Acting, Fast or Slow: Partisanship and Local Government COVID-19 Policy Response

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Abstract:

There were large variations in the frequency and intensity of county and city governmental policy responses at the very beginning of the COVID-19 pandemic. In this paper, we aim to determine whether the political leanings of a given locality affect whether its government imposes a mandatory policy on its constituents before any government superior to it does so, where such superior governments allow. Controlling for confounders, among the nationwide set of all qualifying counties, we find that there is a small but strong negative correlation between the partisan leanings of a county (Trump vote-share) and the probability it will issue a stay-at-home order before the state, controlling for COVID severity. Our results estimate that a hypothetical Democratic county in the 5th percentile of Trump vote share would be 15.43 percentage points more likely than a Republican county at the 95th percentile to act before its state. However, at the city level, we find no evidence of the same partisanship effect among the twenty-five largest cities in Texas.

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Introduction

During March and early April 2020, communities across the United States grappled with the fact that the COVID-19 pandemic was spreading or soon to be spreading among them—more severely in some places than others. Governments at all levels realized that action may be needed to prevent widespread illness and overwhelmed health care systems. Faced with the tasks of balancing the intended public health benefit of policies with their economic consequences, responding to citizens' views on the situation, and dealing with orders from superior and/or inferior levels of government, leaders made decisions based on an intriguing variety of factors. Among these factors is partisanship, both of leaders and of their constituencies. It is generally thought that Republicans at first took the problem less seriously than Democrats, but less clear is whether partisan differences in government actions were due to ideology itself or simply demographic factors correlated with party and the varying geographical severity of the disease.

The dynamics existing between local governments and their superior governments in pandemic response, especially when those governments differ in partisanship, also merits investigation. Certain communities were much harder hit than others within the same state and thus might have been better served by local policies, yet blanket state action had the potential to limit spillover and NPI avoidance. Once a state had enacted a policy, the localities within it no longer had reason to implement the same policy; however, before state action, localities had the option to act on their own. Why did some counties and cities take this opportunity and some did not? Do the partisan leanings of a given locality affect whether its government imposes a non-pharmaceutical intervention (NPI) on the population it serves before any superior government does so, where such superior governments allow?

Non-Pharmaceutical Interventions

Various governments implemented non-pharmaceutical interventions (NPIs) in order to combat the spread of COVID-19. As opposed to direct medical interventions used to treat a coronavirus patient, non-pharmaceutical interventions are undertaken by communities to respond to the pandemic and target non-medical behaviors. At the national, state, and local levels, governments undertook NPIs such as either encouraging or mandating social distancing, size limitations on gatherings, business closure, and restrictions on the movement of individuals. Because it is difficult to compare levels and methods of encouragement across actors, we have focused on NPIs that are binding to citizens and more formally codified into law, so that it is easy to verify their existence and content. The two NPIs we studied were prohibition of dine-in services at restaurants (though take-out, drive-through, and delivery may still be allowed) and stay-at-home orders (referred to by some as “shelter-in-place” orders). Stay-at-home orders mandate that residents under a government’s jurisdiction remain at their place of residence unless performing certain “essential” tasks. These essential tasks can be defined slightly differently, but they generally refer to activities such as grocery shopping, seeking medical care, and work at an “essential” business. Though these two NPIs can differ in their minute specifications when implemented by different localities, any order that falls under these definitions is what we mean when we refer to “restaurant closures” or “stay-at-home orders.”

Superior Governments

For the purposes of this paper, we define superior government as any level of government which partially or fully geographically subsumes and is legally empowered to supersede the public health laws of the level of government question if desired. In most cases, this practically means that the superior level of government to a city can be either a county (or county equivalent) and a state, and that the superior level of government to a county (or county equivalent) is a state. As we used Census Bureau data in the production of this paper, we have adopted their definitions for both cities and states. Thus, a city is defined as an incorporated place but not a Census Designated Place; a county is defined as a county-equivalent, which also includes combined or consolidated city-county governments.

