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Comparing the channels of US states' COVID-19 policy contagion

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Abstract

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1. Introduction

According to the "domino theory", changes in a country's political and economic policies can trigger changes in neighboring countries' policies, producing ripple effects to other countries as well. Dogbey et al., (2024) employed this idea to study the spread US COVID-19 policy stringency among US states. They find that beside geographic neighbors, COVID-19 policies in the US states spread to their political "neighbors" (those whose governors share same political identity with theirs). The combined effect of the geographic and political contagion was estimated to be 30%, while they individually account for 11% and 24% respectively.

Using the same approach, our paper examines whether the political channel extended beyond governor party affiliation to state party affiliation and whether including this channel in the estimation increases the size of the overall contagion they estimated.

Dogbey et al., (2024) employed both static and dynamic Spatial Durbin models to estimate the overall size of the COVID-19 policy contagion but did not use the dynamic model in the estimation of individual channels. To compare our estimates with theirs, we re-estimate all the models in the dynamic setting since the lag dependent variable in their benchmark model was significant (signifying internal habit persistence in the data). Other researchers suggest that spillover effects in Stay-at-Home policies and Shelter-in-Place policies exist at the state level (Lin and Meissner, 2020 and Cui et al., 2020), but did not estimate the size of the contagion. We find that, COVID-19 policy stringency contagion is greater by state party affiliation channel than governor party affiliation and geographic channels and that including the state party affiliation channel in the estimation increases the overall estimated size of the contagion from 30% to 44%.

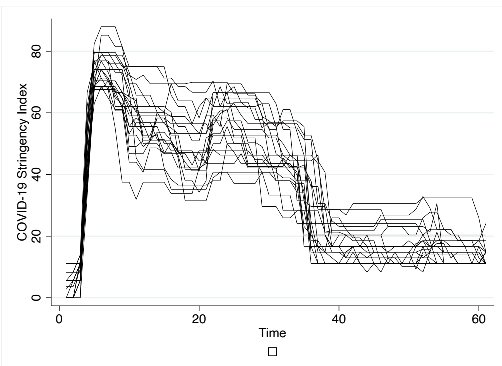
2 Channels that spread COVID-19 Policy

Policy contagion is a situation where related regions inherit spillover policies from each other (Edwards, 2000). An example of this is a phenomenon called "Tiebout Competition" where states or countries copy each other's policies in a bid to compete for Foreign Direct investment or attract residents from related regions in order to increase their tax base (Simmons, Dobbin, and Garrett, 2006).

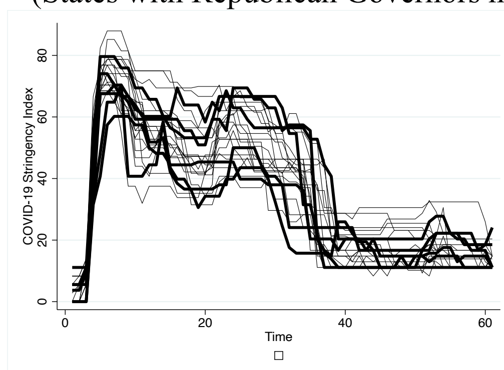
Several reasons could explain the spread of COVID-19 policy. State residents could put pressure on their state leaders to act in line with their political peers. This can also be appealing to state leaders since it can allow them to share blame should those policies fail to achieve their intended results. Barrios and Hochberg (2021) also illustrated that attention paid to COVID-19 was correlated with states' position during the 2020 presidential election. They found that political parties became more homogenous in the way they affected the risk perception of their members and their health-related reactions to the COVID-19 health crisis.

