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Abstract

Physical distancing reduces transmission risks and slows the spread of COVID-19. Yet compliance with shelter-in-place policies issued by local and regional governments in the United States is uneven and may be influenced by science skepticism and attitudes towards topics of scientific consensus. Using county-day measures of physical distancing derived from cellphone location data, we demonstrate that the proportion of people who stay at home after shelter-in-place policies go into effect is significantly lower in counties with a high concentration of science skeptics. These results are robust to controlling for other potential drivers of differential physical distancing, such as political partisanship, income, education and COVID severity. Our findings suggest public health interventions that take local attitudes toward science into account in their messaging may be more effective.

Keywords: COVID-19, physical distancing, science skepticism, belief in science, political partisanship.

JEL-Classification: I12, I18, H12, H75, D04.

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**Introduction**

Physical distancing reduces interpersonal transmission risks related to the COVID-19 virus [1, 2, 3]. Government policies that mandate physical distancing slow the spread of COVID-19 [4]. Local non-compliance with these shelter-in-place orders creates public health risks and may cause regional spread [5, 6]. Understanding which local factors impact compliance is a first-order public policy concern and informs evidence-based policy interventions to heighten their efficacy and mitigate the effects of the pandemic.

Recent research highlights several factors that influence compliance: partisanship [7, 8, 9, 10, 11, 12], political polarization [13], poverty and economic dislocation [14], and differences in risk perception [15, 7, 16, 17]. These factors also influence physical distancing in the absence of government mandates [18]. Our central contribution is to highlight the role of science skepticism and attitudes regarding topics of scientific consensus in shaping patterns of physical distancing.

We leverage the most granular, representative data on science skepticism in the United States—beliefs about the anthropogenic (human) causes of global warming [19]—to study how physical distancing patterns vary with skepticism towards science. We combine this county-level science skepticism measure with location trace data on the movement of around 40 million mobile devices as well as data on state-level shelter-in-place policies. Our findings suggest that science skepticism is an important determinant of local compliance with government shelter-in-place policies, even after accounting for the role of partisanship, population density, education, and income, among other factors. In particular, we find that shelter-in-place policies increase the proportion of devices that stay at home by 2 p.p. (p-value < 0.001) more in counties with low levels of science skepticism compared to counties with high levels of skepticism. This corresponds to an 8% increase in devices that stayed at home, compared to the February average of 25%.

We also benchmark our measure of science skepticism against other measures of belief in science available at the state-level, illustrating that our measure captures a more general notion of skepticism towards topics of scientific consensus.

Adapting science-based policy communication to account for the target audience’s bias [20] can mitigate the risk that the message is rejected and the associated policy undermined. This can be achieved by correcting [21] or pre-emptively debunking [22] falsely held beliefs about science, thereby countering the dissemination of disinformation through modern media [23]. Taken together, our results underline the importance of tailoring public health interventions and associated messaging campaigns to account for local attitudes towards science.

**Results**

**Main Results** We analyze how physical distancing changes with the imposition of a state-wide shelter-in-place policy. First, we use an event study design with a sample split implemented for counties with high and low degree of science skepticism. We then complement this approach with a staggered DiD design, where we additionally control for a series of potentially confounding factors.
Panel a) in Figure 1 shows the results from the event study approach. Before the introduction of a shelter-in-place mandate, day-to-day changes in physical distancing remain consistently close to zero. Crucially, any slight upward or downward shifts in movement prior to the onset of a policy are mirrored across high-belief and low-belief counties. 2 out of the 18 estimated pre-trend dummies are close to but statistically significantly different from 0. However, there is no systematic pattern in the pre-trends and it is not unexpected to have some false positives when estimating a large number of pre-implementation effects. The parallel evolution of the pre-trends indicates that the common trends assumption is plausible, such that the difference in effects between the two event studies (high- and low-skepticism) is consistently estimated. After the first full day of a shelter-in-place order, non-skeptic counties see an increase in physical distancing that is about 2 p.p. higher than skeptic counties (.039, \( p \leq 0.001 \) versus .018, \( p \leq 0.001 \)). The differences in local compliance across counties is stark, with all estimated post-treatment physical distancing responses for non-skeptic counties being statistically different from zero, while nearly half of the estimated responses for skeptic counties are not statistically different from zero.

We now turn to the staggered DiD approach, which allows us to control for a wide range of possible factors that could confound the relationship between belief in science and physical distancing. The results are shown in Panel b) of Figure 1. The figure shows, for several different specifications, the point estimates alongside 95% confidence intervals for the marginal effect of science skepticism, i.e. the additional physical distancing response in high-belief relative to low-belief counties. As a benchmark, we start by estimating the same specification as in the event study approach, pooling the post-treatment lags and without further controls except for the day and county fixed effects. This corresponds to the first point estimate on panel b). The marginal effect of being a non-skeptic county is 2 p.p. (\( p \leq 0.001 \)) in this specification, a similar magnitude as the event study design in Panel a). To put this in context, the average share of devices staying home on a given day in February 2020 was around 25%, so this constitutes an additional increase for non-skeptic counties of about 8%. Considering that a device is only counted as staying home if it is not seen anywhere outside its designated nighttime location on a given day, this is a sizeable difference.

