Poverty and Economic Dislocation Reduces Compliance with COVID-19 Shelter-in-Place Protocols

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Abstract

Shelter-in-place policies reduce social contact and mitigate the spread of COVID-19. Inconsistent compliance with social distancing creates local and regional interpersonal transmission risks. Using county-day measures on population movement derived from cellphone location data, we investigate whether compliance with local shelter-in-place ordinances varies across counties differentially exposed to the US trade war. In communities more exposed to retaliatory tariffs, compliance is significantly lower. Measures of local income and partisanship are also strongly predictive of compliance. Findings suggest targeted economic relief and non-partisan messaging could improve future compliance.

Introduction Shelter-in-place policies reduce social contact and risks of interpersonal COVID-19 transmission (Hsiang et al., 2020; Viner et al., 2020; Anderson et al., 2020; Bai et al., 2020; Matrajt and Leung, N.d.). Though the economic consequences of these policies are substantial (Stapleton, 2020; Baker et al., 2020; Gormsen and Koijen, 2020), local non-compliance creates public health risks and may cause regional spread (Lewnard and Lo, 2020; Chen et al., 2020). Understanding which dynamics enhance or mitigate compliance is a first order public policy concern (Briscese et al., 2020). We model how economic dislocation and variation in regional income impact compliance (Autor, Dorn and Hanson, 2016). We anticipate lower compliance rates in counties exposed to economic dislocation due to the US trade war. Retaliatory tariffs have significantly impacted wages in targeted counties (Fajgelbaum et al., 2020). Income may offset these shocks. Partisanship may also play a role (Painter and Qiu, 2020; Barrios and Hochberg, 2020). We study these dynamics using novel data on population movement, local policy reforms, and variation in economic dislocation and voting patterns. We also present an assessment of the role of slanted media in shaping local compliance (Martin and Yurukoglu, 2017). Clarifying these mechanisms provides actionable insights for policy makers and public health officials responding to the COVID-19 pandemic.

Study Setting and Movement Data We study changes in population movement ("social distancing") after the onset of local shelter-in-place ordinances in the United States. Cellphone location data enables us to quantify population movement within and across origin counties by day. Patterns of cellphone use vary across counties. To standardize measures of population movement, all data is compared to a local day-of-week base rate calculated using data prior to the onset of COVID-19 in the United States (March 8). The outcome of interest is county-day variation in standardized population movement. This is illustrated in Figure 1 Panel A. Where individuals comply with local shelter-in-place laws, we observe a reduction in intersecting sets (less distance traveled on average). Although population movement has declined by approximately 25% (national average) between March 8 and April 1, there is high variance in movement (Figure 1 Panel B). This suggests variation in compliance with government ordinances. The secondary quantity of interest is how compliance varies across fixed county characteristics (economic dislocation, income, partisan identification).

Theory We developed a theoretical model (presented in Supporting Information) to clarify the observable implications of economic dislocation and income on compliance with shelter-in-place ordinances. Economic impacts of the ongoing US trade war are substantial and exposure is uneven (Fajgelbaum et al., 2020). The median county is exposed to a 3% increase in share-weighted tariff rates on exports, but at the 75^{th} percentile the rate increase is 7.37% or greater. We predict that negative trade shocks should heighten economic insecurity among exposed counties and reduce compliance with government social distancing policies. Economic dislocation due to the trade war interacts with two other mechanisms: local income and political partisanship (Painter and Qiu, 2020; Barrios and Hochberg, 2020). Local income and trade-induced shocks have similar implications with respect to the theoretical mechanism, though each may have a separate impact on compliance (either intensifying or offsetting). Consistent with prior work, we anticipate local support for Trump in 2016 will reduce compliance with shelter-in-place policies, though unpacking the mechanism will require additional research. Trump supporters are more skeptical of mainstream media and federal government policies in general (Iyengar et al., 2019), and early statements by Trump dismissed or deflected the COVID-19 threat (Figure SI-2).

Research Design We employ a difference-in-difference design to estimate the impact of the shelter-in-place ordinances on population movement. Introduction of social distancing policies was staggered across states in time (Figure 2 Panel A). 125 counties adopted policies prior to state-wide mandates. We leverage this data to examine how localized population movement changes after the introduction of a county-level policy (either via county- or state-wide mandates). The research design controls for county-specific factors that do not change over time (county fixed effects) and country-wide dynamics that are common across counties (day fixed effects). These factors include population density, industrial sector shares, and federal mandates. The difference-in-differences provides a causal estimate of effectiveness of the shelter-in-place policies so long as trends in the outcome of interest in untreated counties represent a valid counterfactual for treated counties (Donald and Lang, 2007).

We assess the plausibility of this identifying assumption using an event study design with leads and lags of the policy change. We introduce these results in Figure 2 Panel B. Notice that the effect of shelter-in-place policies is statistically indistinguishable from zero prior to the onset of local mandates (green line). Population movement significantly declines after the first full day of shelter-in-place ($\widehat{\beta_{t+1}} = -.054, p = 0.016$) and remains stable in subsequent days. This provides baseline support for a causal interpretation of our statistical estimates. To further increase the robustness of our difference-in-differences design, we account for county-specific, time-varying factors in the main specification (cumulative COVID-19 cases; cumulative deaths; related policy changes: school closures, bans on social gathering, restrictions on eviction notices, utility cutoffs). We calculate heteroskedasticity-robust standard errors, clustered by state.

