The Political Economy of Responses to COVID-19 in the U.S.A.

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Abstract

Social distancing via shelter-in-place (SIP) strategies, and wearing masks, have emerged as the most effective ways to combat COVID-19. In the United States, choices about these policies are made by individual states. Here we show that the policy choice made by one state are strongly influenced by the choices made by others, i.e. that there is social reinforcement between states, and that these choices can be viewed as strategic complements in a supermodular game. Under certain conditions, if enough states engage in social distancing or mask wearing, they will tip others that have not yet done so to follow suit and thus shift the Nash equilibrium. Political orientation is an important factor in determining a state's willingness to implement mask-wearing or SIP strategies. We consider a situation where interactions amongst states are strongest between those of similar political orientations and show there can be equilibria where states with different politics adopt different strategies. In this case a group of states of one political orientation may by changing their choices tip others of the same orientation, but not those whose orientations differ. We test these ideas empirically using linear, probit and logit regression models and find strong confirmation that inter-state social reinforcement is important and that equilibria can be tipped as

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the theory predicts. Overall, policy choices are influenced by the choices of other states, especially those of similar political orientation, and to a much lesser degree by the number of new COVID-19 cases in the state. The choice of mask-wearing policy shows more sensitivity to the actions of other states than the choice of SIP policies, and republican states are much less likely to introduce mask-wearing policies. Both policies are influenced more by political than public health considerations.

Key Words: COVID-19, social distancing, shelter-in-place, masks, non-pharmaceutical interventions, supermodular, strategic complementarity, tipping set, cascades, probit and logit

1 Introduction

Our aim in this paper is to model the factors that influence whether and when States in the United States introduce non-pharmaceutical interventions (NPIs) directed to reducing the incidence of COVID-19. These interventions can take many forms. They may involve testing and contact-tracing, quarantining those who test positive and their contacts, shelter-in-place (SIP) orders, which have emerged as one of the most widespread policies for mitigating the spread of COVID-19, or requiring the wearing of masks in public. On wearing masks, see Sunstein [12]. These NPIs are common to most countries, and in most countries (in fact, in all except the U.S.) these policies are implemented at the federal or equivalent level.[1] Rather uniquely, the U.S. has left state governors to choose whether to implement such policies: there is no Federal policy on any of these issues. As a result the majority of states, but not all of them, have had such policies in place, and the choice has become a political one, with most Democratic governors implementing such orders but many - though not all - Republican governors more reluctant to do so. From April to July, at least 2/3 of Democratic states launched mandatory orders for residents to wear masks whenever they are not able to maintain a 6-feet

[1] For a review of COVID-19-related policies see Dalton et al. [4]

distance from others. In contrast, most Republican states did not introduce such orders, or merely gave the power to do so to cities. This remained true until mid to late July, when the second wave of coronavirus cases mainly took place in these states. After these orders took effect in states with high incidence of COVID-19, the curve of COVID-19 flattened (from early August), although the causal effects of such orders remain unstudied.

SIP orders have costs and benefits (see Thunstrom et al. for a cost-benefit analysis [13]). The costs are obvious and largely economic: they bring the local economy to a grinding halt, as many businesses cannot continue to operate in a world of SIP orders. There are also social costs associated with isolation and lack of social interactions. To set against these there are health benefits, since illnesses spread much less rapidly and fatalities are reduced when most people are required to stay at home. In New York in the absence of social distancing the R_t - the reproduction rate in the classic SIR epidemiological model - was about 5, but after several months of social distancing it fell to below 1.[2] [3]The timing of NPIs matters: they need to be introduced before the SARS-Cov-2 virus is widespread, but not too early because there are generally political constraints on how long NPIs can be maintained, and introducing them too early leads to some of their potential being wasted. The factors we model in the following sections help understand the timing of NPIs though an understanding of the factors that influence states' decisions about whether or not to introduce them.

Our first step is to show in a simple game-theoretic model that a state's decision on whether to introduce shelter-in-place or mask-wearing regulations in the U.S. depends on how many other states have already instituted such orders. The larger the number of states with such policies, the more effective

[2]See https://rt.live/?campaign_id=116&emc=edit_pk_20200623&instance_id=19638&nl=paul-krugman&regi_id=62166175&segment_id=31644&te=1&user_id=6af929c17b98864ef47928b40024cba8

[3]For a discussion for the data for New York City see Harris [7], and for a general discussion of social distancing in epidemic models see Kelso et al.[10], who analyze how social distancing can reduce the rate at which a disease spreads from infected to susceptible populations.

a new one is and more likely it is that a new state will follow suit. More formally, state $i's$ payoff from implementing a restrictive policy depends on the choices of states $j \neq i$ for the following reason: if state j does **not** implement such a policy, then the virus can continue to spread in state j and people who travel between j and i can infect people in i, undercutting $i's$ shelter-in-place policy. (Quarantine requirements for interstate travelers are hard to enforce and indeed Governor Cuomo of New York explicitly stated in October that he would like to impose quarantine on people coming from New Jersey but that this is not practicable.)

A good illustration is provided by the tri-state area of New York, New Jersey and Connecticut. Residents of all these states commute to and work in New York City, meaning that if New York closes down its businesses, residents of all three states are affected. Many residents of New Jersey and Connecticut will now have less reason to travel to New York. So a move by New York to have people shelter-in-place and to close businesses will make it easier for the governors of adjacent states to do likewise: the incremental economic costs are lower because part of the work was already done by New York. The fact that so many people in the tri-state area travel 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 diseases in one state will reduce its incidence in others with whom residents of the first state interact.

In addition, the introduction of SIP policies by one state may makes it politically easier for others to follow suit: such policies are clearly disliked by those who stand to lose from them (business owners and workers who cannot work from home), so that governors who introduce them need a strong rationale and their adoption by other states can go some way to providing this.

Given that the spreading of a virus depends not only on a state's own action but those of others, the decisions on whether or not to implement

NPIs by individual states can be formalized as a game. This particular game is supermodular and so will have multiple Nash equilibria, including a greatest and a least equilibrium (Topkis [3]). If the effectiveness of an NPI in state i depends on whether such orders 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 what Heal and Kunreuther ([8]) call uniform strict increasing differences, a strong form of strategic complementarity.

Section 2 models this interdependence and shows how the existence of *tipping sets* arises. A tipping set in such a game is a set of players (states) with the following property: if all member of this set choose to implement particular policies, then the best response of every other agent will be to follow suit and choose the same policies. So the member of the tipping set can drive all others to the adoption of NPIs, even in the absence of a federal mandate for such policies.

One can also have local tipping sets. In the context of the social distancing problem facing states, the Nash equilibria may be regional rather than national, so that if one or more states change their strategy, some nearby states may follow suit. For example, a change in policy by New York may force New Jersey and Connecticut to do likewise. Similarly there may be strong links between Georgia, South Carolina and Tennessee. Proximity does not necessarily have to be geographic: it could be measured in terms of economic or political links between the states.

There are other more complex elements of the relationships between states. They do assist each other in attaining health goals through the reinforcement we have discussed, but they also compete for scarce medical equipment such as personal protective equipment and ventilators, bidding up prices. New York Governor Andrew Cuomo frequently complained in his daily COVID press briefings of the lack of a centralized national purchasing policy and the way in which this pits states against each other. This means that one state's actions in response to COVID-19 raises the costs of the actions that others wish to take. This behavior is a result of policies for obtaining medical equipment to deal with illnesses from COVID-19 and not due to social distancing policies.

Heal and Kunreuther ([8]) provide a simple example of a game that meets all the conditions mentioned above. There are I players and each may choose as a strategy either zero or one: think of zero as no policy and one as an SIP or mask-wearing policy. The payoff to choosing zero, is always 0.1. The payoff to agent j of choosing 1 is equal to the number of others who choose 1. If no one else chooses 1, the payoff is 0. It then increases linearly depending on how many others choose 1 so if n agents choose 1, the payoff to the $n + 1 - th$ agent to making this choice is n. In this particular game there are only two Nash equilibria: every agent chooses 0 or every agent chooses 1. If every agent has chosen 0 and a single agent switches to 1, then all the other agents will also want to switch to 1. In other words, the game has been "tipped" from a Nash equilibrium where everyone chooses 0 to a Nash equilibrium where everyone chooses 1.

As mentioned above, there is also a political dimension to choices in dealing with the coronavirus pandemic. Democratic governors have been more likely than their Republican counterparts to recognize the seriousness of COVID-19 and the need for collective action to mitigate the spread of the virus. In section 3 we address this issue. We divide states into democratic and republican and assume that the payoff to a state depends more on the actions of those of the same political affiliation than on those that differ in this respect. Using a very simple framework, we show that there are Nash equilibria at which all democratic states adopt NPIs such as SIPs or mask-wearing, while no republican states do so: there are also equilibria at which all states don't adopt NPIs and others at which all states do. At the equilibrium where no states have NPIs, a subset of the democratic states can tip the remaining democratic states to the equilibrium where all have NPIs and no republican states do. Similarly, at the equilibrium where all states have NPIs, a subset of the republican states can tip the remainder to the equilibrium where only democratic states have NPIs. Figure 1 illustrates.

In Section 4 we take these ideas to data, and test them in the context of the introduction of the introduction of SIP and mask-wearing orders. 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 linear probability models and linear regressions, we show that the number of other states to have introduced SIP or mask-wearing orders is the most important factor in a state's decision on these issues. We also show clearly the existence of tipping sets, particularly for mask-wearing orders. The empirical results show that states' decisions about whether or not to introduce mask-wearing policies respond differently to the actions of other states than their decisions about SIP policies. Mask-wearing choices show little response to other states' choices for many values of mask-wearing rates, and then respond very sharply in a small region of the state space.

The recent paper by Sebhatu et al. [11] has some similarity to ours. They look at all OECD countries and study the extent to which the policies chosen by one country influence the choices of other countries, and argue that there is strong "policy diffusion" from one country to another, particularly between adjacent countries. Their paper is entirely empirical, with no formal model, and uses different statistical techniques. Another related paper is Adolph et al. [1], which like us looks at the timing of U.S. states' introduction of NPIs, and the factors influencing these. They argue that the political make-up of the states is the factor that determines whether they introduce NPIs. Cui et al. [14] study the differences between states' responses to the COVID-19 outbreak in the U.S., showing the importance of political and social issues for the management of outbreaks, but with no formal model of the states'

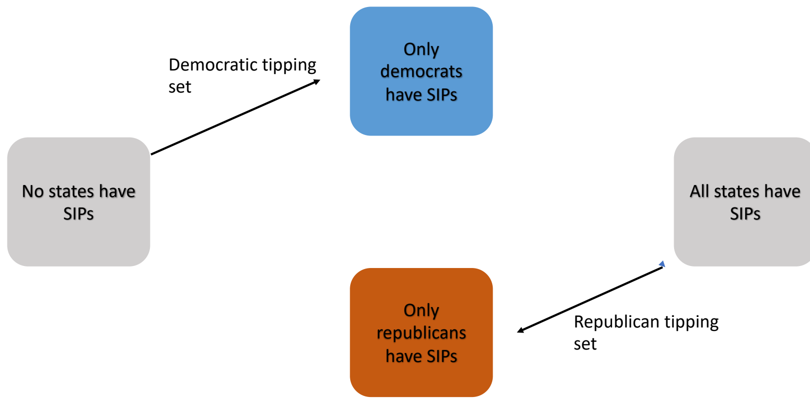


Figure 1.1: Tipping possibilities

choices.