Panel b) of Figure 1 also shows the estimates under different sets of control variables, interacted with the post-treatment period, to confirm that the estimated relationship is not driven by confounding factors. One potential concern is that differences in belief in science just proxy partisan divides. Figure SI-1 shows that this is a reasonable concern, as counties that were majority democrat have a higher fraction of non-skeptics. This partisan gap across parties has also become more polarized over the last decade, for a variety of proxies of science skepticism (Figure SI-2). To take into account this potential source of bias, we allow the physical distancing response to a shelter-in-place policy to depend on whether the 2016 Republican vote share exceeded 50% of the total two-party ballot count. The marginal effect estimate remains similar (\( \sim 1.5 \) p.p, \( p \leq 0.001 \)) and statistically indistinguishable from the benchmark at the 95% level.
Thus, even after partialling out the differential effects due to partisanship, there is a significantly higher response to the shelter-in-place policy in non-skeptic counties. We consider several other potential sources of bias by sequentially adding further interacted control variables, including how rural (model 3; $p \leq 0.001$), educated (model 4; $p \leq 0.003$), wealthy (model 5; $p \leq 0.006$), religious (model 6; $p \leq 0.004$), and institutionally robust (model 7; $p \leq 0.005$) a county is. This approach allows the estimated effect of shelter-in-place policies to vary with all these additional factors. We also take into consideration whether related business or school closure policies have been introduced (model 8; $p \leq 0.004$), the local severity of COVID-19 cases and deaths (model 9; $p \leq 0.007$), and state-wide cases and deaths (model 10; $p \leq 0.01$). In model 11, we additionally allow the effect of local and state-wide COVID-19 cases and deaths on physical distancing to vary with the introduction of the shelter-in-place policy ($p \leq 0.004$). Even though several of these measures, especially religiosity, income, and education, may over-control for variation in the outcome of interest (i.e., these covariates are colliders), the estimate remains robust and statistically precise at the 95% level, even in the fully saturated model that includes the complete set of interactive control variables. The robustness of the point estimates supports the idea that the patterns of non-compliance will likely also hold for alternative measures of science skepticism, as discussed in the theory section.

**Robustness** In Supplementary Information, we investigate several potential concerns. We begin by demonstrating the robustness of the main results to a number of alternative sampling and model specifications. We introduce these results in Figure [SI-3](#). In panels a) and b), we demonstrate that the main results hold if we leverage a longer pre-sample window of 10 days. Use of the 10-day window means that the number of days used as a baseline period balances the number of leads and lags. In panel c), we estimate the main event study without an omitted treatment lead. In panel d), we estimate the main specification with a saturated set of covariates by date fixed effects. In panels e) and f), we use a one-day pre-sample window. This means the number of omitted treatment leads (one) matches the number of omitted pre-window dates. Panels g) and h) replicate the main event study and difference-in-differences models without weighting units by population. In each of these additional variants, we observe a similar pattern of results: parallel pretrends in physical distancing across high-belief and low-belief counties; large increases in physical distancing among high-belief counties after the introduction of a shelter-in-place; robust and statistically precise marginal effects of belief in science after accounting for the battery of potential confounders discussed earlier (partisanship, rurality, education, income, religiosity, institutional health, related government policies, local and state-wide COVID-19 severity).

**Construct Validity** We next consider the construct validity of our measure of belief in science. It is possible that attitudes towards the anthropogenic causes of climate change are bundled together with a range of other ideological considerations, especially partisanship. Climate
Dependent variable: percent of devices fully at home. **Panel a)**: Difference-in-difference estimates with pre-policy event study set-up. *Light grey:* below median belief in man-made global warming (skeptics); *Dark blue:* above-median belief in the same (non-skeptics). See Supplemental Information for a more detailed discussion of the event study approach. Sample goes from 15 days before to 10 days after the policy for each county; effect sizes shown are changes relative to the period 15-11 days, as well as 3 days, before the policy. County and date fixed effects are employed. 95% confidence intervals are shown, based on standard errors triple-clustered by county, date and state-week. The regressions employ population weights; for unweighted results, see panel g) of Figure SI-3. **Panel b)**: Difference-in-differences estimates for the differential effect of a shelter-in-place policy for counties with above-median (non-skeptics) relative to below-median belief in science (skeptics) across different specifications. See Supplemental Information for a more detailed discussion of the event study approach. Each point estimate and confidence interval comes from the interaction post_{c,t} × BiS_{c}, the post-treatment period and a dummy that takes value 1 if a county exhibits above-median belief in science. “Benchmark model” controls for date and county fixed effects. The further models build on the previous one as follows: “+Voting” equals the benchmark model, additionally controlling for post_{c,t} × vote_{c,t}, where vote_{c,t} = 1 if c was majority republican in the 2016 presidential election; “+Rural” additionally controls for post_{c,t} × rural_{c}, where rural_{c} = 1 if c has below-median population density; “+Education” additionally controls for post_{c,t} × educ_{c}, where educ_{c} = 1 if c has above-median college education levels; “+Income” additionally controls for post_{c,t} × income_{c}, where income_{c} = 1 if c has above-median income; “+Religiosity” additionally controls for post_{c,t} × relig_{c}, where relig_{c} = 1 if c has above-median levels of religiosity; “+Inst. Health” additionally controls for post_{c,t} × health_{c}, where health_{c} = 1 if c has above-median levels of institution health; “+Govt. Policies” additionally controls for whether the c had a school closure, business closure, or state of emergency declaration; “+Local COVID” additionally controls for the number of confirmed COVID cases and deaths in c; “+State COVID” additionally controls for the number of confirmed COVID cases and deaths in the state of county c; and “+SiP by COVID” additionally controls for the interaction of COVID cases and deaths with post_{c,t}. 95% confidence intervals shown, based on standard errors triple-clustered by county, date and state-week. The regressions employ population weights; for unweighted results, see panel h) of Figure SI-3. N = 87,040.

skepticism, as Kahan 24 points out, bundles together what subjects know and who they are—their cultural and political ties. In the difference-in-differences design, we address some of these concerns. We also address potential concerns that perceived changes in climate dynamics are associated with religiosity. It is also possible that beliefs about climate change are static and do not respond to changes in available scientific information, though McDermott 25 argues climate skeptics do update their beliefs in the presence of new information. Thus, we assess how our measure of science skepticism relates to other measures of attitudes towards science, scientific inquiry, and scientific breakthroughs.