Fig. 1: Comparing the COVID-19 Stringency Graphs of Democrat States and Republican States (highlighting those who flipped in the 2018 Governor election)

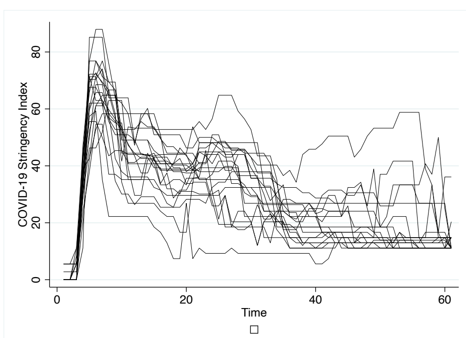
a) Stringency Graph of Democrat States



b) Stringency Graph of Democrat States (States with Republican Governors highlighted)



c) Stringency Graph of Republican States



d) Stringency Graph of Republican States (States with Democrat Governors highlighted)

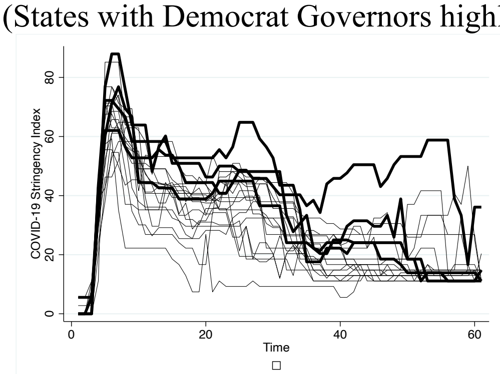


Fig. 1 shows that the stringency graphs of the few states which voted Democrat (Vermont, Rhode Islands, Virginia, Massachusetts, Arizona, New Hampshire, and Georgia) or Republican (Louisiana, Kansas, Kentucky and North Carolina) in the 2018 governor elections but flipped in the 2020 presidential elections seem to have trends identical to the rest of the states they identified with in the 2020 presidential election. This suggests that state party affiliation played a role in the spread COVID-19 policy stringency.

3. Methodology

We follow Dogbey et al., (2024) who used Spatial Durbin Model (SDM) to model COVID-19 policy stringency. The dynamic SDM model is specified as:

$$y_t = \rho(I_T \otimes W_N)y_t + \tau y_{t-1} + \eta(I_T \otimes W_N)y_{t-1} + X_t\beta + (I_T \otimes W_N)X_t\theta + \mu + \alpha_t \iota_N + \epsilon_t$$

where ρ is the spatial dependence coefficient, $t = 1, \dots, T$ is the time index and N is the number of panel cross sections (i.e., the 48 contiguous US states and Washington DC). The dependent variable y_t represents the stringency index and is an $NT \times 1$ vector. X_t is an $NT \times k$ matrix of explanatory variables, namely the infection rate, death rate, and fully vaccinated rate. I_T is a $T \times T$ identity matrix. ϵ_t is an independently and identically distributed disturbance term with zero mean and a constant variance σ_ϵ^2. μ is a vector of spatial (state-specific) fixed effects; α_t is a vector of time-specific fixed effects. I_N is an $N \times N$ identity matrix. W_N is an $N \times N$ row-normalized weights matrix.

3.1 Weights Matrices

The weights matrix models the dependence structure between the sampled spatial units. Weights matrices are typically spatial in nature (e.g., contiguity matrices, distance-based matrices, k-nearest neighbors' matrices and gravity model matrices), but they need not be. Depending on the data or research question, a binary matrix (assigns a weight of one to two units that are similar or zero otherwise), a distance decay weights matrix (assigns a weight inversely proportion to the distance between two units) or a bilateral trade weights matrix (assigns a weight equal to the volume of imports or exports between two countries expressed as a percentage of their total imports or exports) is used.

Our geographic weights matrix employs the "queen" case of first-order contiguity. This means that each state assigns a weight to any state it shares borders with vertically, horizontally, or at its vertexes. In this case, each state assigns a weight of one to every state that it shares borders with and a weight of zero to other states. For the governor party affiliation weights matrix, a state gives a weight of one to other states whose governors share identical affiliation with theirs and zero otherwise. In the state party affiliation weights matrix, states give a weight of one to others identical to them (blue or red) and zero otherwise; this matrix is what we have added to our estimation in addition to those of Dogbey et al., 2024. The final weights matrix is the summation of all three weights matrices, ensuring that states give weights to those who share one, two or all three identities with them or, zero otherwise.

