



Modeling state preferences for Covid-19 policies: Insights from the first pandemic summer

Michelle Duren^{a,*}, Bryce Corrigan^b, Johnathon Ehsani^a, Jeffrey Michael^a

^a Johns Hopkins Bloomberg School of Public Health, 615 N Wolfe St, Baltimore, MD, 21205, USA

^b Johns Hopkins Krieger School of Arts and Sciences, 3400 N Charles St, Baltimore, MD, 21218, USA

ARTICLE INFO

Keywords:

Transport policies
Public support
COVID-19
Survey research

ABSTRACT

Introduction: During the COVID-19 pandemic, governments have experimented with a wide array of policies to further public health goals. This research offers an application of multilevel regression with post-stratification (MRP) analysis to assess state-level support for commonly implemented policies during the pandemic.

Methods: We conducted a national survey of U.S. adults using The Harris Poll panel from June 17–29, 2020. Respondents reported their support for a set of measures that were being considered in jurisdictions in the U.S. at the time the survey was fielded. MRP analysis was then used to generate estimates of state-level support.

Results: The research presented here suggests generally high levels of support for mask mandates and social distancing measures in June 2020—support that was consistent throughout the United States. In comparison, support for other policies, such as changes to the road environment to create safer spaces for walking and bicycling, had generally low levels of support throughout the country. This research also provides some evidence that higher support for coronavirus-related policies could be found in more populous states with large urban centers, recognizing that there was low variability across states.

Conclusion: This paper provides a unique application of MRP analysis in the public health field, uncovering noteworthy state-level patterns, and offering several avenues for future research. Future research could examine policy support at a small geographic level, such as by counties, to understand the distribution of support for public policies within states.

1. Introduction

With the onset of the coronavirus pandemic, local and state government officials turned to a new set of policy approaches to control the spread of the virus. Policy measures, such as social distancing and mask mandates, are intended to reduce the spread of the coronavirus while maintaining the possibility of routine activities such as commerce and education (Courtemanche et al., 2020; Lyu and Wehby 2020). Significant variation across states exists in terms of the strength of the policies, when they were implemented, and which locations had the most effective reductions in the spread of the virus following the implementation of such measures (Dave et al., 2021). Existing literature suggests perceived risk, perceived seriousness, and trust in authority are significant factors influencing compliance with public health measures (Fisher et al., 2020). An emerging literature is investigating support for coronavirus-related

* Corresponding author.

E-mail address: mduren3@jhmi.edu (M. Duren).

policies as well as some of its socio-political determinants (Fisher et al., 2020). To the best of our knowledge, such research has yet to examine geographical differences in policy support.

Recent research on understanding public support for and compliance with public health measures has largely been conducted in relation to COVID-19 (Clinton et al., 2021; Bargain and Aminjonov 2020). The COVID-19 pandemic has led to a greater appreciation for the importance of public health policy, and its reliance on collective action and collective support; a relatively understudied area of research. One initial study comparing survey results across 67 countries found that respondents identifying more strongly with their nation reported greater adoption of and support for public health measures aimed at reducing the spread of COVID-19 (Van Bavel et al., 2020). Within the U.S. context, partisanship was found to be an important indicator of policy preferences of public health measures at the start of the pandemic, such as restricting travel and closing schools (Gadarian et al. 2021). Such results point to an important role of social cohesion, social capital, and political affiliation—all measures that typically correspond to specific geographies and can be used to describe certain communities.

Within the field of public health, an extensive body of literature and set of theories exist to help explain health behavior change. Although there is limited research that connects behaviors to support for related policies, the two are generally believed to move in tandem. For example, within studies of climate change, the same predictors are used to explain support for government policies protecting the environment and individual behaviors that protect the environment (Hart 2011; Brick and Lai 2018). Behavior change theories can be readily applied to understanding what might lead someone to adopt measures to stop the transmission of infectious diseases, such as mask wearing (Jones et al., 2015). However, classic health behavior theories such as the Health Belief Model, fail to explain variation in community-level responses to a health threat.

The study offers an insight into geographic variation in support for a series of public health measures in the context of the COVID-19 pandemic. In doing so, it aims to help guide future research and generate hypotheses that can be tested as the study of both policy preferences and relevant behaviors continues to grow. One major limitation to analyzing geographical differences in policy support is having sufficient sample size to construct reliable subnational estimates of support. The following study uses multilevel regression with post-stratification (MRP) analysis to overcome this challenge of obtaining reliable and representative state-level estimates of policy support. This method is common in the political science literature (Lewis and Jacobsmeier 2017; Ghitza and Gelman 2013) but has yet to be commonly applied to public health research.

