the first max temperature ventile and the first 9 precipitation ventiles since these indicators always took a value of 1[14]. The remaining county-level level covariates are then multiplied by the social-weighting matrix[15] to form the peer weather covariates ($W_{-it} = V_{-it}^{\text{prcp},10}, ..., V_{-it}^{\text{prcp},20}, V_{-it}^{\text{prcp},2}, ..., V_{-it}^{\text{prcp},20}$).

These peer weather covariates are then interacted with the entire set of peer shift-share variables S_{-it} (also constructed by multiplying the county-level shift-shares with the social-weighting matrix) as well as D_{-it}^{social} (specifically only the shelter-in-place component, since there's relatively less variance in the gyms, movies, and restaurants ban) to form a set of 1610 potential instruments. We partialed out all the fixed effects and then used the DML procedure described above to remove the effect of "own" county weather. This large number of possibly weak instruments could produce an highly biased or asymptotically inconsistent estimator (*33–35*). To address this issue and to systematically select instruments, we use a post-LASSO IV procedure (*32*), in which an L1-penalized regression (*31*) is first used to select the set of variables and then the selected set are used in standard unregularized model. We select the largest penalty λ that is within within one standard error of the minimum MSE in 3-fold cross-validation. This procedure selected a total of 377 instruments that we use in our primary estimation results.

[13]For example $V_{it}^{\text{prcp},1} = \mathbf{1}(\text{prcp}_{it} > q) : q = \arg_x Pr(\text{prcp}_{it} \geq x) = 0$, $V_{it}^{\text{prcp},2} = \mathbf{1}(\text{prcp}_{it} \geq q) : q = \arg_x Pr(\text{prcp}_{it} \geq x) = 0.5$, etc. It is also worth noting that this construction means that if $V_{it}^{\text{prcp},k} = 1$, then $V_{it}^{\text{prcp},j} = 1 : j < k$.

[14]In the case of the first ventile, all values will be greater than or equal to the minimum value, meaning that the first indicators will always take a value of 1 based on how they are constructed. In the case of the other precipitation ventiles, there is a large mass at 0 since rain doesn't occur that frequently in most counties.

[15]More formally: $V_{-it}^{\text{prcp},k} = \sum_j w_i j * V_{jt}^{\text{prcp},k}$ and $V_{-it}^{\text{tmax},k} = \sum_j w_i j * V_{jt}^{\text{tmax},k}$.

S3.4 Results

The primary results of this instrumental variables analysis are shown in Table S8. Across all four of our main outcomes, we find extremely strong and highly consistent evidence of extremely strong positive endogenous social effects in social distancing. If we take the average across our the parameter estimates of our four outcome variables, our results suggest that a 1% increase in social distancing behavior of all other counties will lead to a 2% increase in social distancing behavior within a focal county. While this estimate may seem extreme, the COVID-19 pandemic certainly does count as extraordinary circumstances: a single family member or friend, let alone all of them, has the capability to drastically influence an individuals' social distancing behavior[16].

Beyond just the peer effect, several other clear trends emerge. First, we find that county policy does have a statistically significant direct effect on social distancing behaviors. Moreover, largely consistent with the results of sections S2.2 and S2.3, this direct effect is notably less impactful than what the naive DiD estimates in S2.1 would suggest. Furthermore, our results strongly suggest that the peer policy spillovers a largely mediated by endogenous peer behavior. Comparing the total policy spillover effects in section S2.3 with those seen here, we see that the effect is generally much closer to generally quite close to 0.

S3.4.1 Visualization of the Instrumental Variables

It is common to visualize instrumental variables analyses with binned scatterplots that show how the outcome varies with the instrument, sometimes expressed in terms of first-stage fitted values (*36*). Often these plots partial out other covariates, as we do here. Figure S29 show how two illustrative instruments are associated with one outcome, the measure of Facebook devices leaving their home location, asinh(NSBTUs). The precipitation instrument (Figure S29 top

[16] `https://www.nytimes.com/2020/03/31/opinion/coronavirus-fox-news.html`

left) is the first selected by the LASSO regularization path. Percentiles of this measure of rain in alter counties are associated with mobility in the focal county. Percentiles of the shift-share instrument (Figure S29 bottom left) for the arts, entertainment, and recreation sector, which is one of the first shift-share instruments selected by the LASSO regularization path, measure exposure of the county-day to national shifts in visitation of those locations. Bins formed by the intersection of deciles of these two instruments (Figure S29 right) are highly associated with both residuals of mobility in the peer counties and residuals of mobility in the focal county.

S3.5 Robustness Checks

S3.5.1 Varying the Number of Selected instruments

Fig. S30 shows the estimate results of adding number of instruments based on their importance as obtained by LASSO selection. The first instrument selected is the most important instrument with the higher entry λ, followed by the second instruments; that is, this shows how the post-LASSO regularization path translates into our second-stage estimates of endogenous peer effects and effects of policies. When there is a very small number of instruments, the estimates are similar to what we have when we have a large number of instruments, with some variation as a few more instruments are added. This observation is consistent with what we observe when conducting randomization inference with a single instrument.

S3.5.2 Only Weather Instruments

Table S9 presents results from an instrumental variable regression analysis using only the weather instruments. Although the estimated peer effect coefficient is consistently smaller compared to Table S8, the magnitudes are still quite comparable. Moreover, the remainder of the results are largely both qualitatively and quantitatively consistent with our main results.

Table S8: Effects of policy interventions and endogenous alter behaviors (Full set of instruments)

	Dependent variable:			
	BTVRC	asinh(NSBTUs)	asinh(NHDF)	log(dCBGVs)
	(1)	(2)	(3)	(4)
Close gyms, movie theaters, restaurants	-0.011^{**}	-0.003	-0.003	-0.007
	(0.005)	(0.002)	(0.002)	(0.006)
Close gyms, movie theaters, restaurants (social alters)	0.004	-0.001	0.007	0.002
	(0.012)	(0.005)	(0.007)	(0.020)
Close gyms, movie theaters, restaurants (geo alters)	0.011	0.003	-0.003	0.006
	(0.009)	(0.003)	(0.005)	(0.012)
Shelter-in-place	-0.033^{***}	-0.010^{***}	-0.015^{***}	-0.030^{***}
	(0.009)	(0.003)	(0.004)	(0.011)
Shelter-in-place (social alters)	0.051^{***}	0.020^{***}	0.042^{***}	0.066^{**}
	(0.019)	(0.007)	(0.012)	(0.029)
Shelter-in-place (geo alters)	-0.005	-0.004	-0.016^{**}	-0.020
	(0.010)	(0.004)	(0.007)	(0.016)
Social alters' BTVRC	1.650^{***}			
	(0.039)			
Social alters' asinh(NSBTUs)		1.620^{***}		
		(0.054)		
Social alters' asinh(NHDF)			1.630^{***}	
			(0.052)	
Social alters' log(dCBGVs)				1.910^{***}
				(0.052)
Conley s.e.	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes	Yes
Observations	122,598	122,598	122,598	122,598
R^2	0.824	0.876	0.816	0.818
Adjusted R^2	0.821	0.874	0.812	0.814
Residual Std. Error (df = 120016)	8.420	2.950	4.800	8.140

Notes: NSBTU refers to the fraction of FB users in a given county who visit multiple Bing tiles on a given day. NHDF refers to the fraction of devices that are not completely at home, as measured by Safegraph. dCBGVs refers to the mean number of Census block groups devices from a given county visit, as measured by Safegraph. BTVRC refers to the relative change in the number of Bing tiles users visit, as measured by FB. *p<0.1; **p<0.05; ***p<0.01

Table S9: Weather instruments only

	Dependent variable:			
	asinh(NSBTUs)	BTVRC	asinh(NHDF)	log(dCBGVs)
Close GMR	−0.003	−0.009	−0.004	−0.007
	(0.003)	(0.006)	(0.003)	(0.007)
Close GMR (Social Alters)	−0.003	−0.006	0.005	0.001
	(0.008)	(0.015)	(0.009)	(0.024)
Close GMR (Geo Alters)	0.005	0.009	−0.002	0.004
	(0.005)	(0.010)	(0.006)	(0.015)
Shelter-in-place	−0.010**	−0.030***	−0.015**	−0.030**
	(0.005)	(0.010)	(0.006)	(0.013)
Shelter-in-place (Social Alters)	0.006	0.013	0.025	0.045
	(0.015)	(0.031)	(0.017)	(0.039)
Shelter-in-place (Geo Alters)	−0.0003	−0.001	−0.011	−0.020
	(0.007)	(0.015)	(0.009)	(0.020)
Peer Effect	1.393***	1.362***	1.515***	1.477***
	(0.114)	(0.079)	(0.084)	(0.080)

