

1 **Governor’s Party, Policies, and COVID-19 Outcomes: Further Evidence of an Effect**

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13 **Abstract:**

14 **Introduction:** This study connects the aggregate strength of public health policies taken in  
15 response to the COVID-19 pandemic in the U.S. states to the governors’ party affiliations and to  
16 the state-level outcomes. Understanding the relationship between politics and public health  
17 measures can better prepare our communities for what to expect from their governments in a  
18 future crisis and encourage advocacy for delegating public health decisions to medical  
19 professionals.

20 **Methods:** The Public Health Protective Policy Index (PPI) captures the strength of policy  
21 response to COVID-19 at the state level. We estimate a Bayesian model that links the rate of  
22 disease spread to PPI. The model also accounts for the possible state-specific undercounting of  
23 cases and controls for state population density, poverty, number of physicians, cardiovascular  
24 disease, asthma, smoking, obesity, age, racial composition, and urbanization. We employ a  
25 Bayesian linear model with natural splines of time to link the dynamics of PPI to governors’  
26 party affiliations.

27 **Results:** A 10-percentage-point decrease in PPI is associated with an 8-percent increase in the  
28 expected number of new cases. Between late March and November 2020 and at the state-specific  
29 peaks of the pandemic, the PPI in the states with Democratic governors was about 10 percentage  
30 points higher than in the states with Republican governors.

31 **Conclusions:** Public health measures were stricter in the Democrat-led states, and stricter public  
32 health measures were associated with a slower growth of COVID-19 cases. The apparent  
33 politization of public health measures suggests that public health decision-making by health  
34 professionals rather than political incumbents could be beneficial.

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## 38 **Introduction**

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40 In a recent AJPM research brief, Neelon and colleagues<sup>1</sup> demonstrate a correlation between the  
41 partisanship of a governor in US states and the morbidity and mortality during the COVID-19  
42 epidemic. They also conjecture that “the political affiliation of state leaders and specifically  
43 governors might best capture the omnibus impact of state policies.”<sup>1</sup> While studies to-date show  
44 impact of individual types of mitigation policies<sup>2,3,4</sup> on health outcomes, they do not speak to  
45 their combined effect nor do they look specifically into the US states.

46

47 The present study uses the Public Health Protective Policy Index (PPI)<sup>5,6</sup> to connect the  
48 aggregate strength (stringency) of state-originating public health policies to both the party  
49 affiliation of its governor and to the state-level outcomes. Understanding the relationship  
50 between politics and public health measures can better prepare American communities for what  
51 to expect from their governments in a future crisis and encourage the medical community to  
52 advocate for greater delegation of public health policy-making to professional actors.

53

## 54 **Methods**

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56 The Public Health Protective Policy Index (PPI) is an aggregated measure of public health policy  
57 stringency, calculated for each day in each state based on 15 categories of public health measures  
58 (see Appendix). For each observation, three indices are calculated. National PPI aggregates

59 measures adopted by the federal government, according to the stringency in each of the  
60 categories. State PPI aggregates measures adopted by the state government. Finally, Total PPI  
61 aggregates the highest values from each of the 15 categories when comparing the federal and  
62 state-originating policies.<sup>5,6</sup> While normal policymaking includes multiple political and societal  
63 actors, this attribution of policy stringency to governors is justified because over 88% of all  
64 COVID-19 policies in the US states came directly through executive actions rather than from the  
65 legislature, bureaucracy, or judiciary.

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67 Estimations use the Total PPI thus combining state-originated policies with federal-originated  
68 policies.. Unlike State PPI, Total PPI does not penalize governors for failing to enact policies  
69 that would be redundant to federal policies. While many states duplicated or exceeded federal  
70 actions in specific categories, others did not issue their own versions of otherwise available  
71 policies.<sup>5</sup> The analysis, following Neelon and colleagues,<sup>1</sup> covers mitigation policies between  
72 March 1 and November 30, 2020.