2. Data and methods

We conducted an online survey of 2011 U.S. adults aged 18 or older using a panel of respondents managed by The Harris Poll. Data were weighted to reflect nationally representative demographic proportions in the U.S. population and propensity score weighting was used to adjust for respondents' propensity to be online. See Table 1 for characteristics of our study population. The survey was conducted between June 17 and 29, 2020. Respondents were also asked if they support, oppose or are unsure about eight policies to reduce transmission of COVID-19, including: (1) require people to sit apart on public transit, (2) require people to wear masks on public transit, (3) require people to wear masks in all indoor spaces where people congregate, (4) stagger school and work start and end times to eliminate peak commuting hours, (5) expand walking and biking areas by closing a vehicle traffic lane, (6) reduce speed limits to accommodate pedestrians and bicyclists, (7) continue or expand remote/telework practices, and (8) continue or expand practices for curbside pick-up of food and other products.

MRP analysis was used to generate state-level estimates of support for each policy considered in our survey. MRP uses three main

Table 1
Weighted descriptive statistics.

Sample Characteristic	Total Sample (N = 2011)
Sex	
Male	974 (48.4%)
Female	1037 (51.6%)
Race	
White	1291 (64.2%)
Black	225 (11.2%)
Asian	129 (6.4%)
Hispanic	315 (15.7%)
Other	50 (2.5%)
Urbanicity	
Urban	659 (32.8%)
Suburban	968 (48.1%)
Rural	385 (19.1%)
Household Income	
Less than \$50,000	654 (32.5%)
\$50,000 to \$99,999	629 (31.3%)
\$100,000 or more	728 (36.2%)
Age Group	
18-29	373 (18.5%)
30-54	867 (43.1%)
≥55	772 (38.4%)

stages (1) model the relationship between the dependent and independent variables with multilevel regression, (2) construct a sampling frame based on the independent variables' frequency in the populations of interest—in this case, the 50 states in the United States and the District of Columbia, and (3) generate predictions for the model from step one applied to the populations represented in step 2. We used the same independent variables when modeling each of the policies—specifically, age, race, sex, household income, educational attainment, marital status, size of household, occupation, and state of residence. The model was estimated for the Harris Poll survey data. The 2019 American Community Survey (U.S. Census Bureau 2020) was used to construct the stratification weight to represent the state populations (and the District of Columbia). Lastly, the model estimates were used to generate predictions in the target populations. These predictions used a Bayesian approach; after convergence of the Markov Chain for the multi-level model (using four randomly initialized Markov chains, each for 2000 iterations), 250 Monte Carlo replications were performed to construct each state-level prediction. All statistical work was performed using R 4.0.3 (R Core Team 2020), including using the ggplot2 (Wickham 2016), rstanarm (Goodrich et al., 2020) and tidybayes (Kay 2020) packages.

3. Results

The analysis generates predicted levels of state support for each of the eight policies we considered. The results show greater variation among policies than among states, as demonstrated in Fig. 1. Fig. 2 shows the distribution in state levels of support for each policy. When considering each policy separately, the range in support was 14 percent on average. The lowest variation among states was for requiring masks in indoor public spaces (4 percent) and the highest was for requiring social distancing on transit (26 percent). Every state had less than 50 percent support for reducing speed, staggering work times, and expanding street space for bicycling and walking. In contrast, every state had a majority of its population supporting mask mandates—both in public and on transit. The majority of people in all states support policies requiring social distancing on transit, with the exception of Nebraska, where support for this policy was 46 percent. The distribution of support for the remaining policies—expanding curbside pick-up and teleworking—was centered around 50 percent.

In Fig. 3, each state is arranged in order of its levels of public support for each policy from lowest to highest, moving left to right. The red outline in Fig. 3 surrounds the ten states with the highest levels of support for each policy. Concentrating on these most supportive states, we can see patterns in support across the various policies reviewed. For example, California and the District of Columbia are generally among the states with the highest levels of support. California is in the top ten for five of the eight policies, but then has relatively low levels of support for requiring social distancing and masks on public transit and for staggering work times. D.C. appears either in the top ten states or just outside of it for all of the policies except for expanded telework and curbside pick-up practices—where its level of support falls closer to the median. When considering the states with the highest levels of support across the policies, the states seem to skew to the more populous states and those with large metropolitan areas and high population

