Modeling and testing strategic interdependence and tipping in public policy implementation

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We develop a game-theoretic model of strategic interdependence and tipping in public policy choices and show that the model can be estimated by probit and logit estimators. We test its validity and applicability by using daily data on state-level COVID-19 responses in the United States. Social distancing via shelter-in-place (SIP) strategies and wearing masks emerged as the most effective nonpharmaceutical ways of combatting COVID-19. In the United States, choices about these policies are made by individual states. We develop a game-theoretic model of such choices and test it econometrically, confirming strong interdependence in the implementation of these policies. If enough states engage in social distancing or mask wearing, others will be tipped to follow suit. Policy choices are influenced mainly by the choices of other states, especially those of similar political orientation and to a lesser degree by the number of new COVID-19 cases. The choice of mask-wearing policies is more sensitive to peer choices than the choice of SIP policies, and Republican states are much less likely than Democratic to introduce mask-wearing policies. The choices of policies are influenced more by political than public health considerations. These findings emphasize strategic interdependence in policy choice and offer an analytical framework for these complex dynamics.

tipping | COVID-19 | social reinforcement | strategic complementarity

Significance

We develop a game-theoretic model of strategic interdependence and tipping in public policy and show that the model can be estimated by probit and logit estimators. We test its validity and applicability by using daily data on state-level COVID-19 responses in the United States. Social distancing via shelter-in-place (SIP) strategies and wearing masks emerged as the most effective nonpharmaceutical ways of combatting COVID-19. The choices of policies are influenced more by political than public health considerations.

The concept of tipping in social dynamics revolves around the idea that some choices are mutually reinforcing. Once a certain number of people have made a choice, it becomes more attractive to others, thereby increasing the likelihood of them making the same choice. If these interactions are sufficiently strong, a change of choices by a subset of agents can lead to an abrupt change of regime. The earlier models (1–3) address this issue in the context of racial segregation in housing, yet they differ significantly from each other. Schelling's model (1) is a simple dynamic one where a racially mixed equilibrium is inherently unstable, while Card et al. (2, 3) employs a comparative static model where a racially mixed equilibrium disappears as a preference parameter shifts, interpreting this disappearance as tipping. The tipping of social equilibria has been systematically applied to describe various policy-relevant phenomena such as segregation (1, 2), climate change policies and negotiation (4–6), sustainable management of natural resources (7, 8), and social norms (9, 10).

Our model, based upon Heal and Kunreuther (11), extends these concepts by applying a game-theoretical approach to illustrate how the decisions of agents regarding the implementation of new policies are influenced by the actions of others. We demonstrate that tipping may occur when an agent's decision to adopt a policy is contingent on the number of agents who have already implemented similar policies. This leads to a tipping point where a small change in policy by some agents can trigger an abrupt regime shift.

A real-world illustration is provided by pandemic response in the tri-state area of New York, New Jersey and Connecticut, many of whose residents commute to and work in New York City. During the COVID pandemic, when NYC closed down its businesses, residents of all three states were affected. Many residents of New Jersey and Connecticut would now have less reason to travel to New York. When New York introduced a shelter-in-place (SIP) order that shut down businesses, the governors of adjacent states found it easier to do likewise, because the incremental economic costs decreased as part of the cost was already incurred by New York. The intensive flow of people traveling between states for work, shopping and entertainment also illustrates well the ease with which a virus can spread from one state to another. Reducing the incidence of a disease in one state will reduce the likelihood that its neighboring states' residents encounter it through cross-state traveling.

In this example, the introduction of SIP policies by one state may make it politically easier for others to follow suit. When faced with the opposition from potential losers of this policy, the governors could cite the neighboring state's adoption as a strong rationale. We formalize our logic as a game between states. This game is supermodular and so will

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have multiple Nash equilibria, including a greatest and a least equilibrium (11–14). If the effectiveness of a policy depends on whether such policies are in place elsewhere and increases with this number, then the game between states is characterized by social reinforcement, and in particular. its payoffs may show uniform strict increasing differences, a strong form of strategic complementarity. This type of complementarity is a common assumption in the policy diffusion literature (7, 8).

We formally model this interdependence and showcase how the existence of tipping sets arises in supplementary materials. A tipping set in such a game is a set of agents (US states in our example) with the following property: if all members of this set choose to implement a particular policy, then the best response of every other agent will be to follow suit and choose the same policy. The members of the tipping set, by adopting a policy, can drive all others to adopt the same policy, even in the absence of a centralized plan (9). This can be a mechanism of policy diffusion (15, 16).