*p<0.1; **p<0.05; ***p<0.01

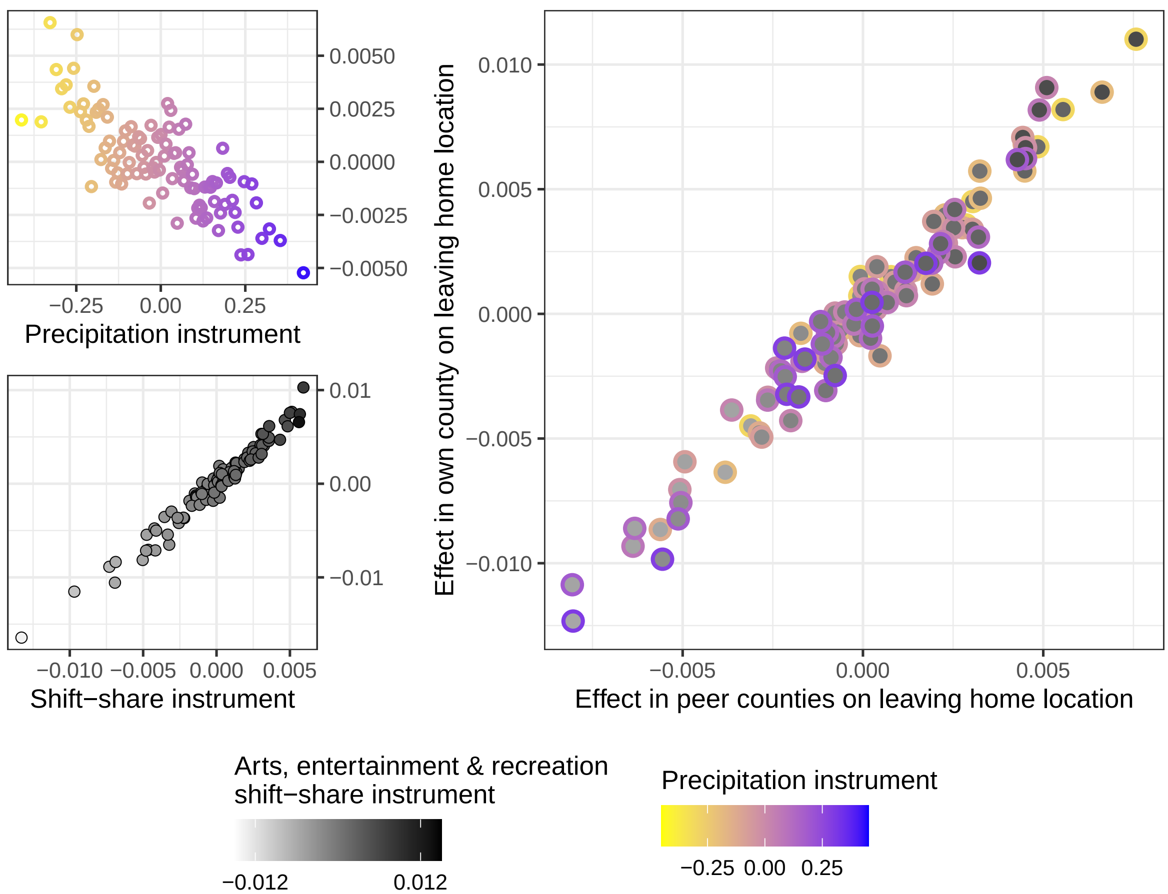


Figure S29: Visual instrumental variables plot for a selected weather instrument and a selected shift-share instrument and Facebook devices leaving their home location, asinh(NSBTUs). (left) Binned scatter plots of instrument residuals and outcome residuals. (top left) As precipitation in more alter counties exceeds a low threshold (0.06cm), more devices remain in their home location in the focal (ego) county. (bottom left) For ego counties with alter counties that are more exposed to national, negative shifts in people going to arts, entertainment, and recreation locations (NAICS sector 71), more devices remain in their home location in the ego county. (right) Forming bins by the deciles of each instrument, we see that their combined effect on mobility in alter counties translates to effects on mobility in the ego county.

S3.5.3 Only Shift-share Instruments

Table S10 presents results from an instrumental variable regression analysis using only the shift-share instruments. Much like our analysis using only weather instruments, these results again

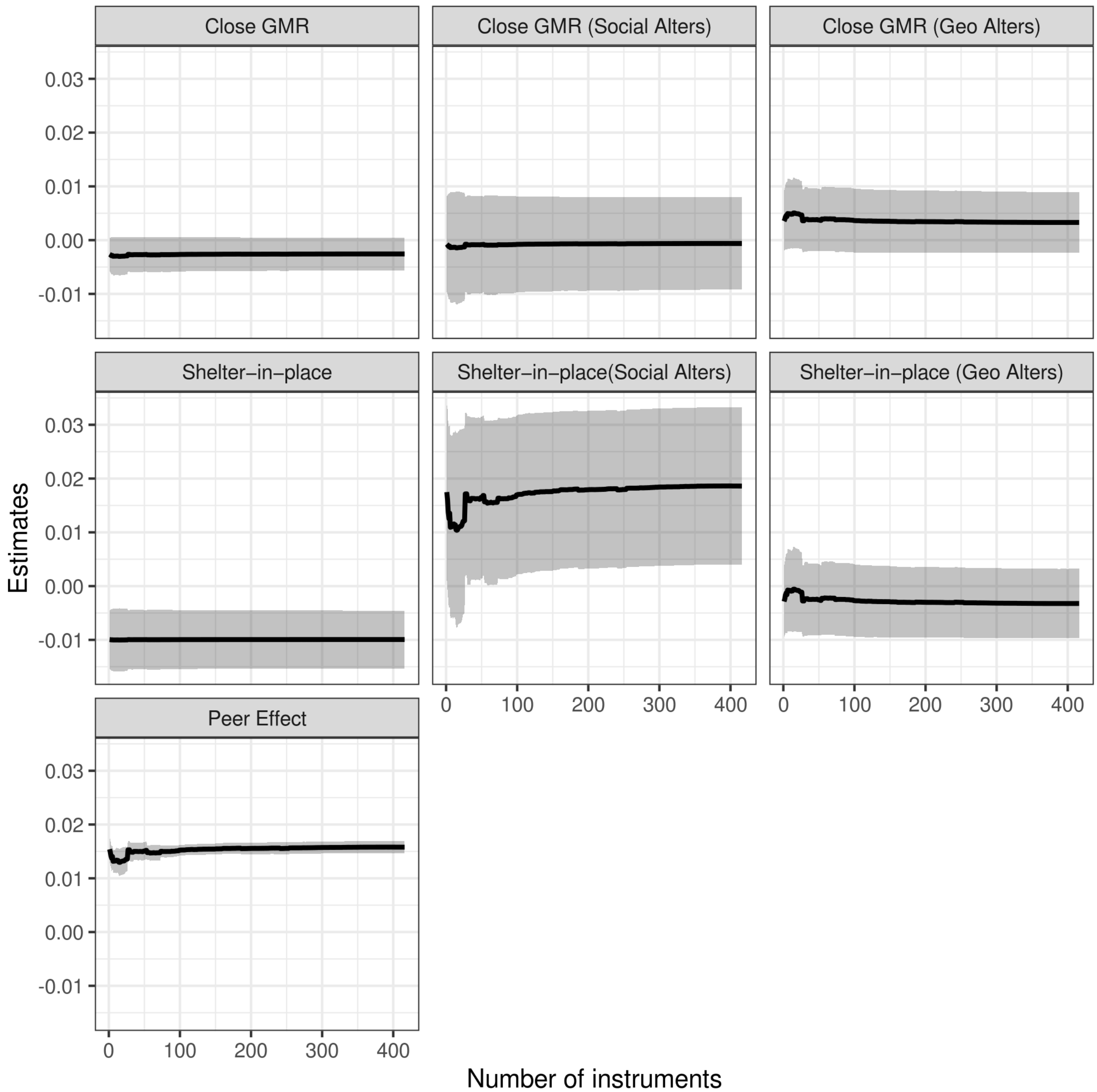


Figure S30: Varying the number of instruments, where instruments are added according to the LASSO regularization path.

confirm our main results. We find strong evidence of large, positive endogenous social effects in social distancing behavior. Moreover, we again see that these endogenous social effects are largely mediating the effect of peer county policy spillovers.

Table S10: Shift-share instruments only

	Dependent variable:			
	asinh(NSBTUs)	BTVRC	asinh(NHDF)	log(dCBGVs)
Close GMR	−0.003	−0.011	−0.003	−0.007
	(0.003)	(0.006)	(0.003)	(0.008)
Close GMR (Social Alters)	−0.001	0.005	0.007	0.005
	(0.007)	(0.016)	(0.009)	(0.025)
Close GMR (Geo Alters)	0.004	0.008	−0.003	0.004
	(0.005)	(0.012)	(0.006)	(0.016)
Shelter-in-place	-0.010^{***}	-0.032^{***}	-0.015^{***}	-0.031^{**}
	(0.004)	(0.010)	(0.005)	(0.013)
Shelter-in-place (Social Alters)	0.017^{*}	0.055^{**}	0.042^{***}	0.079^{**}
	(0.009)	(0.025)	(0.015)	(0.037)
Shelter-in-place (Geo Alters)	−0.003	−0.008	-0.016^{*}	−0.025
	(0.006)	(0.015)	(0.010)	(0.022)
Peer Effect	1.528^{***}	1.602^{***}	1.616^{***}	1.694^{***}
	(0.067)	(0.073)	(0.082)	(0.092)

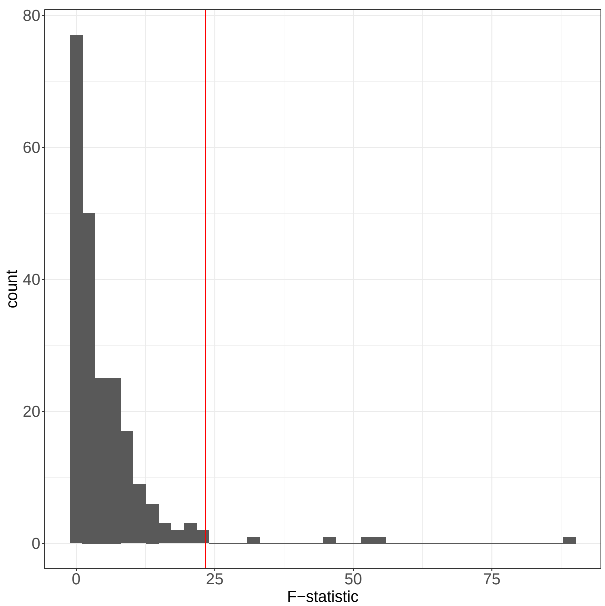
*p<0.1; **p<0.05; ***p<0.01

S3.5.4 Randomization Inference

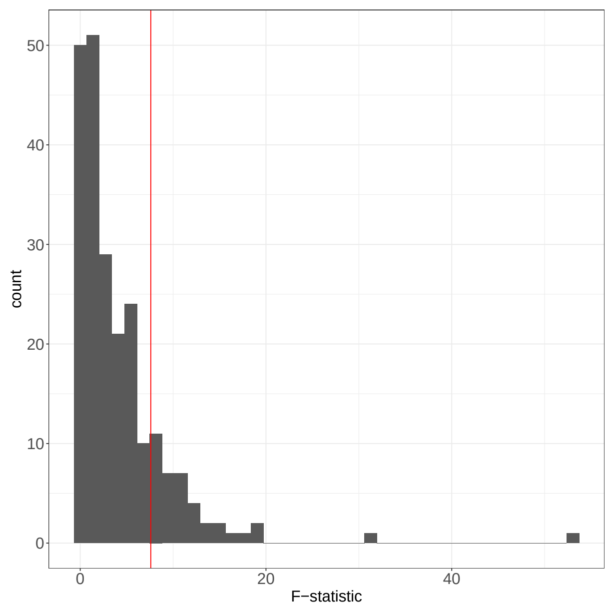
While our primary asymptotic inference described above was selected to be robust to network and within-state dependence, we use Fisherian randomization inference (FRI) to further examine the robustness of our instrumental variable results to dependence in key regressors — in particular, the weather instruments (*37, 38*). Let $\tilde{Y}_{it}$ be the outcome, $\tilde{Y}_{-it}$ the endogenous peer behavior, and $\tilde{W}_{-it}$ the vector of instrumental variables. Under the maintained exclusion restriction and the sharp null hypothesis that the potential outcomes are given by $\tilde{Y}_{it}(d) = \tilde{Y}_{-it}(0) + \beta_0 \tilde{Y}_{-it}$, then $\tilde{Y}_{it} - \beta_0 \tilde{Y}_{-it}$ is invariant to changes to $\tilde{W}_{-it}$. For the special case of $\beta_0 = 0$, this null hypothesis implies that $\tilde{Y}_{it}$ is invariant to changes in $\tilde{W}_{-it}$.