Importantly, this definition of superior government excludes the federal government by definition; states are empowered by the Constitution to set the public health laws within their territory, and therefore are subsequently invalid to be directly examined in this paper.

Data Sources

Our initial county level dataset on implemented non-pharmaceutical interventions came from the National Association of Counties (NACO), which contained some information about a county, as well as the dates each policy was enacted, if available. The three available policies were an emergency declaration, a mandatory stay-at-home policy, and an essential business order. Additionally, this dataset contained a set of up to date information on when states enacted each of the three recorded NPIs. NACO did not distinguish between verified no-policy counties and counties with no information, so we were unfortunately forced to treat both types the same. Short of searching every single county, however, this dataset appears to contain the most counties with populated dates currently available. In order to validate the dataset and incorporate as many dates of county policies as possible in our dataset, we matched the data on a dataset collected by a separate team at AgroImpacts, and added any missed county policy dates, of which there were approximately twenty.

For our Texas city-level analysis, we hand-collected data directly from the website for each city and county, relying on news articles if the PDF of city or county level orders were not available. If we could not find an order from a city, or if the city only linked to the county order, we marked it as deferring to the county. If the dates from sources conflicted on the specific dates, we coded what the “most primary” source recorded. A dataset of direct source links to PDFs is available upon request.

In order to control for demographics in our analysis, we utilized Census Bureau demographic data at both the city and county level. We scraped a separate NACO webpage for population information on each county (which itself was sourced from the Census Bureau). Additionally, to analyze the initial object of interest - the vote share allocated to Trump in each county - we utilized USAGov elections data. Finally, we utilized recorded COVID cases at the county level in our analysis, which was gathered from the Johns Hopkins data on May 15th.

Methods

County-Level Method

To analyze the role partisanship played in preemption of county-level NPIs by state action, we implemented an OLS regression, using a binary variable as our outcome of interest, which indicated whether a county or a state implemented a stay-at-home order first. If neither a county nor its state implemented, the observation was coded the same as if the state had preempted county action to provide a lower bound on our estimates. We included controls for different combinations of other measurable factors such as confirmed COVID-19 case load, population and demographics, urban areas, wealth, and whether a given state ever enacted a stay-at-home order.

Because we are only interested in cases in which counties had discretion to implement a stay-at-home, we excluded states from our analysis that formally prohibited counties from implementing NPIs such as restaurant closing or stay-at-home orders (AZ, IA, NY, PA, and SC). In these states, the state government either publicly indicated that counties did not have the constitutional authority to restrict the activities of citizens, or evidence was found that a local leader sought and was denied permission by the state to implement an NPI. If the governor of the state placed an NPI order on only certain counties, we also counted this as a formal restriction on county action, since this made it clear that local restrictions were considered to be a state rather than local decision, and these states were also excluded. Out of the five states that fit this criteria, three had Republican governors, and two had Democratic governors. If no evidence was found of such prohibition, a locality within the state imposed a non-essential business closure or stay-at-home order, or the governor stated that localities could take action more strict than the state if they deemed it necessary, we considered no such prohibition to exist and included the state in our analysis. Additionally, we focused only on the contiguous 48 states, excluding HI and AK from our analysis because of the unique relationship between county governments and the state there. In Hawaii, counties are imbued with a unique level of power, acting as cities as well, and some areas of Alaska are not included in any county.

County-Level Assumptions and Limitations

The largest assumption we made in the county-level analysis was the assumption that the quality of the data from NACO—and as verified and combined with AgroImpacts—was a rigorously-collected quality dataset. Our major worry was and continues to be that the NACO and AgroImpacts data is a combination of incomplete hand-collected and (as partially the case with NACO) county-self-reported data. While this is not inherently a problem, we feel it is quite likely that the dataset is not as-if-randomly selected, and is almost certainly differentially likely to contain orders from larger counties over smaller ones due to the nature of limited resources (both at NACO and in instances where counties self-report). As a result, the dataset could contain differentially more instances of larger counties acting before a state than smaller ones, causing it to look as if the Trump 2016 vote-share is significant when in fact it is not. As will be detailed in the section below, we attempted to control for this as much as possible in the data by including population and income data, but there is no guarantee of the complete efficacy of these controls.