Table 1: Moran's I Statistic

Weights matrix	Statistic	Z-value	P-value
Geography	0.259***	3.125	0.001
Gov. affiliation	0.350***	12.659	0.000
State affiliation	0.238***	8.880	0.000

Fig. 1 indicate a high political (state identity) similarity among the contiguous US states around the times COVID-19 began, suggesting a possible spatial dependence in our data. The presence of spatial dependence in the data is known to bias the OLS estimator (LeSage and Pace, 2014) in the form of omitted variable bias. The weights matrices control for this dependence. But to use them we need to compute the Moran's I static on our weights matrices under the null hypothesis the observed spatial pattern could be attributed to complete spatial randomness. As indicated by the Moran's I statistic results in Table 1, we reject the null hypothesis for all three weights matrices at the 1% significance level, indicating the presence of spatial dependence. The next step is to compute the magnitude of the contagion in our models, ρ.

3.2 Data

Our study employed biweekly panel data on the 48 contiguous US states and Washington DC over the period from 02/05/2020-05/28/2022 (61 time periods). Our variables are the stringency index from the Oxford COVID-19 Government Response Tracker (OxCGRT) stringency index, infections rate, deaths rate, and vaccinations rate in each state from the United States Center for Disease Control and Prevention (CDC).

The stringency index (0: low, 100: high) is a measure of the strictness of closures and containment policies aimed at restricting behavior during the pandemic and this information can be found on the OxCGRT website.

The infection rate is computed as the total percentage of a state's population infected with COVID-19. The death rate is computed as the percentage of the infected whose cause of death was COVID-19. The vaccination rate is the percentage of the population that received the full dosage of the COVID vaccine. The insured unemployment rate is the number of people currently receiving unemployment insurance as a percentage of the labor force.

Our parameter of interest, ρ, measures the spillover that the dependent variable of one spatial unit receives from the dependent variables of other spatial units. The direct effect measures the effect that a change in each explanatory variable of a particular state has on its own stringency index averaged over all states. The indirect effect captures the effect that each explanatory variable of all states has on the stringency index of a state except its own explanatory variable. The total effect is a measure of the effect that a change in an explanatory variable (of all states) have on the stringency index of a particular state averaged over all states. It is the sum of the direct and indirect effects.

3.3 Estimation

The dynamic SDM uses the biased-corrected quasi-maximum likelihood (QML) estimator. In STATA, it uses the *xsmle* command, which implements the fixed effect (FE) variant. By treating the lagged dependent variable as exogenous regressor, the maximum likelihood estimates are computed. The coefficient estimates and their standard errors are then adjusted with computed bias corrections due to individual and time effects in the dynamic panel data setting. The *xsmle* command also computes a one-way clustered standard errors similar to the derivation of robust standard errors for nonspatial models using the command vce(robust), which is similar to vce(panelvar). The default asymptotic variance-covariance matrix of the coefficients is derived from the observed information matrix (Yu, et al., 2008, and Belloti et al., 2017). All estimation is done is STATA.

4. Results

Table 2 reports the results using each of the weights matrices individually. It shows that the size