To benchmark our primary measure, we conducted a comprehensive search of all datasets listed by the Inter-university Consortium for Political and Social Research and the Roper Center for Public Opinion Research, two large-scale social science database archives. We identified two databases with questions about attitudes towards science as well as geographical information. These are the General Social Survey (GSS) at the NORC (https://bit.ly/3yFvZew)
and the American Values Survey (AVS) by Pew Research Center [https://pewrsr.ch/3oRdHlZ]. Geographical identifiers in the GSS are only available under restricted access. Moreover, neither survey has a sufficiently large or representative sample to replicate our main county-level results. To confirm that our measure of skepticism about the human causes of climate change proxies more general attitudes towards topics of scientific consensus, we test to what extent it correlates with these other measures of belief in science. As an initial benchmark we use the Pew AVS survey, pooled over the years 2002-2009. The sample period has the advantage that it precedes the pronounced increase from 2008 onwards in both climate change skepticism [26, 27], driven by partisan polarization, as well as polarization in attitudes towards science, which we document in Figure SI-2. We supplement this datasource with information from the World Values Survey (WVS). The data are pooled over two waves (2011 and 2017) and report average levels of trust in science at the state level. The latter is determined as the first polychoric principal component of 6 questions concerning beliefs on science and technology. We also leverage data on the average state-level number of MMR vaccinations received by children at the age of 36 months. The use of MMR vaccinations in this age group has been found to reflect broader vaccine hesitancy, [28, 29].

We begin by visualizing the relationship between these alternative measures of attitudes towards science in Figure SI-4. Panels a) and b) present the principal component from the WVS survey (trust in science) and healthier life factor loading respectively. Notice the robust, positive relation. In panel c), we illustrate the association between the Pew AVS measure and the Howe et al. [19] measure. In panel d), we introduce the scatterplot of MMR vaccination rates and climate change beliefs. We find similarly consistent positive associations. In Table SI-1 we introduce regression-based estimates. The estimated associations are large, ranging from 0.331 (R² = 0.11, WVS factor loading for ‘science is important for daily life’) to 0.635 (R² = 0.4, WVS PCA). These results suggest our primary measure of belief in science is a representative measure of the more general public attitude towards science.

Discussion Science skepticism significantly influences physical distancing patterns after a local shelter-in-place policy is enacted. These patterns highlight the importance of science education in shaping the resilience of populations to pandemics. Adapting science communication during the COVID-19 pandemic to account for the target audience’s bias [20] and countering the dissemination of disinformation through modern media [23] can help mitigate the risk of non-compliance with public health interventions. Yet our study has several important limitations. Our measure of science skepticism leverages the most granular, representative data available but measures beliefs about a uniquely polarized issue: climate change. In our analysis, we have taken care to address concerns that climate skepticism is embedded within various cultural, political, and economic dynamics. We also benchmarked this proxy against alternative but less granular measures of science skepticism, showing that the measure used in this study is representative of the more general public attitude towards science. Although our results demonstrate a robust link
between skepticism and policy compliance, future research should develop more direct measures of public attitudes towards science. The dearth of large-scale data collection at the county-level or below represents an important knowledge gap. Our observational approach, while yielding plausible estimates of the skepticism-compliance relationship, also makes it difficult to rigorously evaluate the theoretical mechanisms that serve as the microfoundation of the empirical patterns we observe. Experimental, primarily survey-based approaches offer an advantage in exploring potential mechanisms, but typically rely on self-reports rather than behavioral outcomes. Future work could advance our understanding of skepticism and science communication by combining experimental interventions with meaningful behavioral outcomes through field-based assessments. These experimental investigations would need to carefully consider the potential for unintended harm to human subjects by priming or reinforcing anti-science biases, but could yield important contributions to understanding the origins and consequences of science skepticism that subsequent research could address.

Although our analysis is primarily focused on physical distancing, the role of belief in science is much broader, potentially influencing other mitigating behaviors such as mask use and vaccine hesitancy. Scientific skepticism may undermine public mask use and reinforce hesitancy, thwarting attempts to establish herd immunity. To explore these policy relevant issues, we gather data on county-level mask use and vaccine hesitancy across the United States. In Figure SI-5, we show that the correlation between belief in science and mask use at the height of the pandemic in the United States (July 2020) is positive and robust to accounting for local partisanship, the primary confounding factor of concern in our main analysis. In Figure SI-6, we replicate this analysis for vaccine hesitancy in April 2021. We find a similarly striking pattern with belief in science and local hesitancy being negatively correlated (strong belief in science reduces hesitancy), which is robust to conditioning out the role of partisanship, an especially poignant concern in light of recent evidence that hesitancy is disproportionately high among polled Republicans. Although data limitations restrict a comparable investigation of mask use and hesitancy, these preliminary findings suggest a persistent effect of belief in science on pandemic-related measures beyond physical distancing.