The interdependence above characterizes a case in which agents are homogeneous and behave according to similar interests. *SI Appendix*, Fig. S1 illustrates the rapid dissemination of two non-pharmaceutical interventions (NPIs) for COVID-19—mask-wearing mandates and SIP orders in the United States—across Democratic states, achieving near-universal adoption within two quarters of 2020. Comparable trajectories are observed in both Republican and swing states. Despite the inherent heterogeneity among these states, particularly in terms of the pandemic's progression at that juncture, the uniformity in the pattern of policy implementation is noteworthy.

However, real-world agents (such as states and countries) may exhibit negative interdependence if they have competing political affiliations. This phenomenon is systematically documented as polarization (17, 18). In this regard, the political policy interdependence among agents can be either positive or negative dependent on their ideologies. When this effect coexists with the mutual reinforcement above, the equilibrium structures may differ. We quantify this case with a two-party game theoretical model and demonstrate that under certain regularization conditions, the model can be directly estimated by logit/probit models. Formal proofs regarding this case are in *SI Appendix*, section 2.

In Section 2, we use US COVID-19 response data to test these predictions by examining the timing of the introduction of SIP and mask-wearing policies by states. We model the probability that any state introduces an SIP or a mask-wearing order as a function of whether it is Democratic or Republican, how many Democratic, Republican, and swing states have already introduced such orders, and the numbers of new COVID-19 cases in the state. Using probit, logit, and a variety of linear probability models, we robustly show that the number of other states to have introduced SIP or mask-wearing orders is by far the most important determining factor of a state's policy decision, confirming the importance of social reinforcement at the state level. We also show the existence of tipping sets, particularly for mask-wearing orders. The probability of introducing a mask order responds sharply to the proportion of states of similar political orientation which have already launched such an order. For SIP orders, however, the response is much less sharp.

1. Results

1.1 Mask Mandates. In this subsection, we use discrete choice models to estimate the probability of a state launching or removing a mask-wearing order on day *t*. We used the daily data from April 1 to August 30, 2020, for mask mandate regressions (The dates on when mask-wearing policies are introduced or rescinded come from https://edition.cnn.com/2020/06/19/us/states-face-mask-coronavirus-trnd/index.html.). The underlying hypothesis is that the probability of a state adopting a mask-wearing policy depends on the number of same-party and opposite-party states that have implemented the policy and on the control variables. We control for the number of daily state-level new cases per 100,000 population due to COVID-19 using data from the Covidtracking (https://covidtracking.com/data) and the US census (https://www.census.gov/data/tables/time-series/demo/popest/2020s-state-total.html). Our approach assumes that the probability of choosing to implement a mask-wearing policy is independent of whether an SIP order is in place (we test and confirm the validity of this assumption in *SI Appendix*).

Fig. 1 shows marginal effects using probit regressions for Republican and Democratic states. The first panel shows that according to the probit model, a change in the fraction of Democratic states with effective mask-wearing mandates from 0.3125 to 0.3750 increases the probability of a Democratic state implementing a mask-wearing order by 0.54. So Democratic states have a considerable impact on Democratic states. The probit analysis in the left panel shows the tipping threshold: Once 43% of Democratic states have adopted mask-wearing orders, the probability that any remaining Democratic state will follow suit is one. The second panel repeats

