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The spread of social distancing

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1. Introduction

In response to the COVID-19 pandemic, stay-at-home orders (SAHs) restricted non-essential activities to reduce the spread of the virus. Without a clear federal mandate, states (and counties within some states) have decided when to implement and lift these SAHs. If there are spillovers between neighboring counties, implementing SAHs in the counties that neighbor a hard-hit county would be beneficial. While many states have joined multi-state agreements, e.g., Western States Pact, to coordinate policies, there has been heterogeneity in when SAHs are lifted and implemented.

We analyze multiple datasets constructed from cellphone location data and find that social distancing is affected by the policies of neighboring counties. People may infer that there is less risk in an area from the policies of neighboring counties or the actions of residents in neighboring counties. A mechanical explanation is also possible, i.e., residents of one county travel to a neighboring county to engage in activities. We find that both policies and social distancing in neighboring counties have an effect. Regarding the mechanical explanation, we find that the effect of policies in neighboring counties is greater when the neighboring counties are smaller.

Our results control for county-level factors that could affect social distancing, including confirmed COVID cases and deaths. It is important to control for the number of confirmed COVID cases, as the risks related to moving about a region depend on the number of infected individuals in that area. We also include other policies affecting the county (e.g., closure of non-essential businesses and declarations of states of emergency). It is important to control for other policies because governors of some states (e.g., Iowa) have claimed that closures of non-essential businesses and schools have had an impact similar to a SAH. All of our specifications also include county fixed effects to control for time-invariant county characteristics (e.g., demographics, geography, and beliefs) and date fixed effects to control for country-wide news (e.g., issuance of the President’s coronavirus guidelines).

We contribute to the literature on regulatory spillovers across jurisdictions. There is extensive literature on these spillovers, especially in environmental and criminal settings (for example, Siggman (2002) and Bronars and Lott (1998)). The presence of these spillovers often implies that there would be benefits from centralized policymaking (Fell and Kaffine, 2014).

Our paper also contributes to the growing literature about social distancing during the pandemic. SAHs have been effective at increasing social distancing (see, for example, Painter and Qiu).
The dependent variable is the percent of county residents (excluding those who go to work) that stay home the entire day. All regressions include county and date fixed effects. Controls for other county policies include closures of non-essential businesses, dine-in restaurants, and schools and declarations of states of emergency.

| (i) | (ii) | (iii) | (iv) |
|-----|-----|-----|-----|
| Own SAH | 1.328* | .900* | 1.052* | .687* |
| Neighbor SAH | 552* | .482* | .552* | .482* |
| Log of COVID cases | .787* | .785* | .776* | .774* |
| Log of COVID deaths | .228* | .226* | .225* | .224* |
| Log of precipitation | .794* | .794* | .792* | .792* |
| Min temperature | .059* | .060* | .060* | .060* |
| Max temperature | −.118* | −.118* | −.117* | −.117* |
| Control for other county policies | No | No | Yes | Yes |
| Observations | 312,494 | 312,494 | 312,494 | 312,494 |

*Denotes significance at the .01 level.

We use multiple measures of social distancing that are based on geolocation data from SafeGraph and Google COVID-19 Community Mobility Reports. Data from both SafeGraph and Google are constructed from anonymized mobile devices’ location data. From the SafeGraph data we calculate the percent of mobile devices belonging to people that are not going to work (so that we exclude essential workers) that stayed at home that day. This measure has been used in other work (see, for example, Allcott et al. (2020)). Our results based on the data from Google are provided in an online appendix.

### 3. Estimation and results

For each county in our dataset, we identify the counties it borders and whether those neighboring counties have implemented or relaxed a SAH at any time. We regress our social distancing measure for county \( c \) at time \( t \) on SAHs in that county and neighboring counties and a host of controls:

\[
\text{(Staying at home)}_{c,t} = \beta \text{(Neighbor SAH)}_{t} + \delta \text{(Own SAH)}_{c,t} + \phi \text{(controls)}_{c,t} + \alpha_t + \gamma_c + \epsilon_{c,t}, \tag{1}
\]

where “Neighbor SAH” is an indicator for an active SAH in a county that borders county \( c \) (i.e., it only takes a value of one for periods in which the SAH is in effect) and “Own SAH” refers to county \( c \)’s own policy. Qualitatively similar results are obtained if we use the portion of \( c \)’s neighbors with an active order instead of an indicator for whether any neighbor has a SAH (as shown in the online appendix). We include date fixed effects to control for federal announcements about the virus and county fixed effects to control for demographics, geographical differences, and county-level perceptions of the risk posed by the virus (which may be partisan driven as shown by Barrios and Hochberg (2020) and Allcott et al. (2020)). We also control for the perceived prevalence of the virus in the county (log of one plus the number of confirmed COVID cases), the severity (log of one plus the number of confirmed COVID deaths), and weather. In addition, we control for policies that affect the county–closures of non-essential businesses and schools, bans of dine-in restaurants and bars, and declarations of states of emergencies. We cluster standard errors at the county level.