Results Figure 2 Panel C presents four main results. First, on average, we find a significant decline in population movement after the local shelter-in-place policies were enacted ($\widehat{\beta}_{s-i-p} = -.035, p = 0.001$). Second, a one standard deviation increase in local income enhances the baseline policy impact by 65% ($\widehat{\beta}_{income} = -.023, p = 0.001$). Third, a one standard deviation increase in tariff-induced economic dislocation significantly reduces compliance by approximately one-third ($\widehat{\beta}_{tariffs} = .01, p = 0.039$). Fourth, a one standard deviation increase in Trump vote share in 2016 reduces compliance by 74% ($\widehat{\beta}_{trump} = .027, p = 0.001$). These core results are highly stable when we allow additional confounding factors to vary with the onset of shelter-in-place. Exposure to retaliatory trade shocks might be correlated with trade-induced import tariffs (trade inflows), variation in industrial sector shares in agriculture and manufacturing, and variation in the intensity of unemployment during the last presidential election cycle. Population density might explain variation in movement and compliance. Partisan media consumption might also influence compliance. We allow the effect of these measures to change with the onset of local social distancing measures and sequentially add them to a fully saturated model. These results are presented in Figure 2 Panel C as additional coefficient estimates. The results are statistically indistinguishable when we compare the benchmark and fully saturated models.

Figure 3 Panels A/C/E present supplement the event study designs by separately estimating the leads and lags splitting each dynamic at the median. These results illustrate two key insights. First, we find no systematic evidence that population movement statistically differs across samples prior to the onset local shelter-in-place policies. This is additional evidence that the 'common trends' assumption is valid with respect to the marginal effects in Figure 2 Panel C (income; economic dislocation; voting patterns). Second, we observe stark divergence in compliance across populations in each category. Population movement in counties above the median in income decreases sharply the day after policies go into effect ($\widehat{\beta}_{t+1}^{above\_income} = -.084, p = 0.004$), but the population movement below the median remains unaffected ($\widehat{\beta}_{t+1}^{below\_income} = -.002, p = 0.950$). Movement also declines sharply in counties below the median of retaliatory trade exposure and Trump vote share ($\widehat{\beta}_{t+1}^{below\_trade} = -.066, p = 0.007$; $\widehat{\beta}_{t+1}^{below\_trump} = -.07, p = 0.01$), while movement is unaffected in counties above the median in both categories ($\widehat{\beta}_{t+1}^{above\_trade} = -.029, p = 0.261$; $\widehat{\beta}_{t+1}^{above\_trump} = -.007, p = 0.764$). Figure 3 Panels B/D/F map variation in these measures by county. Variation in income, economic dislocation, and voting patterns suggest interpersonal transmission risk in some regions is geographically concentrated (midwestern states) and diffuse in others (southeastern states).

The theoretical model highlights the potential role of slanted media in influencing public compliance with shelter-in-place protocols. In Figure 2, we control for the time-varying effects of exposure to Fox station broadcasts operated by the Sinclair Broadcast Group. In Figure SI-1, we replicate the event study design in Figure 3 and find that compliance is significantly lower in counties with exposure to one of these stations. Future assessments might leverage more precise information about the geographical spread of disinformation and rumors.

Conclusion Shelter-in-place policies effectively reduce population movement overall and slow the spread of COVID-19 by reducing interpersonal transmission risks. Compliance with shelter-in-place directives is individually costly and requires behavioral changes across diverse subpopulations (Levi, 1997). Variation in compliance, however, represents a local and regional risk to public health. Local income, economic dislocation from the US trade war, and voting patterns in the 2016 presidential each impact behavioral change. Targeted economic aid and consistent non-partisan messaging about COVID-19 may enhance the effectiveness of local shelter-in-place policies.

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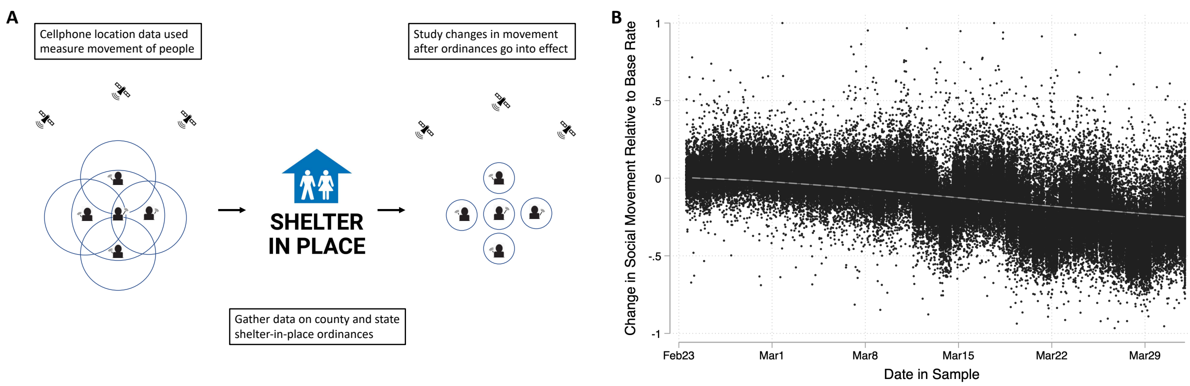

