Shelter in Place? Depends on the Place:

Corruption and Social Distancing in American States

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1 Introduction

Social distancing is the main policy in the global public health and policy response to the COVID-19 pandemic. Understanding the determinants of compliance with this policy is important as the virus spreads to ever more vulnerable communities which are less able to handle large numbers of critically ill patients. Many of these communities lack not only the physical and social infrastructure needed to fight the COVID-19 pandemic but are also often viewed as having endemic corruption.

Motivated by several related literatures ranging from sociology, to political science, to economics, we investigate the role of corruption in determining compliance with social distancing using data from 50 American states. Using two corruption measures, one based on corruption convictions and the other based on news stories related to corruption, and a measure of compliance based on cell phone activity constructed by *SafeGraph*, we find that states with higher corruption have lower levels of compliance.

Our findings suggest that communities in which corruption is endemic will find it difficult to employ effective containment and mitigation strategies based on social distancing. As such communities typically already suffering from poor health infrastructures and outcomes (Azfar and Gurgur, 2008; Ciccone et al. 2014; Friedman, 2018; Dincer and Teoman, 2019) will face this crisis with very few effective weapons in their arsenal. An implication of this is that additional funding will have to be directed towards fighting the virus. While there are valid concerns that corruption will prevent such funds reach the intended targets and beneficiaries (Suryadarma and Yamauchi, 2013; Briggs 2014), there is some evidence that public health aid can be effective even in corrupt communities (Dietrich, 2011).

1.1.Corruption and compliance with shelter in place

Starting with California in mid-March, the majority of American states instituted *shelter in place*/*stay at home* orders as part of their greater social distancing policies. Schools, restaurants, and bars were closed, and all nonessential businesses were ordered to keep workers home and let them work remotely. People were asked not to leave their homes unless necessary (see Table 1).

Penalties for the violators, on the other hand, varied significantly across the states. While in some states, there were no penalties, in most of the states, violation of the orders was considered a misdemeanor punishable with a small fine, though never enforced. Arizona, for example, violators may be charged with a class 1 misdemeanor, which has a fine up to $2,500, but golf courses were exempted. In Tennessee, there was a stay at home order, but no fines or penalties were specified (see Mazziotta 2020 for the state by state fines and penalties). In states such as Kentucky, Maryland, Michigan, and Pennsylvania, protesters, sometimes armed with assault rifles, packed state capitols and streets violating the states' orders, while in London, police arrested people protesting social distancing orders in Hyde Park (Estes 2020 and Parveen 2020). In other words, although it was mandated in theory, in practice, states depended heavily on voluntary social distancing. This resulted in a significant variation in social distancing behavior across the states.

There are several variables that can plausibly explain the variation in compliance with *shelter in place*/*stay at home* orders across American states including corruption. Corruption affects how people behave through its effects on trust in government and. Governmental trust is crucial not only for social capital but also for government legitimacy both of which are important determinants of compliance with *shelter in place*/*stay at home* orders.

1.1.1. Trust in government and social capital

Trust in government is an important determinant of social capital which is defined as networks, together with a set of norms, shared among people that allows cooperation to help solve collective action problems (Fukuyama 1995, Putnam 2000). Social capital manifests itself in communities as a reciprocal relationship between levels of civic participation and interpersonal trust. The more that people participate in their communities, the more that they trust others; the greater trust that people hold for others, the more likely they are to participate (Fukuyama 1995 and Brehm and Rahn 1997). Interpersonal trust depends heavily on trust in government (Levi 1998, Levi and Stoker 2000, Rothstein 2000, 2005). According to Rothstein and Eek (2009), when forming their beliefs about the other people in a community, people make inferences from the behavior of government officials. In other words, they simply form their beliefs based on the following way of thinking: ‘‘if it proves that I cannot trust the local policemen and judges, then whom in the society can I trust?’’ (Rothstein and Eek 2009, 90). Several studies in political science literature find negative effects of corruption on trust in government (Anderson and Tverdova, 2003, Chang and Chu, 2006, Rothstein and Eek, 2009). Because trust in government and interpersonal trust are positively related, corruption affects interpersonal trust negatively.

As Rothstein and Eek (2009) argue, if government officials in a society are known to be corrupt, people will believe that they cannot be trusted. They will therefore think that most other people cannot be trusted.Lower interpersonal trust means lower civic participation, and lower civic participation means lower social capital. Since social distancing can be considered as a collective action problem, we expect people not to comply with the *shelter in place*/*stay at home* orders in corrupt states with low social capital. Collective action problem arises when short-term interests of individuals conflicts with long-term collective interests. According to Olson (1971),

> if the members of a large group rationally seek to maximize their personal welfare, they will not act to advance their … group objectives unless there is coercion to force them to do so, or unless some separate incentive, distinct from the achievement of the … group interest, is offered to the members of the group individually on the condition that they help bear the costs or burdens involved in the achievement of the group objectives (Olson 1971, 2).

Sønderskov (2009) argue that social capital facilitates collective action in large groups. Individuals cooperate in collective action dilemmas when others are expected to cooperate. Given the large number of individuals, it is very costly and difficult, even impossible, to get specific information on other individuals' trustworthiness in large groups. In such situations, social capital serves as a short-cut to information on trustworthiness (Sonderskov 2009, 53-54).