Our results are presented in Table 1. The effect of a neighbor implementing a SAH is roughly half the magnitude as the county’s own order. The decrease in the effect of “Own SAH” once “Neighbor SAH” is included (i.e., 1.328 to .900 and 1.052 to .687) is about 50%. For the average county, which has a population of about 99,000, the difference between an effect of 1.328 and .900 is about an additional 400 people leaving home each day. To put this into...
perspective, the effect of "Own SAH" of .887 would mean, for the average county, an increase of about 680 people staying at home each day.

Also in our appendix, we provide the coefficients on all control variables and the results from other specifications. We show that similar results are obtained if workers are not excluded from staying home variable. We also show that the effects of implementing and easing SAHs are similar. To explore the possible heterogeneity of the effects, we provide results that include interactions of county characteristics with SAHs. One takeaway if that the effect of a neighbor SAH is greater for geographically smaller counties, which would be the case if residents of one county travel to another for activities.

Lastly, we want to understand whether the behavioral changes that are observed by the policies of neighboring counties, the actions of residents in neighboring counties, or both. We estimate the following spatial autoregressive model:

\[
\begin{align*}
\text{(Staying at home)}_{i,t} &= \lambda \ W_i \text{(staying at home)}_{i,t} \\
&+ \beta \text{ (Neighbor SAH)}_{i,t} \\
&+ \delta \text{ (Own SAH)}_{i,t} + \phi \text{ (controls)}_{i,t} \\
&+ \alpha_t + \gamma_c + \epsilon_{i,t},
\end{align*}
\]

where \( W_i \) is a row vector weights and \( \text{(staying at home)}_{i,t} \) is a column vector of social distancing in all counties at time \( t \). We define \( W_i \) as taking a value of zero for non-neighboring counties and equal weights for neighboring counties. The parameter \( \lambda \) indicates the degree to which social distancing in a county is affected by behavior in neighboring counties. In Table 2, we see that both \( \lambda \) and the coefficients on neighbor's SAH are significant, indicating that both policies and the actions of neighbors affect beliefs about the risks of the virus. To interpret the magnitude of \( \lambda \), if the average portion of neighboring counties that stayed at home increase by one standard deviation (.85), staying at home in that county would change by .68. This is comparable to the effect of a SAH in county found in column (iv) of Table 1.

4. Conclusion

We find an impact of both social distancing in neighboring counties as well as orders in neighboring counties. Implementing SAHs in counties that neighbor high-risk areas could further increase social distancing in the high-risk areas. Coordination at the regional or federal level could improve compliance with SAHs. We have also seen that failure to control for policies in neighboring counties can cause the efficacy of SAHs to be overstated. For our main specification, we see that the effect of SAHs is overstated by 50%. For the spatial autoregressive model, which controls for social distancing in neighboring counties, this overstatement is reduced.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2020.109511.

References

Alcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M., Yang, B.Y., 2020. Polarization and Public Health: Partisan Differences in Social Distancing During the Coronavirus Pandemic. Working paper.

Barrios, J.M., Hochberg, Y., 2020. Risk Perception Through the Lens of Politics in the Time of the Covid-19 Pandemic. Working paper.

Bronsars, S.G., Lott, J.R., 1998. Criminal deterrence, geographic spillovers, and the right to carry concealed handguns. Amer. Econ. Rev. 88 (2), 475–479.

Bursztyn, L., Rao, A., Roth, C., Yanagizawa-Drott, D., 2020. Misinformation During a Pandemic. Working paper.

Dave, D.M., Friedson, A.J., Matsuoka, K., Sabia, J.J., 2020. When Do Shelter-In-Place Orders Fight Covid-19 Best? Policy Heterogeneity Across States and Adoption Time. Working paper.

Fell, H., Kaffine, D.T., 2014. Can decentralized planning really achieve first-best in the presence of environmental spillovers?. J. Environ. Econ. Manag. 68 (1), 46–53.

Holtz, D., Zhao, M., Benzell, S.G., Cao, C.Y., Rahimian, M.A., Yang, J., Jennifer Allen and, A.C., Moehring, A., Sowirjana, T., Ghosh, D., Zhang, Y., Dhillon, P.S., Nicolaides, C., Eckles, D., Aral, S., 2020. Interdependence and the Cost of Uncoordinated Responses to COVID-19. Working paper.

Painter, M., Qiu, T., 2020. Political Beliefs Affect Compliance with Covid-19 Social Distancing Orders. Working paper.

Sigman, H., 2002. International spillovers and water quality in rivers: Do countries free ride?. Amer. Econ. Rev. 92 (4), 1152–1159.

Wellenius, G.A., Vispute, S., Espinosa, V., Fabrikant, A., Tsai, T.C., Hennessy, J., Williams, B., Gadepakal, K., Boulange, A., Pearce, A., et al., 2020. Impacts of State-Level Policies on Social Distancing in the United States Using Aggregated Mobility Data During the COVID-19 Pandemic. Working paper.