Using the data we collected for the analysis of Texas cities, we did find evidence that our county-level data is less than complete. Potter and Webb counties in Texas are not listed as having local stay-at-home orders in the county-level data, yet we found that they did in fact implement them. Webb county voted 23% for Trump in 2016, and Potter had 71% of votes for Trump, so this finding does not necessarily imply that the incompleteness of the data is biased towards any one political party. Potter and Webb account for two of the seventeen counties on which we personally collected information—both sets of data contained matching information for the other fifteen. While it is theoretically possible to verify the data in the remaining 2600 counties where no policy exists, this was infeasible with resources we had available and as such it may be worthwhile for others to verify in the future.

Additionally, by including fixed effects at the state level, we successfully controlled for any degree of inter-state variation in the data, but not for intra-state variation at a level higher than just one individual county acting alone. It is possible that some or all states treat certain groups of counties differently, from any combination of subtle differential treatment between regional and metropolitan areas in confidential discussions with the state or regional health board or state and local officials. It's also possible that certain groups of counties banded together in an informal but regional capacity through the personal friendships of their leaders or necessity, which could serve as one potential explanation for partisanship playing a factor—leaders of the same party in different counties could be more likely to form potential friendships. Most obviously, though, we see evidence from Texas that bordering counties with large overlapping metropolitan populations are more likely to informally coordinate and therefore act together which, though not necessarily a source of bias, is not accounted or controlled for in the structure or method of our analysis.

We also limited ourselves by only looking for specific NPIs—emergency declarations, non-essential business closures, and stay-at-home orders, for which we focused on stay-at-home orders specifically. However, it is certainly possible that strongly worded guidance from a county suggesting but not requiring either of these three would serve most of the same purpose as the legally binding orders we analyzed, meaning we could therefore miss measuring some of the county pre-state action. On the same vein, by only looking at stay-at-home orders, we miss any of the county pre-state actions from every other NPI, so future research into either of these areas may be warranted to verify or expand upon the results of this paper. Additionally, there may be some unknown but special difference between implementing a legally binding stay-at-home order and any other NPI from the point of view of a policymaker, so follow-up research into this area should consider interviews with relevant policymakers to verify these assumptions. Finally, we assume that Trump vote-share in the 2016 presidential election is a good measurement of county partisanship in general—a higher Trump vote share thus would make a county more Republican—but, due to the relatively unique nature of the 2016 election, it may be that certain counties over or underperformed their "true" partisanship differentially (along demographic lines, etc). This was likely controlled for in the data, but it is possible there are additional unobservables.

County-Level Controls

In addition to our primary independent variable of interest (Trump 2016 Vote-Share), as can be seen in the first table, we controlled for the intensity of COVID in a county as measured by cases on an arbitrarily picked day, March 31, 2020—the choice of which we justify in the following section—as well as whether a state had issued a stay-at-home order. Additionally, we controlled for population density, the log of population due to the intense variation between large and small counties, and the median household income in thousands of dollars in a county. We also controlled for the percentage of the population that was in a Census-defined urban area, the percentage of the population above 65, and state fixed effects. These were chosen for potential confounding demographic effects, as well as to see if there was any correlation which might imply policymaker consideration of given factors

As can be seen in the first table, only population density, log of population, the median household income, and the percentage of the population in an urban area are significant at the $p < 0.05$ level. We tested but did not include the racial makeup of the county, as well as the percent of the county in poverty, in the presented models; they seemed to only serve as a proxy for the percent urban population in a district and household income respectively, and added no real additional explanatory power to the model. These results can be seen in Appendix B. Additionally, as mentioned previously, we tested both the emergency declaration and non-essential business NPIs as dependent variables in the same way, but found their data was too incomplete to analyze.