73

74 The analysis of the link between governors' party affiliations and the dynamics of new COVID-  
75 19 cases is broken into two steps: (1) a study of the link between the policy stringency and the  
76 dynamics of new COVID-19 cases, and (2) a study of the link between the policy stringency and  
77 governors' party affiliations. The first step employs a Bayesian model that follows the logic of  
78 the "Susceptible-Infected-Removed" (SIR) model.<sup>7</sup> In it the expected number of newly infected  
79 is proportional to the number of the infectious and the share of the susceptible in the population:

80

$$E[I_{j,(t+1)}^{\text{new}}] = \lambda_{j,t} S_{j,t} I_{j,t},$$

81 where  $I_{j,(t+1)}^{\text{new}}$  is the number of new infections in state  $j$  in period  $(t+1)$ ,  $I_{j,t}$  is the estimated  
 82 number of currently infectious,  $s_{j,t}$  is the share of those susceptible, and  $\lambda_{j,t}$  is a coefficient  
 83 incorporating the density of contacts and transmissibility of the infection.  $I_{j,(t+1)}^{\text{new}}$ ,  $I_{j,t}$ , and  $s_{j,t}$  are  
 84 constructed using the state-wide counts of new cases<sup>8</sup> and additional parameters for the state-  
 85 specific rates of potential undercounting of new cases and the rate of removal of the infectious.  
 86  $\ln(\lambda_{j,t})$  depends linearly on the stringency of current policies:

$$87 \quad \ln(\lambda_{j,t}) = \beta_0 + P_{j,(t-3)}\beta_1 + X_j\alpha,$$

88 where  $P_{j,(t-3)}$  is the value of total PPI with a 3-day lag, and  $X_j$  are state-specific control  
 89 variables. In the appendix, 7- and 14-day lags are used in robustness checks. The number of new  
 90 cases is assumed to follow a negative binomial distribution. The posterior samples for the model  
 91 parameters are drawn using weakly informative priors and Gibbs sampler.<sup>9,10</sup> Model details,  
 92 including the model specification, parameter estimates, the list of control variables, the  
 93 covariates of the undercounting of new cases, and the data sources, are provided in the  
 94 Appendix.

95  
 96 To examine the association between the party affiliation of the governor and policy stringency, a  
 97 Bayesian linear model is estimated, which treats the average PPI as a function of time and  
 98 governor's party affiliation. It uses natural cubic splines of time and a separate set of coefficients  
 99 for each state in the analysis. State-specific coefficients have multivariate normal priors with  
 100 different hyperpriors for the states with Democratic and Republican governors. Gibbs sampler<sup>9,10</sup>  
 101 is employed to compute the posterior distribution of state-specific trajectories and the average  
 102 trajectories of policy stringency in the states with Democratic and Republican governors.