Methods

Data We analyze differential changes in county-level movement patterns and physical distancing after the implementation of shelter-in-place policies in the United States (see Supplementary Information for more detail). Daily panel data aggregated to the county-level from GPS pings of more than 40 million mobile devices, obtained from SafeGraph, a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places, via the PlaceKey Community. This data allow us to track the percentage of devices that stayed home all day. The latter is defined as the ratio of the number of devices that remained home all day in a given county over the total number of devices observed in the county that day. A device’s home is determined as the common night-time location over a 6-week period.
The underlying anonymized data was subjected to exhaustive data processing with the aim to guarantee reliability, granularity, anonymity and accuracy. The panel of devices in the sample is designed to be geographically and demographically representative, with a 97% correlation between the panel’s population density and the American Census’s population density at the county level.

To mitigate the spread of COVID-19, county and state governments implemented shelter-in-place policies during the second half of March 2020. We collect implementation dates of state- and county-level school and business closures, state-of-emergency declarations and shelter-in-place policies from various sources. When a policy goes into effect after 12pm on a given day, we assign it an implementation date one day later. We measure science skepticism using data assembled by Howe et al. [19] at the county level. Our main measure is the estimated percentage of people who agree with the statement that global warming is caused by humans. Despite scientific consensus that humans are the primary cause of present and projected climate change dynamics, there is substantial variability in local beliefs about this topic in the United States. We leverage this variation to study how patterns of physical distancing differ across counties with lower levels of science skepticism (higher belief in science).

Figure 2 provides a first descriptive view of the data. The left panel depicts the percentage of devices that stayed home each day of the sample period (March 1 to April 19), with a polynomial trend fitted for the subsample of counties above (dark) and below (light) the median belief in man-made global warming. We document a substantial uptick in physical distancing in most counties over the sample period (panel a)) that appears more pronounced in areas with lower levels of science skepticism (dark line). These trends depict a clear difference in physical distancing outcomes between counties with contrasting attitudes towards climate change—a topic of scientific consensus. Panel b) documents the substantial variation in the geographic distribution of such attitudes.

**Research Design** We adopt two related empirical approaches to analyze how physical distancing behavior depends on whether a county exhibits above- or below-median levels of science skepticism (see Supplementary Information for more detail). First, we perform a county-day level event study design where we focus on the impact of shelter-in-place policies on physical distancing, in line with related studies [8] [18] [14]. We estimate the response separately for counties with above-median and below-median levels of science skepticism. The event study design serves to check for the presence of pre-treatment effects. If there are any pre-trends, then our approach allows us to assess whether these shifts in physical distancing covary in a parallel fashion in counties with below- and with above-median science skepticism. The main effects will be consistently estimated even if there is some evidence of anticipation effects as long as those anticipation effects are parallel across the two event studies. An additional benefit of the event study design is that it allows to estimate and visualize how the policy responses change dynamically after the introduction of shelter-in-place mandates.
Figure 2: Science Skepticism and Physical Distancing: Descriptive Evidence

(a) Data: Full Sample

(b) Belief In Man-Made Global Warming

Panel a): Light: below-median belief in man-made global warming (skeptic); Dark: above-median belief in the same (non-skeptic). Plots show the percentage difference in devices that stayed home during the sample period (March 1 to April 19) from the day-of-week-specific average during February. Solid lines are from local polynomial smoothing with bandwidth 5. N = 161,363. Panel b): percent of people in county who believe that global warming is man-made [19]. N = 3,006.

Second, we use a staggered Difference-in-Differences (DiD) approach to estimate the differential response to shelter-in-place policies for counties with above-median versus below-median belief in science. The split-sample event study is a powerful approach when stratifying over one dimension with a well-balanced binary classification. This is the case with the event study design we use for our measure of science skepticism. However, the introduction of additional dimensions requires stratification over all of them simultaneously. With a large number of potential confounding factors, the split-sample event study design is statistically underpowered. Instead, to address the fact that there likely is a range of potential sources of bias, as discussed in the Theory section, we adopt a staggered DiD design. This enables us to partial out the effect of additional covariates on the physical distancing response to a shelter-in-place policy. One primary control variable is local partisanship, which is correlated with belief in science (see Figure SI-1). Political polarization with respect to climate change and attitudes towards science generally in the United States has been amplified over the past decade (see Figure SI-2). We attempt to address this concern by partialling out any marginal effects associated with partisanship using voting records from the 2016 presidential election. Effects of belief in science may also be confounded by how rural, educated, religious, and wealthy a given community is. Institutional health and local and regional exposure to COVID-19 may similarly influence our primary estimates. We incorporate these additional controls as well.

For each of the two approaches, we weigh each county by its population within the regression framework in order to provide representative results. In Supplementary Information Figure SI-3, we show that the main results are robust to estimating each design without population weights and varying baseline periods. We discuss this further below.

Theory Our main hypothesis is that counties with lower levels of skepticism about topics of scientific consensus (non-skeptics) will comply with shelter-in-place mandates at a higher rate
than counties with higher levels of science skepticism (skeptics). Skeptics are expected to be less likely to accept the motivations underlying science-based public policies.

When a policy has imperfect enforcement, compliance will be incomplete among people who believe that the policy has no beneficial or harm-reducing effects. In the case of the COVID-19 pandemic, estimates of such effects hinged crucially on scientific assessments and medical research that indicated the virus spread through interpersonal contact and could be mitigated by physical distancing (see Chu et al. [30] for an early review of this literature). Moreover, in the United States, policy enforcement was indeed imperfect [31, 32]. As a result, the success of shelter-in-place policies in combating the spread of the virus necessarily relied for a large part on voluntary compliance [33, 34, 35]. In areas where scientific skepticism is widespread, we anticipate that fewer people would believe in the benefits to social distancing, reducing policy effectiveness.