This kind of "reduced form" test with instrumental variables (*37*) is known to have low power when overidentified (*39*), so we focus on the case of a single weather instrument. We draw a permuted weather instrument W_{-it} from a historical weather distribution that preserves the correlation across consecutive days and geographic locations. In particular, we draw historical weather within a 28 days time window before and after the focal days of the year from dates in 2015–2019 for all counties. This gives us a total of $28 \times 2 \times 4 = 224$ counterfactual weather conditions. We compute alters' weather as in the primary analysis, partialing out i's weather and fixed effects as with the observed data to create $\tilde{W}_{-it}$.

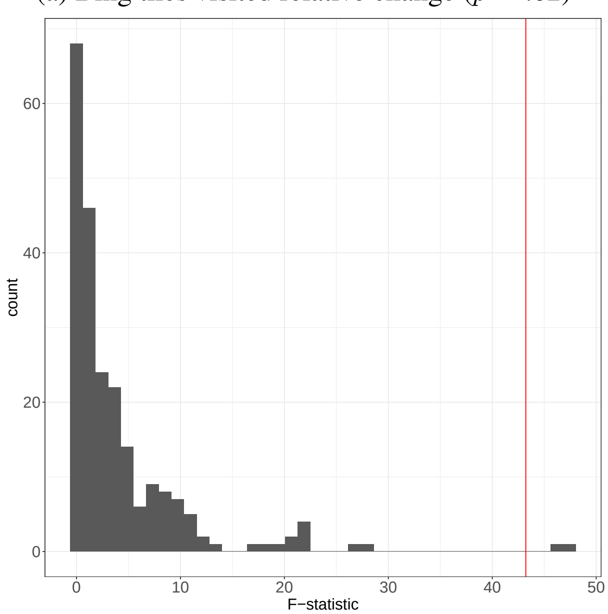
For each of these permuted sets of weather instruments, we compute a test statistic measuring the association of $Y_{it} - \beta Y_{-it}$ with W_{-it}. Here we use the F-statistic for a single weather instrument that measures precipitation in alter counties. For each of the 4 primary movement outcomes we look at (BTVRC, asinh(NSBTUs), log(dCBGVs), and asinh(nhd)), we plot this null distribution of F-statistics and the observed F-statistic in Figure S31. The red vertical lines correspond to the F statistics under current weather, the p-value (fraction of times the F-statistic is equal to or bigger than the F-statistic corresponding to the current weather) is reported under each test. Even with only this single instrument, we can reject all null hypotheses at the 5% level except for the outcome asinh(NSBTUs). This provides some evidence for our results for endogenous peer effects that does not rely on asymptotic approximations.



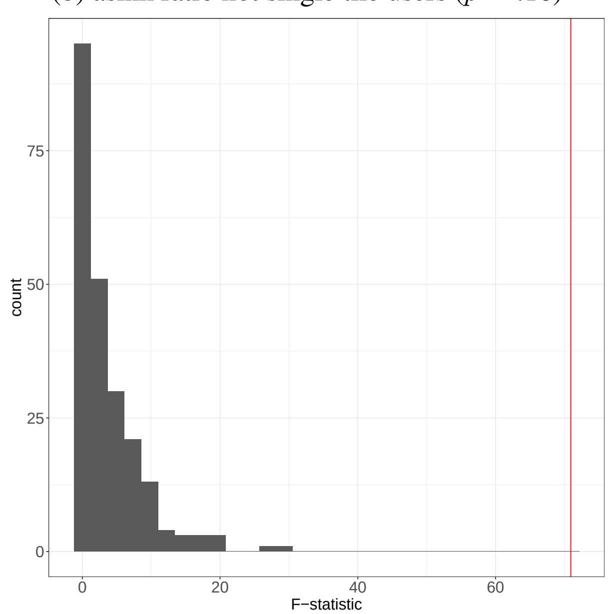
(a) Bing tiles visited relative change ($p = .02$)



(b) asinh ratio not single tile users ($p = .16$)



(c) log mean census block groups visited ($p = .01$)



(d) asinh not home devices ($p < .01$)

Figure S31: Null distribution (grey) and observed value (red line) of test statistic (F-statistic) for association between a single weather instrument and the outcomes from Fisherian randomization inference using historical weather data.

S3.5.5 Excluding Counties with Correlated Weather

As a robustness check on the conditional ignorability assumption of our weather instruments, we conduct a sensitivity analysis where we exclude counties with sufficiently correlated weather to a focal county i from our analysis. Our model specifications in this section only make use of the weather instruments. We run 3 styles of analysis following this selection procedure:

1. Renormalized: the weights used to construct Y_{-it} and W_{-it} are renormalized to sum to 1. This procedure changes the interpretation of β to be the endogenous social effect of all peer counties with sufficently uncorrelated weather.

2. Non-renormalized: the weights used to construct Y_{-it} and W_{-it} are not renormalized. As such the maximum sum of all the weights equals the (weighted) fraction of non-excluded peer counties.

3. Full Endogenous Variable: regardless of the threshold, no counties are excluded from the construction of Y_{-it}. However, non-renormalized weights are used to compute W_{-it}.

We report the results using both 2SLS and LIML estimation for each of our 4 outcome variables with thresholds starting at 0.05 until 1 in 0.05 increments. The corresponding figures and outcomes are as follows:

- Figure S32: asinh(NSBTUs)
- Figure S33: asinh(NHD)
- Figure S34: log(dCBGVs)
- Figure S35: BTVRC

A couple of major patterns emerge from our results. The direct policy effects stay quite consistent across outcomes, estimation methods, thresholds, and model types. We also see, that generally, as we decrease the threshold, the estimated impact of peer policy becomes more significant, at least for both the renormalized and non-renormalized model types. This is consistent with the idea that these endogenous peer mobility behaviors are causally mediating many of the effects of peer policies.

Beyond this, we also see that as the threshold decreases, the peer effect for the renormalized models drops to 0. This also makes sense, since as we exclude more and more peer counties, their total effect is becoming less and less. Looking at the non-renormalized models, we see that there is some fluctuation as the threshold decreases, however it remains relatively stable across a wide range of possible thresholds. The full endogenous variable results are even more consistent, with LIML estimates that are nearly flat line across the entire range of thresholds.

Overall, we see these results as extremely consistent with our main results. As such, we believe the DML approach is effectively controlling for the impact of own weather, and giving us confidence that our weather instruments are indeed conditionally ignorable.

S4 Asymptotic Inference with Adjacency- and Cluster-robust Standard Errors

Spatial and network econometricians have previously made use of estimators for variance-covariance matrices that are consistent in the presence of spatially correlated errors (*40, 41*). These estimators are Huber–White "sandwich" estimators with the functional form:

$$\widehat{\text{Var}}\left[\hat{\beta}\right] = \left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{X}\left(\hat{u}\hat{u}'\odot\mathbf{B}\right)\mathbf{X}\left(\mathbf{X}'\mathbf{X}\right)^{-1}, \tag{S11}$$

where $\hat{u}$ is the vector of residuals, $\odot$ is element-wise multiplication, and $\mathbf{B}$ is an $n\times n$ matrix that selects and/or weights pairs of observation. In versions of this estimator that are "adjacency-robust," $\mathbf{B}$ is related to a given network's adjacency matrix, whereas in versions of this estimator that are robust to one-way clustering, $\mathbf{B}$ is a block diagonal matrix with $B_{ij} = 1$ if and only if i

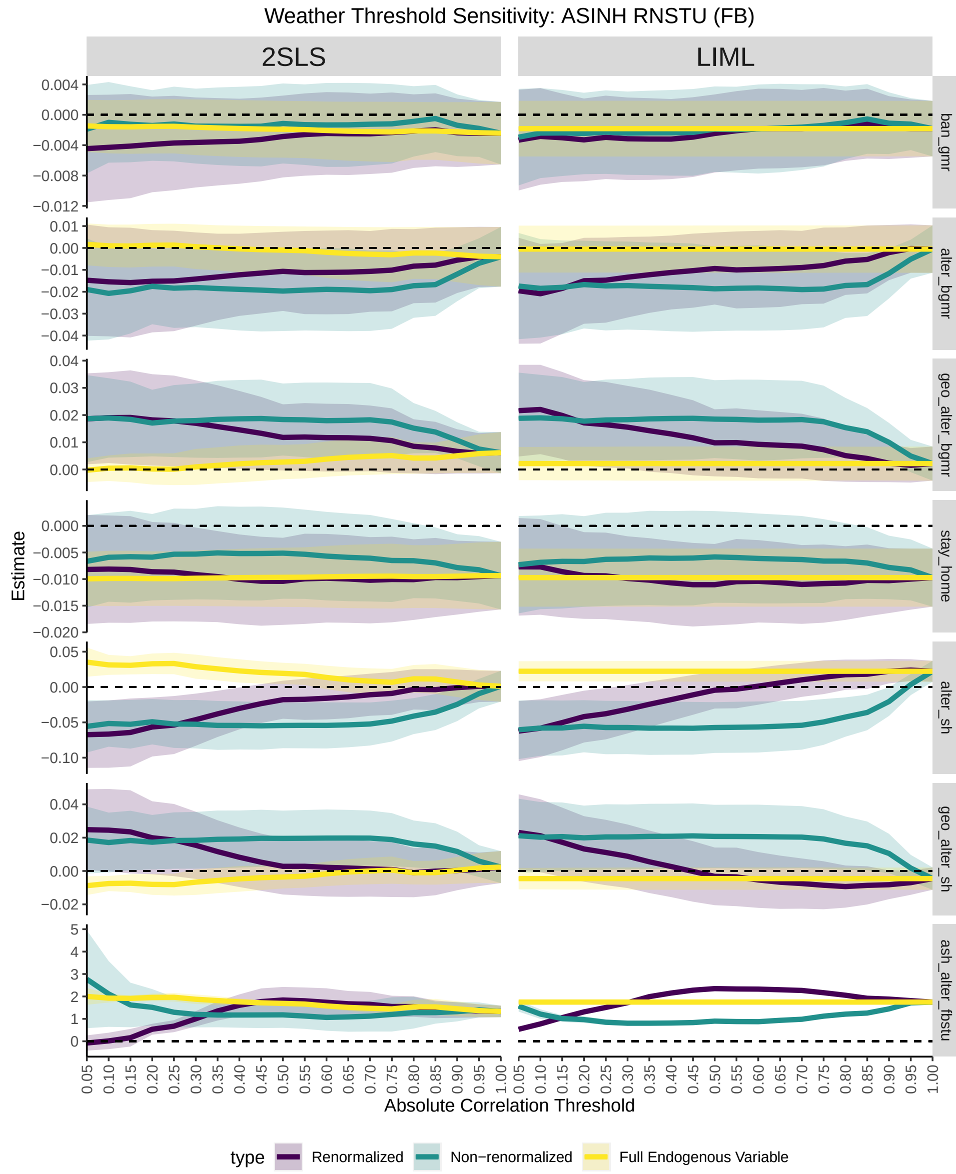


Figure S32: Coefficient plots showing how the estimated parameters $\hat{\beta}$, $\hat{\delta}_1$, $\hat{\delta}_2$, and $\hat{\delta}_3$ change as counties with correlated weather are excluded for the outcome variable of asinh(NSBTUs). Starting at the right where all counties are included, we move in 0.05 increments until we reach the left side, where only counties with less than 0.05 absolute precipitation correlation are included. 2 types of models are estimated: Renormalized (purple), Non-renormalized (green), and Full Endogenous Variable (Yellow). Coefficient estimates produced using both 2SLS (left) and LIML (right) are included. Due to the high computational cost of adjacency-robust SEs, state-clustered standard are reported here instead.