Table 2: Comparing the Spread of COVID 19 Policy Stringency Channels

Dependent Variable: COVID-19 Stringency Index

Independent Variables	Weighted by geography	Weighted by gov. party affiliation	Weighted by state party affiliation
ρ	0.27***	0.32***	0.38***
	(8.31)	(9.71)	(11.73)
Lag stringency	0.6480***	0.4940***	0.5200***
	(22.42)	(13.38)	(18.08)
Infection rate	0.6914	0.6696**	0.2879
Long term direct	(1.37)	(2.18)	(0.77)
Death rate	1.1416	1.3685***	1.5888*
Long term direct	(0.46)	(2.98)	(1.92)
Vaccination rate	-0.2276	-0.2103***	-0.1377*
Long term direct	(-1.18)	(-2.62)	(-1.95)
Insured unemployment rate	0.3613	-0.0049	-0.1279
Long term direct	(0.69)	(-0.02)	(-0.34)
Infection rate	-0.4799	0.5900	0.6406
Long term indirect	(-0.12)	(0.93)	(0.87)
Death rate	6.3371	28.2695***	36.5907*
Long term indirect	(0.05)	(3.90)	(1.87)
Vaccination rate	-0.2650	-0.5939**	-0.7663
Long term indirect	(-0.03)	(-2.10)	(-1.42)
Insured unemployment rate	-1.1201	-5.0551***	-7.659*
Long term indirect	(-0.09)	(-3.38)	(-1.65)
Infection rate	0.2115	1.2595***	0.9286
Long term total	(0.05)	(2.59)	(1.42)
Deaths rate	7.4787	29.6381***	38.1796*
Long term total	(0.06)	(3.95)	(1.89)
Vaccination rate	-0.4927	-0.8042***	-0.9041*
Long term total	(-0.06)	(-3.10)	(-1.65)
Insured unemployment rate	-0.7587	-5.0601***	-7.659*
Long term total	(-0.06)	(-3.4)	(-1.65)
Infection rate	0.2421	0.3303**	0.1295
Short term direct	(1.35)	(2.08)	(0.70)
Death rate	0.1273	0.4018**	0.2793
Short term direct	(0.43)	(2.06)	(1.33)
Vaccinations rate	-0.06342**	-0.0996**	-0.0558
Short term direct	(-2.06)	(-2.38)	(-1.62)
Insured unemployment rate	0.1595	0.04876	0.0382
Short term direct	(1.11)	(0.36)	(0.22)
Infections rate	-0.1923	-0.0025	0.0108
Short term indirect	(-1.02)	(-0.01)	(0.06)
Deaths rate	1.1932***	7.3812***	5.2651***
Short term indirect	(2.74)	(8.20)	(7.94)
Vaccinations rate	-0.0238	-0.1103*	-0.0969*
Short term indirect	(-0.69)	(-1.70)	(-1.77)
Insured unemployment rate	-0.2875*	-1.3744***	-1.1351***
Short term indirect	(-1.73)	(-4.97)	(-3.98)
Infections rate	0.0498***	0.3277***	0.1403*
Short term total	(0.71)	(3.63)	(1.91)
Deaths rate	1.3206***	7.7831***	5.5444***
Short term total	(3.06)	(8.63)	(8.73)
Vaccinations rate	-0.0873***	-0.2099***	-0.1301***
Short term total	(-3.24)	(-5.08)	(-4.73)
Insured unemployment rate	-0.1280	-1.3256***	-1.0969***
Short term total	(-0.83)	(-5.97)	(-4.50)
R^2	0.86	0.83	0.83
Log-pseudolikelihood	-1.010e+04	-1.016e+04	-1.010e+04

t-statistics in parentheses. *, **, and *** denote rejections of the null hypothesis of no significance at the 5%, and 1% significance level, respectively of the spread of COVID-19 policy stringency is 38%, 32% and 27% for state affiliation, governor affiliation and geography respectively, suggesting that state affiliation is relatively more important in the spread of COVID-19 policy.