Science skepticism can influence potentially costly social behaviors through several plausible mechanisms. Skepticism may reduce the willingness of individuals to engage with scientific information that contradicts their prior beliefs [27]. Skeptics may also engage in less information-seeking behavior, preferring to rely on anecdotal or “common sense” assessments of the risks they or their community face. Further, skeptics may specifically seek out slanted coverage that reinforces their existing beliefs or biases. If individuals are less willing to engage with expertise generally or only seek out slanted expertise that reinforces their prior beliefs, subsequent risk perceptions will remain unchanged by new information or conform to existing assessments of potential threats [36]. Research on science communication during the COVID-19 pandemic provides ample evidence of these mechanisms. Pennycook et al. [37] find that experimental subjects with lower cognitive reflection and scientific knowledge were more willing to share fake or false stories about the pandemic. Uscinski et al. [38] find that survey respondents were more likely to believe COVID-19 risks were exaggerated and that the virus was purposefully manufactured and spread if they had a psychological predisposition to reject expert assessments and engage in conspiratorial thinking. Merkley & Loewen [39] provide evidence that anti-intellectualism—which is closely related to what we describe as science skepticism—is linked to diminished concern regarding COVID-19, perceptions of risk factors, and willingness to engage with and seek out information from experts. Gitmez et al. [40] introduce a theoretical model whereby information seeking is slanted, leading skeptics to seek out media coverage that minimizes the reported threat posed by non-compliance with shelter-in-place mandates. These studies provide an empirical and theoretical foundation for our core hypothesis.

There remain important unresolved questions about the psychological, political, and social origins of science skepticism. It is possible that skepticism emerges due to a real or perceived challenge to an existing set of beliefs or principles (“identity-protective cognition”) [41]. These beliefs may be informed by misconceptions about causal relationships [42], motivated by political affiliations [43], exposure to slanted sources of information [44, 45], conspiracy theories [27], or related cultural mythologies [46]. Principles may be ideological heuristics that are challenged by
scientific inquiry, triggering psychological reactance and, as a consequence, a rejection of scientific expertise [47, 48]. Political and social institutions may also emerge to reinforce these dynamics. Rekker [49] provides a review of these dynamics, noting that skepticism may lead to either the rejection of a narrow set of scientific facts or of scientific expertise as an entire epistemic system. Indeed, the drivers of science skepticism have been shown to be more heterogeneous than previously thought, with political partisanship being an important predictor of climate skepticism [41, 50, 51], while religiosity better predicts vaccine and evolution skepticism [52, 53].

Figure SI-1 illustrates that political partisanship is indeed related to science skepticism using our county-level measure of climate change skepticism from Howe et al. [19], while Figure SI-2 documents an across-the-board increase in political polarization around science attitudes over the last decade in the US. Kahan [24] provides a psychological explanation for self-reported climate skepticism as being rooted in individuals’ cultural or political ties, rather than their cognitive capacity. Taken together, it is clear that a robust exploration of science skepticism through the lens of climate dynamics (our primary measure) requires a careful consideration of the cultural and political systems within which this skepticism is embedded. These systems include partisanship, religiosity, rurality and urbanicity, and educational attainment. We take these factors into account empirically so as to address important concerns about the construct validity of our measure—whether the patterns of non-compliance we observe are likely to hold for alternative measures of science skepticism. Our findings complement recent research that finds COVID-19 skepticism to have similar antecedents as vaccine and climate skepticism [54].

Our central contribution is to investigate the skepticism-compliance link using a granular measure of real-world behavioral outcomes, documenting how science skepticism can undermine public health interventions. In this sense, our research complements earlier experimental and survey-based results on the drivers of such skepticism, and affirms their importance [37, 38, 39]. Our findings suggest that it would benefit the effective implementation of public policies to tailor public messaging so as to correct or preempt falsely held beliefs about the scientific evidence these policies are based on [23, 20]. The science communication literature offers many potential strategies to achieve these goals [55]. For example, recent research focusing on the Zika virus and yellow fever in Brazil found that such corrective messages have some effect when they discuss well-known viruses, though they may have little to no effect in the case of new viruses about which little is known [21]. Additionally, adaptive communication strategies such as reducing emphasis on model uncertainty when faced with high science skepticism may increase support for public policies in the short run, though there may be negative long-run consequences if case model projections are reversed [56] (see Gustafson & Rice [57] for a review of the role of uncertainty in science communication). Finally, science institutions can attempt to preempt skeptical reception of and non-compliance with science-based policy by “pre-bunking” false beliefs about science and promoting education and scientific literacy training [58]. Such “psychological inoculation” [59] has been applied with some success in the context of vaccination [60] and climate change [61]. Similarly, experimental evidence suggests that simple nudges can
induce a shift in the willingness to share disinformation about COVID-19 [37]. We contribute to this body of research by documenting that substantial behavioral harm can arise when science skepticism undermines compliance with public policy.