2 Formal Model

There are I agents (states) indexed by $i = 1, 2, ..., I$. Each has a strategy s_i and a strategy space given by two alternatives $\{0, 1\}$ where $s_i = 0$ denotes either no SIP or no mask-wearing policy and $s_i = 1$ indicates that such a policy is in place. We model the choices of SIP or mask-wearing policies separately, and do not consider the interactions between them. The vector $S \in R^I$ represents the list of strategies chosen by all agents $S = (s_1, s_2, ...s_I)$. Each agent's payoff function $U_i(S) : S^I \rightarrow R^1$ depends on the choices of all agents, its own and those of others. We let 0_i or 1_i denote a zero or a one in the $i - th$ position of S and the vector S_{-i} be the vector of all choices made by states other than i. We assume that the U_i all satisfy uniform strict increasing differences, that is using the usual vector ordering on R^I,

$\exists\epsilon > 0 :\ S'_{-i} > S_{-i}\ \Rightarrow$

$$U_i\left(1_i, S'_{-i}\right) - U_i\left(0_i, S'_{-i}\right) \geq \epsilon + U_i\left(1_i, S_{-i}\right) - U_i\left(0_i, S_{-i}\right) \tag{2.1}$$

In words, consider two configurations of strategy choices by players other than i, denoted S_{-i} and S'_{-i}. Then if in S'_{-i} at least one state has changed from zero to one relative to S_{-i}, which is implied by $S'_{-i} > S_{-i}$, then the payoff to state i to changing from zero to one is strictly and uniformly greater at S'_{-i} than at S_{-i}. This means that agent j changing from zero to one raises the payoff to this change for agent $i \neq j$ for any i and j. This is implied by the interactions between state strategies discussed above: the adoption of an SIP or mask policy by state j makes such a policy more attractive for state i. In the inequality (2.1) the parameter ϵ is a measure of the degree of social reinforcement: the greater is ϵ, the greater is the degree of social reinforcement or strategic complementarity and as we will see below the smaller is the tipping set. For simplicity we are assuming the ϵ to be independent of the states involved, though the discussion above of the tri-state area makes it clear that in reality some pairs of states reinforce each other more than other pairs. Think of New York and New Jersey versus New York and Alabama.

Tipping sets are important in this analysis. Intuitively a tipping set is a subset T of players which has the following property. If all the members of T choose strategy 1, then the best response for any other player is strategy 1. If all members of T choose SIP orders, then every other state finds that its best strategy is also to choose an SIP order. Formally, if $S_i = 1 \forall i \in T$, then $\forall i \notin T,\ U_i\left(1_i, S_{-i}\right) \geq U_i\left(0_i, S_{-i}\right)$. A minimal tipping set is a tipping set with the property that no strict subset is also a tipping set.

The set of possible strategy vectors S in this game is the set of vectors of the form $(0, 1, 1, 0, 0, ...)$ where every coordinate is a zero or a one. These vectors form the vertices of the unit cube in R^I, which is a lattice. By assumption (2.1), the game is supermodular. Hence we know by a theorem of Topkis ([3]) that the set of pure strategy Nash equilibria is non-empty and contains greatest and least elements which we call $\bar{S}$ and $\underline{S}$ respectively. From Dhall, Lakshmivarahan and Verma ([5]) we know that for two players $\bar{S} = (1, 1)$ and $\underline{S} = (0, 0)$ (corollary 3.2) and for three players these are $(1, 1, 1)$ and $(0, 0, 0)$ (Corollary 3.6). For two and three players, then, the greatest and least Nash equilibria are where all agents choose 1 or all choose 0. We assume this is also true for I players: the maximal Nash equilibrium is where all players choose 1 and the minimal where they all choose 0. In the Appendix we will give simple conditions that are necessary and sufficient for this to be the case.

Under these conditions, we can prove that there is a tipping set $T < I$ of states with the ability to tip the no-SIP (or no mask) equilibrium to the all-SIP (or all mask) equilibrium. Furthermore there is a tipping set that will tip *any* equilibrium with less than every state having SIP orders to one where all do so. Our proof that there is a set that will tip the equilibrium of all zeros to that of all ones applies with minor modifications to showing that there is a set that will tip from the least Nash equilibrium to the greatest, whatever these may be. A formal statement of our results is:

Theorem 1. *Under assumption (2.1), there is a minimal tipping set T consisting of less than $I - 1$ agents, which will tip the least Nash equilibrium to the greatest Nash equilibrium. Furthermore, any Nash equilibrium with less than $I - 1$ SIP or mask-wearing orders can be tipped to the equilibrium with I such orders.*

The proof is given in the appendix.

In addition to tipping, we can have the related phenomenon of cascades. A cascade occurs when a change of policy by agent 1 causes 2 to change her policy, which in turn causes 3 to change and so on, a classical "domino effect." This process may take in all agents or only a subset. A simple example from Heal and Kunreuther ([8]) is as follows. There are 10 agents. For any agent i the return to setting $s_i = 0$ is $0.9i$. The return to $s_i = 1$ is $\#(1)$, the number of other agents also choosing one. Clearly all zeros and all ones are both Nash equilibria. Suppose that all are choosing zero and agent 10 decides to switch to one. Then the return to agent 1 to choosing 1 is now $1 > 0.9i$ and she will switch to 1. Agent two will now find that the return to choosing 1 is $2 > 1.8$ and will switch. And so on for all agents up to and including 9. Agent 10, by switching, started a cascade of all the other agents beginning with 1. Heal and Kunreuther ([8]) give sufficient conditions for a cascade to occur. It is possible that the connections between New York and adjacent states are best described by a cascade rather than by tipping.

3 Political Differences

Returning to the issue of political differences on SIP policies, we model these by differences in the states' payoff functions $U_i(S_{-i}, S_i)$: republican states may value the outcomes associated with SIP policies - reduced morbidity and mortality - but have a preference against the action of implementing an SIP policy. The might prefer a world in which good public health outcomes are attained by other states implementing SIP policies while they don't: they strongly prefer $(1_{-i}, 0_i)$ (the vector of ones everywhere except in their $i-th$ position to $(1, 1, ..., 1)$, the vector of all ones. In this case there can be no Nash equilibrium where all agents choose one: the greatest Nash equilibrium $\bar{S}$ will satisfy $\bar{S} < (1, 1, ..., 1)$. The fact that states with conservative governors, such as Georgia, moved first to relax SIP policies, is consistent with them having a strong negative preference for these policies. The importance of political orientation for attitudes towards COVID-19 is studied by Barrios and Hochberg ([2]), who show that the attention paid to COVID-19 is negatively correlated with support for Donald Trump in the last presidential election. Using Google search data, they show that areas showing high Trump support only started paying attention when there were COVID-related deaths in their region, or when prominent conservative figures emphasize the reality of the epidemic. Their work actually suggests that there is support for social distancing in conservative states, but only once lives are being lost. They suggest that preferences evolve over the course of the epidemic.

We now distinguish between democratic and republican states and assume that each is more effected by the policies that its fellows choose than by those chosen by states run by the other party. We can write a state's utility function as

$$U_i^D(S) = U_i^{DD}(S_D) + U_i^{DR}(S_R) \tag{3.1}$$

Here the superscript D denotes the preferences of a democratic state: this is assumed to be separable in the strategies of democratic and republican states, with the superscripts DD and DR respectively denoting the democratic state's preferences over strategies chosen by democratic and republican states, with S_D and S_R being the vectors of strategies chosen by democratic and republican states respectively. For a republican state, the super- and subscripts D and R would be interchanged. Clearly, provided that the utility function meets the increasing differences condition, all the results established so far are applicable with these preferences.

Suppose for the moment that U_i^{DR} and U_i^{RD} are identically zero, so that each group's preferences depend only on the actions of its peers within its group. Then we now have two separate games being played, one amongst the democrats and one amongst the republicans. It is possible that the democratic game has a Nash equilibrium of ones while the republican game has an equilibrium of zeros. Now consider a more realistic and interesting case in which what republican states choose does matter to democrats, but less than what democrats do, and vice versa. So the values of U_i^{DR} and U_i^{RD} are less than those of U_i^{DD} and U_i^{RR}. A simple example illustrates this. Let the payoff to a democratic state choosing one [zero] be

$$U_i^D(1[0]) = \#D1[0] + \alpha_D \#R1[0] \tag{3.2}$$

where $\#D1\,[0]$ and $\#R1\,[0]$ are the numbers of other democratic or republican states choosing 1 (or zero) and $\alpha_D \in [0,1]$ is the weight that a democratic state puts on the actions of the republican states. Additionally let N_R and N_D be the numbers of republican and democratic states, and γ_R and γ_D be the fractions of republican and democratic states choosing strategy 1. For this formulation of the game we can establish the following results:

Theorem 2. *(1) There is a Nash equilibrium at which all states choose 0. (2) There is a Nash equilibrium at which all states choose 1. (3) There is a Nash equilibrium at which all democratic states choose 1 and all republican states choose 0 (or vice versa). (4) If all states are choosing 0 then there is a tipping set of democratic states that can tip the remaining democratic states to choosing 1 so that the equilibrium is that democratic states choose 1 and republicans choose 0. (5) If all states are choosing 1 then there is a tipping set of republican states that can tip the remaining republican states to choosing 0 so that the equilibrium is that republican states choose 0 and democratic states choose 1.*

The proofs are in the Appendix.