Table 3: The size of COVID 19 Policy Stringency Spillover

Dependent Variable: COVID-19 Stringency Index

Independent Variables	Weighted by geography, state and gov. party affiliations	Weighted by geography, state and gov. party affiliations	Weighted by geography and gov. party affiliations (Dogbey et al., 2024)	Weighted by geography and gov. party affiliations (Dogbey et al., 2024)
ρ	0.44***	0.44***	0.30***	0.35***
	(12.85)	(8.89)	(8.89)	(10.18)
Lag stringency	0.4933***	0.51627***	0.4914***	0.4841***
	(14.21)	(14.77)	(12.97)	(12.75)
Infections rate	0.3329	0.4024	0.6316**	0.6254*
Long term direct	(0.78)	(0.76)	(1.96)	(1.86)
Deaths rate	1.1449	0.7739	0.4646	0.9636**
Long term direct	(0.08)	(0.23)	(1.21)	(2.23)
Vaccinations rate	-0.1557	-0.1612	-0.2096***	--0.2123***
Long term direct	(-0.74)	(-1.15)	(-2.64)	(-2.65)
Insured unemployment rate	-0.1901			-0.0420
Long term direct	(-0.05)			(-0.15)
Infections rate	1.1406	2.7841	0.8526	0.7497
Long term indirect	(0.13)	(0.17)	(1.46)	(1.03)
Deaths rate	43.1555	31.7219	15.8041***	33.775***
Long term indirect	(0.06)	(0.20)	(4.49)	(3.55)
Vaccinations rate	-0.7573	-0.9598	-0.4711**	-0.6613**
Long term indirect	(-0.08)	(-0.17)	(-2.14)	(-2.01)
Insured unemployment rate	-9.1420			-6.3221***
Long term indirect	(-0.05)			(-3.28)
Infections rate	1.4736	3.1866	1.4842***	1.3751**
Long term total	(0.16)	(0.19)	(3.45)	(2.42)
Deaths rate	44.3004	32.4959	16.2687***	34.7391***
Long term total	(0.06)	(0.20)	(4.57)	(3.57)
Vaccinations rate	-0.9131	-1.1210	-0.6808***	-0.8737***
Long term total	(-0.10)	(-0.19)	(-3.50)	(-2.83)
Insured unemployment rate	-9.3321			-6.364***
Long term total	(-0.05)			(-3.34)
Infections rate	0.1562	0.1659	0.3132*	0.3137*
Short term direct	(0.84)	(0.92)	(1.88)	(1.78)
Deaths rate	0.1872	.07034	0.2012	0.1994
Short term direct	(0.97)	(0.35)	(0.62)	(1.05)
Vaccinations rate	-0.0712*	-0.0679*	-0.1026**	-0.1029**
Short term direct	(-1.79)	(-1.78)	(-2.50)	(-2.43)
Insured unemployment rate	-0.0149			0.0335
Short term direct	(-0.09)			(0.23)
Infections rate	0.0417	0.0750	0.1219	0.0210
Short term indirect	(0.19)	(0.36)	(0.61)	(0.10)
Deaths rate	7.9907***	2.6684***	4.6726***	8.3383***
Short term indirect	(8.42)	(3.88)	(7.10)	(8.32)
Vaccinations rate	-0.0748	-0.01625	-0.0969	-0.1103*
Short term indirect	(-1.23)	(-0.28)	(-1.55)	(-1.66)
Insured unemployment rate	-1.9133***			-1.5956***
Short term indirect	(-5.95)			(-5.44)
Infections rate	0.1979**	0.2409***	0.4351***	0.3347***
Short term total	(2.13)	(2.69)	(4.82)	(3.53)
Deaths rate	8.1778***	2.7388***	4.7927***	8.5378***
Short term total	(8.77)	(4.27)	(7.66)	(8.62)
Vaccinations rate	-0.1460***	-0.0842**	-0.1995***	-0.2132***
Short term total	(-3.51)	(-2.08)	(-5.01)	(-4.89)
Insured unemployment rate	-1.9282***			-1.5621***
Short term total	(-7.34)			(-6.81)
R^2	0.81	0.84	0.84	0.82
Log-pseudolikelihood	-1.013e+04	-1.013e+04	-1.018e+04	-1.017e+04

t-statistics in parentheses. *, **, and *** denote rejections of the null hypothesis of no significance at the 10%, 5%, and 1% significance level, respectively

Table 3 presents the results when all three weights matrices are combined to estimate the overall size of the spread of COVID-19 policy stringency, compared to Dogbey et al., (2024) which only combined geography and governor affiliation weights. Our model reports 44% compared to theirs of 30%.

Our results (for ρ) remain the same even when we include insured unemployment rate (which was not included in their model) as a macroeconomic control variable. However, most of the independent variables in their model (in Table 3) that were significant become insignificant once we add state affiliation to our combined weights matrix to measure the overall size of the contagion. Also, we run the model of Dogbey et al. (2024) again and control for insured unemployment rate to see how the results compare with ours. The magnitude of the contagion increases from 30% to 35% but still fall short of the estimate of our model of 44%, indicating that the inclusion of state party affiliation in our combined weights matrix does make a difference in capturing the magnitude of the overall contagion.

The pseudo-loglikelihood is used for model fit. Our models that employ state party affiliation weights matrices produce the lowest pseudo-loglikelihood compared to those which include governor party affiliation, or a combination of governor and geography only as shown in Table 3.

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