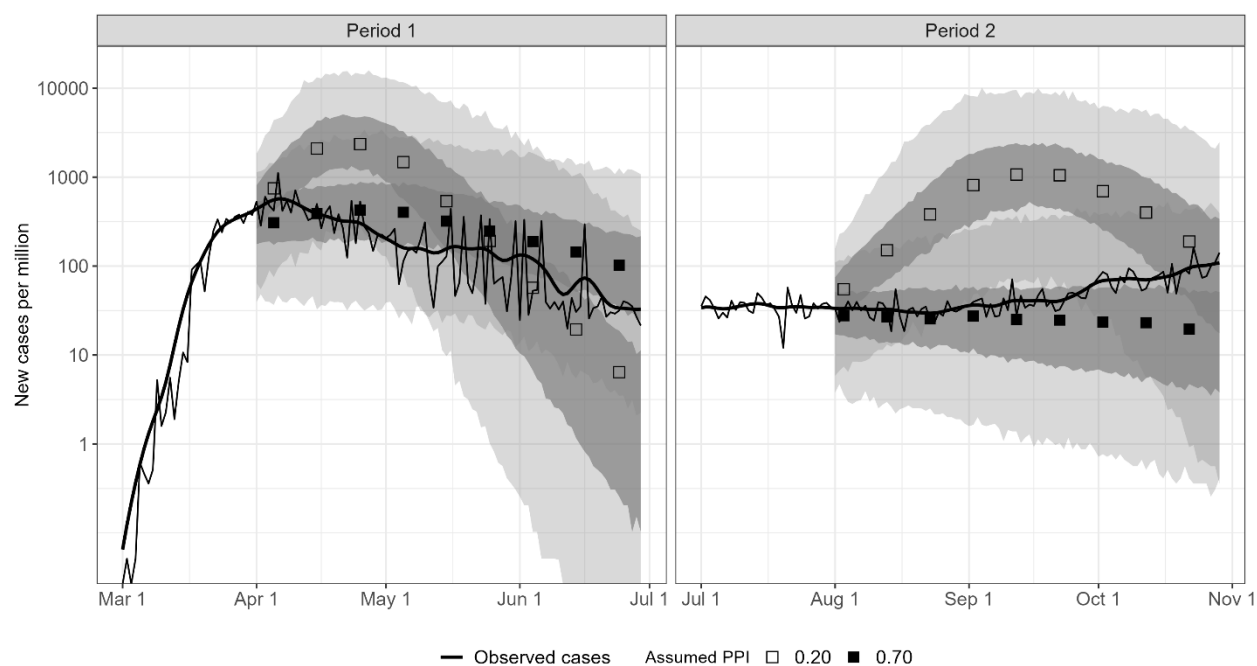
103

104 **Results**

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106 According to the estimates of the first model, the posterior mean of  $\beta_1$  is -0.839, with the central  
 107 95% posterior interval between -0.806 and -0.630. Thus a 10-percentage-point decrease in the  
 108 policy stringency is associated in the model with an 8-percent increase in the expected number of  
 109 new cases.

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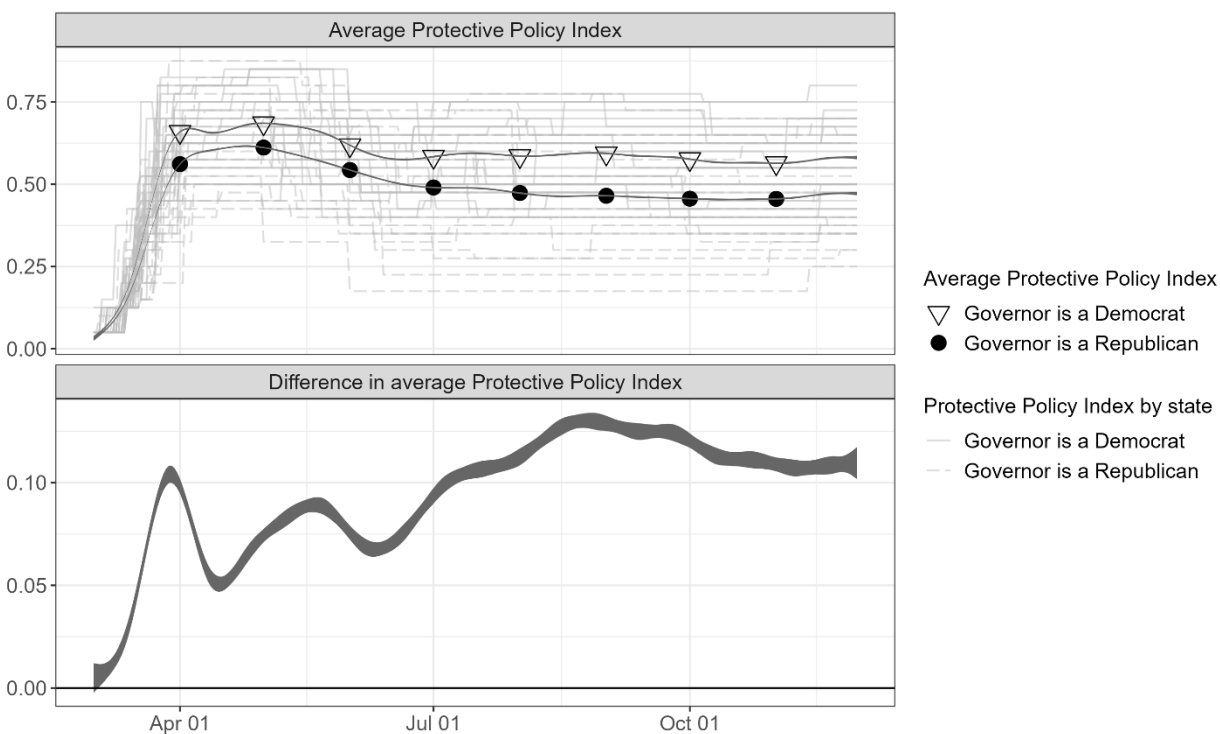
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112 *Figure 1 Simulated dynamics of new cases with high and low PPI*

113 Bands represent central 50% and 95% posterior predictive intervals.

114 Figure 1 illustrates the estimates. The left panel shows the simulated trajectories of the new cases  
 115 in New York after April 1 in continuation of the dynamic observed over March 2020. The

116 simulations are conducted under the assumptions that the PPI is fixed at 0.70 and that the PPI is  
 117 reduced to 0.20. These simulations show that a reduction of the stringency of policies would  
 118 have delayed reaching the peak in the number of cases until May and lead to an overall higher  
 119 number of cases. The right panel shows similar simulations conducted for the period starting on  
 120 August 1, 2020.