4 Empirical Testing

In this section we use data on shelter-in-place orders, mask-wearing orders and COVID-19 cases at the state level to test the ideas discussed above. We know the date at which each state in the U.S. introduced (or rescinded) a mask-wearing order or SIP order (if in fact it did), and we have data on the numbers of COVID-19 cases by state by day. We classify each state as Democratic, Republican, or swing: a state is Democratic (Republican) if it has two Democratic (Republican) senators at least 48% of the vote was for Clinton (Trump) in 2016, or if it has one Democratic (Republican) senator and at least 50% of the vote was for Clinton (Trump) in 2016. The remainder are swing states. We have 51 states in total (we treat Washington D.C. as a state) and of these 16 are Democratic, 26 Republican and 9 are swing states. [4]

We use discrete choice models (probit, logit and linear probabilities) and also conventional linear regression models to test whether the policies of one state can have an impact on the choices of others, and find unambiguous support for this. We also test for tipping, which in the probit-logit context we define as follows. States in category A (republican, democrat, swing) can tip those in category B to adopt a policy (shelter-in-place, wear masks) if whenever the fraction of states in category A which have adopted the policy exceeds $x < 1$, the the probability of a state in category B adopting the policy is one. Formally, states in category A tip those in category B with tipping point x if

$$Pr \left\{ State\ in\ B\ chooses\ policy \mid fraction\ of\ A\ choosing\ policy \geq x \in [0,1] \right\} = 1$$

4.1 Shelter-in-Place Orders

In this subsection we use discrete choice models to estimate the probability of a state without an SIP order, adopting one on day t. The estimating equation is (4.1): the dependent variable is the probability of state i with no SIP order introducing an SIP order on day t, $\mathit{\Pi}_{i,t}$.

$$\mathit{\Pi}_{i,t} = a_i N_{D,SIP,t} + b_i N_{R,SIP,t} + c_i N_{S,SIP,t} + d_i NC_{i,t} + K_i + \epsilon_{i,t} \tag{4.1}$$

Here $N_{D,SIP,t}$ is the fraction of democratic states that already have SIP orders in effect on day t, with similar interpretations for $N_{R,SIP,t}$ (republican) and

[4] The number of new cases per day for each states is taken from https://covidtracking.com/api/v1/states/daily.json . 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 . Population data comes from https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-total.html . We experiment with other definitions of republican, democratic and swing states and find that our results are not sensitive to these choices.

	Probit		*Logit*		*LPM*	
	Rep	*Dem*	*Rep*	*Dem*	*Rep*	*Dem*
$N_{D,SIP,t}$	5.739^{***}	2.587^{***}	10.65^{***}	4.289^{***}	-0.058	0.77^{***}
$N_{S,SIP,t}$	-2.010^{**}	2.800^{***}	-3.677^{**}	5.536^{***}	0.208^{**}	0.315^{***}
$N_{R,SIP,t}$	8.393^{***}	3.600^{***}	15.22^{***}	9.0669^{***}	0.782^{***}	-0.623
$NC_{i,t}$	0.0378	0.0428^{***}	0.055	0.0817^{***}	0.00017	-0.0004
K_i	-9.273^{***}	-2.892^{***}	-16.89^{***}	-5.405^{***}	-0.0128	0.0196
$lnsig2u$	2.713^{***}	0.514	3.905^{***}	1.873^{***}		
N	2756	1696	2756	1696	2756	1696

Table 1: Probit, logit and LPM regressions for republican and democratic states. Dependent variable is the probability of an SIP order. *, ** and *** denote significant at 5%, 1% and 0.1% levels. *Dem* is Democratic and *Rep* is Republican.

$N_{S,SIP,t}$ (swing). $NC_{i,t}$ is the number of new cases per 100,000 of population in state i on day t, K_i is a constant and $\epsilon_{i,t}$ an error term. This approach assumes that the probability of choosing to implement an SIP policy is independent of whether or not there is a mask-wearing policy in place. In the appendix, where we conduct robustness checks, we allow the selection of an SIP policy to depend on whether there is a mask policy in place: the results show that it does not, and that this specification is robust. The results of estimating this equation by probit, logit and linear probabilities are given in table 4.

The probit and logit models both show highly significant coefficients on all of the SIP shares for both democratic and republican states, though surprisingly republican states show negative coefficients on the share of swing states with SIP orders in place. The number of new cases is significant for democratic states but not for republican. Republican governors appear to be taking their leads from other states rather than from the domestic incidence of COVID-19.

To assess the impact of a change in one state's policies on the choice made by another, we need to calculate the marginal effect of a change in an independent variable on the probability of implementing an SIP policy. In a probit estimation the underlying equation is

$$P_{i,t} = \Phi \left\{ \alpha_i N_{D,m,t} + \beta_i N_{R,m,t} + \gamma_i N_{S,m,t} + \delta_i CC_{i,t} + K_i + \epsilon_{i,t} \right\} \qquad (4.2)$$

where $\Phi \{.\}$ is the cumulative normal distribution. The derivative of $P_{i,t}$ with respect to $N_{D,m,t}$ is $\alpha_i \Phi' \{.\} = \alpha_i \phi \{.\}$ where ϕ is the normal density function. Clearly the derivative depends on the values of the other independent variables. It will also depend on the value of $N_{D,m,t}$. In the tables that follow we set the variables other than the SIP rate with respect to which we are differentiating equal to either their sample means or their maximum values, and report the marginal effect for all possible SIP rates. The first column in table 2 shows $N_{D,m,t}$ the democratic SIP rate, the second the probability of an SIP policy being implemented in a democratic state without such a policy according to the probit model, the third the change in probability (the marginal effect), the fourth and fifth columns the same for a republican state, and the remaining columns repeat this for the logit model. Overall this table shows the effects of changes in the fraction of democratic states with SIP orders on the probability that a democratic or republican state without such an order will change, with other independent variables at their mean values. For republican states this effect is zero: for democratic states it is positive. According to the logit analysis, once 69% of democratic states have adopted SIP orders, then with probability one all others will follow suit. 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.

Table 3 shows a similar analysis for the marginal effect of a change in the fraction of republican states with SIP orders, with other independent variables again at their mean values. In this case the increase in the number of republican states with SIP orders tips the democratic states without such orders once the fraction of republicans with SIP orders exceeds 0.61 in the

	Probit				*Logit*			
	Democratic		*Republican*		*Democratic*		*Republican*	
$N_{D,SIP,t}$	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ
0.000	0.36		0.00	0.00	0.51		0.00	0.00
0.0625	0.42	0.06	0.00	0.00	0.62	0.11	0.00	0.00
0.1250	0.55	0.07	”	”	0.72	0.10	”	”
0.1875	0.61	0.06	”	”	0.80	0.08	”	”
0.3125	0.67	0.06	”	”	0.87	0.07	”	”
0.3750	0.73	0.06	”	”	0.92	0.05	”	”
0.4375	0.78	0.05	”	”	0.95	0.04	”	”
0.5000	0.82	0.04	”	”	0.97	0.02	”	”
0.5625	0.86	0.04	”	”	0.99	0.02	”	”
0.6250	0.9	0.04	”	”	0.99	0.01	”	”
0.6875	0.92	0.02	”	”	1.00	0.00	”	”
0.7500	0.94	0.02	”	”	”	”	”	”
0.8125	0.96	0.02	”	”	”	”	”	”
0.8750	0.97	0.01	”	”	”	”	”	”
0.9374	0.98	0.01	”	”	”	”	”	”
1.0000	0.99	0.01	”	”	”	”	”	”

Table 2: Marginal effect of change in democratic SIP rate: other independent variables set equal to **sample means**

	Probit				*Logit*			
	Democratic		*Republican*		*Democratic*		*Republican*	
$N_{R,SIP,t}$	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ
0.000	0.62		0.00	0.00	0.60		0.00	0.00
0.03846	0.67	0.06	0.00	0.00	0.68	0.08	0.00	0.00
0.07692	0.72	0.07	”	”	0.75	0.07	”	”
0.11538	0.77	0.06	”	”	0.81	0.068	”	”
0.19231	0.81	0.06	”	”	0.86	0.05	”	”
0.23077	0.84	0.06	”	”	0.90	0.04	”	”
0.26923	0.87	0.05	”	”	0.92	0.02	”	”
0.30769	0.90	0.04	”	”	0.95	0.03	”	”
0.34615	0.92	0.02	”	”	0.96	0.01	”	”
0.38462	0.94	0.02	”	”	0.97	0.01	”	”
0.42308	0.95	0.01	”	”	0.98	0.01	”	”
0.46154	0.97	0.02	”	”	0.99	0.01	”	”
0.53846	0.98	0.01	”	”	0.99	0.00	”	”
0.57692	0.99	0.01	”	”	1.00	0.01	”	”
0.61538	0.99	0.00	”	”	1.00	0.00	”	”
0.65385	1.00	0.00	”	”	1.00	0.00	”	”

Table 3: Marginal effect of change in republican SIP rate: other independent variables set equal to **sample means**

probit regression and 0.53 in the logit. It is interesting that an increase in the number of republican states with SIP orders can tip the democratic states into following suit. We will not see this cross-party effect in the case of mask-wearing orders, studied below.

Table 4 shows a similar effect going the other way - the effect of democratic states' choices on republican states' choices, when other independent variables are set in this case at their maximum values. In this case the probability of a republican state adopting an SIP order only reaches one when all democratic states have already adopted such orders. Recall from table 2 that when other independent variables are set at the sample means, a change in the number of democratic states with SIP orders has no impact on the

	Probit				*Logit*			
	Democratic		*Republican*		*Democratic*		*Republican*	
$N_{D,SIP,t}$	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ
0.000	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
0.0625	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
0.1250	"	"	0.01	0.01	"	"	0.01	0.01
0.1875	"	"	0.03	0.02	"	"	0.01	0.01
0.2500	"		0.07	0.03	"		0.02	0.01
0.3125	"	"	0.13	0.06	"	"	0.05	0.02
0.3750	"	"	0.22	0.09	"	"	0.09	0.04
0.4375	"	"	0.33	0.12	"	"	0.16	0.07
0.5000	"	"	0.47	0.14	"	"	0.27	0.11
0.5625	"	"	0.61	0.14	"	"	0.41	0.15
0.6250	"	"	0.74	0.13	"	"	0.58	0.16
0.6875	"	"	0.84	0.10	"	"	0.73	0.15
0.7500	"	"	0.91	0.07	"	"	0.84	0.11
0.8125	"	"	0.96	0.04	"	"	0.91	0.07
0.8750	"	"	0.98	0.02	"	"	0.95	0.04
0.9375	"	"	0.99	0.01	"	"	0.97	0.02
1.0000	"	"	1.00	0.00	"	"	0.99	0.01

Table 4: Marginal effect of change in democratic SIP rate: other independent variables set equal to **maximum values**

probability of a republican state adopting such an order.

In table 5 we look at the case of other independent variables at their maximum values and the republican adoption rate varying. In this case the democratic states are already choosing SIP orders with probability one. The republican states tip at a fraction 0.69 (probit) or 0.61 (logit).