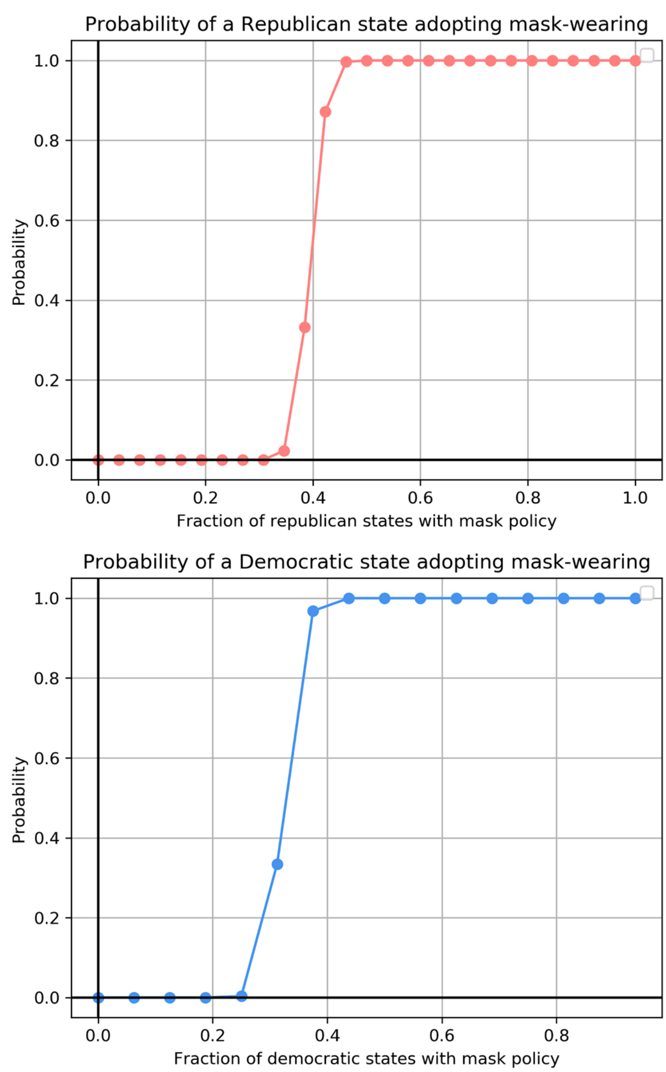

Fig. 1. Estimated probability for a state adopting mask-wearing mandates. For Democratic States (*First panel*), the proportions of adoption in other two groups are set to the mean. For Republican States (*Second panel*), the proportions of adoption in other two groups are set to the maximum.

the first but for changes in Republican states. We see that a change in the Republican mask policy adoption rate significant impacts the choices of Republican states. According to the probit model, a change in the fraction of Republican states with a mask policy in place from 0.3846 to 0.4231 raises the adoption probability by 0.47. The probit analysis in the right panel shows that once 46% of Republican states have adopted mask-wearing orders, then the probability that the remaining state will also adopt such orders is one. In both cases there is clearly an abrupt change in the equilibrium as the fraction of states with a policy in place passes a critical value.

In Fig. 2, we explore how the probabilities of choosing a mask-wearing policy respond to independent variables more multidimensionally, looking at two-dimensional subspaces of the four-dimensional space of independent variables. We vary the mask-wearing rates for Democratic, Republican, and swing states, holding the rate of new COVID-19 cases constant at its mean value.

Fig. 2*A* illustrates the adoption of mask policies of a Democratic state in response to the behaviors of other Democratic states, Republican states, and swing states. For low Democratic rates of adoption of mask policies (left panel), there is an area of low swing and Republican rates where there is zero probability of a Democratic state adopting a policy (lower left of the diagram), and one of high swing and Republican rates where this probability is one (upper right of the diagram), with a rather sharp transition between them: For higher Democratic rates, the area of zero probability is almost nonexistent and corresponds to zero rates for the other two categories of states. The sharp transitions here from probabilities of zero to one do seem to correspond well to the notion of tipping discussed in the theoretical model. Fig. 2*B* shows the same data for Republican states and portrays a very different story. It is almost impossible for other states to induce a Republican state to adopt a mask-wearing policy. Only if both other categories are at 100% adoption and nearly 50% of Republican states have also adopted, will the probability of a remaining Republican state adopting go to one (see also Fig. 1). Again, the large gradient of the response suggests a sharp transition, showing that there is also tipping but in much more limited circumstances. *SI Appendix*, Figs. S2 and S3 show the impact of the number of new cases on mask-wearing choices by Democratic and Republican states. These effects are small.

1.2 SIP Orders. In this subsection, we use discrete choice models to estimate the probability of a state without an SIP order choosing such an order. We used the daily data from March 18 to July 1, 2020, for SIP regressions (The dates on when SIP policies are introduced or rescinded come from https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html.).

Fig. 3 shows marginal effects using probit regression for Republican and Democratic states. The left panel calculates the marginal effect of a change in an independent variable on the probability of implementing an SIP policy among Democratic states. The probit analysis does not indicate a tipping point in this case: The probability of a state without an SIP order choosing such an order only reaches one when the fraction of states with SIP orders is also one. The right panel shows a similar analysis for the marginal effect of a change in the fraction of Republican states with SIP orders, though here there is a tipping point at about 60% of Republican states having adopted.