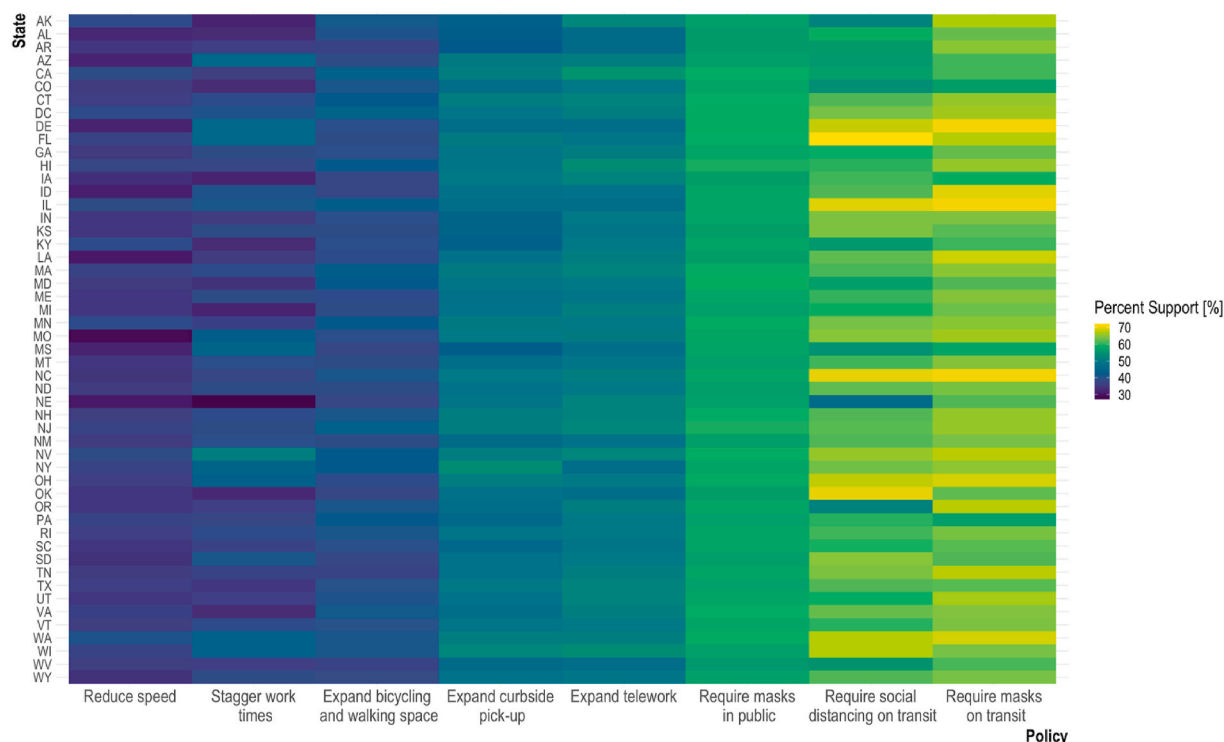


Fig. 1. Percent support for coronavirus-related policies, by state and by policy.