Tables 2 through 5 show how the chances of a democratic or republican state choosing an SIP policy vary with the number of other states that already have such a policy in place, holding all other independent variables at either their mean or maximum values. The space of independent variables is four dimensional (three policy rates and the number of new cases), so we are looking at the response of probabilities along a one-dimensional subspace

	Probit				*Logit*			
	Democratic		*Republican*		*Democratic*		*Republican*	
$N_{R,SIP,t}$	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ
0.000	1.00		0.00	0.00	1.00		0.00	0.00
0.03846	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
0.07692	”	”	0.01	0.01	”	”	”	”
0.11538	”	”	0.02	0.01	”	”	”	”
0.15385	”	”	0.04	0.02	”	”		
0.19231	”	”	0.08	0.04	”	”	”	”
0.23077	”	”	0.14	0.06	”	”	0.00	”
0.26923	”	”	0.23	0.08	”	”	0.02	0.01
0.30769	”	”	0.33	0.11	”	”	0.06	0.04
0.34615	”	”	0.46	0.12	”	”	0.17	0.11
0.38462	”	”	0.59	0.13	”	”	0.35	0.18
0.42308	”	”	0.71	0.12	”	”	0.58	0.23
0.46154	”	”	0.81	0.10	”	”	0.79	0.20
0.53846	”	”	0.93	0.13	”	”	0.98	0.19
0.57692	”	”	0.97	0.03	”	”	0.99	0.02
0.61538	”	”	0.98	0.02	”	”	1.00	0.00
0.65385	”	”	0.99	0.01	”	”	1.00	0.00
0.69231	”	”	1.00	0.00	”	”	1.00	0.00

Table 5: Marginal effect of change in republican SIP rate: other independent variables set equal to **maximum values**

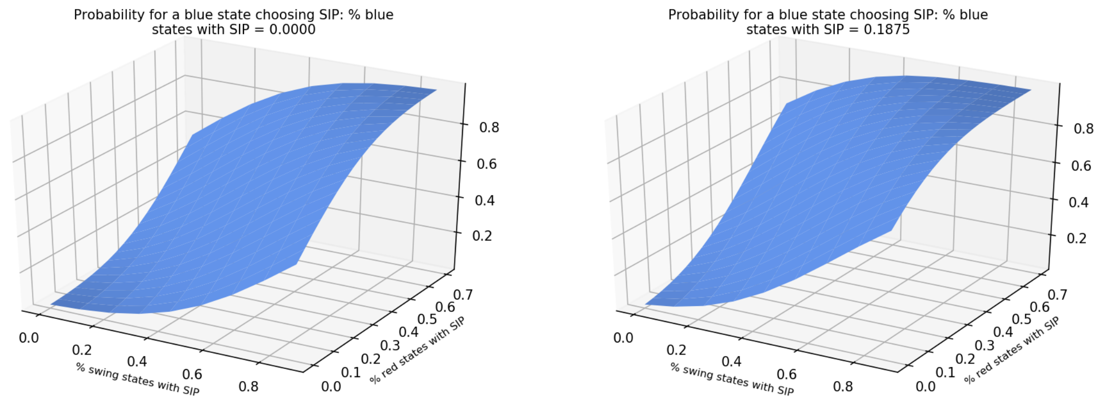


Figure 4.1:

in this space. In figures 4.1 and 4.2, we explore the response of probabilities of choosing a SIP policy to independent variables in a more complex way, looking at three-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. Figures 4.1 and 4.2 show on the horizontal axes the percentages of states adopting SIP policies (red = republican, blue = democratic), on the vertical axis the probability of a democratic state that has not adopted an SIP policy doing so, with the percentage of democratic states that have SIP policies in place increasing from figure 4.1 to figure 4.2, going from 0% to 18% then 43% and ending at 63%.

The figures show the 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 four 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. They also show that for low levels of democratic adoption (0% and 18%) the probability is relatively insensitive to the swing state adoption rate, whereas for higher values of demo-

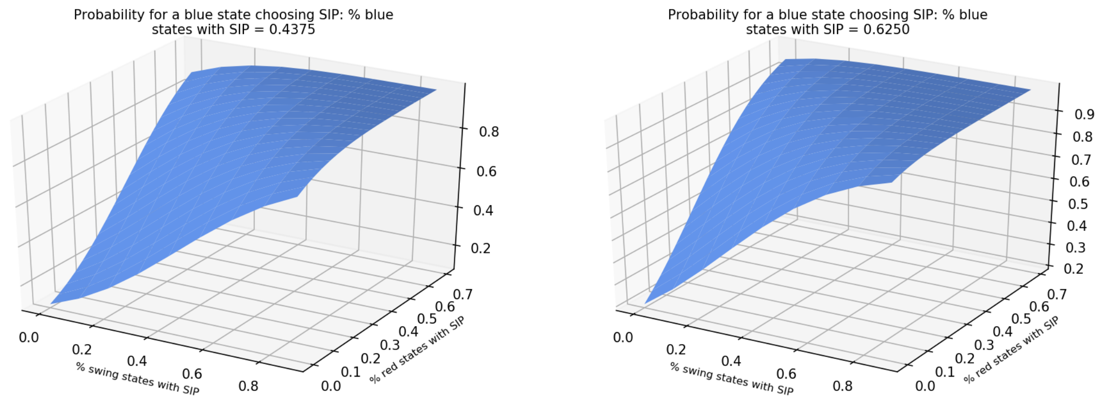


Figure 4.2:

cratic adoption the swing states can drive bigger changes in the democratic probability of adoption. Tables 2 to 5 show one-dimensional slices through figures 4.1 and 4.2, taken vertically at the mean or maximum values of the variables on the horizontal axes and the case rate.

Figures 4.3 to 4.5 show the same information for republican states. The probability of choosing an SIP policy is much less - the surface 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 table 1. In general other states (swing, democratic) seem to have less influence on republican choices than they do with democratic choices.

The next step in our analysis is to investigate the effect of the number of new cases of COVID-19 in a state on the probability of its adopting an SIP policy. We do this by looking at the probability of adopting as a function of the number of new cases and the percentage of democratic or republican states with SIP policies: these results are contained in figures 4.6 and 4.7. In these figures the horizontal axes are the number of new cases and the percentage of republican states with SIP policies, the vertical axis is the probability of a democratic state without a policy implementing one, and

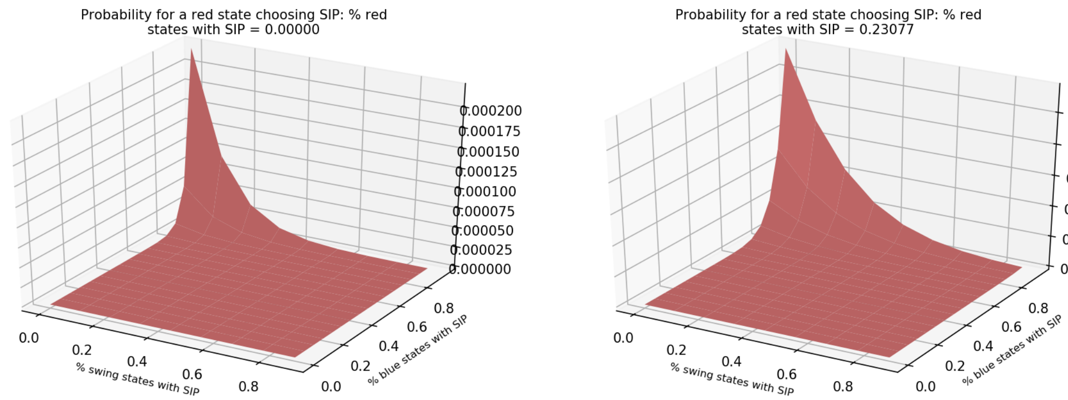


Figure 4.3:

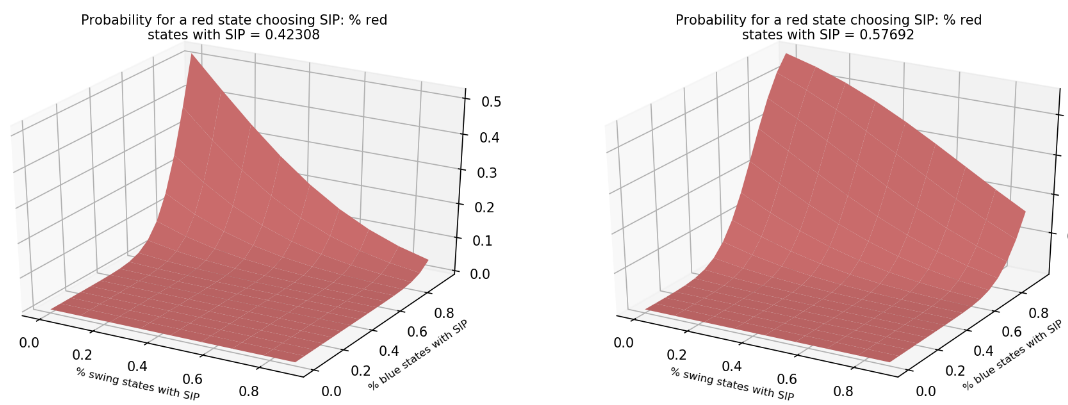


Figure 4.4:

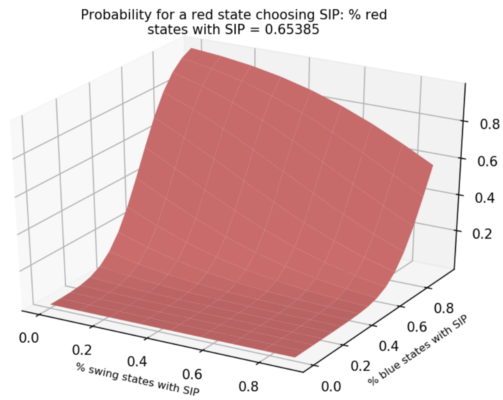


Figure 4.5:

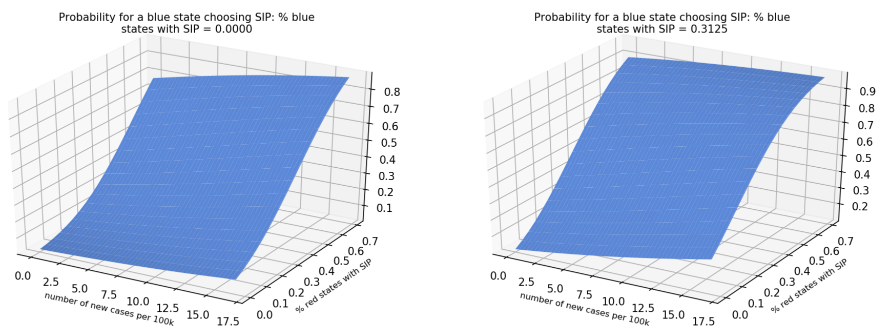


Figure 4.6:

each diagram corresponds to a different fraction of democratic states with SIP policies - these percentages are 0%, 31%, 56% and 93%.

What these figures demonstrate very clearly is that a change in the number of new cases in a democratic state has little impact on the probability of that state choosing an SIP policy, except when the percentage of democratic states with an SIP policy is already high and the percentage of republican states is low. The selection of an SIP policy appears to be driven more by social and political reinforcement rather than by a focus on the basic facts of public health.