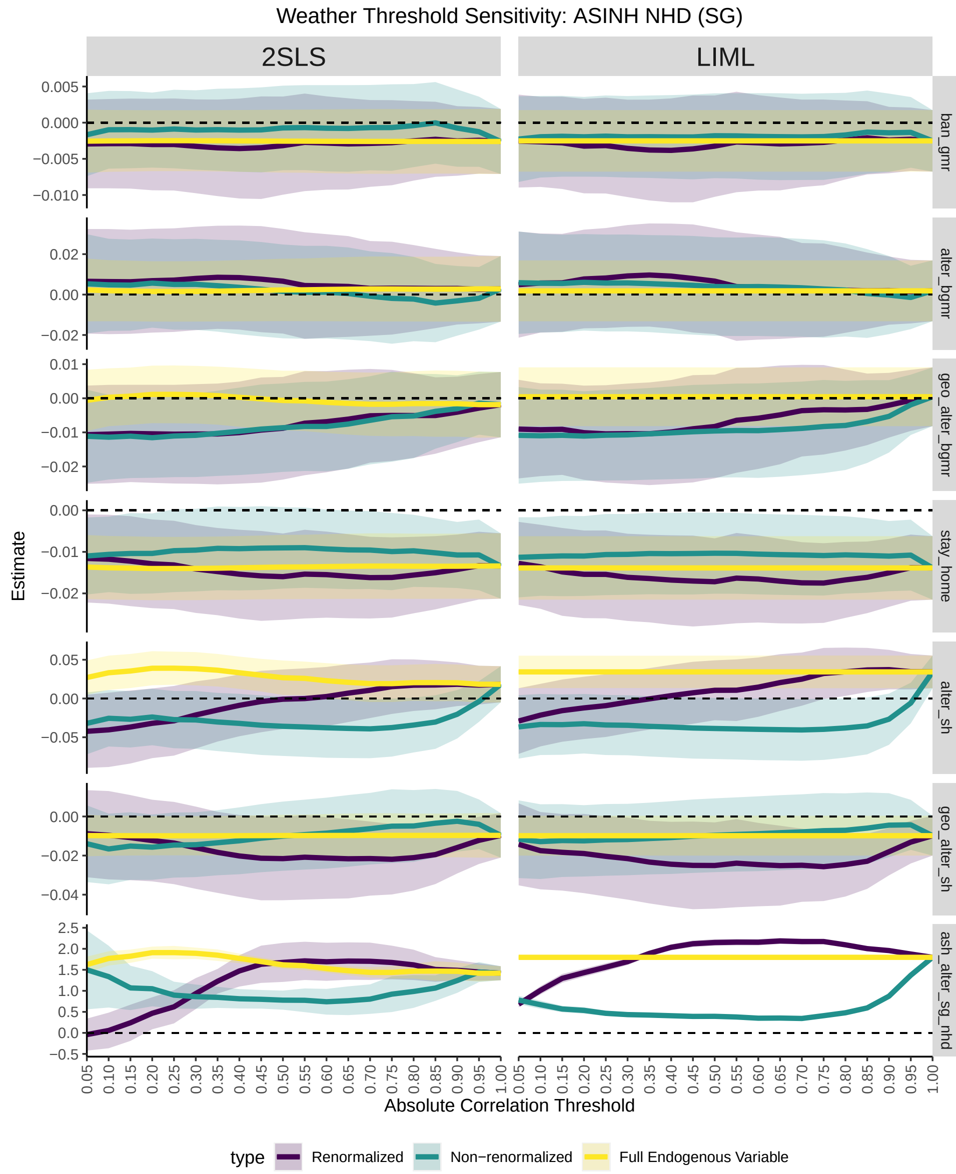


Figure S33: Coefficient plots showing how the estimated parameters $\hat{\beta}$, $\hat{\delta}_1$, $\hat{\delta}_2$, and $\hat{\delta}_3$ change as counties with correlated weather are excluded for the outcome variable of asinh(NHDF). Starting at the right where all counties are included, we move in 0.05 increments until we reach the left side, where only counties with less than 0.05 absolute precipitation correlation are included. 2 types of models are estimated: Renormalized (purple), Non-renormalized (green), and Full Endogenous Variable (Yellow). Coefficient esimates produced using both 2SLS (left) and LIML (right) are included. Due to the high computational cost of adjacency-robust SEs, state-clustered standard are reported here instead.

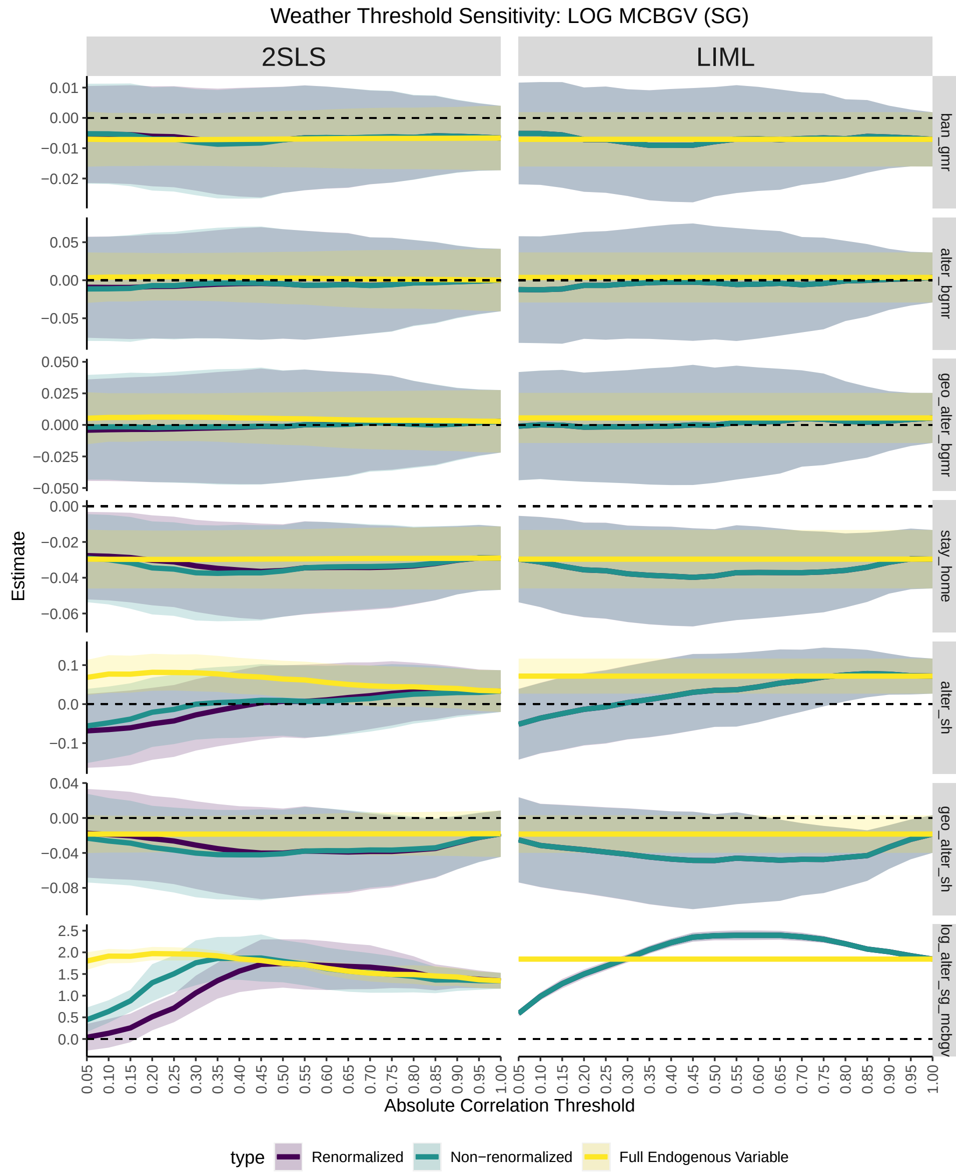


Figure S34: Coefficient plots showing how the estimated parameters $\hat{\beta}$, $\hat{\delta}_1$, $\hat{\delta}_2$, and $\hat{\delta}_3$ change as counties with correlated weather are excluded for the outcome variable of log(dMCBGVs). Starting at the right where all counties are included, we move in 0.05 increments until we reach the left side, where only counties with less than 0.05 absolute precipitation correlation are included. 2 types of models are estimated: Renormalized (purple), Non-renormalized (green), and Full Endogenous Variable (Yellow). Coefficient estimates produced using both 2SLS (left) and LIML (right) are included. Due to the high computational cost of adjacency-robust SEs, state-clustered standard are reported here instead.