References


Supplementary Information

Materials and Methods

Data

Physical distancing. We leverage data from SafeGraph, linking GPS pings from up to 40 million mobile devices across the US. This data has previously been used in Allcott et al. [7], Brzezinski et al. [18] and Painter & Qiu [8] to study behavioral responses to the outbreak of COVID-19. We rely on SafeGraph’s physical distancing Metrics dataset to assess the differential responses to the shelter-in-place policies at the county level. The dataset is based on an underlying panel of mobile devices in nearly all 200,000+ Census Block Groups (CBG) in the United States, which we aggregate to the county-day level. Only CBGs with less than 5 devices are excluded to preserve privacy. A device’s home is defined as its common nighttime location narrowed down to Geohash-7 (153m x 153m) precision. As our main outcome variable, we determine the percentage of devices that stayed home all day by taking the ratio of all such devices for each day over the total number observed in a county during a given day. As discussed, geographic bias of the data is small. The absolute difference between the panel’s density and the true population density according to the US census remains below 1% for all counties in the sample; the correlation between both measures is 0.97. The data is similarly representative at the county level in terms of race, demographic and income groups [62].

Science skepticism. To proxy science skepticism (i.e., belief in science), we leverage data on county-level attitudes towards climate change as described in Howe et al. [19]. In particular, we use the item human, the estimated percentage of people who think that global warming is caused mostly by human activities (see panel b) in Figure 2). The data builds on 12 nationally representative climate change opinion surveys conducted between 2008 and 2013 that have been combined to an overall dataset (n=12,061). Based on geographic and demographic covariates, Howe et al. [19] apply multilevel regression and post-stratification to predict county-level opinion data. Their estimates from cross-validation and external validation exercises yield county-level error margins of ±8 percentage points at the 95% confidence level. Hamilton et al. [63] confirm the validity of this approach.

Alternative belief in science proxies. We collect several alternative measures of belief in science to test the validity of the belief in climate change proxy.

• American Values Survey: as an alternative proxy for belief in science, we calculate the percent of the population in each state for which we have respondents that disagree with the statement, “I am worried that science is going too far and is hurting society rather than helping it”. The sample consist of 6,292 unique responses pooled from several large
national surveys carried out over the years 2002-2009. The surveys were administered over landlines and cell phones. We weight each response by its respective survey weight, as calculated by Pew based on demographic characteristics and survey design.²

- World Values Survey: we also proxy belief in science using a number of variables from the WVS. The questions read: (1) “Science and technology are making our lives healthier, easier, and more comfortable”; (2) “Because of science and technology, there will be more opportunities for the next generation”; (3) “The world is better off, or worse off, because of science and technology”; (4) “We depend too much on science and not enough on faith”; (5) “Whenever science and religion are in conflict, religion is always right”; (6) “It is not important for me to know about science in my daily life”. If necessary, the measures have been inverted such that higher values refer to higher levels of belief in science. State identifiers are only contained in the latest two waves of the WVS (2011 and 2017). For the scatterplot in Figure [SI-4], we pool the data from these waves together in order to increase the sample size and extract the first polychoric principal component from all variables (N=4,582). Two of the questions ((4) and (6)) have not been asked in earlier waves of the survey. For this reason, Figure [SI-2] is only based on the remaining variables and their corresponding first polychoric principal component.

- Attitudes towards vaccination: We rely on vaccine hesitancy rates estimated at the county-level using the Census Bureau’s Household Pulse Survey (HPS) data. These data are provided by the Assistant Secretary for Planning and Evaluation under the Department of Health and Human Services. ASPE uses the Census Bureau’s 2019 American Community Survey (ACS) 1-year Public Use Microdata Sample (PUMS) and a PUMS-to-county crosswalk from the Missouri Census Data Center to estimate county-level variation. The survey collection period was from March 3, 2021 to March 15, 2021. The HPS question used was: “Once a vaccine to prevent COVID-19 is available to you, would you...get a vaccine?” Hesitancy was calculated as the rate of respondents responding probably or definitely not.

- The New York Times commissioned Dynata, an online market research firm, to collect a large scale survey in the United States about mask use. The survey was conducted online between July 2 and July 14, 2020 and includes approximately 250,000 survey responses. Each participant was asked “How often do you wear a mask in public when you expect to be within six feet of another person?” with answer options of “Never,” “Rarely,” “Sometimes,” “Frequently,” and “Always.” These responses are then normalized to create our primary outcome of interest described in The New York Times’s introduction of the data: the probability (chance) that, if one has five random encounters, all people encountered are wearing masks. County-level data was retrieved from the article’s online

²For more information, see https://bit.ly/3vS33P

- Child vaccination data: we draw data on the number of MMR-containing shots received by children at age 36 months from the National Immunization Survey for the years 2007 and 2019.

Policies. We compiled a comprehensive dataset on county-specific and state-wide policies from the National Governors’ Association (NGA); the National Association of Counties (NACO); and Education Week, an independent news organization that compiled school closure data from government websites, staff reporting and the National Center for Education Statistics. This data incorporates information about the onset of school closures, closures of non-essential businesses and the introduction of shelter-in-place policies.

COVID-19 cases and deaths. County-day and state-day level information on COVID-related deaths and cases are collected by the Johns Hopkins Coronavirus Research Center.

Election results. Data on county-level vote shares by party in the 2016 presidential election was drawn from the MIT Election Lab. We classify a county as Democratic if the Democratic vote share exceeds the Republican one (and vice versa).

County Shapefile. The maps shown in Figure 2 are based on the 2016 TIGER/Line county-level shapefile provided by the US Census Bureau (Department of Commerce).

Data availability. All data used in this manuscript are publicly available (see links on this page), except the SafeGraph data, which is proprietary but made freely available to academic researchers through the SafeGraph COVID-19 Data Consortium.