Much the same is true for republican states. Figures 4.8 and 4.9 illustrate

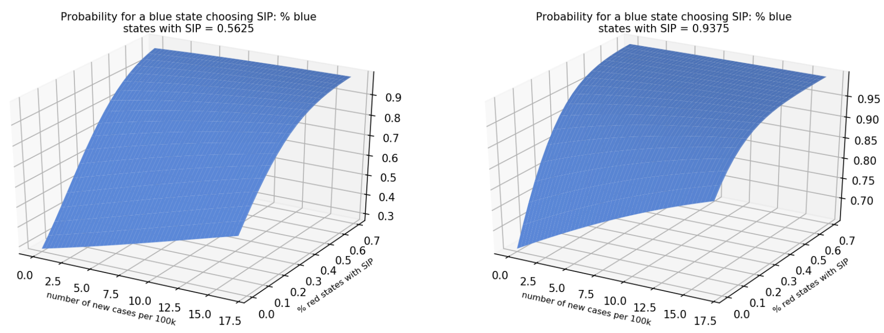


Figure 4.7:

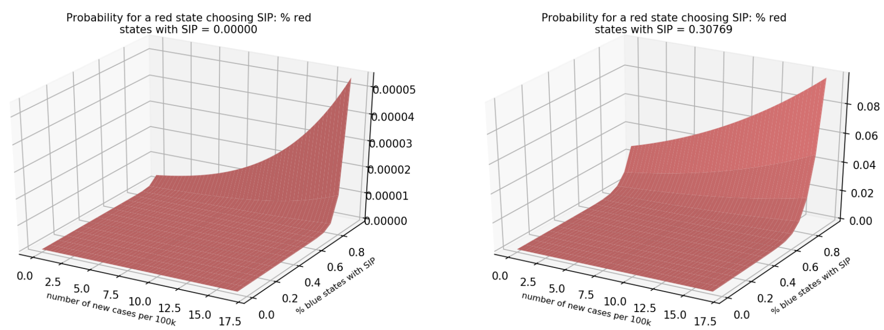


Figure 4.8:

this: their interpretation is the same as for democratic states. What we see in this case is that for high values of the percentage of blue states with SIP policies and low values of the percentage of red states with such policies, an increase in the number of cases in a republican state will increase the probability of the remaining republican states choosing an SIP policy.

4.2 Mask-Wearing

In this subsection repeat the analysis of the last section but for mask-wearing rather than SIP policies: we use discrete choice models to estimate the probability of a state adopting a mask-wearing order. The underlying hypothesis is that the probability of a state without such a policy adopting a mask-wearing

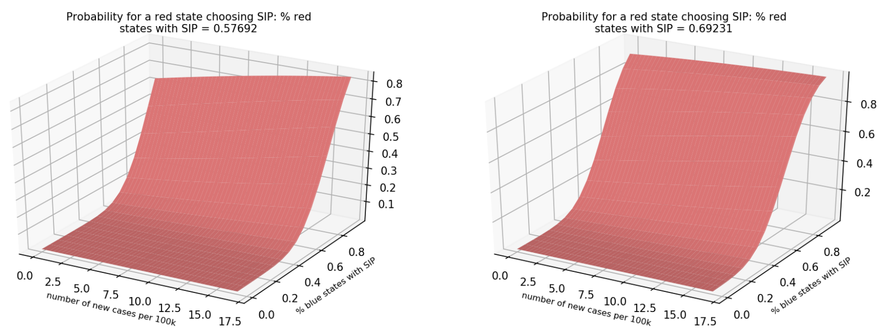


Figure 4.9:

policy depends on the number of other states of its political orientation that have already done so, the numbers of other states of different political orientations that have done so, and the number of COVID-19 cases in the state. So the basic estimating equation is

$$P_{i,t} = \alpha_i N_{D,m,t} + \beta_i N_{R,m,t} + \gamma_i N_{S,m,t} + \delta_i C_{i,t} + K_i + \epsilon_{i,t} \tag{4.3}$$

where $P_{i,t}$ is the probability that state i adopts a mask-wearing order on day t, $N_{D,m,t}$ is the fraction of democratic states that have adopted mask-wearing orders by date t, $N_{R,m,t}$ is the fraction of republican states that have done likewise by date t and $N_{S,m,t}$ the fraction of swing states that have mask-wearing orders in place. $C_{i,t}$ is the number of new COVID-19 cases per 100,000 of population in state i at date t, K_i is a constant and $\epsilon_{i,t}$ is a NID serially independent error process. This approach assumes that the probability of choosing to implement a mask-wearin policy is independent of whether or not there is an SIP policy in place. In the appendix, where we conduct robustness checks, we allow the selection of a mask policy to depend on whether there is an SIP policy in place: the results show that it does not, and that this specification is robust. We run equation (4.3) using Probit, Logit and Linear Probability models, separately for Democratic and Republican states. The results are summarized in table 1.

	Probit		*Logit*		*LPM*	
	R	*D*	*R*	*D*	*R*	*D*
$N_{D,m,t}$	30.37^{**}	36.43^{***}	18.14^{***}	41.39^{***}	-0.212^{***}	0.553^{***}
$N_{S,m,t}$	12.70^{*}	29.89^{***}	10.44^{**}	46.208^{***}	0.844^{***}	1.300^{***}
$N_{R,m,t}$	40.76^{***}	28.77^{**}	28.61^{***}	62.55^{***}	0.108	-0.816^{***}
$NC_{i,t}$	0.0269	-0.0204	0.0287	-0.0261	-0.00059	0.0102^{***}
K_i	-53.19^{***}	-27.26^{***}	-31.07^{***}	-25.36^{***}	-0.0135	-0.0789^{**}
$lnsig2u$	6.433^{***}	5.05^{***}	5.893^{***}	5.45^{***}		
N	3978	2448	3978	2448	3978	2448

Table 6: Probit, logit and LPM regressions for republican and democratic states. Dependent variable is the probability of a mask-wearing order. *, ** and *** denote significant at 5%, 1% and 0.1% levels

This shows clearly that the numbers of other states that have adopted mask-wearing rules has a significant and positive impact on the likelihood of a state adopting such rules, whether it is Republican or Democratic. The number of current COVID-19 cases, however, has no significant impact, rather surprisingly. These being probit and logit regressions, as noted above we cannot deduce anything about the relative importance of different independent variables from the magnitudes of their coefficients: only the significance of the coefficients matters. Note that the coefficient of democratic states on the number of other democratic states having adopted, are more significant than those on the number of republican states. The same is true in reverse, so it appears that states may be more sensitive to actions by their political peers than to those of other states, though they are sensitive to the actions of both.

To assess the impact of a change in one state's policies on the choice made by another, as in the previous subsection we need to calculate the marginal effect of a change in an independent variable on the probability of implementing a mask-wearing policy. Table 7 shows the marginal effect of a change in the democratic mask rate $N_{D,m,t}$ as it varies from zero to one

	Probit				*Logit*			
	Democratic		*Republican*		*Democratic*		*Republican*	
$N_{D,m,t}$	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ
0.0625	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.1250	”	”	”	”	0.01	0.01	”	”
0.1875	”	”	”	”	0.21	0.20	”	”
0.3125	0.31	0.31	”	”	0.99	0.78	”	”
0.3750	0.85	0.54	”	”	1.00	0.01	”	”
0.4375	1.00	0.00	”	”	1.00	0.00	”	”
0.5000	”	”	”	”	”	”	”	”
0.5625	”	”	”	”	”	”	”	”

Table 7: Marginal effect of change in democratic mask rate: other independent variables set equal to **sample means**

and all other variable are at their sample means,[5] according to both probit and logit models.[6] The first column shows $N_{D,m,t}$ the democratic mask rate, the second the probability of a mask-wearing policy being implemented in a democratic state according to the probit model, the third the change in probability (the marginal effect), the fourth and fifth columns the same for a republican state, and the remaining columns repeat this for the logit model.

Table 7 shows that according to the probit model, a change in $N_{D,m,t}$ from 0.3125 to 0.3750 increases the probability of a democratic state implementing a mask-wearing order by 0.54. The equivalent number for the logistic model is even larger, 0.78, and occurs when the mask rate changes from 0.1875 to 0.3125. So democratic states have a big impact on democratic states: table 7 also shows that they have no impact on republic states. All these comments are conditioned on the values of the other independent variables being equal to their sample means. The probit analysis in Table 7 shows that once 43% of democratic states have adopted mask-wearing orders, the probability that

[5]When they are at their maximum values, the probability of a democratic state introducing a mask-wearing policy is constant at one.

[6]The table omits mask rate below 0.0625 and above 0.5625 as the probability is constant at zero and one respectively in these ranges.

	Probit				*Logit*			
	Democratic		*Republican*		*Democratic*		*Republican*	
$N_{R,m,t}$	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ	*Prob*	Δ
0.07692	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
0.15385	"	"	0.00	0.00	"	"	0.06	0.06
0.19231	"	"	0.02	0.02	"	"	0.58	0.52
0.23077	"	"	0.20	0.18	"	"	0.97	0.39
0.26923	"	"	0.67	0.47	"	"	1.00	0.03
0.30769	"	"	0.95	0.28	"	"	1.00	0.00
0.34615	"	"	1.00	0.05	"	"	1.00	0.00
0.38462	"	"	1.00	0.00	"	"	1.00	0.00
0.42308	"	"	1.00	0.00	"	"	1.00	0.00

Table 8: Marginal effect of change in republican mask rate: other independent variables set equal to **maximum values**

any remaining democratic state will follow suit is one. The logit analysis places the tipping point slightly lower, at 38%.

Table 8 repeats table 2 but for changes in $N_{R,m,t}$, the republican mask rate with other independent variable set at their maximum values.[7] We see that a change in the republican mask rate has no impact on democratic choices, but a significant impact on the choices of republican states. According the the probit model a change in $N_{R,m,t}$ from 0.23077 to 0.26923 raises the probability by 0.47, and according to the logistic model an increase from 0.15385 to 0.19231 raises the probability by 0.52. The probit analysis in Table 8 shows that once 35% of republican states have adopted mask-wearing orders, then the probability that the remaining state will also adopt such orders is one. The logistic analysis gives a slightly lower tipping point, 26%.

We now explore the space of independent variables in three-dimensional slices, as we did for SIP policies.

Figures 4.2 and 4.2 show the democratic mask-wearing response surfaces

[7]When the other variables are at their sample means, the probability of a republican state choosing a mask-wearing policy is always zero.