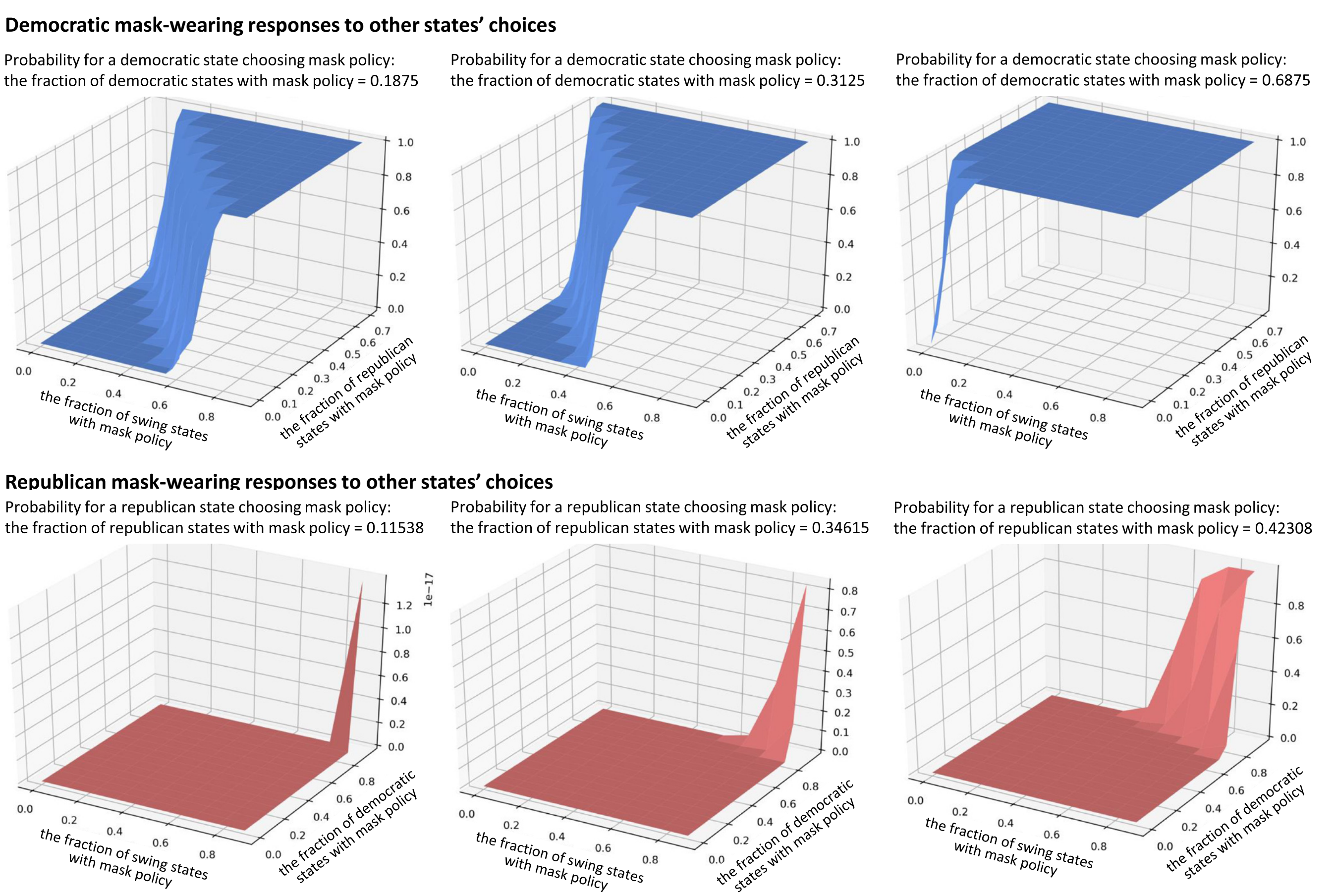

Fig. 2. Estimated probability for a state adopting mask-wearing mandates. We vary the mask-wearing rates for democratic, republican, and swing states, holding the rate of new COVID-19 cases constant at its mean value. (*Top panel*) refers to Democratic states, and (*Bottom panel*) to Republican states.