Figure 1: Design for quantifying and studying localized population movement using cellphone data

Panel (A): Cellphone location data is gathered passively and used to measure population movement by origin county and day. Intersecting circles indicate social proximity. Data is gathered on timing of shelter-in-place ordinances. Study assesses change in travel patterns which indicate social distancing (reduced social contact). Panel (B): Variation in cellphone-derived movement data over study period (February 23 to April 1, 2020). Base rate for daily movement after March 8 (onset of COVID-19 in United States) is history of day-of-week movement data collected in prior periods. Local polynomial regression indicates 25% decline (national average) in movement during study period.

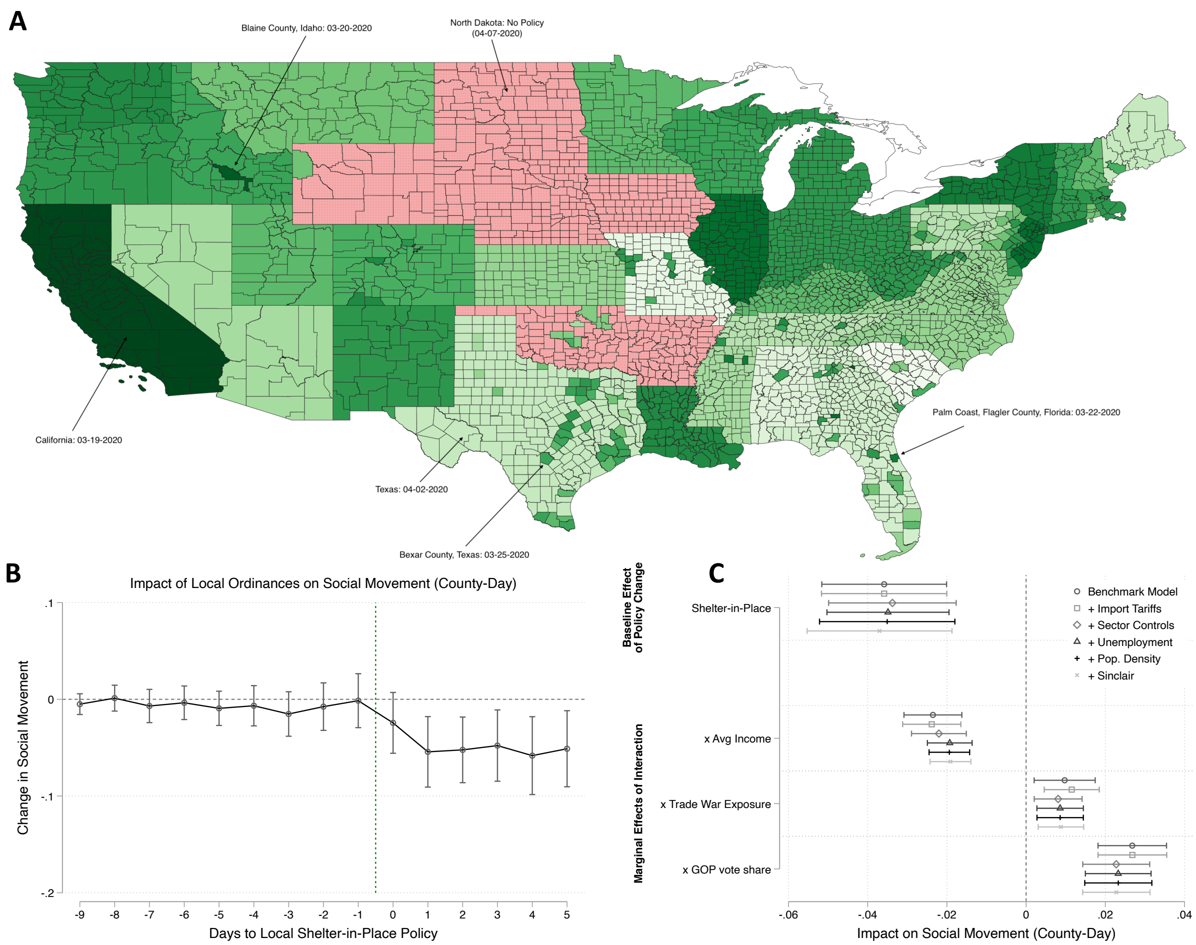

Figure 2: Staggered introduction of shelter-in-place ordinances and localized impact on population movement

Panel (A): Map of staggered introduction of shelter-in-place policies across the United States. Darker shades of green indicate earlier policy dates, beginning on March 19 (California). Localized policies were adopted in 125 counties. Data on state-level policies corrected for additional policies up until April 7. Data on county-level policies is from Painter and Qiu (2020). Additional details in Supporting Information. Panel (B): Event study design using leads and lags of policy change to assess pre-treatment and post-treatment changes in population movement. No evidence of anticipation effects. Substantive and stable declines in movement estimated after the first full day of shelter-in-place. 90% confidence intervals reported using heteroskedasticity robust standard errors clustered by state. Panel (C): Difference-in-differences results for estimated impact of shelter-in-place. Baseline effect of policy plot in upper left. Heterogeneous (marginal) effects plotted below ($\times$ average county income (2016); $\times$ exposure to retaliatory export tariffs; $\times$ Trump vote share in 2016 election). Additional coefficient plots represent sequential regression models with additional control variables ($\times$ import tariffs; $\times$ industrial sector shares; $\times$ unemployment; $\times$ population density; $\times$ exposure to Sinclair Fox station). See Fajgelbaum et al. (2020) for details on trade exposure measures.