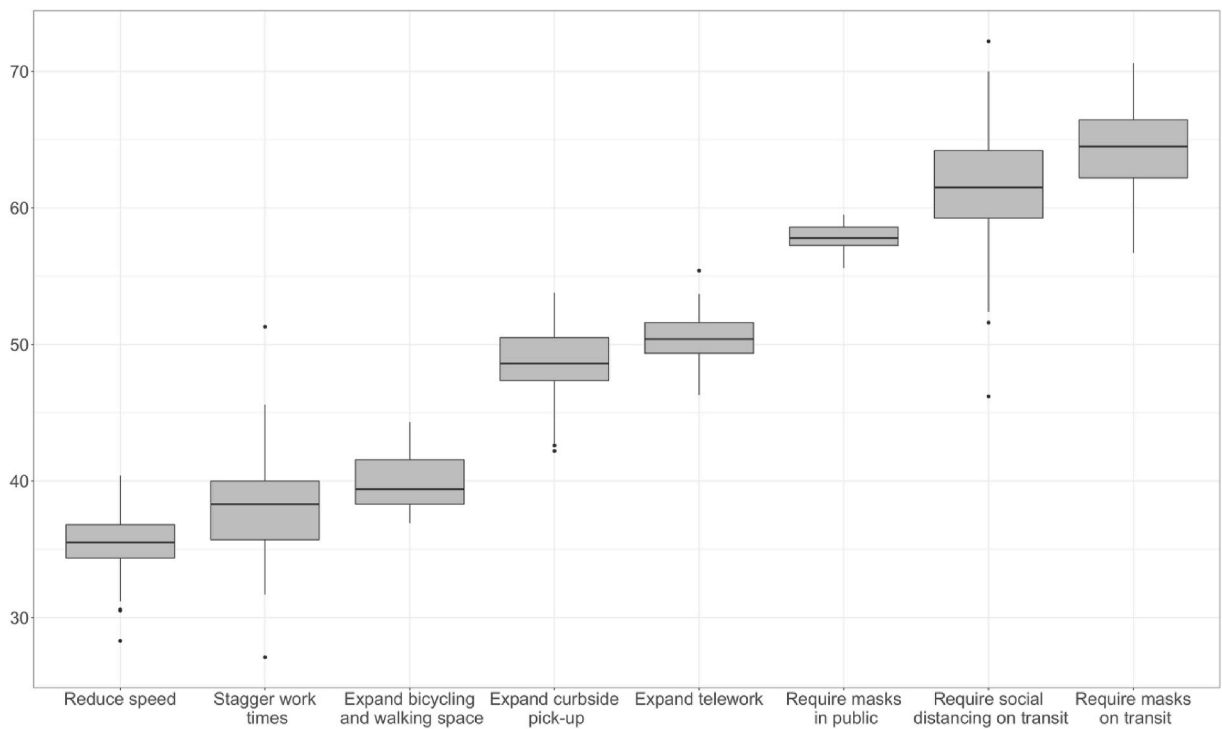


Fig. 2. Boxplots of support for coronavirus-related policies, by state and by policy.

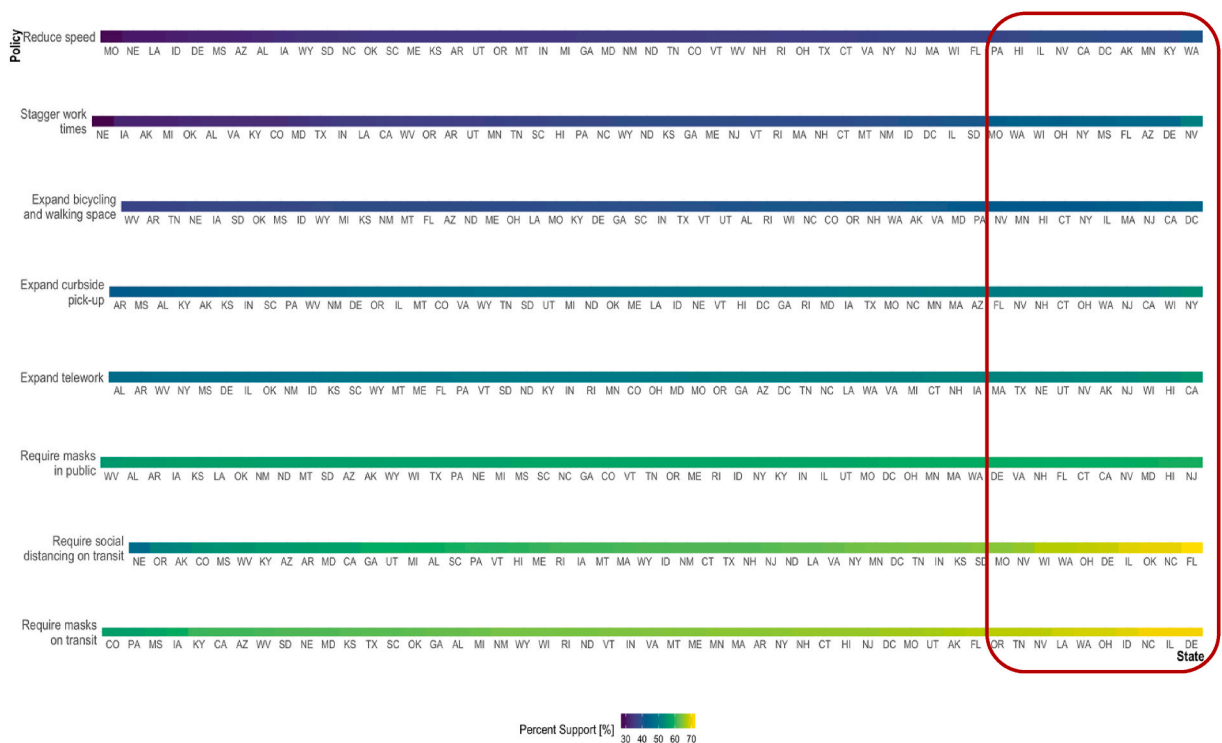


Fig. 3. Support for coronavirus-related policies, by state and by policy, highlighting the 10 states with highest support.

density. Washington, Florida, Illinois, Ohio, Nevada, and Hawaii feature prominently in the states with the ten highest levels of support for the policies being considered.