Code availability. The code for our computations is available in the supplementary materials.
**Event study design**

The following presents the event study methodology employed for the analysis of policy-related physical distancing. Our specification aims at isolating the differential impact of shelter-in-place policies on physical distancing. We use an event study methodology to compare counties within states with shelter-in-place policies to those without any measure implemented. Our empirical strategy follows a difference-in-differences approach with variation in treatment timing as proposed in Goodman-Bacon [64] and previously applied to the study of behavioral responses to COVID-19 in Brzezinski et al. [18], Painter & Qiu [8], and Wright et al. [14].

To disentangle differential movement patterns according to our covariates of interest, we estimate the following equation separately for the counties with above-median (non-skeptics) and below-median (skeptics) values of the variable *human*:

\[
pd_{c,t} = \gamma + \alpha_c + \delta_t + \sum_{j=-10}^{-4} \rho_j D_{s,t0+j} + \sum_{j=-2}^{10} \rho_j D_{s,t0+j} + u_{c,t}, \tag{SI-1}
\]

where \(pd_{c,t}\) is the percentage of devices that stay home all day in county \(c\) at time \(t\). \(\alpha_c\) and \(\delta_t\) refer to county and date fixed effects, respectively. The dummies \(D_{s,t0+j}\) are centered around the state policy’s implementation date \(t_0\), such that \(D_{s,t0+j}\) equals 1 at time \(t\) if the state policy was enacted \(j\) days ago. As such, we construct the dummies \(D_{s,t+j}\) for the 10 days preceding as well as the 10 days following the implementation date. Panel a in Figure 1 plots our coefficients of interest, the sequence \(\{\rho_j\}_{j=-10}^{10}\) for both subgroups. As a baseline period, we use the 15 to 11th day before our state-specific policy was enacted, as well as the third day before the implementation of the policy. We omit the third treatment lead since policy implementation in some states occurred in the afternoon of the previous date (we use the first full date of each shelter-in-place policy as the zero date for centering) and members of the public may have been able to anticipate the implementation of the policy due to announcements by government officials in the days immediately before the policy entered effect. As recommended by Painter & Qiu [8], we drop those counties from the sample that moved ahead of their state in implementing shelter-in-place policies. This is primarily done to counter concerns that the timing of local policy adoption is endogenous to local virus severity and physical distancing patterns (counties moving ahead of states in implementing a local shelter-in-place).

The different roll-out dates of policies across counties and states allow to construct control groups composed of areas that have not yet experienced the event. To account for the staggered treatment, we incorporate county- and day fixed effects in our analysis. On one side, this eliminates latent, time-invariant heterogeneity across counties that may be correlated with movement patterns, such as differences in income, political partisanship or geographic features. On the other side, the day fixed effects rule out the possibility that changes in physical distancing may be driven by nation-wide common shocks in terms of information or protocols.
Difference-in-differences design

The Difference-in-Differences (DiD) research design follows closely the logic of the event study, with three main differences. First, instead of allowing the policy impact to be different in each of the pre- and post-implementation periods (leads and lags), we estimate a single $post_{c,t}$ effect, whereby $post_{s,t} = 1$ at or after the policy implementation in state $s$. Second, we do not estimate the equation separately for counties with above- and below-median belief in science, but instead we estimate the interactive effect $post_{s,t} \times BiS_c$, whereby $BiS_c = 1$ if county $c$ has an above-median measure of human (non-skeptics). Finally, we also include a vector of control variables $x_{c,t}$, which includes interactions with the $post_{s,t}$-dummy, in order to control for potential confounding factors.\(^\text{10}\) This leads to the following specification for our DiD:

$$pd_{c,t} = \tilde{\gamma} + \tilde{\alpha}_c + \tilde{\delta}_t + \rho post_{s,t} + \psi post_{s,t} \times BiS_c + \Phi x_{c,t} + \tilde{u}_{c,t} \quad (\text{SI-2})$$

The key parameter of interest is $\psi$, which estimates the additional physical distancing response to shelter-in-place policies of counties with above-median belief in science (non-skeptics) relative to counties with below-median belief in science (skeptics). This is the parameter that is plotted on panels c) and d) of Figure [1]. The vector $x_{c,t}$ includes different sets of control variables and their interactions with $post_{s,t}$ depending on the specification, as is described in the Notes to Figure [1].

---

\(^{10}\)Note that the vector $x_{c,t}$ contains some time-varying as well as some constant controls. The control variables which are constant over time will be perfectly collinear with the county dummies $\alpha_c$, and hence for these we only include their interactions with $post_{s,t}$. For the time-varying controls, we include the levels as well as their interactions (model 11).
Supplemental Results

Science Skepticism and Partisanship

**Figure SI-1:** Distribution of Belief in Man-Made Global Warming, by Party

The figure shows smoothed Gaussian kernel densities using Silverman bandwidth. Data comes from Howe et al. [19] and measures percent of county population that believes in anthropogenic global warming from surveys conducted over 2008-2013. The left (red) distribution is for all Republican counties, the right (blue) distribution is for all Democratic counties. Dotted vertical lines are party-specific medians. A county is classified according to which party had a higher vote share than the other party in the 2016 presidential election.
**Figure SI-2:** Distribution of Other Measures of Science Skepticism, by Party