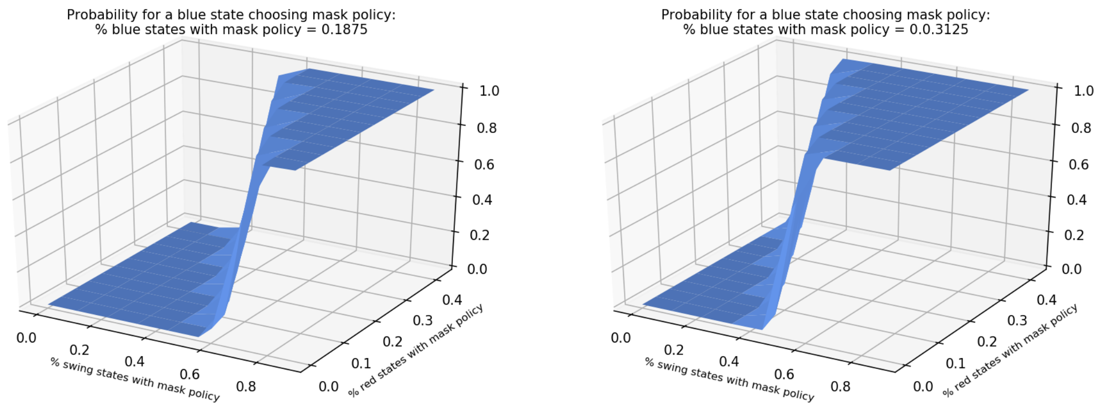


Figure 4.10:

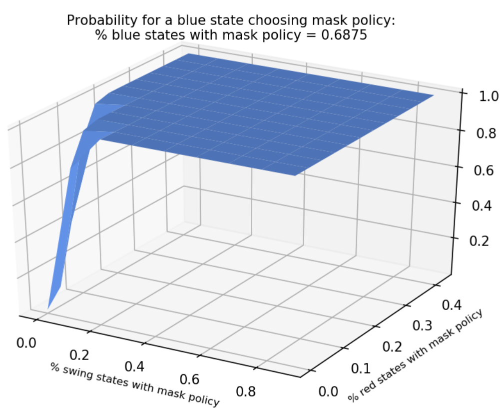
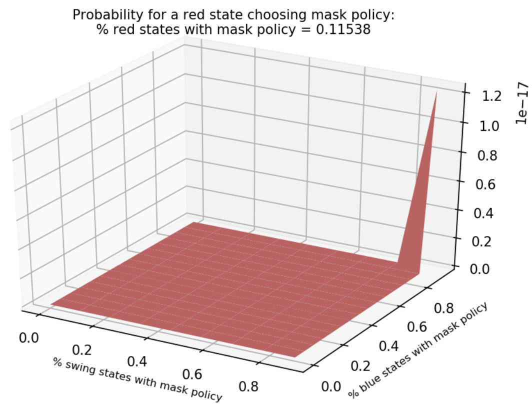


Figure 4.11:



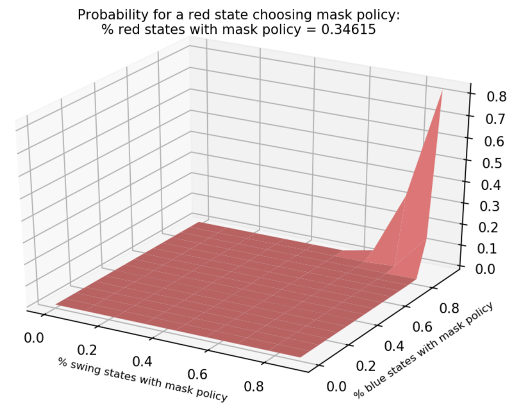


Figure 4.12:

as the democratic mask rate varies from 19% to 69%, as a function of swing and republican mask rates. Clearly the response surface is very different from the SIP case. For low democratic rates, there is an area of low swing and republican rates where the probability is zero, and one of high swing and republican rates where it is one, with a rather sharp transition between them: for higher democratic rates the area of zero probability is almost non-existent 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 to the intuitive notion of tipping.

Figures 4.2 and 4.2 show the same data for republican states, 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 adopted too, will the probability of a remaining republican state go to one. Again the transition is sharp, the gradient of the response surface high.

The final step in this subsection, as in the previous one, is to look at the impact of the number of new cases in a state on the probability of implementing a mask-wearing policy. As before, we do this by looking at the probability of adopting as a function of the number of new cases and the

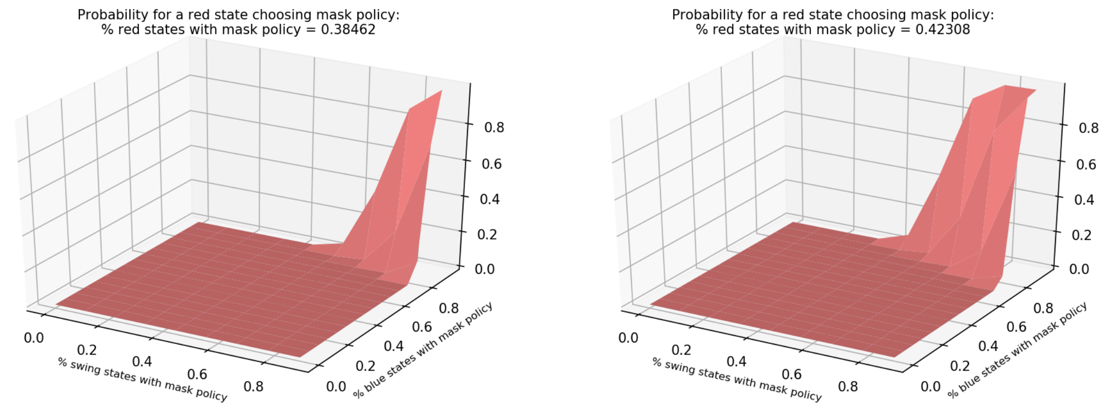


Figure 4.13:

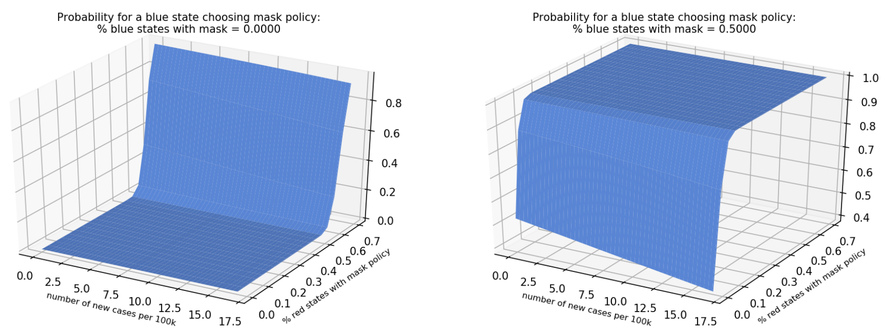


Figure 4.14:

percentage of democratic or republican states with mask-wearing policies: these results are contained in figures 4.14 and 4.15. In these figures the horizontal axes are the number of new cases and the percentage of republican states with SIP policies, the vertical axis is the probability of a democratic state without a policy implementing one, and each diagram corresponds to a different fraction of democratic states with SIP policies - these percentages are 0%, 25%, 62.5% and 93%.

Figures 4.14 and 4.15 show that there is essentially no impact of the number of new cases on the probability of a democratic state adopting a mask-wearing policy, which is consistent with the coefficients on NC in table

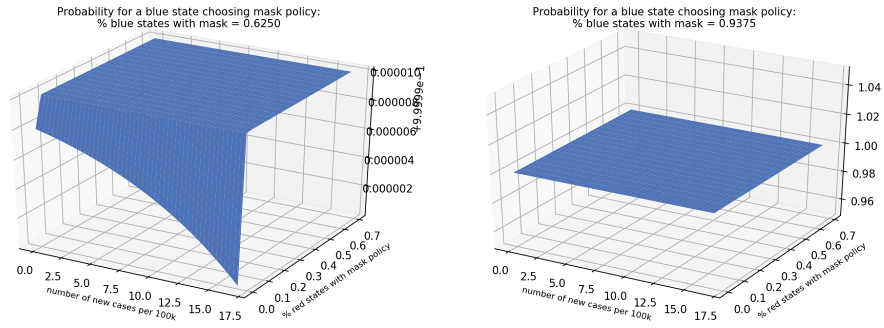


Figure 4.15:

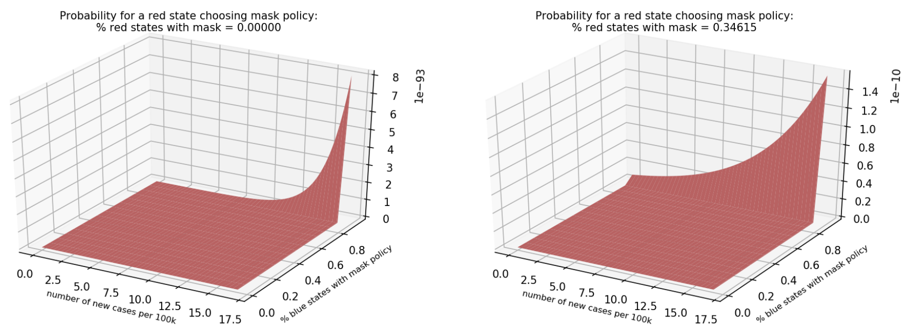


Figure 4.16:

6: these coefficients are never significant. This is different from the position with SIP policies shown in figures 4.6 and 4.7, where the impact of case numbers is more significant.

Figures 4.16 and 4.17 present the same analysis for republican states: they show that for low values of the republican mask rate and high value of the democratic rate, there is sensitivity of the probability of a republican state choosing a mask policy, but otherwise it has no effect. This is similar to the situation shown in figures 4.8 and 4.9 for republican states deciding whether to introduce an SIP policy.