Fig. 4 below focuses only on support for expanding street space for bicyclists and pedestrians—a policy many cities experimented with during the course of the pandemic. Displaying support geographically shows clear regional patterns in support for this policy. This map shows the greatest amount of support concentrated in the Northeast, with also relatively high levels of support in the West and Upper Midwest. The remaining parts of the country have noticeably lower levels of support for this policy, with support in the 30s for these remaining states.

Considering support for requiring masks in public—a policy with significantly higher levels of support than was shown for expanded street space for bicyclists and pedestrians—similar patterns are evident. As depicted in Fig. 5, the West and East indicated higher levels of support than the rest of the country for requiring masks in public.

4. Discussion

Research in the wake of the coronavirus pandemic has found that certain policies implemented during the pandemic, such as mask mandates, have been very effective at controlling the spread of the coronavirus. Public support for such policies is an important element to examine, influencing the likelihood that states and other localities will implement related policies. Additionally, and possibly more importantly, understanding geographic variation in policy support could indicate the degree to which people are likely to comply with these coronavirus-related policies. Further research is needed to investigate connections between policy support and behavior change. Such research should also consider the role of state political culture as a possible key determinant for both policy support and behavior change.

The research findings presented here suggest that the majority of the U.S. and the majority of the population residing in each state support the primary policies promoted in the U.S. during the June 2020 timeframe—namely, social distancing measures and mask mandates. These are encouraging results that suggest that despite high profile instances of people refusing to wear masks or protests against state policies aimed at reducing coronavirus transmission, there was still widespread support throughout the country for these measures.

In contrast, support was consistently low across the U.S. for other policies aimed at changing the road environment or commuting-related behaviors. These policies have the potential to have public health impacts that extend beyond the coronavirus pandemic—such as lower carbon emissions, reduced motor vehicle crashes, and increased physical activity levels that can reduce the high chronic disease burden in the U.S. Identifying the areas with higher support for these policies could guide efforts to implementing additional such policies. Although many of the policies considered in this research were generally implemented at the local level—by cities and counties—important policy levers exist at the state level as well. One such policy lever is pre-emption. In relation to the policies considered here, this state-versus-local control issue arose with mask mandates in Georgia, with the Governor issuing an Executive Order blocking the enforcement of any local policies that were any more or less restrictive than those at the state level ([Georgia Executive Order, 2020](#)). Furthermore, transportation policies are a unique area of government, where local, state, regional, and federal transportation authorities are involved.

When concentrating on variation in support for the policies under consideration individually, support correlates with population and population-density. Explanations for this finding are ambiguous. The correlation with population measures could relate to support being linked to locations that were more impacted by the coronavirus; when the survey was fielded in June 2020, coronavirus cases were concentrated in more populated urban centers. It could also suggest that general urbanicity is an important factor in explaining variation in policy support. Relatedly, since more urban areas lean Democratic, this finding could also be suggestive of partisanship being an important determinant, but more research is needed to investigate this possible relationship. Despite observable patterns in states with higher versus lower support for coronavirus-related public policies, the more surprising finding is the high degree of similarity across states.

While the data and findings are U.S.-focused, implications can be extended to other contexts as well. The work presented here is a case study of one nation that experienced public debate over the role of government and individual freedom in enacting a public health response to an emergent global health threat. The similarity in support for public health measures across U.S. states at the start of the pandemic is suggestive of two possibilities: (1) political rhetoric created a growing divide among states where none previously existed, or (2) states are a less meaningful unit of analysis than smaller geographies or different geographic divisions (e.g., rural versus urban). Such geographic analyses are relevant and needed in varied contexts. Comparative case studies would be particularly useful involving countries with contrasting experiences in terms of acceptance of public health measures—such as by comparing and contrasting the U. S. to a country with high vaccination rates and a relatively fast uptake of vaccines, like Uruguay or Iceland ([The Economist 2021](#)).