County-Level COVID-Intensity Robustness Testing

We anticipated that the level of threat COVID-19 posed to a specific community would be an important factor in local decisions about NPIs. Therefore, we endeavored to control for the local severity of the pandemic by including a COVID-19 cases variable in our analysis. This variable measures the amount of cases confirmed in a county on an arbitrary date around the time when most localities were announcing their NPI orders: March 31 in the county analysis and March 20 in the Texas city analysis. Using a measurement from the same date for each locality was done in order to prevent the outcome of interest from causally acting upon the control value, since NPIs are intended to affect case counts by their implementation. However, some localities did impose NPIs before the arbitrary date. Choosing a date before *any* policies had been enacted would have resulted in very low case levels for many localities, giving small noise in COVID-19 case counts a disproportionate amount of influence on the results. As can be seen in *Appendix A*, robustness testing of our model reveals that varying the specific date chosen for the case load control does not have any effect on the significance or magnitude of the Trump vote share coefficient.

Of separate concern is that the level and accuracy of testing almost certainly varied among the localities studied, meaning that our attempt to proxy COVID severity in a county is very likely flawed; while we attempt to control for this with state fixed effects, available resources almost certainly varied within states. However, insofar as the measure is intended to control for the level of severity as it informed government response, it reflects the most top-level information that would have been available to decision-makers. Common convention in some separate COVID studies appears to be to control for deaths instead of cases to further control for the level. However, due to the nature of deaths as a lagging indicator, and that deaths were in the low single digits for most localities at the time around policy implementation (potentially introducing large amounts of noise), we opted for the less accurate but less noisy option of cases instead.

City-Level Method

To determine if local partisanship's influence on first-action holds for relationships between local governments besides counties and states, we turned to an analysis of the 25 most populous cities in Texas. Authority to set local public health policy in Texas can rest with a number of different actors, including counties or cities. Additionally, the state of Texas waited longer than many other states in imposing a stay-at-home order and restaurant closure. Thus, there was a period of weeks in which Texas localities could observe others across the country taking action and yet experienced an absence of a statewide order. For these reasons, we could observe variation in which local counties or cities enacted policies and when each did so.

The 25 most populous cities in Texas were chosen for analysis both due to time-constraints on data collection and because we determined the most variation in NPIs would likely be found in more populous cities. Because we know of no centralized reputable repository of information on city-level NPIs, we collected the information by visiting each city's website. If the website contained an official document declaring an NPI, or if a local news organization reported on such an order, we recorded the date that the NPI was set to take effect. We repeated this process for both restaurant closings and stay-at-home orders and did the same to verify data for the counties in which those cities were primarily geographically located. Only if the city's NPI took effect on a day prior to the corresponding county's order of the same NPI, or if the city acted while the county never enacted such an order, was the city considered to have acted before its county government. The share of the 2016 election vote that went to Donald Trump in the city's county was used to indicate the partisanship of a given city; there was no significant difference between the county and a city's vote-share as constructed from precincts overlapping city boundaries, and as such we went with the less complicated variable to reproduce.

City-Level Assumptions, Controls, and Limitations

Like with the county method, we structured our analysis in such a way that assumed there was no inter-city coordination, either within or in between counties. Since most cities are in a different county than all other cities, we have no county level fixed effects that might help capture and thus potentially inform the extent of intra-county coordination (among other things). Future research may want to collect multiple smaller cities per county in order to control for fixed effects. Additionally, this method importantly assumes that there is no informal coordination between a city and a county, the result of which would create a city-county partnership rather than a city acting before a county. In the data, this would be coded the same as a city waiting for a county to act unilaterally, which seems like a poor assumption. Unfortunately, the limitations of our data (brief newspaper articles and legal orders) don't allow us to dig any deeper than who acted first - to understand the true level of coordination, one would need to conduct interviews with or survey the relevant stakeholders, which would likely be a promising direction for future research conducted after the pandemic is over and policymakers have more time to talk. Finally, similarly to the assumption we made while looking at counties, we assume that restaurant closures are the best NPI to investigate in terms of city level variation, which may well not be the case. However, by having to read all of the orders, our impression was that this was in fact by far the most likely thing for a city to do before a county.