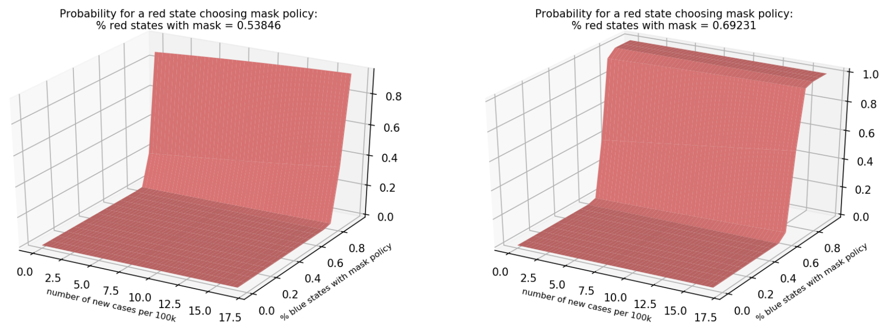


Figure 4.17:

	D	R	D	R	D	R
Period, days	1		7		14	
Dem mask %	0.907***	−0.112	0.930***	−0.141	0.944***	−0.188
Swing mask %	0.29	0.598***	0.291	0.676***	0.287	0.828***
Rep mask %	−0.233	0.119	−0.256	0.016	−0.262	−0.18
New cases/100k	0.0035	0.00074	0.00055	0.00055	0.00031	0.0000
Const	−0.0043	−0.025	−0.022	−0.022	−0.034	−0.0183

Table 9:

4.3 Linear Regressions

Another alternative that we have investigated is the use of linear regressions rather than discrete choice models, with the dependent variable now the fraction F of democratic or republican states that have so far adopted an SIP or mask-wearing policy. So the regression equation in this case is

$$F_{A,X,t} = \alpha_i N_{D,X,t} + \beta_i N_{R,X,t} + \gamma_i N_{S,X,t} + \delta_i C_{i,t} + K + \epsilon_{i,t} \tag{4.4}$$

where $A = D$ or $A = R$ for democrat or republican, and $X = SIP \quad or \quad M$ for having an SIP or a mask-wearing policy in place at time t. We have estimated this equation using as the dependent variable the fractions on a single day, the fractions averaged over seven days and fourteen days. The results are all similar and are shown in tables 9 and 10.

	D	R	D	R	D	R
Period, days	1		7		14	
Dem SIP %	0.819***	−0.0187	0.825***	−0.412	0.851***	−0.066
Swing SIP %	0.259	0.121	0.272	0.132	0.254	0.152
Rep SIP %	−0.055	0.872***	−0.072	0.885***	−0.072	0.888***
New cases/100k	0.0007	0.00232	0.0000	0.00034	0.00002	0.00004
Const	0.0122	−0.0252	0.0052	−0.021	−0.0008	−0.008

Table 10:

Table 9 shows the results of these regressions for mask-wearing policies. Several aspects of these results are worth mentioning. One, as noted, is that the period over which data is aggregated makes no difference: patterns of coefficient significance are the same across all three, and the coefficients are very similar in the three cases. The next point is that they show a very robust effect of democratic mask-rates on the choices of democratic states. This is entirely consistent with the logit and probit results in table 6, which are reinforced by table 7 and figures 4.10 and 4.11. The significance of the coefficient on swing states for republican choices is also consistent with the discrete choice results in table 6. However the absence of a significant positive coefficient on the republican mask rate is inconsistent with the earlier results as shown in table 6, though it is consistent with figures 4.12 and 4.13 - which are themselves at variance with table 6, except in regions of the state space where the mask rates of democratic and swing states are both high.

Table 10 shows the analogous results for SIP policies. Democratic states show a significant positive constant on the democratic policy rate, as do republican states on the republican rate. The results are completely consistent across the differing time periods (the key entries in the table are underlined, and are (dem on dem) 0.819, 0.825 and 0.851: (rep on rep) 0.872, 0.885 and 0.888.) The coefficients on new cases are never significant. These results are consistent with those shown in table 1 and figures 4.1 to 4.9, although table 1 does suggest more of a role for the SIP rates of states of the opposite political orientation. However the figures make it clear that this is true only for limited regions of the state space.

5 Conclusions

Shelter-in-place strategies and mask-wearing are integral to overcoming a pandemic. In the U.S., these strategies have to be implemented by states, which face complex combinations of economic and political costs and benefits from their possible choices. Their decisions are affected by those of other states since strategy choices demonstrate social and political reinforcement. A compelling illustration of this interdependence is the interactions between New York and its neighboring states: the tri-state region can be seen as a single unit in terms of employment, commuting, entertainment and retail shopping. A move towards SIP orders or compulsory mask-wearing by any of these states will affect the other two, and its effectiveness will depend on the reactions of the others. Because of this, we can model their choices as a game. Specifically, we show that the choice of a policy by a single state or a group of states may tip a system to a new Nash equilibrium at which many more agents have adopted shelter-in-place or social distancing policies. It could also cause a cascade from one equilibrium to another. There may be equilibria at which all democratic states adopt such policies while no republicans do, and a subset of democratic states may tip its fellows into adopting these policies, while a subset of republican states may tip their fellows into dropping or adopting these policies.

Our empirical work on the introduction of shelter-in-place 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. 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 far more reluctant to adopt either SIP or mask-wearing policies. Overall, responses to the greatest public health challenge the US has faced in a century have been shaped more by political considerations than by public health requirements.

As of late 2020, states have had access to vaccines against COVID-19 and have had to set vaccination priorities. There may also be an element of social reinforcement in the choice of vaccination strategies, so the framework we have developed here may be applicable in that context too.

6 Theoretical Appendix

Theorem 3. *Under assumption (2.1), there is a minimal tipping set T consisting of less than $I-1$ agents, which will tip the least Nash equilibrium to the greatest Nash equilibrium. Furthermore, any Nash equilibrium with less than $I-1$ SIP or mask-wearing orders can be tipped to the equilibrium with I such orders.*

Proof. We study the effect on agent $j's$ payoff of changing from no SIP to an SIP (changing from 0 to 1) and how this effect is altered by changes in the strategy choices of another agent i. We know by (2.1) that if i switches from 0 to 1 then this will increase the incremental payoff to j from the same switch. Let $S_{-i-j}, 1_i, 0_j$ denote the vector of strategies in which all agents other than i, j are choosing $S_k \in S_{-i-j}$ and i, j are choosing 1 and 0 respectively. (S_{-i-j} is the vector of strategies chosen by all agents other than i and j.) Define

$$\Delta_j\left(i=0, S_{-i-j}\right)=U_j\left(S_{-i-j}, 0_i, 1_j\right)-U_j\left(S_{-i-j}, 0_i, 0_j\right) \tag{6.1}$$

and

$$\Delta_j\left(i=1,S_{-i-j}\right)=U_j\left(S_{-i-j},1_i,1_j\right)-U_j\left(S_{-i-j},1_i,0_j\right) \tag{6.2}$$

These are the returns to j from changing from 0 to 1 when i chooses either 0 (first line) or 1 (second line) and everyone else chooses $s_k \in S_{-i-j}$. The difference between these is

$$\Delta_{ij}\left(S_{_{-i-j}}\right)=\Delta_j\left(i=1,S_{-i-j}\right)-\Delta_j\left(i=0,S_{-i-j}\right)\geq 0 \tag{6.3}$$

This is the increase in the return to $j's$ change of strategy as a result of $i's$ change of strategy and from (2.1) we know that this is positive. We focus on equation (6.3) when all agents other than i and j are choosing strategy 0 so as to derive conditions for tipping the Nash equilibrium of all zeros to that of all ones:

$$\Delta_{ij}\left(0\right)=\left\{U_j\left(0^{I-2},1_i,1_j\right)-U_j\left(0^{I-2},1_i,0_j\right)\right\}-\left\{U_j\left(0^{I-2},0_i,1_j\right)-U_j\left(0^{I-2},0_i,0_j\right)\right\} \tag{6.4}$$

where 0^{I-2} indicates that there are $I-2$ zeros in position other than i and j. Consider the following sequence of inequalities, which link the equilibrium with all 0s to that will all 1s in a series of steps in each of which an additional state changes strategy from 0 to 1, and which hold because of (2.1):

$$U_i\left(0^{I-1},1_i\right)-U_i\left(0^{I-1},0_i\right)+\epsilon<U_i\left(0^{I-2},1_1,1_i\right)-U_i\left(0^{I-2},1_1,0_i\right) \tag{6.5}$$

$$U_i\left(0^{I-2},1_1,1_i\right)-U_i\left(0^{I-2},1_1,0_i\right)+\epsilon<U_i\left(0^{I-3},1_1,1_2,1_i\right)-U_i\left(0^{I-3},1_1,1_2,0_i\right)$$

$$U_i\left(1_1,..1_{I-2},0_j,1_i\right)-U_i\left(1_1,..1_{I-2},0_j,0_i\right)+\epsilon<U_i\left(1_1,..1_{I-1},1_i\right)-U_i\left(1_1,..1_{I-1},0_i\right)$$

The first inequality here (6.5) shows that the payoff to state i from a strategy change is raised by at least ϵ when state 1 also picks strategy 1. The second inequality shows that the payoff to i from the change is again increased by ϵ when state 2 also changes from 0 to 1. Working back from a typical inequality in this sequence we find that

$$U_i\left(0^{I-k},1_1,1_2,...,1_i\right)-U_i\left(0^{I-k},1_1,1_2,...,0_i\right)>(k-1)\,\epsilon+U_i\left(0^{I-1},1_i\right)-U_i\left(0^{I-1},0_i\right)$$

Note that $U_i\left(0^{I-1},1_i\right)-U_i\left(0^{I-1},0_i\right)<0$ as the vector of zeros is a Nash equilibrium so zero is a best response. Note also that the last difference in this sequence $U_i\left(1_1,1_2,...1_{I-1},1_i\right)-U_i\left(1_1,1_2,...1_{I-1},0_i\right)>0$ as the vector of all ones is a Nash equilibrium and therefore 1 is a best response. As the sequence of differences starts negative and ends positive it must change sign: there will be a $k<I-1$ such that $(k-1)\,\epsilon-U_i\left(0^{I-1},1_i\right)+U_i\left(0^{I-1},0_i\right)>0$ and the first k states will form a tipping set. To be precise we need k to satisfy

$$(k-1)\,\epsilon>U_i\left(0^{I-1},1_i\right)-U_i\left(0^{I-1},0_i\right)\ \forall i \tag{6.6}$$

In this case each of the other states finds it in its interest to change its strategy from zero to one and the equilibrium of zeros is tipped to that of ones if the first k states all change from zero to one. Equation (6.6) shows a tradeoff between the social reinforcement parameter ϵ and the size of a tipping set k : the great the social reinforcement (the greater ϵ) the smaller the number k in the tipping set. □

Next we turn to the characterization of the greatest and least Nash equilibria of the game $\bar{S}$ and $\underline{S}$, whose existence is assured by the theorem of Topkis ([3]).