MRP analysis provides insights by leveraging multilevel modeling and of national survey data and finer-grained data from sources such as the U.S. Census Bureau. This methodology can enable more reliable estimates of survey responses for subpopulations relative to simple stratification. Despite these clear benefits, limitations remain. Most importantly, although the post-stratification technique helps to adjust the survey population to more closely resemble the population of interest, any characteristics that differ systematically between the survey and target populations that are not directly accounted for in the multilevel model will become a source of bias. This risk for bias between the survey and target population is particularly severe for non-probability surveys—such as the survey used for this work. For non-probability surveys, participant selection is a matter of convenience, so there is no assurance that there is a degree of randomness among respondents in comparison to the general population. Surveys with probability-based sampling are generally greatly improved in this respect, but with increasing nonresponse rates for general population surveys, concerns of survey respondents not adequately representing the population they are meant to represent is a significant concern that all survey research will have to

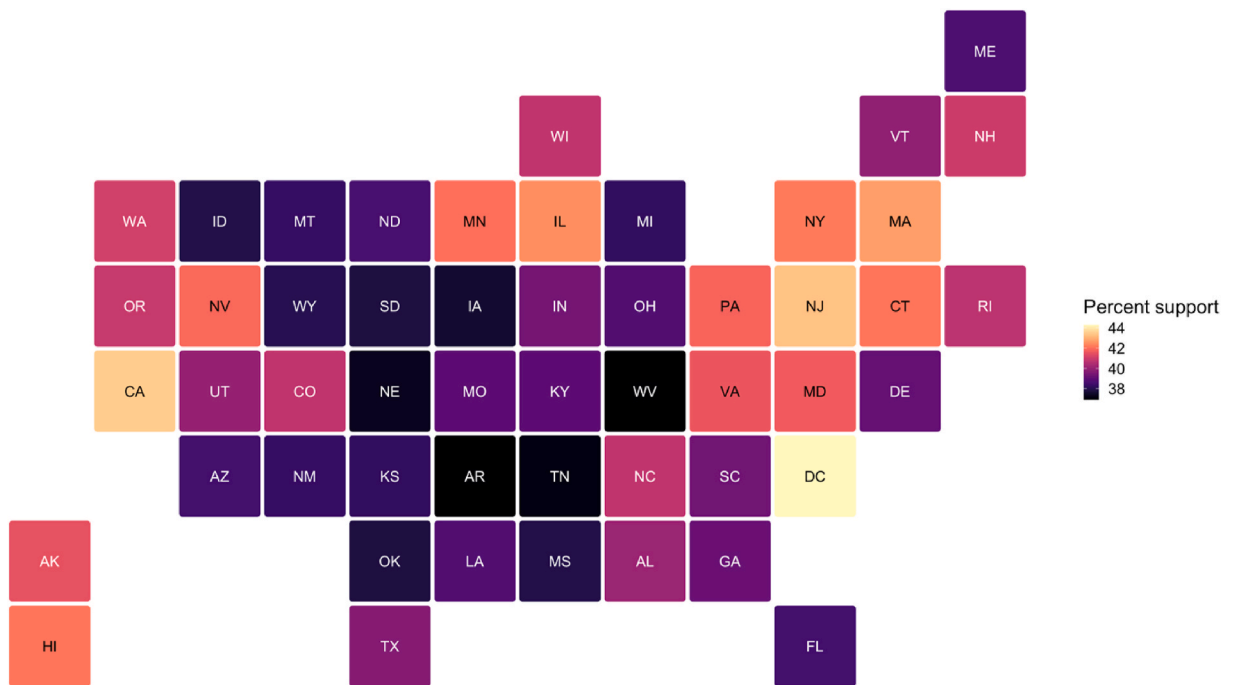


Fig. 4. Geographic variation in support for expanded street space for active transportation.