(a) Lives healthier, easier, more comfortable

(b) More opportunities

(c) World better or worse off

(d) Religion always right

(e) Principal Component

(f) Vaccination Rate

Panels a) - d): plots the density of measures for trust in science obtained from the World Value Survey (WVS), smoothed using the Epanechnikov kernel function. The red distributions refer to all individuals that identify as Republicans, the blue distributions refer to Democrats. Dashed vertical lines are party-specific means. See Table SI-1 for more details on the variables. Panel e): shows the first polychoric principal component of the other four variables from the WVS. Panel f): shows the density of the number of MMR vaccination shots received by children during the first 36 months, calculated at the state level. A state is classified according to which party had a higher two-party vote share in the 2016 presidential election.
Figure SI-3: Compliance With Shelter-in-Place Policy: Additional Results

Panel a)-h): The specifications are the same as in the corresponding panels in Figure 1, except: panels a) and b) use a 10 day baseline period (rather than five); panel c) includes all leads in the event study specification; panel d) includes saturated covariates × date fixed effects; panels e) and f) use an alternative one day baseline period (rather than five); panel g) and h) are not population weighted. See Figure 1 for additional details.
Benchmarking Measures of Science Skepticism

**Figure SI-4**: Benchmarking Science Skepticism (main specification) with Alternative Measures of Trust in Science (Pair-wise Visualization)

- **(a)** Trust in Science (WVS), PCA
- **(b)** Trust in Science (WVS), Healthier Life
- **(c)** Science Too Far (Pew)
- **(d)** Childhood Vaccination Rates

Panel a), b), c): scatterplots of baseline proxy for belief in science from Howe et al. [19], aggregated to state-level using population weights, against various alternative measures. Higher values of belief in science correspond to weaker skepticism. *Trust in Science (WVS)*: first polychoric principal component of six variables measuring attitudes toward science from the World Values Survey (2011 and 2017 waves pooled). All variables were standardized, survey-weighted and averaged at the state level. *Trust in Science (WVS), Healthier Life*: “Science and technology are making our lives healthier, easier, and more comfortable.” Higher values refer to higher levels of trust in science. See Table SI-1 for more details. *Science Too Far (Pew)*: percent of state sample population in Pew Research Center’s American Values Survey (2002-2009) reporting disagreement with the statement ‘I am worried that science is going too far and is hurting society rather than helping it’. Panel d): using state-level vaccination rates to benchmark our baseline proxy for Science Skepticism. *Child Vaccination*: average number of MMR vaccination shots received by children during the first 36 months of their lives at the state level.
Table SI-1: Benchmarking Science Skepticism (main specification) with Alternative Measures of Trust in Science (Regression-Based Estimates)

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<td>0.476***</td>
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<td>0.584***</td>
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<td>(0.129)</td>
<td>(0.126)</td>
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<tr>
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<td>0.187</td>
<td>0.226</td>
<td>0.179</td>
<td>0.341</td>
<td>0.376</td>
<td>0.110</td>
</tr>
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</table>

Shows coefficients from state-level regressions of science skepticism from Howe et al. [19], aggregated to state-level using population weights, on different measures for trust in science derived from Pew surveys and the World Value Survey (WVS). Higher values of belief in science correspond to weaker skepticism. All variables have been standardized to have mean zero and standard deviation one. The WVS data have been pooled over survey waves 6 and 7 (conducted in 2011 and 2017, respectively) and denote survey-weighted averages at the state level. The WVS variables are: (2) PC: “The first polychoric principal component of the other variables”; (3) Life: “Science and technology are making our lives healthier, easier, and more comfortable”; (4) Opp.: “Because of science and technology, there will be more opportunities for the next generation”; (5) Better Off: “The world is better off, or worse off, because of science and technology”; (6) Better Off: “We depend too much on science and not enough on faith”; (7) Faith2: “Whenever science and religion are in conflict, religion is always right”; (8) Import: “It is not important for me to know about science in my daily life.” If necessary, the measures have been inverted such that higher values refer to higher levels of trust in science. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1)
Science Skepticism and related COVID-19 behaviors: mask use and vaccine hesitancy

**Figure SI-5:** Correlation with Mask Use (County Level)

(a) Raw Data  
(b) After Controlling for Partisanship

Panel a): Figure plots belief in science from Howe et al. [19] against county-level mask use in July 2020. Higher values of belief in science correspond to weaker skepticism. Mask use is defined as the share of people that stated to always wear a mask, which is then standardized to have mean of zero and standard deviation of one. These data have been obtained from a large-scale survey commissioned by the New York Times, which was conducted online between July 2 and July 14 and includes 250,000 survey responses. For details on the data, see Milosh et al. [65]. Panel b): Figure equals the one from Panel a), but shows residuals from regressions on an indicator of a county’s partisanship. Each county is classified according to which party had a higher vote share than the other party in the 2016 presidential election.
Figure SI-6: Correlation with Vaccine Hesitancy (County Level)

(a) Raw Data

Panel a): Figure plots belief in science from Howe et al. [19] against county-level vaccine hesitancy in April 2021. Higher values of belief in science correspond to weaker skepticism. Hesitancy is measured as the share of county residents with little or no interest in receiving a COVID-19 vaccine, which is then standardized to have mean of zero and standard deviation of one. These data have been obtained from the county-level estimates provided by U.S. Census Bureau, leveraging their Household Pulse Survey. For additional information, see https://bit.ly/3osf1M5

(b) After Controlling for Partisanship

Panel b): Figure equals the one from Panel a), but shows residuals from regressions on an indicator of a county’s partisanship. Each county is classified according to which party had a higher vote share than the other party in the 2016 presidential election.