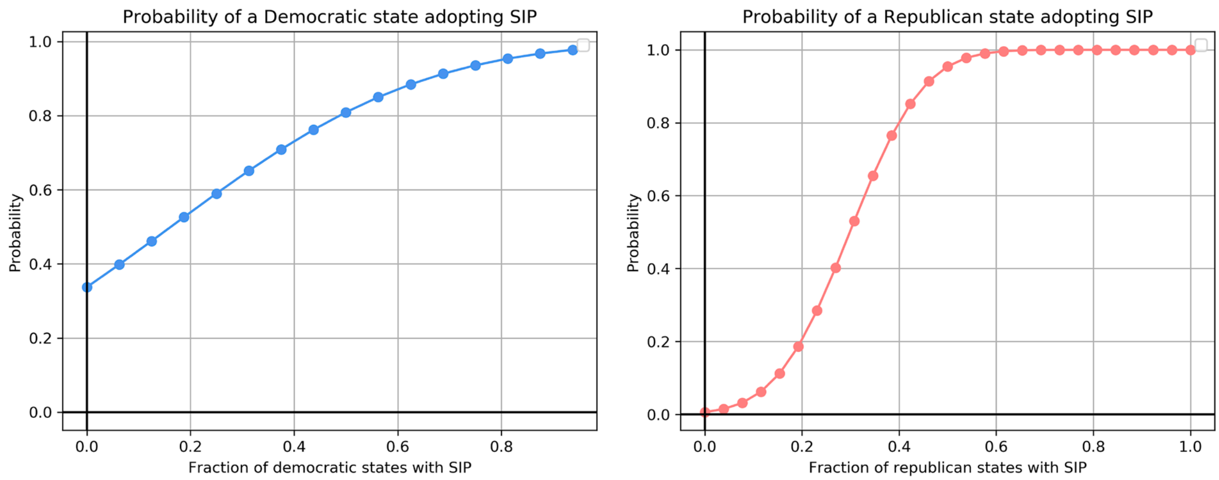

Fig. 3. Estimated probability for a state adopting SIP. For Democratic States (*Left panel*), the proportions of adoption in other two groups are set to the mean. For Republican States (*Right panel*), the proportions of adoption in other two groups are set to the maximum.

In Fig. 4, we explore the response of probabilities of choosing an SIP policy to independent variables in a more multidimensional way, looking at two-dimensional subspaces of the four-dimensional space of independent variables. We vary the SIP rates for Democratic, Republican, and swing states, holding the rate of new COVID-19 cases constant at its mean value.

The top row shows the Democratic adoption probability increasing with increases in the percentages of swing and Republican states that have already adopted, and also increasing with the percentage of Democratic states that have already adopted. All three figures show that when the percentages of swing and Republican states are zero, the probability of a Democratic state adopting is zero; however, many such states have already adopted. Comparing the first and last panels, corresponding to blue SIP = 0% and SIP = 63%, it is clear that the probability of adoption has risen substantially for low values of the percentages of swing and Republican states with SIP policies in place. The second row shows the same information for Republican states. The probability of choosing an SIP policy is much less—the surface