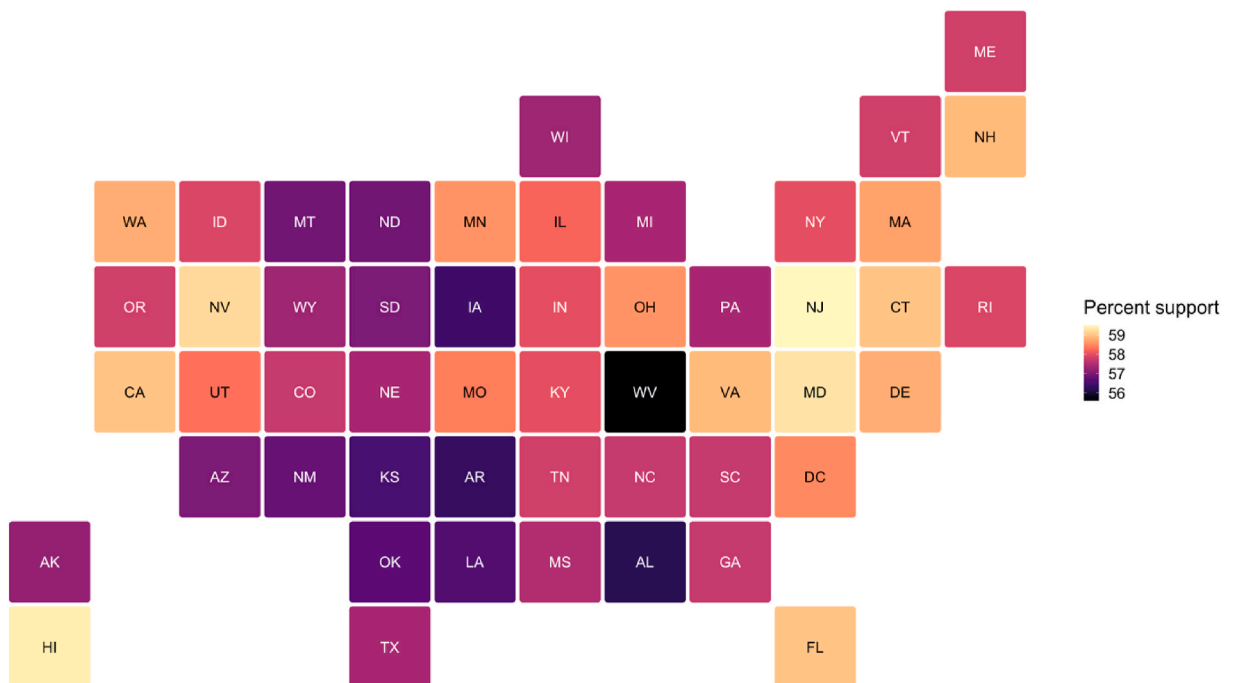


Fig. 5. Geographic variation in support for mask mandates.

grapple with in coming years (Peytchev 2013).

5. Conclusion

As the research community begins to investigate the unprecedented public health challenges faced during the pandemic and the

behavior and public policies changes that occurred—it will be important to develop an understanding of the determinants for public support and adherence to effective measures for reducing the impact of the coronavirus on communities. The research presented here suggests generally high levels of support for mask mandates and social distancing measures in June 2020—support that was consistent throughout the United States. Support for other policies, such as changes to the road environment to create safer spaces for walking and bicycling, has generally low levels of support throughout the country. This research also provides some evidence that higher support for coronavirus-related policies could be found in more populous states with large urban centers, but these findings are within the broader context of generally low variability across states. Thus, while state differences are a common focus within policy studies, given the critical role that states have in public health policy, the research here suggests that other location-based factors, such as population density, may be other important determinants. Future research should review public support at a more micro-level, such as by counties, to understand the distribution of support for key public policies within states. Smaller units of analysis could yield more applicable correlates of important predictors suggested by the literature, such as social cohesion; if social cohesion is high in one part of the state but weak in another, then averaging across the state fails to capture this important variation. More refined research could investigate whether support for progressive public health and transportation policies varies by regions e.g. urban centers. Furthermore, research might identify policies that enjoy high levels of public support and a favorable local political climate.

Author statement

Michelle Duren: Conceptualization, Methodology, Software, Formal analysis, Writing- Original Draft, Visualization. **Bryce Corrigan:** Conceptualization, Methodology, Supervision, Writing -Review & Editing. **Johnathon Ehsani:** Investigation, Resources, Writing -Review & Editing. **Jeffrey Michael:** Investigation, Resources, Writing -Review & Editing.

Financial disclosure

The Authors did not receive any specific funding for this work.

Acknowledgements

This research was supported in part by Johns Hopkins Institute for Health and Social Policy, a grant from the National Center for Injury Control and Prevention, Centers for Disease Control and Prevention to the Johns Hopkins Center for Injury Research and Policy (grant number 1R49CE003090), and by a grant from the U.S. Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health to the Johns Hopkins Education and Research Center for Occupational Safety and Health (award number T42 OH0008428).