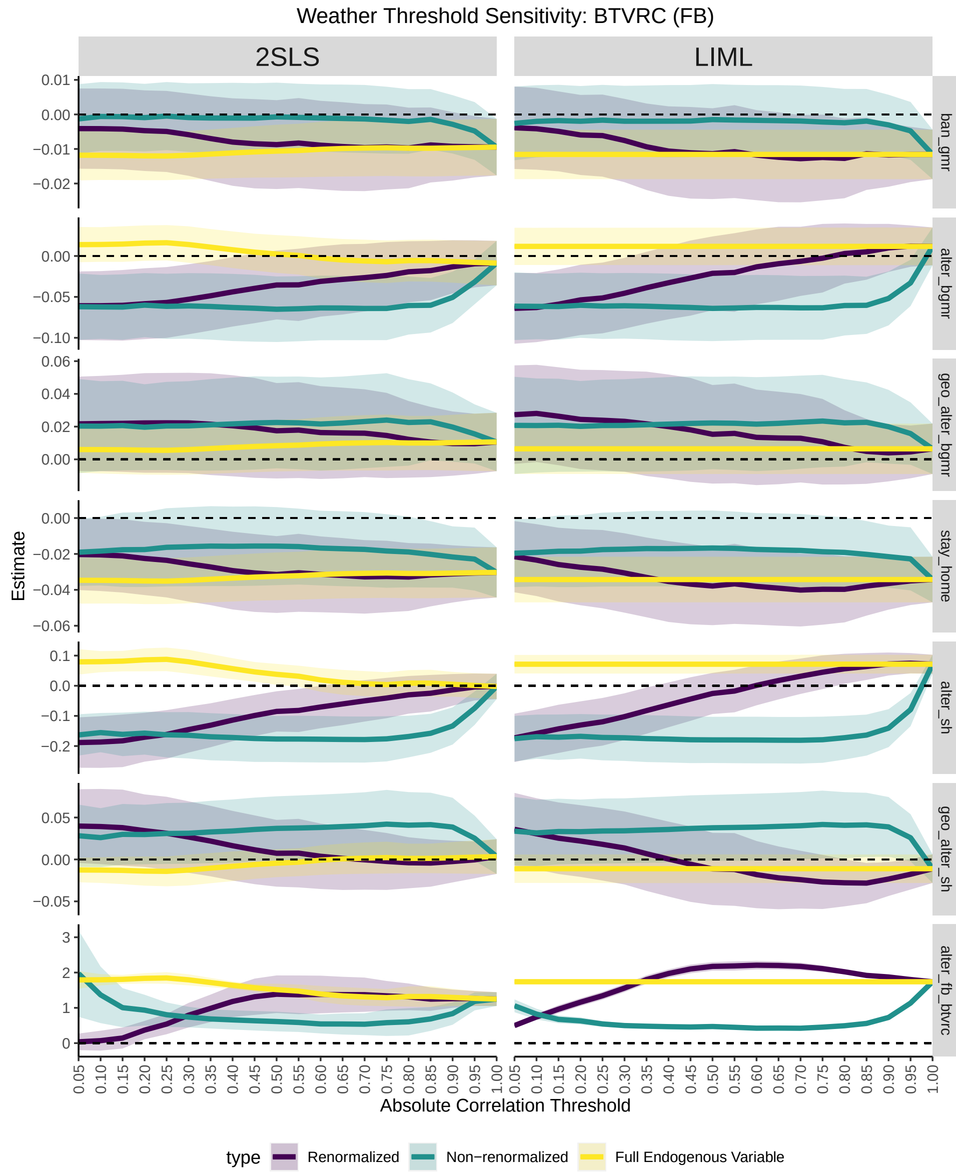


Figure S35: Coefficient plots showing how the estimated parameters $\hat{\beta}$, $\hat{\delta}_1$, $\hat{\delta}_2$, and $\hat{\delta}_3$ change as counties with correlated weather are excluded for the outcome variable of BTVRC. Starting at the right where all counties are included, we move in 0.05 increments until we reach the left side, where only counties with less than 0.05 absolute precipitation correlation are included. 2 types of models are estimated: Renormalized (purple), Non-renormalized (green), and Full Endogenous Variable (Yellow). Coefficient estimates produced using both 2SLS (left) and LIML (right) are included. Due to the high computational cost of adjacency-robust SEs, state-clustered standard are reported here instead.

and j are in the same cluster.

In our setting, we believe that there is the potential for errors to be correlated for counties that are connected according to our social and/or geographic connectedness networks, as well as counties that are located in the same U.S. state (since the enactment of many COVID-19 related policies was made at the state-level, as opposed to the county-level). In order to account for this, we use a variance-covariance estimator that combines both adjacency- and cluster/state-robust estimators with the functional form provided in Eq. 11. The adjacency-robust estimator consists of Eq. 11, with the "selector" matrix $\mathbf{B}$ equal to the elementwise maximum of the social adjacency matrix used in our analyses and the state clustering matrix, i.e., $B_{ij}^{both} = \max(B_{ij}^{\text{ad}}, B_{ij}^{\text{clu}})$ (*41–44*). Our difference-in-differences and instrumental variables analyses make use of this combined adjacency-and cluster-robust sandwich estimator.

S5 Ranking States' Influence

In order to rank the extent to which each individual U.S. state's shelter-in-place policy decision impacts each other U.S. state, we combined the different-state coefficient estimates obtained in our difference-in-differences models (with asinh(nhd) as the outcome of interest) with the social adjacency and geographic adjacency matrices that we use throughout our analysis. In other words, we define state i's influence on state j as:

$$\text{Inf}_{ij} = \delta_2^{ds} A_{ij}^{geo} + \delta_3^{ds} A_{ij}^{social}. \tag{S12}$$

Fig. S36 and Fig. S37 show the 20 alter states that would cause the largest reduction in the focal state by implementing their own shelter-in-place policy. We next define the spillover between alter state i and ego state j as the ratio of the indirect effect of i's shelter-in-place policy on mobility levels in j to the direct effect of j's shelter in place policy on mobility levels in j. Fig. S38 shows the empirical CDF for the set of state pairs consisting of each ego state's most influential alter state. The min spillover is 0.22, the maximum spillover is 0.83, and the median spillover is 0.42.

For each state j, we can also estimate it's "total influence" by taking the weighted sum of our estimated state-level influence across all states. In other words,

$$TI_j = \sum_i n_i \left(\delta_2^{ds} A_{ij}^{geo} + \delta_3^{ds} A_{ij}^{sci} \right) , \tag{S13}$$

where n_i is the population of state i. TI_j captures the total reduction in mobility that j would trigger across the rest of the U.S. by implementing their own shelter-in-place policy (assuming no other states have implemented their own). Fig. S39 shows the relationship between total state influence and state population. In general, more populous states have greater capacity to impact other states' mobility levels.

Finally, we can estimate the total influence that each region of the U.S. has on each focal state by summing individual "influences" at the region-level, i.e.,

$$I_{ir} = \sum_{j \in r} \left(\delta_2^{ds} A_{ij}^{geo} + \delta_3^{ds} A_{ij}^{sci} \right) . \tag{S14}$$

S6 Analytical Model of the Loss From Anarchy

To illustrate the "loss from anarchy", that is, states failing to cooperate over network effects, we introduce a simple game-theoretic model. This model is inspired by both the classic literature on inneficiencies arising from unpriced externalities and non-cooperative game theory (*45*) as well as the more modern reinterpratation of these losses as a "price of anarchy" (*46*). We refer to a loss from anarchy because in the main text we focus on a difference in utilities rather than the ratio which is more common to the price of anarchy literature.

The agents in our model are a set of states, indexed by s, each attempting to achieve a target

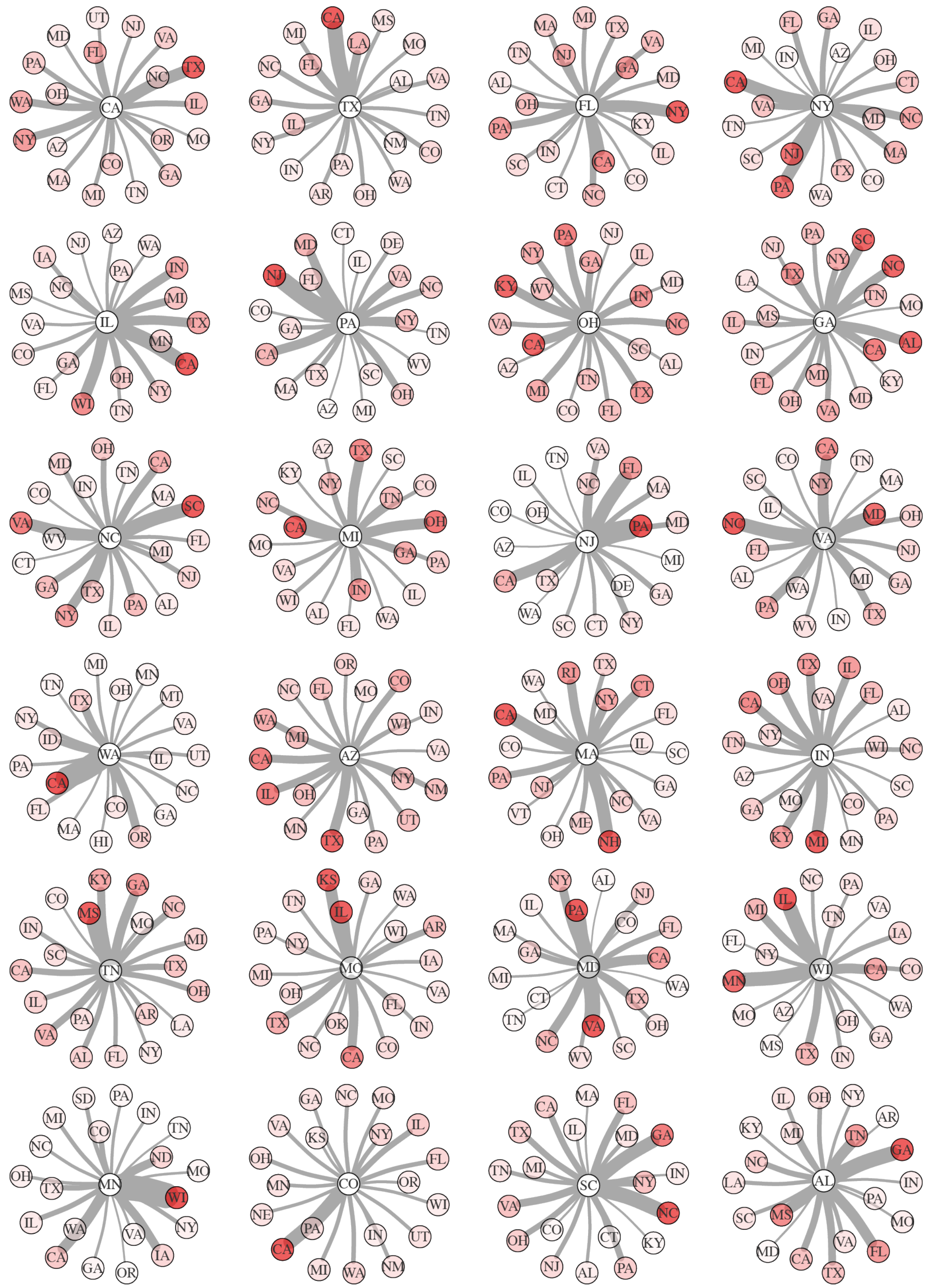


Figure S36: Each ego network shows the alter states whose own shelter-in-place policies would cause the greatest mobility reductions in the ego state. Edge thickness and alter node color both correspond to the log of this mobility reduction. Estimates are obtained by combining point estimates from our difference-in-differences model, our social adjacency matrix, and our geo-adjacency matrix. From left-top to right-bottom focal states are sorted by their population.