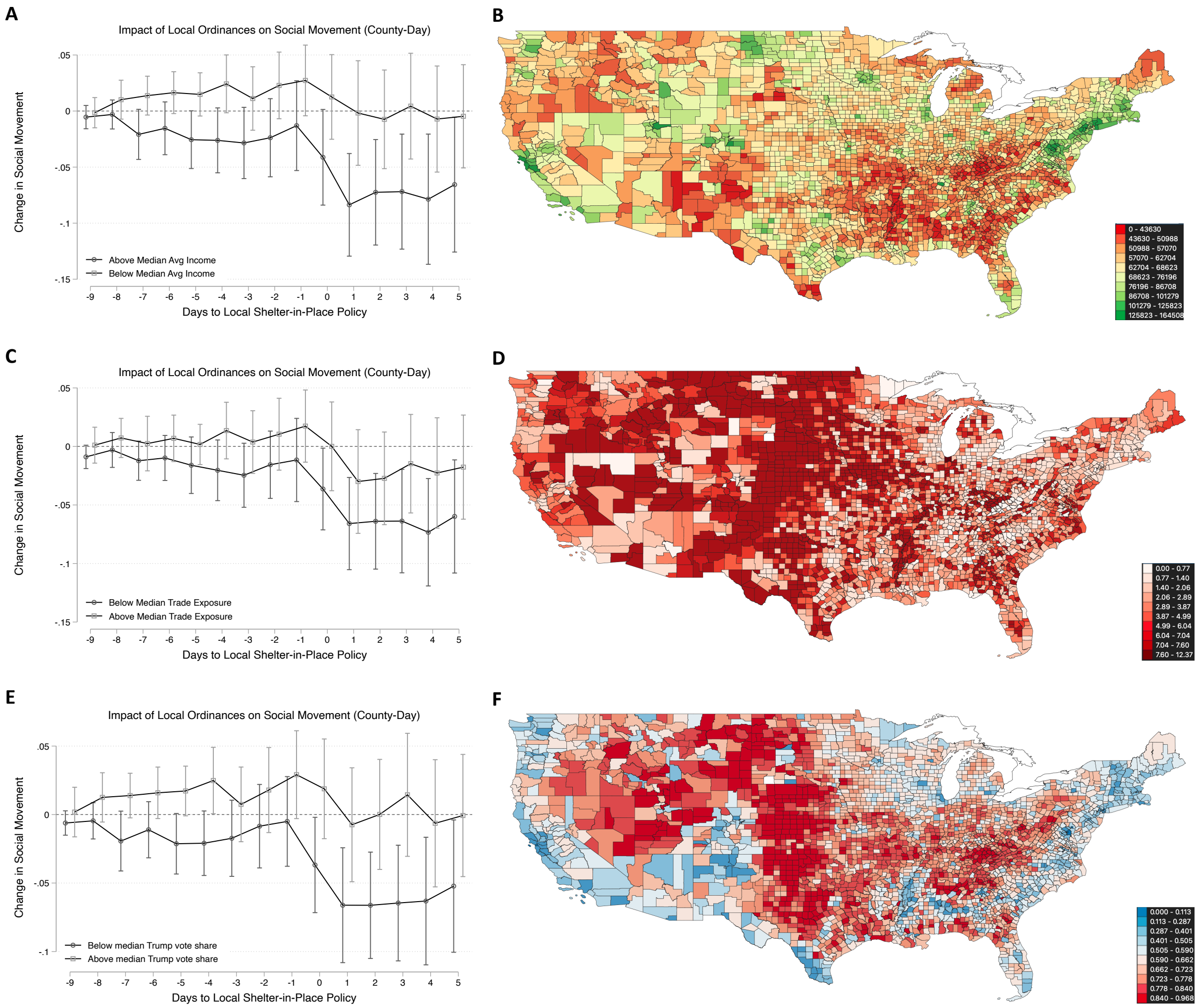

Figure 3: Event study designs indicate varying compliance

Panel (A): Event study design using leads and lags of policy change in above versus below the median level of income by county. Event study results suggest large reduction population movement in above median counties; no change in below median counties. 90% confidence intervals reported using heteroskedasticity robust standard errors clustered by state. Panel (B): Map of varying income levels by county (2016). Legend in lower right corner. Panel (C): Event study design using leads and lags of policy change in above versus below the median level of exposure to retaliatory tariffs from US trade war. Event study results suggest large reduction in population movement in below median counties (less trade exposure); no statistically significant changes in above median counties (more economic dislocation). Panel (D): Map of retaliatory tariff exposure by county. Legend in lower right corner. Panel (E): Event study design using leads and lags of policy change in above versus below the median GOP vote share in 2016 presidential election (Trump). Event study results suggest large reduction in population movement in below median counties (fewer votes cast for Trump); no statistically significant changes in above median counties (more Trump votes). Panel (F): Map of Trump vote share by county. Legend in lower right corner.