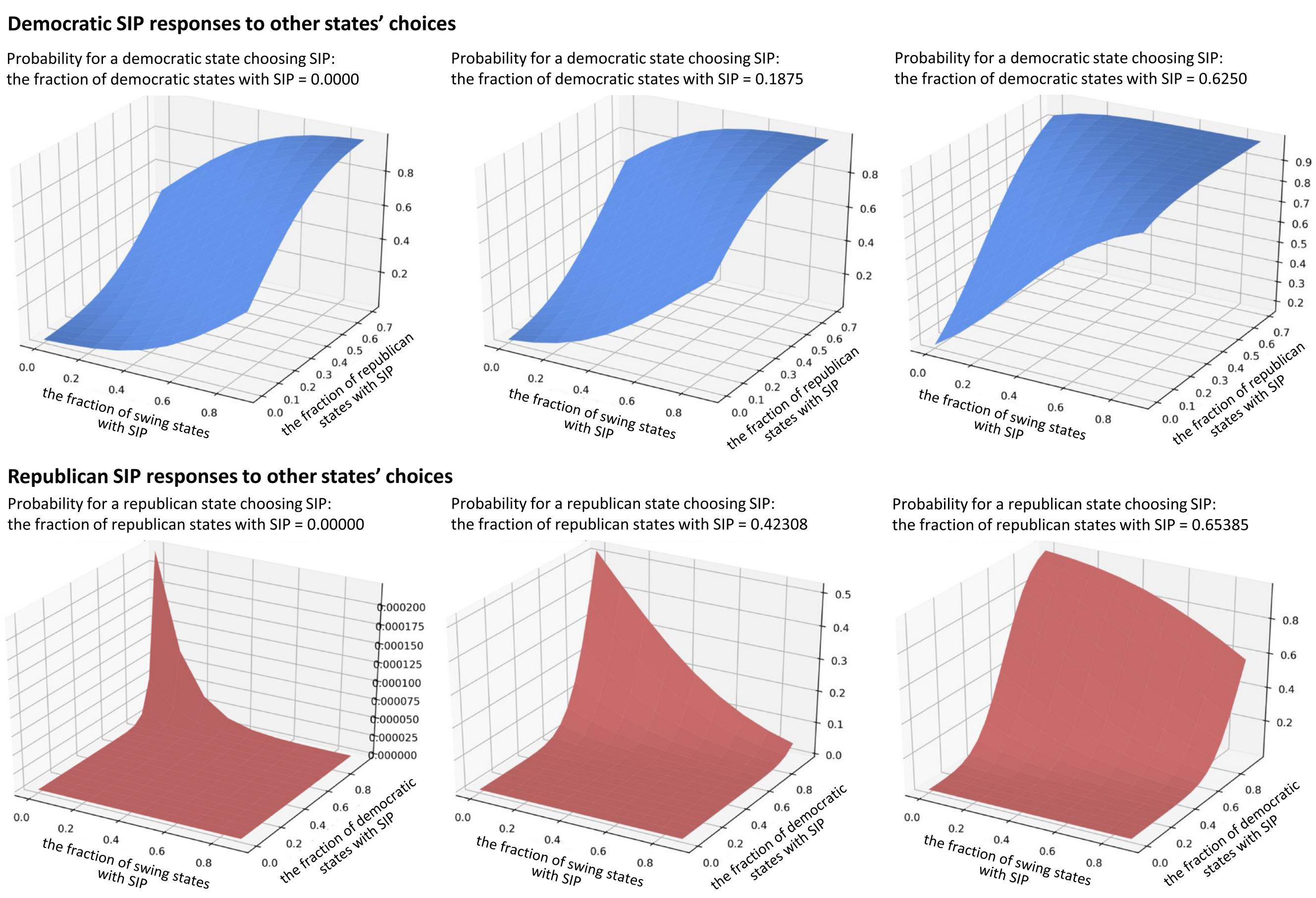

Fig. 4. Estimated probability for a state adopting SIP. We vary the SIP rates for democratic, republican, and swing states, holding the rate of new COVID-19 cases constant at its mean value.

is uniformly lower than in the Democratic cases—and decreases rather than increases with the percentage of swing states choosing an SIP policy, reflecting the negative regression coefficient on swing state adoption rates. In general, other states (swing, Democratic) seem to have less influence on Republican choices than they do with Democratic choices. It is interesting that an increase in the number of Republican states with SIP orders can tip the Democratic states into following suit. We do not see this cross-party effect in the case of mask-wearing orders, studied above. *SI Appendix*, Figs. S4 and S5 show the effect of the number of new cases on the choices of SIP policies by Democratic and Republican states: These are small, as was the case with mask-wearing policies.

1.3 Network Regression using Spatial Autocorrelation Model (SAR). Estimation of peer effects always suffers from reflection problems—it is impossible to distinguish the effect of peers on the individual from the effect of the individual on peers if both are determined simultaneously. To cope with this endogeneity, recent literature usually uses spatial models to identify peer effects in social networks. Here, we follow Zekhnini et al. (19, 20) and set up a network regression based on the Spatial Durbin Model (21) that allows unbalanced panel data and time-varying network structures on spatial weight matrices. The estimated directed effects are reported in Table 1. After controlling for immediate peers' effect, peers of peers' effect, and so on, linear probability regression results also show a clear within-partisanship impact: A change in the fraction of Democratic (Republican) states with an effective policy can significantly increase the probability of a Democratic (Republican) state to follow suit. There are no cross-partisanship impacts.

1.4 Identification from State Pairs Across Borders. To further address endogeneity issue, we follow Dube at al. (22) and Huang et al. (23) to exploit policy discontinuities at state borders. We define neighbor states as a pair of adjacent states with opposite partisanship. It is noticeable that states within a pair are relatively similar in terms of underlying epidemiological conditions during the pandemic, but they tend to be geographically further away from their "peers of the same partisanship," so those states may be less affected by the choices of their "peers of the same partisanship." We can control for state-pair fixed effect and use the linear probability model for estimation. Results are in Table 2. Similar patterns for peer effects can also be found here: The probability of a state adopting a policy is increased by the fraction of states with the same partisanship.