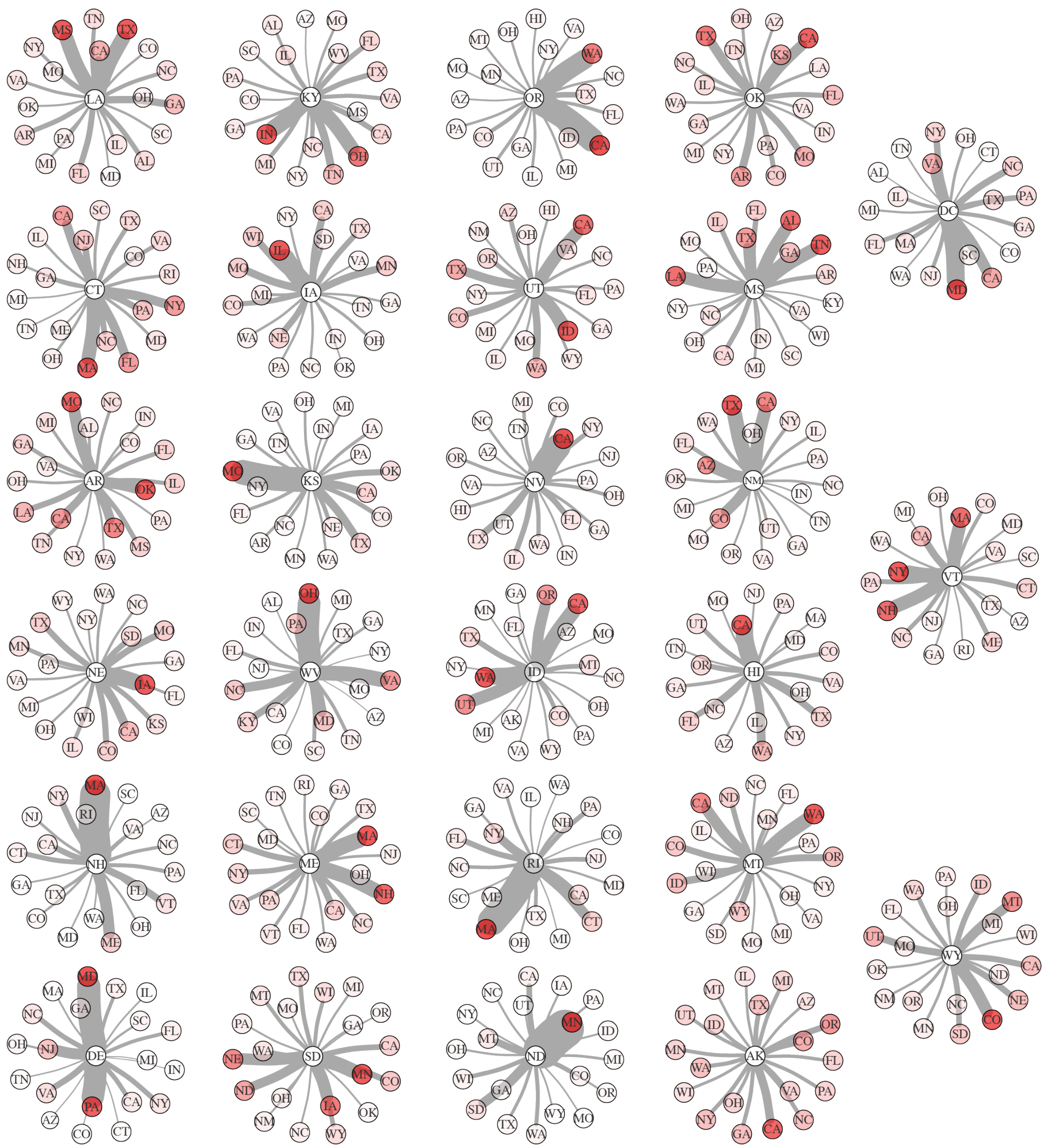


Figure S37: Each ego network shows the alter states whose own shelter-in-place policies would cause the greatest mobility reductions in the ego state. Edge thickness and alter node color both correspond to the log of this mobility reduction. Estimates are obtained by combining point estimates from our difference-in-differences model, our social adjacency matrix, and our geo-adjacency matrix. From left-top to right-bottom focal states are sorted by their population.

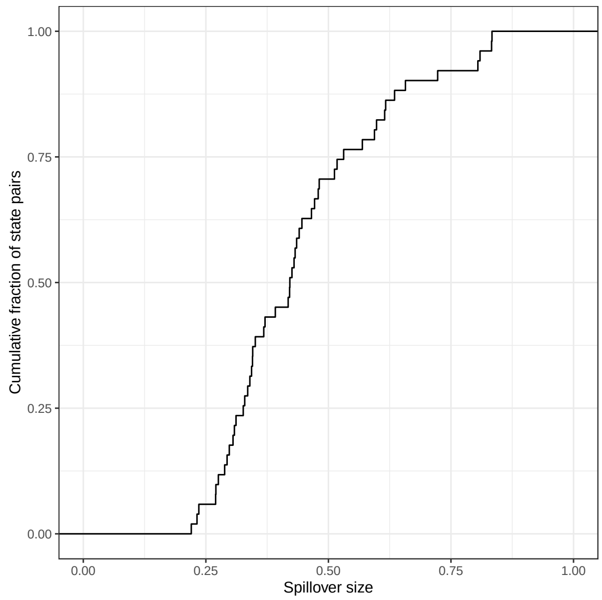


Figure S38: The empirical CDF of the spillover between state i and j, defined as the ratio of the indirect effect of i's shelter-in-place policy on j's mobility to the direct effect of j's shelter-in-place policy on j's mobility. Sample limited to the most influential alter state for each ego state ($n = 51$).

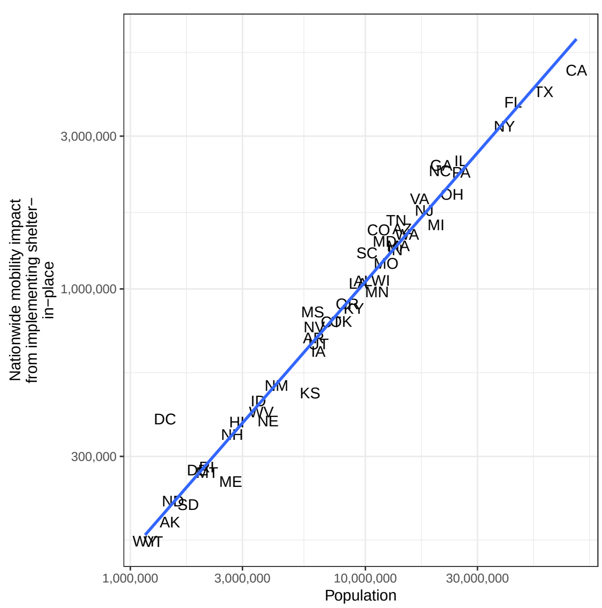


Figure S39: The relationship between a state's "total influence", i.e. how much nationwide out-of-state mobility would reduce after that state implemented shelter-in-place, and the state's population. The two are highly correlated.

mobility level, denoted by $\hat{r}_s$ by choosing an intensity of distancing policy $p_s \in \mathbb{R}$ which has a linear cost c. Restricting attention to two states i and j, the policy decisions of state i spillover to state j linearly (but potentially asymmetrically) according to parameter $0 \leq z_{ij} \leq 1$:

$$r_i = \bar{r}_i - p_i - p_j z_{ji}, \tag{S15}$$

$$r_j = \bar{r}_j - p_j - p_i z_{ij}, \tag{S16}$$

where $\bar{r}_s \geq 0$ is the initial mobility level in state s.

We assume that each state's cost of adopting a policy level p_s is linear at c per unit. We further assume that their cost of missing their target mobility level is quadratic. Their utility function can then be written as

$$U_s(r_s, p_s) = -(r_s - \hat{r}_s)^2 - cp_s. \tag{S17}$$

In the following sections, we solve for the Nash equilibrium outcome of the model, as well as the choice of a social planner who equally weighs states. We solve for the two state problem first, and then for more complex settings.

This simple model generates a loss from lack of cooperation so long as spillovers exist (i.e. $z_{ij} > 0, \forall_{i,j}$), changing policies is not costless $(c > 0)$, and transfer payments between states are not allowed. States with opposed targets will wastefully pull in different directions. Even when states are identical, there is a free rider problem. In equation (S47) we show that the degree of divergence between the social planner and Nash outcomes is increasing in the size of spillovers. To overcome this Coasian challenge, interstate compacts (potentially with monetary or resource transfers to redistribute the surplus from cooperation) are desirable.

S6.1 Nash Equilibrium Solution

Let $\delta_i = \hat{r}_i - \bar{r}_i$ and without loss of generality assume that $\Delta := \delta_j - \delta_i \geq 0$. Replacing (S15) in (S17), the optimal policies, p_i^{NE} and p_j^{NE}, for the two states satisfy:

$$p_i^{NE} = -\frac{c}{2} - \delta_i - p_j^{NE} z_{ji} \tag{S18}$$

$$p_j^{NE} = -\frac{c}{2} - \delta_j - p_i^{NE} z_{ij} \tag{S19}$$

When the spillovers are perfect (i.e. $z_{j,i} = z_{i,j} = 1$) there are no pure strategy equilibria unless $\delta_i = \delta_j = \delta$, in which case $p_i^1 = p_j^1 = -c/4 - \delta/2$, where we use p_s^1 to denote the equilibrium state policies with maximum spillover.

We use p_s^0 to denote the equilibrium state policies with no spillovers. From (S18) we have:[17]

$$p_i^0 = -\frac{c}{2} - \delta_i, \tag{S20}$$

$$p_j^0 = -\frac{c}{2} - \delta_j, \tag{S21}$$

with the corresponding utilities

$$U_i^0 = \frac{c^2}{4} + c\delta_i, \tag{S22}$$

$$U_j^0 = \frac{c^2}{4} + c\delta_j, \tag{S23}$$

and social welfare

$$U^0 = U_i^0 + U_j^0 = \frac{c^2}{2} + c(\delta_i + \delta_j). \tag{S24}$$

Note that with $\delta_j \geq \delta_i$, we have $p_j^0 \leq p_i^0$: the state with the lowest target has to make the most effort and take the highest policy.

[17] We drop "NE" from the notation, as without spillovers the Nash Equilibrium and Socially Optimal strategies are identical.

When $0 \leq z_{ij} < 1$ and $0 \leq z_{ji} < 1$ we can solve (S18) to get the following equilibrium:

$$p_i^{NE} = -\frac{c(1 - z_{ji})}{2(1 - z_{ji}z_{ij})} - \delta_i \frac{1}{1 - z_{ji}z_{ij}} + \delta_j \frac{z_{ji}}{1 - z_{ji}z_{ij}} \tag{S25}$$
$$= p_i^0 \frac{1 - z_{ji}}{1 - z_{ji}z_{ij}} + \Delta \frac{z_{ji}}{1 - z_{ji}z_{ij}} \tag{S26}$$
$$= \alpha_{ji} p_i^0 + \Delta_{ji}, \tag{S27}$$
$$p_j^{NE} = -\frac{c(1 - z_{ij})}{2(1 - z_{ji}z_{ij})} - \delta_j \frac{1}{1 - z_{ji}z_{ij}} + \delta_i \frac{z_{ij}}{1 - z_{ji}z_{ij}} \tag{S28}$$
$$= p_j^0 \frac{1 - z_{ij}}{1 - z_{ji}z_{ij}} - \Delta \frac{z_{ij}}{1 - z_{ji}z_{ij}} \tag{S29}$$
$$= \alpha_{ij} p_j^0 - \Delta_{ij} \leq p_j^0, \tag{S30}$$

where $0 < \alpha_{ji} = (1 - z_{ji})/(1 - z_{ji}z_{ij}) < 1$ is the reduction in the effort by state i to use the spillover from the policy of state j, and vice versa for α_{ij}. On the other hand, $\Delta_{ji} = \Delta z_{ji}/(1 - z_{ji}z_{ij})$ is the correction made by state i to account for the spillovers from the policy of state j with a differing desired target output level ($\Delta > 0$), and vice versa for Δ_{ij}. Note that state j with the higher target δ_j always reduces her policy as a result of spillovers: $p_j^{NE} \leq p_j^0$. Alternatively, state i who has the lower target increases her policy in face of spillovers only if $\Delta > (1 - z_{ij})p_i^0$.