Supporting Information

Theoretical Model

Our basic model considers an environment, in which the "shelter-in-place" ordinance is issued, and agents decide whether to comply with these orders or not. Agents have heterogeneous wealth and receive information about the probability to get infected if they do not comply. The information is provided by a media that might have a bias over the importance of compliance.

Setup

Consider a continuum of agents who have a wealth endowment of w_i; for each agent $i \in [0, 1]$, w_i is obtained from distribution $F(\cdot)$ over $[\underline{w}, \overline{w}]$, $\overline{w} > \underline{w} > 0$. The only decision that each agent makes is whether or not to comply with the "shelter in place" ordinance. If agent i complies, she consumes her endowment, $c_i \leq w_i$. If she does not comply, she gets an additional income r, in which case $c_i \leq w_i + r$, yet risks getting coronavirus.[1] We assume that r incorporates, in addition to benefits of noncompliance, the expected costs, e.g., fines. The utility function of agent i is quasilinear: $u_i = \ln c_i - pH$, where p is the probability to get the disease, and $H > 0$ is the expected health damage to the infected person.

Each agent i has to make a decision, $a_i \in \{C, G\}$, for "comply" and "go". Agents' optimal decisions about compliance depends on their assessment of risk probabilities. There are two possible states of the world, $s \in \{D, N\}$, for "danger" and "no danger"; the *ex ante* probabilities are $P(D) = \theta$ and $P(N) = 1 - \theta$. Agent i's utility depends on both the action and the state of

[1] Of course, in the simple case, in which the only decision that agents make is whether not to shelter, the constraint is trivially binding in equilibrium. Still, writing it down as an inequality is natural as the model extends to a dynamic overlapping-generations model with $u_i = \ln c_{i0} + \beta \ln c_{i1}$.

the world as follows.

$$\begin{aligned} \ln w_i \text{ if } a_i &= C, \\ \ln(w_i + r) - H \text{ if } a_i &= G,\ s = D, \\ \ln(w_i + r) \text{ if } a_i &= G,\ s = N. \end{aligned}$$

Before making the decision, agents get additional information from a media outlet, which operates as follows. The media outlet receives a signal $\omega \in [0,1]$, which is conditional on the true state of the world, and is committed to report a recommendation $\widehat{s} \in \left\{\widehat{C}, \widehat{G}\right\}$ for "comply" and "go".[2] If $s = D$, then signal ω is drawn with c.d.f. $F_D(x) = x^2$; if $s = N$, then ω is drawn with c.d.f. $F_N(x) = 2x - x^2$. The media outlet sets a media policy *ex ante* $m \in [0,1]$ and reports $\widehat{s} = \widehat{C}$ if $\omega > m$ and $\widehat{s} = \widehat{G}$ otherwise. Thus, a media with low m is putting more emphasis on dangers of the virus, while high m corresponds to the desire to downplay the danger.

Analysis

Suppose that citizen i watched the news with the media threshold m. If the media report is $\widehat{s} = \widehat{C}$, then she infers that the probability to get the virus is

$$\begin{aligned} P(s &= D|\widehat{s} = \widehat{C}) = \frac{P(\widehat{s} = \widehat{C}|s = D)P(D)}{P(\widehat{s} = \widehat{C}|s = D)P(D) + P(\widehat{s} = \widehat{C}|s = N)P(N)} \\ &= \frac{\theta}{\theta + \frac{1-m}{1+m}(1-\theta)}, \end{aligned}$$

which is an increasing function of θ, the *ex ante* probability of danger, and m, the media bias.

Similarly, if the media report is $\widehat{s} = \widehat{G}$,

$$P(s = N|\widehat{s} = \widehat{G}) = \frac{1-\theta}{\frac{m}{2-m}\theta + 1 - \theta}.$$

[2] See Gentzkow and Shapiro (2006, 2008), DellaVigna and Gentzkow (2010) for the basics of this approach to modeling media; Kamenica and Gentzkow (2011) provides the theoretical foundation.

Now, when agent i chooses C over G when the media signal is $\widehat{s}=D$? The condition is

$$Eu_i\left(C|\widehat{s}=\widehat{C}\right)\geq Eu_i\left(G|\widehat{s}=\widehat{C}\right).$$

Start with the utility of complaince with orders when the signal is $\widehat{s}=\widehat{C}$:

$$Eu_i\left(C|\widehat{s}=\widehat{C}\right)=P(s=D|\widehat{s}=\widehat{C})\ln w_i+P(s=N|\widehat{s}=\widehat{C})\ln w_i=\ln w_i.$$

Now, the expected utility of non-compliance is

$$\begin{aligned}
& Eu_i\left(G|\widehat{s}=\widehat{C}\right) \\
= \; & P(s=D|\widehat{s}=\widehat{C})\left(\ln(w_i+r)-H\right)+P(s=N|\widehat{s}=\widehat{C})\ln\left(w_i+r\right) \\
= \; & \ln\left(w_i+r\right)-\frac{\theta}{\theta+\frac{1-m}{1+m}\left(1-\theta\right)}H.
\end{aligned}$$

Now let $w^*\left(\widehat{C}\right)$ be a solution of the following equation.

$$\ln w=\ln\left(w+r\right)-\frac{\theta}{\theta+\frac{1-m}{1+m}\left(1-\theta\right)}H.$$

Since $\ln\left(w+r\right)-\ln w$ is a decreasing function of w, there exists at most one such solution; the appropriate choice of $\underline{w}$ guarantees the existence of a solution. $w^*\left(\widehat{C}\right)$ is the critical threshold: agents with less wealth than $w^*\left(\widehat{C}\right)$ do not comply, while those with the wealth exceeding $w^*\left(\widehat{C}\right)$ shelter in place.