To control for confounding variables and to potentially tease out what variables policymakers utilized in determining whether to close restaurants, we controlled for the median household income of a city, the percentage of people under the poverty line in a city, the population of the city in 2018 according to the Census Bureau, the cases on March 20, 2020, and whether the city was the seat of the county government. Not shown or included were our other tested but insignificant controls: namely, the racial demographics of the city and percentage of the population over 65. We specifically controlled for these factors as the cities of Texas are extremely geographically, demographically, and economically diverse, and thus any results may be confounded by the data. Additionally, our hypothesis was that being the county seat would make it more likely to observe coordination between a county and a city government (as in the county would act before the city), and thus it was included.

Results

Counties Acting Before States

County Preemptions

	County Acting Before State (Binary)			
	(1)	(2)	(3)	(4)
Trump Vote Share (%)	-0.003^{***} (0.0003)	-0.003^{***} (0.0003)	-0.002^{***} (0.0003)	-0.002^{***} (0.0003)
Cases March 31	-0.00001 (0.00003)	0.00002 (0.00002)	0.00003 (0.00002)	0.00002 (0.00002)
Population Density	0.00002^{***} (0.00001)			
Population (Log10)	0.051^{***} (0.006)	0.053^{***} (0.005)	0.050^{***} (0.004)	0.042^{***} (0.003)

Median Household Income (thousands)	0.002^{***} (0.0004)	0.002^{***} (0.0004)		
Urban Population Share (%)	-0.001^{***} (0.0002)	-0.001^{***} (0.0002)		
Population Share Above 65 (%)	-0.0003 (0.001)			
Constant	-0.424^{***} (0.070)	-0.439^{***} (0.062)	-0.365^{***} (0.056)	-0.251^{***} (0.048)
State Fixed Effects	Yes	Yes	Yes	No
Observations	2,763	2,763	2,763	2,763
Adjusted R^2	0.270	0.268	0.257	0.114
Note:				*p<0.1; **p<0.05; ***p<0.01

In each model, the effect of the vote share (out of 100%) that Donald Trump received in the county in the 2016 election on the probability that the state would act before a given county was statistically significant. Considering the model with the full set of controls (1), each additional percentage point of vote going to Trump indicates a 0.3 percentage point decrease in probability that county action would occur before the state. In other words, more Republican-leaning counties are less likely to be proactive: to take local action instead of waiting for a higher level of government to enact an NPI order. The overall percentage of first-acting counties is only 6.0% (165 of 2,763 US counties), such that the partisanship effect is more substantial when compared to the baseline probability of a county acting first. Comparing a hypothetical Democratic county in the 5th percentile of Trump vote share (36.24%) to a Republican county at the 95th percentile (87.68%), the Democratic county would be 15.43 percentage points more likely than the Republican county to act before its state. Additionally, model 1 indicates that larger counties were more likely to act before the state, as were counties that were more wealthy on average. These effects were consistent in sign and significance across the models in which they were included.

Interestingly, in the full model (1), two different measures of how urban a county is (urban population share and population density) have coefficients of opposite signs. The model indicates that counties with an increased proportion of their population living in urban areas were more likely to be preempted by state action; however, counties with a higher population density are less likely to be preempted by the state. These are not exactly the same thing: hypothetically there could exist a large county with a small, very populous urban area and very few residents in the rest of the county. This county would have a low or average population density but a high share of residents living in an urban setting. Intuitively, this county would be expected to be likely to implement a stay-at-home order before the state because of the higher threat COVID-19 poses to densely-packed cities. If the population in outlying areas in such a county increased, population density would increase and the share of urban residents would decrease; the county might also be less likely to be a first-actor as its government becomes less dominated by urban interests. It is reasonable to assume that such counties exist, which could help explain the different signs on the population density and urban population share coefficients. Alternatively, this phenomenon could be an artifact of outlier counties with very high population densities.