In fact, the gap between the two policies increases unbounded, with the increasing spillover size. With $z_{ij} = z_{ji} = z$ we have:

$$p_i^{NE} = \frac{p_i^0}{1 + z} + \frac{z\Delta}{1 - z^2},$$
$$p_j^{NE} = \frac{p_j^0}{1 + z} - \frac{z\Delta}{1 - z^2},$$

and

$$p_i^{NE} - p_j^{NE} = \frac{\Delta}{1 + z} + \frac{2z\Delta}{1 - z^2} = \Delta \frac{1 + z}{1 - z^2} \rightarrow \infty, \text{ as } z \rightarrow 1. \tag{S31}$$

The individual utilities and welfare in this equilibrium are as follows:

$$U_i^{NE} = \frac{c^2}{4}(2\alpha_{ji} - 1) + c\alpha_{ji}\delta_i - c\Delta_{ji}, \tag{S32}$$

$$U_j^{NE} = \frac{c^2}{4}(2\alpha_{ij} - 1) + c\alpha_{ij}\delta_j + c\Delta_{ij}, \tag{S33}$$

$$U^{NE} = U_i^{NE} + U_j^{NE} = -\frac{c^2}{2}(1 - \alpha_{ji} - \alpha_{ij}) + c\delta_i\alpha_{ij} + c\delta_j\alpha_{ji} \tag{S34}$$

$$= -\frac{c^2}{2}(1 - \alpha_{ji} - \alpha_{ij}) + c\alpha_{ji}\delta_i + c\alpha_{ij}\delta_j + c(\Delta_{ij} - c\Delta_{ji}) \tag{S35}$$

$$\leq U^0 + c\Delta\frac{z_{ij} - z_{ji}}{1 - z_{ji}z_{ij}} \tag{S36}$$

Hence, if $z_{ij} < z_{ji}$, i.e. the state with the higher target outcome has a higher spillover, then the equilibrium welfare in the presence of spillovers decreases by at least $c\Delta(z_{ji} - z_{ji})/(1 - z_{ji}z_{ij})$. On the other hand, if $0 < z_{ij} = z_{ji} = z$, then

$$U^{NE} = \frac{c^2}{2}\left(\frac{1-z}{1+z}\right) + \frac{c(\delta_i + \delta_j)}{1+z} = \frac{U^0}{1+z} - \frac{c^2 z}{2(1+z)} \leq \frac{U^0}{1+z}. \tag{S37}$$

For c large enough we have $0 < U^{NE} \leq U^0$, in which case the Nash equilibrium welfare in the presence of spillovers decreases by a factor of at least $1/(1+z)$.

S6.2 Socially Optimal Solution

We now shift attention to a social planner's problem who chooses p_i and p_j to maximize the social welfare $U_i(r_i, p_i) + U_j(r_j, p_j)$. The socially optimal policies p_i^{SO} and p_j^{SO} satisfy the following:

$$p_i^{SO}(1 + z_{ij}^2) + p_j^{SO}(z_{ij} + z_{ji}) = -\frac{c}{2} - \delta_i - z_{ij}\delta_j, \tag{S38}$$

$$p_j^{SO}(1 + z_{ij}^2) + p_i^{SO}(z_{ij} + z_{ji}) = -\frac{c}{2} - \delta_j - z_{ji}\delta_i. \tag{S39}$$

Solving for the socially optimal policies we get:

$$p_i^{SO} = -\frac{c(1 + z_{ji}^2 - z_{ij} - z_{ji})}{2(1 - z_{ji}z_{ij})^2} - \delta_i\frac{1}{1 - z_{ji}z_{ij}} + \delta_j\frac{z_{ji}}{1 - z_{ji}z_{ij}} \leq p_i^{NE}, \tag{S40}$$

$$p_j^{SO} = -\frac{c(1 + z_{ij}^2 - z_{ij} - z_{ji})}{2(1 - z_{ji}z_{ij})^2} - \delta_j\frac{1}{1 - z_{ji}z_{ij}} + \delta_i\frac{z_{ij}}{1 - z_{ji}z_{ij}} \leq p_j^{NE}, \tag{S41}$$

The subsequent individual utilities and social welfare under the above policies are as follows:

$$U_i^{SO} = \frac{c^2(1+2z_{ji}^2 - z_{ij}^2 - 2z_{ji})}{4(1-z_{ji}z_{ij})^2} + c\delta_i \frac{1}{1-z_{ji}z_{ij}} - c\delta_j \frac{z_{ji}}{1-z_{ji}z_{ij}}, \tag{S42}$$

$$U_j^{SO} = \frac{c^2(1+2z_{ij}^2 - z_{ji}^2 - 2z_{ij})}{4(1-z_{ji}z_{ij})^2} + c\delta_j \frac{1}{1-z_{ji}z_{ij}} - c\delta_i \frac{z_{ij}}{1-z_{ji}z_{ij}}, \tag{S43}$$

$$U^{SO} = U_i^{SO} + U_j^{SO} = \frac{c^2}{4}(\alpha_{ij}^2 + \alpha_{ji}^2) + c\delta_i\alpha_{ij} + c\delta_j\alpha_{ji}, \tag{S44}$$

Substituting $z_{ij} = z_{ji} = z$ in (S44) we get:

$$U^{SO} = \frac{c^2}{2}\left(\frac{1}{1+z}\right)^2 + \frac{c\delta_i + c\delta_j}{1+z} = \frac{U^0}{z+1} - \frac{c^2 z}{2(1+z)^2} \leq \frac{U^0}{z+1}. \tag{S45}$$

S6.3 Loss from Anarchy

To understand the inefficiency, consider the following cost of anarchy given by the difference between the socially optimal welfare U^{SO} in (S44) and the equilibrium welfare U^{NE} in (S34):

$$U^{SO} - U^{NE} = \frac{c^2}{4}(2 - 2\alpha_{ji} - 2\alpha_{ij} + \alpha_{ij}^2 + \alpha_{ji}^2) = \frac{c^2}{4}((1-\alpha_{ji})^2 + (1-\alpha_{ij})^2) \geq 0. \tag{S46}$$

Using (S37) and (S45), for $z_{ij} = z_{ji} = z > 0$, the disutility from lack of cooperation, ∇_z, is given by:

$$\nabla_z := U^{SO} - U^{NE} = \frac{c^2}{2}\left(\frac{z}{1+z}\right)^2 = \frac{c^2}{2}\left(\frac{1}{1+1/z}\right)^2, \tag{S47}$$

which is strictly increasing in z: *with no spillovers, there is no loss in efficiency but as spillovers increase, the lack of cooperation is a bigger and bigger problem.* As $c \to \infty$, the utility values are dominated by the c^2 terms and they become non-negative. In this regime, we can quantify the inefficiency of the Nash equilibrium in terms of its Price of Anarchy (PoA) as follows:

$$PoA = \frac{U^{SO}}{U^{NE}} \sim 1 + \frac{z^2}{1-z^2}, \text{ as } c \to \infty. \tag{S48}$$

It is instructive to briefly consider the case where policies are cost-less. Setting $c = 0$ in (S20), (S25), and (S34) we get $p_j^0 = -\delta_j \leq p_i^0 = -\delta_i$ and:

$$p_j^{NE} = p_j^0 - \frac{z}{1+z}(\Delta \frac{1}{1-z} + p_j^0) \leq p_j^0, \tag{S49}$$

$$p_i^{NE} = p_i^0 + \frac{z}{1+z}(\Delta \frac{1}{1-z} - p_i^0). \tag{S50}$$

In face of spillovers, state j with the higher mobility target always reduces her policy, while state i that has the lower mobility target reduces her policy only if $\delta_i/\delta_j < 2 - z$.

The case of n symmetric states. To understand the role of spillovers beyond the case of two interacting states, it is useful to take a brief look at the case with n symmetric and identical agents: $z_{ij} = z$ and $\delta_i = \delta$ for all $i, j = 1, .., n$, $i \neq j$. The Nash equilibrium policy and social welfare are as follows:

$$p_i^{NE} = \frac{-c}{2(1 + z(n-1))} - \frac{\delta}{1 + z(n-1)}, \forall_i \tag{S51}$$

$$U_{(n)}^{NE} = \sum_{i=1}^{n} U_i^{NE} = n \left(\frac{1 - z(n-1)}{1 + z(n-1)} \frac{c^2}{4} + \frac{c\delta}{1 + z(n-1)} \right) \sim -n\frac{c^2}{4}, \tag{S52}$$

where $\sim$ denotes asymptotic equality: $f_n \sim g_n \leftrightarrow \lim_{n\to\infty} f_n/g_n = 1$. On the other hand, the socially optimal policy and welfare are given by:

$$p_i^{SO} = \frac{-c}{2(1 + z(n-1))^2} - \frac{\delta}{1 + z(n-1)}, \forall_i, \tag{S53}$$

$$U_{(n)}^{SO} = \sum_{i=1}^{n} U_i^{SO} = n \left(\frac{c^2}{4(1 + z(n-1))^2} + \frac{c\delta}{1 + z(n-1)} \right) \sim \frac{c\delta}{z}. \tag{S54}$$

The disutility from lack of cooperation among n states grows linearly worse as n increases:

$$\nabla_z^{(n)} := U_{(n)}^{SO} - U_{(n)}^{NE} \sim n\frac{c^2}{4}. \tag{S55}$$

Next suppose that the net spillover from other states is bounded; in particular, assume that

$zn \sim z'$ for some fixed $0 < z' < 1$. Then (S51) to (S55) become:

$$p_i^{NE} \sim \frac{-c}{2(1+z')} - \frac{\delta}{1+z'}, \forall_i, \tag{S56}$$

$$U_{(n)}^{NE} \sim n\left(\frac{1-z'}{1+z'}\frac{c^2}{4} + \frac{c\delta}{1+z'}\right), \tag{S57}$$

$$p_i^{SO} \sim \frac{-c}{2(1+z')^2} - \frac{\delta}{1+z'}, \forall_i, \tag{S58}$$

$$U_{(n)}^{SO} \sim n\left(\frac{c^2}{4(1+z')^2} + \frac{c\delta}{1+z'}\right), \tag{S59}$$

$$\nabla_{z'}^{(n)} \sim n\frac{c^2}{4}\left(\frac{z'}{1+z'}\right)^2. \tag{S60}$$

The disutility from lack of cooperation, $\nabla_z^{(n)}$, increases with increasing n, c, and z'. Similarly to (S48), we also have:

$$PoA = \frac{U_{(n)}^{SO}}{U_{(n)}^{NE}} \sim 1 + \frac{z'^2}{1-z'^2}, \text{ as } c \to \infty. \tag{S61}$$

It is worth noting that the mobility outcome, $r_i = \bar{r}_i - (1 + (n-1))zp_i$, at the Nash Equilibrium, is given by $r_i^{NE} = \hat{r}_i + c/2$, which overshoots the mobility target by $c/2$. At the socially optimal solution we get $r_i^{SO} = \hat{r}_i + c/2(1 + z(n-1))$, which, compared to the Nash equilibrium, overshoots the mobility target by a lesser amount: $c/2(1 + z(n-1))$. Due to the nonzero cost of implementing policies $c > 0$, both solution concepts predict mobility outcomes that are above the desired level $\hat{r}_i$; however, $r_i^{SO} \sim \hat{r}_i$, whereas $r_i^{NE} = \hat{r}_i + c/2$, independently of n or z.