The threshold $w^*\left(\widehat{C}\right)$ depends on the parameters of the model. When the expected damage to the infected person, H, goes up, the threshold $w^*\left(\widehat{C}\right)$ goes down, i.e., more people comply with the ordinances. What happens if the *ex ante* probability of danger, θ, increases? Naturally, the threshold $w^*\left(\widehat{C}\right)$ goes down, i.e., more people than before shelter-in-place, complying with the ordinances. When m, the media bias towards non-compliance, increases, the threshold goes down as well. Indeed, the fact that the media that downplays danger recommends sheltering in place, is a stronger signal than that of the media with a lower threshold m.

In addition to results about individual decisions as a function of wealth and income, one can do comparative statics with respect to the wealth distribution. For example, suppose that county 1 is wealthier than county 2. Mathematically, this corresponds to the distribution of wealth with c.d.f. $F_1(\cdot)$ first-order stochastically dominating the distribution with c.d.f. $F_2(\cdot)$: for any w, $F_1(w) \leq F_2(w)$ (Mas-Colell, Whinston and Green, 1995). As the threshold $w^*\left(\widehat{C}\right)$ is independent of the wealth distribution, there is a larger share of agents sheltering in place in county 1.

What happens when the media report is $\widehat{s} = \widehat{G}$? When $Eu_i\left(G|\widehat{s} = \widehat{G}\right) \geq Eu_i\left(C|\widehat{s} = \widehat{G}\right)$?

$$\begin{aligned}
Eu_i\left(G|\widehat{s} = \widehat{G}\right) &= P(s = N|\widehat{s} = \widehat{G}) \ln(w_i + r) + \left(1 - P(s = N|\widehat{s} = \widehat{G})\right)(\ln(w_i + r) - H) \\
&= \ln(w_i + r) - \frac{\frac{m}{2-m}\theta}{\frac{m}{2-m}\theta + 1 - \theta} H. \\
Eu_i\left(C|\widehat{s} = \widehat{G}\right) &= \ln w_i.
\end{aligned}$$

It remains to introduce the new threshold $w^*\left(\widehat{G}\right)$ that separates compliers and non-compliers when the media announcement is $\widehat{G}$. Again, agents with wealth below $w^*\left(\widehat{G}\right)$ do not shelter in place, and those with wealth above the threshold comply. The comparative statics is similar to the previous case. It is a straightforward exercise to show that $w^*\left(\widehat{G}\right) > w^*\left(\widehat{C}\right)$, i.e., more people shelter in place when the report recommends to shelter ($\widehat{C}$), then when the report recommends not to ($\widehat{G}$).

Finally, how does the media bias, m, affect the behavior? When the state is $s = D$, the media report is $\widehat{C}$ with probability $P(\widehat{s} = \widehat{C}|s = D) = 1 - m^2$ and $\int_{w^*(\widehat{C})}^{\overline{w}} dF$ people shelter in place. With probability m^2, $\int_{w^*(\widehat{G})}^{\overline{w}} dF$ people do. To make the calculus tractable, let us assume that F is a uniform distribution over $[\underline{w}, \overline{w}]$. Then the expected number of non-compliers is as follows.

$$En(m|s = D) = \left(1 - m^2\right) \frac{1}{\overline{w} - \underline{w}} \left(w^*\left(\widehat{C}\right) - \underline{w}\right) + m^2 \frac{1}{\overline{w} - \underline{w}} \left(w^*\left(\widehat{G}\right) - \underline{w}\right).$$

To conclude that $En(m)$ is monotonically decreasing with m, observe that both $w^*\left(\widehat{C}\right)$ and $w^*\left(\widehat{G}\right)$ are monotonically increasing with m, and $w^*\left(\widehat{C}\right) < w^*\left(\widehat{G}\right)$ for any m.

Proposition 1 summarizes the above discussion.

Proposition 1 *(i) There exist two thresholds,* $w^*\left(\widehat{C}\right)$ *and* $w^*\left(\widehat{G}\right)$, *such that any agent* i *with* $w_i > w^*(x)$ *shelters in place,* $a_i = C$, *upon receiving signal* $x \in \left\{\widehat{C}, \widehat{G}\right\}$ *while every agent* i *with* $w_i < w^*(x)$ *does not comply (*$a_i = G$*). More people comply when the media report is* $\widehat{C}$, *i.e.,* $w^*\left(\widehat{C}\right) < w^*\left(\widehat{G}\right)$.