Theorem 4. *A necessary and sufficient condition for* $\underline{S}=(0,0,...,0)$ *and* $\bar{S}=(1,1,...,1)$ *is that for every agent i, if all other agents have chosen the same strategy s, then that common strategy s is i's best response.*

Proof. The proposition is immediate. □

In plain English, we have Nash equilibria at all zeros and all ones if it never pays to be the odd-man-out. Proposition 2 has implications in terms of the

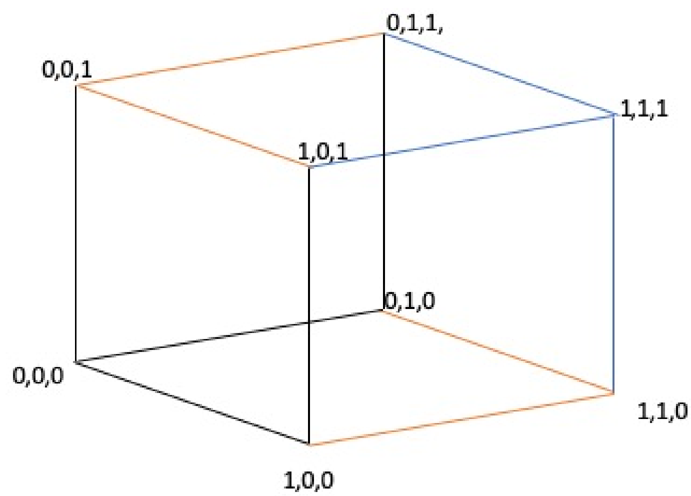


Figure 6.1: All possible plays for three players. Black edges are connected to the least Nash equilibrium and blue to the greatest.

structure of agents' utility functions. It requires that $U_i(0_i, 1_i) - U_i(0_i, 0_i) < 0$ and $U_i(1_i, 1_i) - U_i(1_i, 0_i) > 0$. So the derivative of $i's$ payoff with respect to its strategy depends heavily on the strategy choices of others, to the extent of changing sign if these other strategy choices all change.

Figure 4.1 illustrates how payoffs to a choice by i vary with the choices of others. There are three players and $(0,0,0)$ and $(1,1,1)$ are Nash equilibria. So if starting from $(0,0,0)$ agent 1 changes to 1 and moves to vertex $(1,0,0)$ then she is worse off. Likewise if agent 2 moves to $(0,1,0)$ she is worse off. However if agent 1 changes from zero to one starting from $(0,0,1)$ and so moves from vertex $(0,0,1)$ to vertex $(1,0,1)$ she may gain.

Theorem 5. *(1) There is a Nash equilibrium at which all states choose 0. (2) There is a Nash equilibrium at which all states choose 1. (3) There is a Nash equilibrium at which all democratic states choose 1 and all republican states choose 0 (or vice versa). (4) If all states are choosing 0 then there is a tipping set of democratic states that can tip the remaining democratic states to choosing 1 so that the equilibrium is that democratic states choose 1 and republicans choose 0. (5) If all states are choosing 1 then there is a tipping set of republican states that can tip the remaining republican states to choosing 0 so that the equilibrium is that republican states choose 0 and democratic states choose 1.*

The proofs are simple. The payoffs to democratic and republican states from choosing 1 or 0 are

$$1: \ \gamma_D N_D + \alpha_D \gamma_R N_R : \ 0: \ (1-\gamma_D) N_D + \alpha_D (1-\gamma_R) N_R \tag{6.7}$$

$$1: \ \gamma_R N_R + \alpha_R \gamma_D N_D : \ 0: \ (1-\gamma_R) N_R + \alpha_R (1-\gamma_D) N_D \tag{6.8}$$

If all states choose 0 then $\gamma_R = \gamma_D = 0$ so in both cases the payoff to 0 exceeds that to 1. Hence all choosing 0 is a Nash equilibrium. And if all choose 1 then $\gamma_R = \gamma_D = 1$ so that the payoff to 1 exceeds that to 0. These statements are true for all parameter values.

If all democratic and republican states choose 1 and 0 respectively then the payoffs to 1 and 0 for democrats and republicans are:

$$Dem, 1 \rightarrow N_D : Dem, 0 \rightarrow \alpha_D N_R : Rep, 1 \rightarrow \alpha N_D : Rep, 0 \rightarrow N_R$$

so that we have a Nash equilibrium if and only if

$$N_D \geq \alpha_D N_R \ \& \ N_R \geq \alpha_R N_D \tag{6.9}$$

If we think of N_D, N_R as being roughly the same size and α_D, α_R as less than one half, this condition is generally satisfied.

Now suppose that all states are choosing 0, and look for a set that tips the democrats to 1. If a fraction γ_D change to 1, the payoff to 1 for a democratic state is $\gamma_D N_D$,and the payoff to 0 is $(1 - \gamma_D) N_D + \alpha_D N_R$ and the fraction γ_D forms a tipping set if and only if $\gamma_D \geq \frac{\alpha_D N_D + N_D}{2N_D}$.

Finally suppose that all states choose 1 and look for a set that can tip the republicans to 0. If the fraction of republicans choosing 1 falls from 1 to $\gamma_R < 1$ then the payoff to a republican state from choosing 0 is $(1 - \gamma_R) N_R$ and from choosing 1 is $\gamma_R N_R + \alpha_R N_D$ so 0 is the equilibrium if and only if $\gamma_R \leq \frac{N_R - \alpha_R N_D}{2N_R}$. Of course, as our specification is symmetric, a group of democratic states could also tip its fellows away from SIP policies, just as a group pf republicans could tip their fellows to SIP policies.

7 Robustness Checks

In this section we present results which enable us to assess the robustness of the material presented above. We approach the same questions by different methods.

7.1 Geographical proximity

We use an approach based on the cultural and geographical proximity of states. Rather than assume the the probability of a state adopting a policy depends on the number of other states that have already done so and their political orientations, we assume that the states that matter most may be those that are near to the undecided state and have a similar political culture. Figure 7.1 shows one set of regions that we used. These regions were analyzed by Vandello and Cohen [9], who developed an index of individualism/collectivism and argued that states in these regions have similar political cultures. This motivated us to carry out logit and probit regressions classifying states by regions rather than by political orientation. The probability of each state choosing a policy is now expressed as a linear function of the policy rates in each region (i.e. the fraction of states in the region with the relevant policy in place), rather than as before a function of the policy rates of democratic, republican and swing states:

$$\Pi_{i,X,t} = \sum_j \alpha_{i,j} N_{j,X,t} + \delta_i C_{i,t} + K + \epsilon_{i,t} \tag{7.1}$$

In this equation, i refers to states and t to the day. X denotes the adoption of either an SIP policy or a mask-wearing policy. $N_{j,X,t}$ denotes the fraction of states in region j that have adopted policy X on day t. The results in this case are poor, with few significant coefficients, and it appears that sorting states' by political affiliation rather than culture gives a better explanation of COVID-19 policies.

7.2 Work-from-home ratio

In another extension of the analysis we included as an independent variable the fraction of jobs in each state that can be done while the employee is at home - the work from home ratio. We might expect that the Governor of

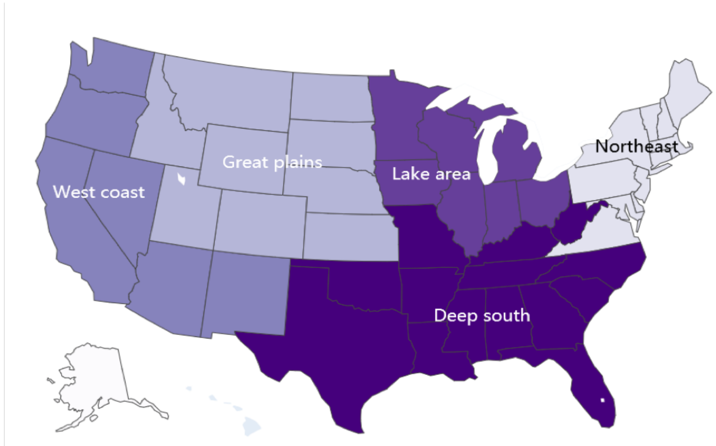


Figure 7.1:

a state would be less willing to implement a shelter-in-place order if most people in the state have to leave home to work: a high value for the work from home ratio suggests a high cost to an SIP order. The data on the work from home ratios comes from Dingel and Neiman [6]. As shown in table 11, the work from home ration does have a negative coefficient in the equation for SIP orders, but in the probit and logit cases it is not significant, and its inclusion does not alter the coefficients of interest.

7.3 Interactions between SIP and mask choices

So far we have treated the decisions about introducing SIP and mask policies as separate and independent. In a final check we allow for the possibility that these may in fact influence each other. We therefore re-estimate our main equations (4.1) and (4.3) for the SIP and mask cases respectively allowing for interactions between these choices. In equation (4.1) estimating the probability of a state introducing an SIP requirement, we introduce an indicator variable that is zero if it has not introduced a mask-wearing requirement and one if it has. Likewise in equation (4.3) estimating the probability of a state introducing a mask-wearing requirement we introduce an indicator variable

	Probit		Logit	
	Rep	Dem	Rep	Dem
Dem SIP %	5.736***	2.60***	10.65***	4.324***
Swing SIP %	−2.009**	2.793***	−3.679**	5.524***
Rep SIP %	8.394***	3.590***	15.23***	8.996***
NewCase/100K	0.0375	0.0431***	0.0542	0.0822***
WFH ratio	−16.2	−5.777	−32.67	−9.991
Const	−4.521	−0.911	−7.701	−1.979
Insig2u	2.659***	0.411	3.919***	1.817***
N	2756	1696	2756	1696

Table 11: WFH ratio = work from home ratio

	Probit		Logit	
	Rep	Dem	Rep	Dem
$N_{D,SIP,t}$	5.768***	2.364***	10.70***	3.988***
$N_{S,SIP,t}$	−2.031**	3.184***	−3.695**	6.159***
$N_{R,SIP,t}$	8.492***	2.760**	15.25***	7.379**
$Mask$	0.104	−0.385	0.253	−0.689
$NC_{i,t}$	0.0386	0.0481***	0.0541	0.0895***
K	−8.183***	−2.683***	−17.13***	−5.019***

Table 12: Dependent variable probability of SIP policy

that is zero if it does not already have an SIP requirement and one if it does. Tables 12 and 13 shows the results of these additions.

The coefficients in table 12 are very similar to those in table 1, which shows the results of the same estimation except that the variable "mask" is not included. The coefficient on "mask" in 12 is never significant. So it is reasonable to conclude that the choice of an SIP policy is not influenced by whether or not there is a mask-wearing policy in place.

The coefficients in table 13 are again similar to those in table 6 where we estimated the probability of introducing a mask-wearing policy: all coefficients have the same sign and the pattern of significance is the same. One of the coefficients on the SIP variable is significant, though only at the 5%

	Probit		Logit	
	Rep	Dem	Rep	Dem
$N_{D,M,t}$	15.83***	31.96***	36.709***	59.35***
$N_{S,M,t}$	8.621**	27.66***	12.81*	57.86***
$N_{R,M,t}$	23.19***	24.756***	35.85***	85.45*
SIP	0.644	−2.371*	11.09	−5.527
$NC_{i,t}$	0.209	−0.0127	0.0375	−0.0193
K	−25.23***	−24.06***	−55.85***	−39.43***

Table 13: Dependent variable probability of mask-wearing policy

level. Interestingly, the coefficients on “mask” and “SIP” in both table 12 and table 13 are positive for republican states and negative for democratic states: however as they are generally not significant we should not read too much into this.

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