The case of two blocks with geographic and social spillovers. Finally, to understand the effect of heterogeneity, we consider the case of n states that are organized in two geographic blocks, I and J, of sizes n_I and n_J, $n_I + n_J = n$. The states in block I all have the same mobility target, δ_I, and states in block J, all have the same mobility target δ_J. Each state $i \in I$ is subject to geographic spillovers (short ties) from other states within her own block, as well as social spillovers from the states in the other block, due to their social connectedness and long ties. We assume that all the states within the same block are subject to the same net spillover effects. In particular, for all $i \in I$, let $0 \leq z_{II} = \sum_{i' \in I, i' \neq i} z_{i'i} \leq 1$ be the net spillovers from within block I and $0 \leq z_{JI} = \sum_{j \in J} z_{ji} \leq 1$ be the net spillovers from outside of block I. Similarly, for any $j \in J$, denote the net spillovers by $0 \leq z_{JJ} = \sum_{j' \in J, j' \neq j} z_{j'j} \leq 1$ and $0 \leq z_{IJ} = \sum_{i \in I} z_{ij} \leq 1$.

By symmetry all states within the same block adopt the same equilibrium policies. We denote the Nash equilibrium policies by p_I^{NE} and p_J^{NE} The equilibrium policies for each block are given by:

$$\begin{aligned}
p_I^{NE} &= \frac{-c}{2} \frac{1 + z_{JJ} - z_{JI}}{(1 + z_{II})(1 + z_{JJ}) - z_{JI} z_{IJ}} \\
&- \delta_I \frac{1 + z_{JJ}}{(1 + z_{II})(1 + z_{JJ}) - z_{JI} z_{IJ}} + \delta_J \frac{z_{JI}}{(1 + z_{II})(1 + z_{JJ}) - z_{JI} z_{IJ}} \\
&= \frac{1 + z_{JJ}}{(1 + z_{II})(1 + z_{JJ}) - z_{JI} z_{IJ}} p_I^0 - \frac{z_{JI}}{(1 + z_{II})(1 + z_{JJ}) - z_{JI} z_{IJ}} p_J^0 \\
p_J^{NE} &= \frac{-c}{2} \frac{1 + z_{II} - z_{IJ}}{(1 + z_{II})(1 + z_{JJ}) - z_{JI} z_{IJ}} \\
&- \delta_J \frac{1 + z_{II}}{(1 + z_{II})(1 + z_{JJ}) - z_{JI} z_{IJ}} + \delta_I \frac{z_{IJ}}{(1 + z_{II})(1 + z_{JJ}) - z_{JI} z_{IJ}} \\
&= \frac{1 + z_{II}}{(1 + z_{II})(1 + z_{JJ}) - z_{JI} z_{IJ}} p_J^0 - \frac{z_{IJ}}{(1 + z_{II})(1 + z_{JJ}) - z_{JI} z_{IJ}} p_I^0,
\end{aligned}$$

where $p_I^0 = -c/2 - \delta_I$ and $p_J^0 = -c/2 - \delta_J$ are the optimal policies in the absence of any spillovers — equation (S20). Assuming further symmetries: $n_I = n_J = n/2$, $z_{II} = z_{JJ} = z_g$, and $z_{IJ} = z_{JI} = z_s$, the Nash equilibrium simplifies as follows:

$$\begin{aligned}
p_I^{NE} &= \frac{-c/2}{1+z_g+z_s} - \frac{1+z_g}{(1+z_g)^2 - z_s^2}\delta_I + \frac{z_s}{(1+z_g)^2 - z_s^2}\delta_J, \\
p_J^{NE} &= \frac{-c/2}{1+z_g+z_s} - \frac{1+z_g}{(1+z_g)^2 - z_s^2}\delta_J + \frac{z_s}{(1+z_g)^2 - z_s^2}\delta_I, \\
U_I^{NE} &= \frac{c^2}{4}\left(\frac{1-z_g-z_s}{1+z_g+z_s}\right) + c\delta_I \frac{1+z_g}{(1+z_g)^2 - z_s^2} - c\delta_J \frac{z_s}{(1+z_g)^2 - z_s^2}, \\
U_J^{NE} &= \frac{c^2}{4}\left(\frac{1-z_g-z_s}{1+z_g+z_s}\right) + c\delta_J \frac{1+z_g}{(1+z_g)^2 - z_s^2} - c\delta_I \frac{z_s}{(1+z_g)^2 - z_s^2}, \\
U_{g,s}^{NE} &= \frac{n}{2}(U_I^{NE} + U_J^{NE}) = n\frac{c^2}{4}\left(\frac{1-z_g-z_s}{1+z_g+z_s}\right) + \frac{nc(\delta_I+\delta_J)/2}{1+z_g+z_s}.
\end{aligned}$$

The social optimum in this case is given by:

$$\begin{aligned}
p_I^{SO} &= \frac{-c/2}{(1+z_g+z_s)^2} - \frac{1+z_g}{(1+z_g)^2 - z_s^2}\delta_I + \frac{z_s}{(1+z_g)^2 - z_s^2}\delta_J, \\
p_J^{SO} &= \frac{-c/2}{(1+z_g+z_s)^2} - \frac{1+z_g}{(1+z_g)^2 - z_s^2}\delta_J + \frac{z_s}{(1+z_g)^2 - z_s^2}\delta_I, \\
U_I^{SO} &= \frac{c^2/4}{(1+z_g+z_s)^2} + c\delta_I \frac{1+z_g}{(1+z_g)^2 - z_s^2} - c\delta_J \frac{z_s}{(1+z_g)^2 - z_s^2}, \\
U_J^{SO} &= \frac{c^2/4}{(1+z_g+z_s)^2} + c\delta_J \frac{1+z_g}{(1+z_g)^2 - z_s^2} - c\delta_I \frac{z_s}{(1+z_g)^2 - z_s^2}, \\
U_{g,s}^{SO} &= \frac{n}{2}(U_I^{SO} + U_J^{SO}) = n\frac{c^2}{4}\frac{1}{(1+z_g+z_s)^2} + \frac{nc(\delta_I+\delta_J)/2}{1+z_g+z_s}
\end{aligned}$$

The loss from anarchy in this case is given by:

$$\nabla_{z_g,z_s}^{(n)} := U_{g,s}^{SO} - U_{g,s}^{NE} = n\frac{c^2}{4}\left(\frac{z_g+z_s}{1+z_g+z_s}\right)^2, \tag{S62}$$

which is the same as $\nabla_{z'}^{(n)}$ in (S60) with $z' = z_g + z_s$.

S6.3.1 Model Calibration

Figure 4 in the main text reports the equilibrium policy choices p, resulting change in mobility $\hat{r} - \bar{r}$, and utility U for a pair of states with similar but not identical target mobility reduction targets $\delta_1 = 1.05$ and $\delta_2 = .95$. The pair of states have symmetrical spillovers z plotted on the horizontal in both panels. The cost of mobility reduction policies c is set to 1 in panel A, and is plotted on the vertical axis.

But what is a realistic value for z, and what can that value tell us about how large the price of anarchy will be? Figure S38 plots a CDF of the spillover sizes for states in the US. The plot is restricted to 51 state pairs: for each state only the spillovers from their most influential outside state is plotted. Spillovers, z, in this figure are calculated to be compatible with the parameter of the model. They are defined as the ratio "Total change in alter state's social distancing due to ego state implementing shelter-in-place/Total change in ego state's social distancing due to ego state implementing shelter-in-place." We transform the spillover sizes for state pairs in Figure S38, under the asymptotic ($c \to \infty$) PoA equation in (S48), to obtain the cumulative distribution of PoAs, plotted in Figure S40. The minimum, median, mean, and maximum values are reported in Tables S11.

Table S11: Spillover sizes and PoAs for state pairs

	minimum	median	mean	maximum
z	0.220	0.421	0.446	0.834
PoA	1.051	1.215	1.248	3.285

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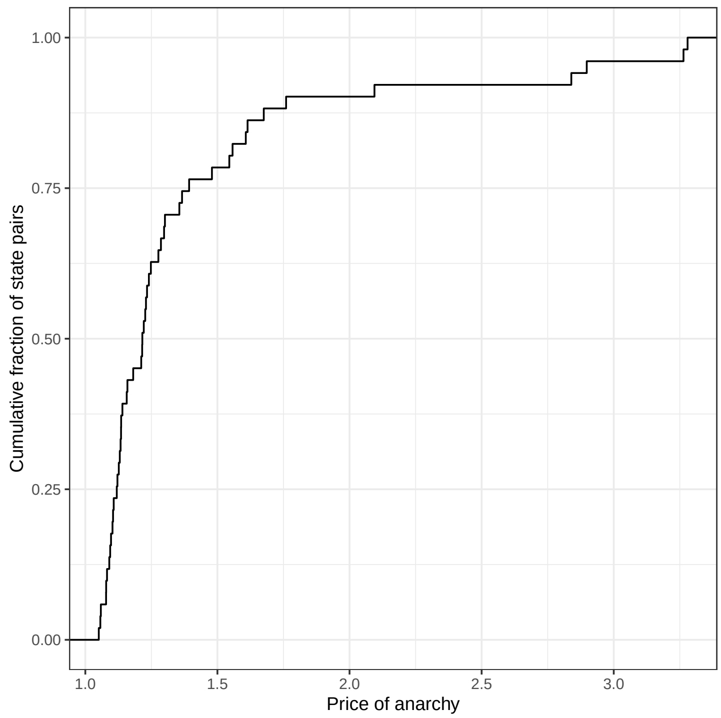

Figure S40: The CDF of spillover sizes (z) in Figure S38 transformed using the asymptotic PoA equation in (S48), $PoA(z) = 1/(1 - z^2)$.

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