(ii) If county 1 *is wealthier than county* 2, *i.e., distribution of wealth* $F_1(\cdot)$ *first-order stochastically dominates distribution* $F_2(\cdot)$, *then there is a larger share of sheltering in place in county* 1.

(iii) The lower is the agent's ex ante belief that there is no danger (the lower is θ*), the higher are both thresholds* $w^*(x)$, $x \in \left\{\widehat{C}, \widehat{G}\right\}$, *i.e., less people shelter in place.*

(iv) Suppose, additionally, that the distribution $F(\cdot)$ *is uniform. Then the expected number of non-compliers increases in media bias towards minimizing the threat,* m.

Remarks

Although our model is concerned with the distribution of wealth, rather than income, the qualitative results would be the same. Also, it is straightforward to incorporate people's ability to borrow against their endowment.

Our model does not differentiate agents by their ability to generate income by non-complying. This might look unrealistic, as there is a high correlation between wealth and earning capacity. However, what matters for the decision to be non-complaint is the relative marginal income due to non-compliance which need not to be correlated with wealth.

Our model abstracts away from many non-economic reasons for non-compliance.

In our basic model, the media is not strategic. However, it is straightforward to extend the model to the case in which the bias m is determined endogenously, e.g., Gehlbach and Sonin (2014). The same model can be used to incorporate strategic censorship by the government.

Perhaps the most significant drawback of our very basic model is that the *ex ante* probability of the environment being dangerous to an individual, θ, is independent of the share of people who decide, in equilibrium, to maintain social distancing and shelter-in-place. However, at the cost of more algebra, this can be incorporated in the model. That would require a new definition of equilibrium that will include the share of people who do not comply, then probability θ being a function of the expected share of non-compliers. By the Brouwer's fixed point theorem, there will be such θ that will be both a function of the equilibrium share of non-compliers and result in every agent satisfying her incentive compatibility constraints.

Material and Methods

Data We study the impact of local shelter-in-place policies on population movement. Supplemental analyses clarify variation (heterogeneity) in compliance with these orders. We outline the sources of each component of our data below.

- **Population movement** We rely on a measure of population movement derived from cellphone location data. Location pings via Global Positioning System (GPS) capabilities of smartphones enable data processing firms to trace population movement across space from an origin site ('home'). Data used in our analysis was shared by UNACAST and is accessible for academic research upon request (https://bit.ly/2RoEN4w). To standardize the scale of movement across counties, the data provider deseasonalizes variation after the onset of COVID-19 in the United States (March 8) using county-specific day-of-week trends from the period before (March 7 and before). Reductions in movement correspond to social distancing and, on average, reduced interpersonal mechanisms for viral transmission.

- **County-specific and state-wide policies** We study state-wide data compiled by Julia Raifman and collaborators. The data are available for download here: https://bit.ly/34p4Duk. The source files are available for review here: https://bit.ly/2Rs1vsg. This data includes information about the onset of shelter-in-place policies, bans on social interaction in group settings (restaurants, movies, gymnasiums), and school closures. We make several updates to the data, noting the dates of policy changes in Connecticut, Kentucky, South Carolina, Tennessee, and Texas. County-specific policies were compiled by Marcus O. Painter and Tian Qiu. For additional details, see Painter and Qiu (2020). This effort builds on data and local sources compiled by the New York Times here: https://nyti.ms/2UZHMCG. We make several adjustments to account for policies introduced after 1200 local time, shifting back the onset of the policy one calendar day. We thank them for generously sharing the pre-release version of this data.

- **Economic and political measures** Economic and political measures are drawn from Fajgelbaum et al. (2020) and available for download here: https://bit.ly/3aTo1SF. Tariff exposure is calculated by Fajgelbaum et al. (2020) by weighting retaliatory tariff changes variety-level 2013–17 trade shares as well as county-level sector data. Source data has multiple sources detailed in the original text.

- **COVID-19 cases and deaths** County-day level information about COVID-19 cases and related deaths are tracked and compiled by the New York Times from various government sources. The tracker is available via their Github page here: https://bit.ly/2wrK0RB.

- **Sinclair exposure** We classify exposure to Fox News stations operated by the Sinclair Broadcast Group using a map published by Sinclair and archived by Reproducible Journalism (https://bit.ly/39U1iVn). The .json file was converted to a .csv and linked with a Designated Market Areas (DMA) shapefile available here: https://bit.ly/3eab8FI. The SBG station data is available for review here: https://bit.ly/3c6w52v (download link). Counties were assigned to the DMA with a larger share of coverage.

- **County Shapefiles** We visualize county-level variation in policy changes and economic and political measures using the 2016 TIGER/Line shapefile made available by the US Census Bureau (Department of Commerce) via the DATA.GOV initiative. Data is available for download here: https://bit.ly/2JU4ZQe.

Research Methods Our main results leverage a difference-in-differences research design. We supplement this approach with an analogous event study design to assess pre-trends in the outcome prior to treatment.