References

- Bargain, Olivier, Aminjonov, Ulugbek, 2020. Trust and compliance to public health policies in times of COVID-19. *J. Publ. Econ.* 192, 104316. <https://doi.org/10.1016/j.jpubeco.2020.104316>. December.
- Brick, Cameron, Lai, Calvin K., 2018. Explicit (but not implicit) environmentalist identity predicts pro-environmental behavior and policy preferences. *J. Environ. Psychol.* 58, 8–17. <https://doi.org/10.1016/j.jenvp.2018.07.003>. August.
- Clinton, J., Cohen, J., Lapinski, J., Trussler, M., 2021. Partisan pandemic: how partisanship and public health concerns affect individuals' social mobility during COVID-19. *Science Advances* 7 (2), eabd7204. <https://doi.org/10.1126/sciadv.abd7204>.
- Courtemanche, Charles, Joseph, Garuccio, Le, Anh, Pinkston, Joshua, Yelowitz, Aaron, 2020. Strong social distancing measures in the United States reduced the COVID-19 growth rate. *Health Aff.* 39 (7), 1237–1246. <https://doi.org/10.1377/hlthaff.2020.00608>.
- Dave, Dhaval, Friedson, Andrew I., Matsuzawa, Kyutaro, Sabia, Joseph J., 2021. When do shelter-in-place orders fight covid-19 best? Policy heterogeneity across states and adoption time. *Econ. Inq.* 59 (1), 29–52. <https://doi.org/10.1111/ecin.12944>.
- Fisher, Kiva A., Barile, John P., Guerin, Rebecca J., Vanden Esschert, Kayla L., Jeffers, Alexis, Tian, Lin H., Garcia-Williams, Amanda, Gurbaxani, Brian, Thompson, William W., Prue, Christine E., 2020. Factors associated with cloth face covering use among adults during the COVID-19 pandemic - United States, april and may 2020. *MMWR. Morbidity and Mortality Weekly Report* 69 (28), 933–937. <https://doi.org/10.15585/mmwr.mm6928e3>.
- Gadarian, Shana Kushner, Goodman, Sara Wallace, Pepinsky, Thomas B., 2021. Partisanship, health behavior, and policy attitudes in the early stages of the COVID-19 pandemic. *PLoS One* 16 (4), e0249596. <https://doi.org/10.1371/journal.pone.0249596>.
- Georgia executive order 07.15.20.01. July 15. <https://gov.georgia.gov/executive-action/executive-orders/2020-executive-orders>, 2020.
- Ghitza, Yair, Gelman, Andrew, 2013. Deep interactions with MRP: election turnout and voting patterns among small electoral subgroups. *Am. J. Polit. Sci.* 57 (3), 762–776. <https://doi.org/10.1111/ajps.12004>.
- Goodrich, B., Gabry, J., Ali, I., Brilleman, S., 2020. rstanarm: Bayesian applied regression modeling via Stan. R package version 2.21.1. <https://mc-stan.org/rstanarm>.
- Hart, Philip Solomon, 2011. One or many? The influence of episodic and thematic climate change frames on policy preferences and individual behavior change. *Sci. Commun.* 33 (1), 28–51. <https://doi.org/10.1177/1075547010366400>.
- Jones, Christina L., Jensen, Jakob D., Scherr, Courtney L., Brown, Natasha R., Christy, Kathryn, Weaver, Jeremy, 2015. The health Belief model as an explanatory framework in communication research: exploring parallel, serial, and moderated mediation. *Health Commun.* 30 (6), 566–576. <https://doi.org/10.1080/10410236.2013.873363>.
- Kay, M., 2020. Tidybayes: tidy data and geoms for bayesian models. URL: R package version 2.1.1. <https://doi.org/10.5281/zenodo.1308151>. <http://mjskay.github.io/tidybayes/>.
- Lewis, Daniel C., Jacobsmeier, Matthew L., 2017. Evaluating policy representation with dynamic MRP estimates: direct democracy and same-sex relationship policies in the United States. *State Polit. Pol. Q.* 17 (4), 441–464. <https://doi.org/10.1177/1532440017739423>.
- Lyu, Wei, Wehby, George L., 2020. Community use of face masks and COVID-19: evidence from A natural experiment of state mandates in the US. *Health Aff.* 39 (8), 1419–1425. <https://doi.org/10.1377/hlthaff.2020.00818>.
- Peytchev, Andy, 2013. Consequences of survey nonresponse. *Ann. Am. Acad. Polit. Soc. Sci.* 645 (1), 88–111. <https://doi.org/10.1177/0002716212461748>.
- R Core Team, 2020. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. URL: <https://www.R-project.org/>.
- The Economist, 2021. Tracking covid-19 across the world. September 10, 2021. <https://www.economist.com/graphic-detail/coronavirus-excess-deaths-tracker>.

U.S. Census Bureau, 2020. 2019 American Community Survey 1-year Public Use Microdata Samples.

Van Bavel, Jay, J., Cichocka, Aleksandra, Capraro, Valerio, Sjøstad, Hallgeir, Nezlek, John B., Alfano, Mark, Azevedo, Flavio, et al., 2020. National identity predicts public health support during a global pandemic: results from 67 nations. PsyArXiv. <https://doi.org/10.31234/osf.io/ydt95>. September 2.

Wickham, H., 2016. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag, New York.