Cities Acting Before Counties

Top 25 Texas Cities

	City Acting Before County (Binary)			
	(1)	(2)	(3)	(4)
Trump County Vote Share (%)	0.004 (0.007)	0.007 (0.008)	-0.006 (0.007)	-0.001 (0.008)
Median Household Income (thousands)	0.023** (0.008)	0.023** (0.008)	0.006 (0.005)	
Poverty Rate (%)	0.070** (0.029)	0.080** (0.029)		0.004 (0.018)
City Population		0.00000 (0.00000)		
COVID Cases March 20	-0.002 (0.004)	-0.005 (0.004)	-0.008** (0.004)	-0.006 (0.004)
County Seat (binary)		-0.388 (0.227)		
Constant	-2.385* (1.192)	-2.492** (1.168)	0.428 (0.393)	0.432 (0.724)
Observations	25	25	25	25
R^2	0.377	0.464	0.187	0.135
Adjusted R^2	0.252	0.285	0.070	0.011

Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Only one city out of the 25 imposed a stay-at-home order before its county, so we instead turned to an analysis of restaurant closures. The baseline probability for a city in the data mandating restaurant closure before a county is 28% (7 out of 25). For both stay-at-home orders and restaurant closures, there were a number of county-city pairs that enacted a given NPIs on the same day as one another: 10 for stay-at-home orders and 6 for restaurant closures. While collecting data, we observed that there was some level of coordination of policies between cities and counties. Some announced the NPIs jointly and several others explained that their orders were intended to "harmonize" with the other government's issuance—this phenomenon is especially evident for stay-at-home orders but less so for restaurant closures.

Unlike the analysis on county-preemption, the models using Texas city data do not show Trump vote share to be a statistically significant predictor of county action preceding a city's. This could be due to a low sample size, or it could be the case that partisanship simply is not an influential factor in the relationship between cities and counties. There may also be some aspect of a restaurant closure that is less political than a stay-at-home order, making partisanship less influential.

Because the same demographic data is not available for Texas cities as is available for US counties, the controls included differ somewhat between the two analyses. Though one would assume poverty rate and MHI to be inversely related to one another—and they indeed display a strongly negative correlation in the data—their coefficients are both positive and significant in models 1 and 2. It is possible there is a non-linear relationship between wealth and preemption which may explain this phenomenon.

Conclusion

Our work has led us to identify several areas of study that may yield interesting findings about partisanship and local COVID-19 action. In the process of collecting data on Texas cities, we intended to include mayoral party affiliation in our analysis. Though mayoral elections in Texas are officially non-partisan, the party of certain mayors is common knowledge to voters. Including the party affiliation, as denoted by Wikipedia, of each city's mayor in the model did yield coefficients with statistical significance, raising the question as to whether the party a city's leader ostensibly belongs to might influence their decision-making about NPIs. The mayors that were not identified with any party were much less likely to act before their county than Democratic mayors, even more so than Republican mayors when compared to Democrats. However, we could not identify a methodology that would allow us to identify mayoral party in a sufficiently consistent manner across mayors; therefore, we did not proceed with this line of inquiry. Other avenues for further refinement of our analysis include: verification of county-level data, a qualitative investigation of inter-governmental coordination on NPIs, and additional data collection for city-level NPIs—either in Texas or another state.

Our existing analysis of the data suggests that partisanship indeed plays a role in Coronavirus prevention actions of localities. We found that more Republican counties are less likely to act before their state when instituting stay-at-home orders: either waiting for a superior government to act or not seeing a need for such measures in the first place. This holds even as other factors that might explain the need for an NPI are taken into account. However, the significance of this relationship does not hold when the dynamic between city and county governments is analyzed in a similar manner. Our findings can serve as a jumping-off point for further investigation of local actions in response to COVID-19, to create a fuller understanding of pandemic policy-making in the United States. Whether partisan differences are an artifact of leaders following public opinion or their own party's example is not yet evident, and would be another avenue for further research; it may be beneficial to interview mayors, county leaders, and key policy-recipient citizen stakeholders involved in the process in a variety of large and smaller communities to test a hypothesis of salient factors.