Difference-in-differences This approach leverages variation in not-yet-treated units to construct a counterfactual for treated units after treatment. In the simplest case, this design compares the difference in the changes across pre versus post treatment periods for the treated and control units. In our case, local ordinances are staggered across states and, in a number of cases, counties within states that have not yet enacted state-wide mandates. To account for this staggered variation in the introduction of the natural experiment (local policy change), we include county and day fixed effects. This partials out any variation in population movement (dependent variable) that is correlated with factors that remain fixed regarding counties during the sample period (February 23 to April 1) or changes in mobility due to nation-wide shifts in policies or protocols ('common shocks'). In addition, we account for other relevant state-wide policy changes that may coincide with the onset of shelter-in-place ordinances (school closures, bans on social gatherings) as well as cumulative COVID-19 cases and deaths. We produce Figure 2 Panel C by studying equation (SI-1):

$$\begin{aligned} y_{c,d} = \alpha &+ \beta_1 active\_policy_{c,d} + \beta_2 active\_policy_{c,d} \times income_c^{2016} \\ &+ \beta_2 active\_policy_{c,d} \times trade_c^{2017-19} + \beta_2 active\_policy_{c,d} \times trump\_voteshare_c^{2016} \\ &+ \gamma active\_policy_{c,d} \times X_c + \omega X_{c,d} + \lambda_c + \theta_d + \epsilon_{c,d} \end{aligned} \tag{SI-1}$$

where $y_{c,d}$ is the measure of population movement derived from cellphone location data, standardized using location-specific day-of-the-week trends prior to March 8, 2020. $active\_policy_{c,d}$ indicates whether a county-specific or state-wide shelter-in-place mandate is active on a given day. We estimate the marginal effects using standardized measures of county-level average income ($\times income_c^{2016}$), exposure to retaliatory tariffs ($\times trade_c^{2017-19}$), and Trump vote share in 2016 ($\times trump\_voteshare_c^{2016}$). All have mean zero and standard deviation equal to one. λ_c indicates county-level fixed effects, θ_d indicates day-level fixed effects, and $\times X_c$ and $X_{c,d}$ is a vector of control variables described in the main text. We supplement the benchmark specification in Figure 2 Panel C. Robust standard errors are clustered by administrative state to account for potential spatial clustering in policy changes, COVID-19 risks, and constraints on population movement.

Event study design This approach leverages leads and lags of local shelter-in-place policies to study variation the outcome variable prior to and following the policy change. This allows us to assess the plausibility of the 'common trends' assumption using placebo treatment leads (Donald and Lang, 2007). It also enables us, when we estimate separate event studies across median thresholds, to assess the validity of this assumption specifically for the marginal effects of interest ($\times income_c^{2016}$, $\times trade_c^{2017-19}$, $\times trump\_voteshare_c^{2016}$). We study equation SI-2 using 10 window prior to the leads as the base period:

$$\begin{aligned} y_{c,d} = \alpha &+ \sum_{i=-1}^{-9} (\beta_i active\_policy_{c,t+i}) + \beta_0 active\_policy_{c,t=0} \\ &+ \sum_{i=1}^{5} (\beta_i active\_policy_{c,t+i}) + \omega X_{c,d} + \lambda_c + \theta_d + \epsilon_{c,d} \end{aligned} \tag{SI-2}$$

Notation follows the difference-in-differences design. One exception is that $active\_policy_{c,t+i}$ coincides with the date of the shelter-in-place policy change, not the policy status (0 or 1) itself. Robust standard errors are clustered by administrative state. We calculate total effects in the threshold-separated tests in Figure 3 Panels A/C/E via a split-sample approach (same with Figure SI-1). We confirm the divergent compliance patterns in the split-sample design correspond to marginal effects in a fully interacted event study design.

Supplemental Results and Figures

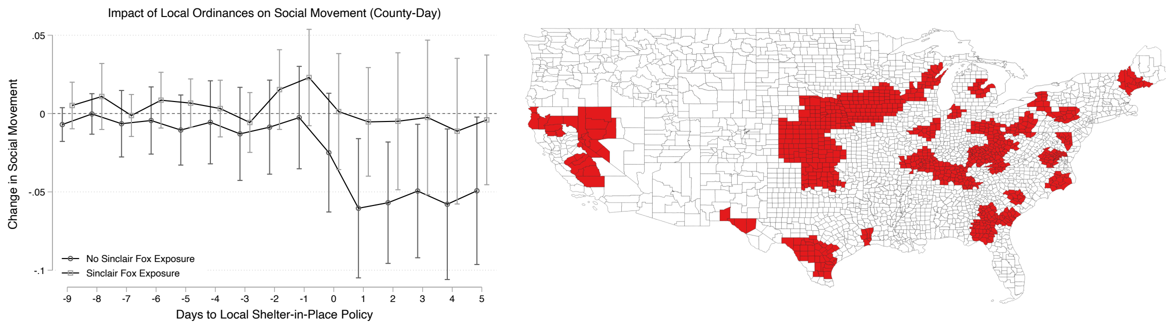

Figure SI-1: Event study designs indicate varying compliance by slanted media exposure

Panel (A): Event study design using leads and lags of policy change in counties with and without exposure to a Sinclair Broadcast Group Fox station. Event study results suggest large reduction population movement in counties without access; no change in counties with access. 90% confidence intervals reported using heteroskedasticity robust standard errors clustered by state. Panel (B): Map of SBG Fox station exposure by county.

Figure SI-2: Select tweets by Donald J Trump regarding COVID-19 pandemic and US response

Tweets available for download here: https://bit.ly/2Xq6nlB.