2. Discussion

Tipping—the abrupt displacement of a socio-economic system from one state to another—is a phenomenon of widespread interest. Schelling developed the first model of this process, and his model has been applied in a variety of contexts, mainly to abrupt changes in the racial composition of populations generated by the mutual reinforcement of choices made within a group of people.

Empirical studies have shown support for his model of the tipping process. Here, we have advanced a more complex and explicitly game-theoretic model of tipping, one applicable to the Nash equilibria of a game involving social reinforcement. We suggest that this is applicable to the choice of state-level strategies for addressing COVID-19 and note that the effect of mutual reinforcement can be estimated empirically by discrete choice modeling of agents' decisions.

Our empirical work on the introduction of SIP orders or mask-wearing confirms that the choices of one state influence strongly those of others and that in several cases, this interaction is powerful enough to lead to tipping to the universal adoption of a policy by one category of states. In general, the strongest interactions are between states of the same political orientation, but there are cases when Democratic states are strongly influenced by Republican states and by swing states and Republican states influenced by swing states. Republican states are influenced little by the actions of Democratic states. The number of new COVID-19 cases also has an impact on the states' choices in some cases, albeit a small one (*SI Appendix*, Figs S2 and S3). The choice of mask-wearing policies appears to be far more sensitive to the actions of other states than the choice of SIP policies. Republican states are far more reluctant than Democratic to adopt either SIP or mask-wearing policies. Overall, responses to the greatest public health challenge the United States has faced in a century have been shaped more by political considerations than by public health requirements.

While we find substantial support for the theoretical framework set out in the theoretical sections, we do also note differences between the factors determining the choices of mask-wearing policies and SIP policies. There is clearer evidence of tipping in the case of mask-wearing: A state's choice of mask-wearing policies

Table 1. Network regression using Spatial Autocorrelation Model (SAR)

	SIP			Mask-wearing	
	Rep.	Dem.		Rep.	Dem.
$N_{D,SIP,t}$	0.00344	1.053***	$N_{D,MASK,t}$	0.0231	1.072***
	(0.07)	(20.66)		(0.70)	(24.09)
$N_{R,SIP,t}$	0.977***	−0.00234	$N_{R,MASK,t}$	1.077***	−0.101
	(20.02)	(−0.05)		(11.26)	(−0.86)
$N_{S,SIP,t}$	−0.00357	−0.00786	$N_{S,MASK,t}$	−0.0395	−0.00357
	(−0.06)	(−0.13)		(−0.56)	(−0.04)
$NC_{i,t}$	0.000652	0.000133	$NC_{i,t}$	−0.00264***	0.00955***
	(0.58)	(0.20)		(−4.83)	(12.49)
_cons	−0.00474	0.00042	_cons	0.00907	−0.156***
	(−0.34)	(0.04)		(0.65)	(−7.05)
C			C		
sip	0.0295	−0.0572**	mask	0.0494*	0.0603***
	(1.32)	(−3.18)		(2.37)	(3.88)
N	2756	1696	N	3978	2448

t statistics in parentheses. *P < 0.05, **P < 0.01, *** P < 0.001.
We use the SAR fixed effect model with a spatial lag of the dependent variable specified by the spatial weighting matrix C. Dependent variable is the probability of a Republican or Democratic state adopting an SIP or Mask-wearing policy at date t.

Table 2. Regression results for neighboring states

	Mask	Mask	SIP	SIP
$N_{same\_partisanship,POLICY,t}$	1.086***	1.091***	0.886**	0.903**
	(4.90)	(4.98)	(3.07)	(3.37)
$N_{swing,POLICY,t}$	−0.0524	−0.0357	0.241	0.161
	(−0.19)	(−0.13)	(0.74)	(0.58)
$N_{opposite\_partisanship,POLICY,t}$	0.177	0.214	−0.0838	−0.00221
	(0.80)	(0.95)	(−0.43)	(−0.01)
newcase_100k		−0.00433		0.00723
		(−0.84)		(1.11)
_cons	−0.0511	−0.0359	0.0349	−0.00638
	(−0.78)	(−0.53)	(1.03)	(−0.14)
state FE	YES	YES	YES	YES
state_neighbor FE	YES	YES	YES	YES
N	4590	4590	3180	3180

t statistics in parentheses. $^*P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$
$N_{same(opposite)\_partisanship,POLICY,t}$ means the fraction of states with effective policy among all the states that have the same (opposite) partisanship at time t. Dependent variable - probability of a state adopting an SIP or Mask-wearing policy.