Our findings may also shed some light on other work that has aimed to determine how partisanship affects individual responses to NPIs. Painter and Qiu found that, before state social distancing policies went into effect, mobility in Democratic-leaning counties decreased more than mobility in Republican-leaning counties. This phenomenon could be partially explained by our finding that Republicans are less likely to be under an NPI before any state action occurs. In counties that Painter and Qui classify as Republican-leaning (a Trump vote share larger than 50%) as compared to Democratic-leaning, we find a difference in mean Trump vote share of 34.8 percentage points, which corresponds to a difference in probabilities of a county taking stay-at-home action before a state of 10.44 percentage points. Painter and Qiu estimate in Figure 1, Panel B an approximately 5 percentage point difference in social distancing between Republican and Democratic leaning counties the day before a state policy goes into effect, which is the last opportunity for the county to act before the state. Rather than not taking social distancing as seriously as Democrats, Republicans might simply be feeling the effects of being 10 percentage points less likely to be affected by mandatory local orders to social distance. Painter and Qiu's analysis is thus potentially flawed without taking into account the very real partisan differences in the existence of local NPI orders before state ones.

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APPENDIX A:

Arbitrary Dates Robustness Testing

	State Acting Before County (Binary)				
	(1)	(2)	(3)	(4)	(5)
Trump Vote Share (%)	-0.002^{***} (0.0003)	-0.002^{***} (0.0003)	-0.002^{***} (0.0003)	-0.002^{***} (0.0003)	-0.002^{***} (0.0003)
Cases March 24	0.0001 (0.0001)				
Cases March 29		0.00003 (0.00003)			
Cases March 31			0.00003 (0.00002)		
Cases April 2				0.00002 (0.00002)	
Cases April 7					0.00000 (0.00001)
Population (Log10)	0.050^{***} (0.004)	0.050^{***} (0.004)	0.050^{***} (0.004)	0.050^{***} (0.004)	0.050^{***} (0.004)
Constant	-0.368^{***} (0.056)	-0.366^{***} (0.056)	-0.365^{***} (0.056)	-0.366^{***} (0.056)	-0.369^{***} (0.056)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	2,763	2,763	2,763	2,763	2,763
R^2	0.269	0.269	0.269	0.269	0.269
Adjusted R^2	0.257	0.257	0.257	0.257	0.257
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix B:

Excluded Variables

	State Acting Before County (Binary)			
	(1)	(2)	(3)	(4)
Trump Vote Share (%)	-0.003*** (0.0003)	-0.003*** (0.0005)	-0.006*** (0.0004)	-0.003*** (0.0003)
Cases March 31	-0.00001 (0.00003)	-0.00001 (0.00003)	0.0001*** (0.00002)	0.0001*** (0.00002)
Population Density	0.00002*** (0.00001)	0.00002*** (0.00001)		
Population (Log10)	0.051*** (0.006)	0.048*** (0.006)		
Median Household Income (thousands)	0.002*** (0.0004)	0.002*** (0.001)		
Urban Population Share (%)	-0.001*** (0.0002)	-0.001*** (0.0002)		
Population Share Above 65 (%)	-0.0003 (0.001)	-0.001 (0.001)		
Black Population Share (%)		-0.001 (0.001)	-0.002*** (0.001)	-0.00003 (0.0004)
Hispanic Population Share (%)		-0.001 (0.0005)	-0.001** (0.0005)	0.003*** (0.0003)
Share Under Poverty Line (%)		-0.0004 (0.001)	-0.006*** (0.001)	-0.005*** (0.001)
Constant	-0.424*** (0.070)	-0.294** (0.117)	0.556*** (0.049)	0.334*** (0.027)
State Fixed Effects	Yes	Yes	Yes	No
Observations	2,763	2,763	2,763	2,763
R^2	0.283	0.284	0.242	0.108
Adjusted R^2	0.270	0.270	0.229	0.106
Note:				*p<0.1; **p<0.05; ***p<0.01