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122 *Figure 2 Dynamics of average PPI in states with Democrat and Republican governors*

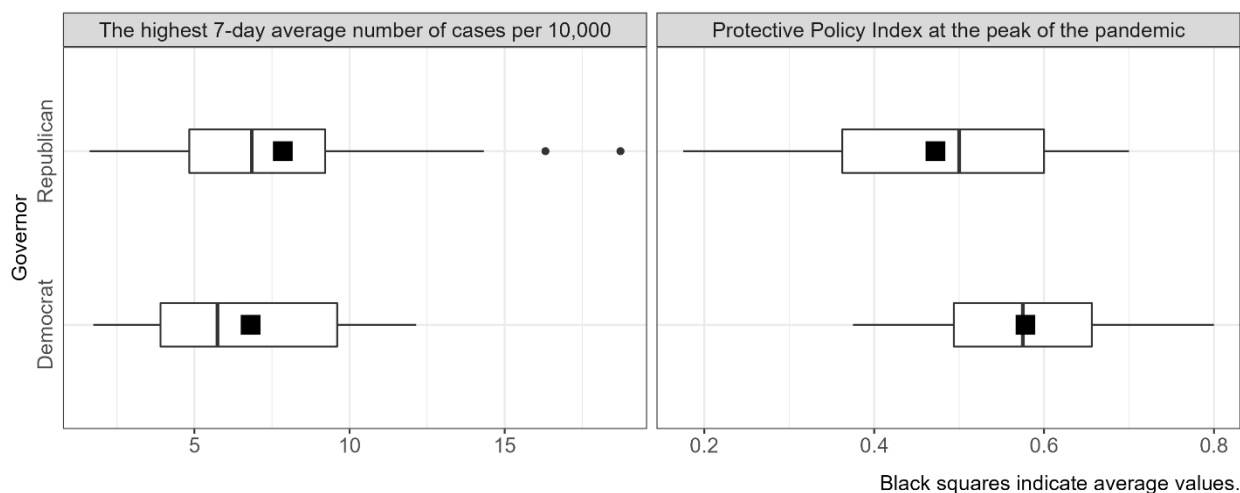
123 Bands represent central 50% and 95% posterior intervals.

124 The estimates indicate that on average the states with Republican governors had weaker public  
 125 restrictions. Figure 2 plots the estimated dynamics of the averages of Total PPI in the states with  
 126 Democratic and Republican governors, as well as the dynamics of the difference in averages.  
 127 Between late March and November 2020, the average difference was between 5 and 15  
 128 percentage points. That said, there is significant variation within both groups of states, possibly

129 attributable to the differences in the epidemiological situation and the ideological characteristics  
 130 of state electorates. Republican governors in more liberal states (Massachusetts, Vermont, and  
 131 Maryland) pursued more aggressive COVID-19 policy.

132

### 133 Discussion



134

135 *Figure 3 Number of new cases and PPI at the peaks of the pandemic*

136 One way to parse out the ideological drivers of the pandemic policy-making from the public  
 137 health expediency is by assuming that the public health incentives were at their highest (and  
 138 uniformly high for all states) at the peaks of the pandemic. Figure 3 shows the distributions of  
 139 new cases (left panel) and policy stringency (right panel) during the state-specific peaks of the  
 140 pandemic. While the average number of cases was at least as high in the Republican-led states as  
 141 in the Democrat-led states, the average PPI was lower by about 10 percentage points.

142

### 143 Limitations

144 The present study quantifies the differences in the average policy stringency between states led  
145 by Democratic and Republican governors over year 2020 and links this differences to the  
146 dynamics of COVID-19 cases. As with most analyses of observational data, the causality cannot  
147 be inferred, and the reader should not interpret the estimates without considering the employed  
148 modelling assumptions, including the constant rates of the underreporting of cases within a state,  
149 the constant rates of the removal the infected from the pool of the contagious, and the absence of  
150 re-infections or the spread of infections across state borders. The analysis of the observed  
151 differences in policy stringency does not separate the consequences of governors' intent from the  
152 constraints in public health policy making.

### 153 **Conclusion**

154

155 The evidence shows that the public health measures taken in the states with Democratic  
156 governors were on average 10 percentage points stricter over most of 2020. According to the  
157 model, these additional 10 percentage points in policy stringency reduced the expected number  
158 of cases by about eight percent.

159

160 These conclusions reinforce and extend the findings of Neelon et al.<sup>1</sup> that application of public  
161 health policy was politicized. This information further supports the need for delegating public  
162 health policy making to health professionals.

163

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165

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173

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