responds more sharply to changes in the choices made by other states than does the choice of an SIP policy. This difference between responses on mask-wearing and SIP policies is predictable because SIP has a real economic cost for anyone who cannot work from home. Hence, it is opposed by economically vulnerable populations. Mask-wearing, in contrast, has no economic cost, but can be seen as a signal. Not wearing a mask was adopted as a signal of support for Trump and skepticism about the importance of COVID-19 and the appropriateness of policy measures aimed at it. This suggests that the factors that influence choices about enacting policies are different in the two cases, with economic factors weighing more heavily in SIP choices and political/symbolic factors more important in mask-related policies. The evidence in previous comparative analyses (24) provides support. This can explain Democratic–Republican differences. Republican states are more likely to contain economically vulnerable populations who stand to lose from SIP policies and so will be more reluctant to such policies. In addition, Republican states can also be expected to be less receptive to mask-wearing because of its symbolism.

Our theoretical model, combined with an analysis of the choices of policies against COVID-19, underscores the importance of strategic interdependence in policy choices. What is true for the choice of COVID-19 policies may also be true for policy choices in epidemiological, climatological and environmental fields, with a strong propensity for social tipping due to the inevitable strategic interdependence. This suggests that a similar framework may be applicable in these areas.

3. Materials and Methods

3.1 Mathematical Model. The mathematical model we use to depict policy interdependence is presented in detail in *SI Appendix*.

3.2 Data and Empirical Estimation. Dependent variables: Public records show the dates when each US state either implemented or rescinded a mask mandate or a SIP order. In the present analysis, the dependent variable is coded as a binary indicator, where 1 shows the implementation of an effective NPI policy in state i on day t, and a value of 0 shows the absence of such a policy.

3.2.1 Independent variables. Based on our theoretical model (detailed derivation available in *SI Appendix, Supplementary Materials*), we divide all the states into three categories by political affiliation: Democratic, Republican, and swing. Within each category, we have daily data measuring fractions of states with effective SIP orders and mask mandates to evaluate our hypotheses.

(1) $N_{D,SIP(MASK),t}$: the fraction of Democratic states with effective SIP (mask-wearing) policy among all Democratic states at time t.
(2) $N_{R,\,SIP(MASK),t}$: the fraction of Republic states with effective SIP (mask-wearing) policy among all Republic states at time t.
(3) $N_{S,\,SIP(MASK),t}$: the fraction of Swing states with effective SIP (mask-wearing) policy among all Swing states at time t.

3.2.2 Control variables. We include new COVID-19 case counts per day for each state ($NC_{i,t}$: the number of new cases per 100,000 people per day for state i at time t) to measure the severity of COVID-19 pandemic, and this appears in both Logit/Probit and linear models with fixed effects

For socioeconomic controls, we have GDP per capita, log population, the unemployment rate, and a health index for each state: These are used only in the logit/probit model. Summary statistics are collected in Supplementary Materials.

3.2.3 Random utility model. To estimate the model empirically, we introduce random utility to address the binary choice decision problem. We argue that under three important assumptions, the model is estimable with standard discrete choice models with peer effects:

(1) Homogeneity. The utility function is the same across all states after controlling for state-level effects, and the ability of each state to influence others is solely related to the political relationship between the two states.
(2) Separability.
(3) Linearity in parameters.

Based on these three assumptions, when the error term ϵ_i follows an extreme value distribution, we can use a logit model; and when ϵ_i is normally distributed, we can use a probit model. The equation estimated is

$$P_{i,t} = \alpha_i N_{D,Mask,t} + \beta_i N_{R,Mask,t} + \gamma_i N_{s,Mask,t} + \delta_i NC_{i,t} + K_i + \varepsilon_{i,t} \qquad [1]$$

where $P_{i,t}$ is the probability that state i adopts a mask-wearing order on day t, K_i is a constant and $\varepsilon_{i,t}$ is an NID serially independent error process.

Data, Materials, and Software Availability. The sources of all data used in this study are indicated in the article and/or *SI Appendix*.

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