Trust is particularly important in the health domain. Gilson (2003) argues the production of health and health care requires cooperation within health systems which in turn requires trust. Trust facilitates the use of the health system and leads to better selfrated health and better health outcomes (Radin 2013). Several empirical studies present persuasive evidence regarding the effects of trust in government in particular, and social capital in general on compliance with public health policies (Buckman et al. 2020). Blair et al. (2017), for example, investigate the behavior of Liberians during the 2014-2015 Ebola outbreak, and they find that people with lower trust in government took fewer steps to protect themselves and were less likely to comply with the government's social distancing orders. Vinck et al. (2019) in the context of a later outbreak in the Democratic Republic of Congo find similar results. They find that low trust in government explains lower willingness to adopt preventative behavior and accept a vaccine. The relationship between trust/social capital and compliance with public health policies is not specific to Sub-Saharan African countries. Nawa and Fujiwara (2019), using data from Japan, Ronnerstrand (2013) from Sweden, Chuang et al. (2015) from Taiwan, Jung et al. (2013) and Ronnerstrand (2014) from America, all find a positive relationship between trust/social capital and vaccination. Yaqub et al. (2014), based on an extensive review of the literature, identify lack of trust/social capital as one of the main causes of vaccine hesitancy in Europe. Trust/social capital are alsofound, in some contexts, to be determinants of mental and physical health (Lochner et al. 2003; Yip et al. 2007; Kim et al. 2008; Almedon and Glandon 2008; Ahnquist et al. 2012; Rodgers et al. 2019). According to Kawachi and Berkman (2000), trust/social capital affect health-related behaviors via diffusion of health information or adoption of healthy norms of behavior (for an excellent review of literature on the relationship between trust/social capital health-related behaviors, see Lindstrom 2008).

1.1.2. Trust in government and legitimacy of government

The second channel through which corruption affects social distancing is *legitimacy of government*. Government legitimacy depends on how much people trust their government. It is defined as the belief that government does what is appropriate and fair most of the time and it affects how people behave toward government in crises such as the one we are experiencing today (Easton 1965, Tyler 2006, and Christensen and Laegreid 2016). Legitimacy increases compliance with government policies (Tyler 2006). Christensen and Laegreid (2020) argue that alleged success of the Norwegian government fighting COVID-19 is partially due to its legitimacy. It is crucial that government policies implemented to fight the pandemic are believed to be appropriate and fair by the people so that they follow them (Christensen and Laegreid 2020). A wide range of studies show how important government legitimacy is regarding compliance with laws and regulations. Paternoster et al. (1997) find that domestic assault suspects who are arrested in a procedurally fair manner are less likely to commit further acts than those arrested in a procedurally unfair manner. Kuperan and Sutinen (1998) find that legitimacy affects compliance of Malaysian fishermen faced with a regulation banning them from fishing in a zone along the coast. Levi and Sacks (2009), using survey data from Sub-Saharan Africa, find that compliance with the tax laws is positively related to government legitimacy. Finally, Chen (2013) finds that a higher rate executions of Irish soldiers relative to British amongst UK's armed forces during WW1 cause Irish desertions to increase.

Several experimental and empirical studies such as Seligson (2002) and Boly et al. (2019), find a negative relationship between corruption and government legitimacy, and Ali et al. (2014) find evidence that corruption weakens tax compliance in South Africa and Uganda. In other words, to the extent that corruption weakens the legitimacy of government, we expect that it will also reduce compliance with *shelter in place*/*stay at home* orders. Figure 2 shows the channels through which corruption affects compliance with social distancing policies.

The study is organized as follows. In the next section, we describe the data and the estimation method. In section 3, we present the results and discuss the limitations of our estimation. In section 4, we conclude.

2. Methods

2.1. Data

Investigating the relationship between corruption and social distancing presents several challenges, perhaps the most important one being the measurement of people's compliance with social distancing. We use the *Shelter in Place Index* constructed by *SafeGraph*. *SafeGraph* measures people's *stay at home* behavior as the percentage of people staying home all day compared to a baseline based on population movement data representing 45 million smartphone devices. The index ranges from -100 to 100, where 0 indicates no change from the baseline. Baseline is defined as the average percentage of people staying home all day and every day across the seven days ending February 12, 2020. Home is defined as the most common nighttime location of the smartphone device in recent months identified to a precision of about 100 square meters. The *Shelter in Place Index* on a particular day is constructed as follows:

Shelter in Place Index = Actual % Staying Home – Baseline % Staying Home

On May 2 (the last day of our sample), for example, the actual percentage of people staying home in Illinois was 40.5 while the baseline was 25. Hence, the index for Illinois on May 2 is equal to 15.5 (see safegraph.com for details). Our sample covers four consecutive Saturdays starting from April 11. Over the last three weeks of April and the first week of May, *shelter in place*/*stay at home* orders were in place in all states except five, and the infections peaked in a majority of the states.

We measure corruption using data from the Justice Department's "Report to Congress on the Activities and Operations of the Public Integrity Section." In response to Watergate and growing concerns about corruption, the Public Integrity Section was established in the Justice Department in 1976 to prosecute corrupt officials. This unit reports the total convictions for crimes related to corruption annually. The data are available starting from 1976. These data cover a broad range of crimes from election fraud to wire fraud. This Corruption Convictions Index (*CCI*) is used in several studies such as Glaeser and Saks (2006), Dincer (2008), and Alt and Lassen (2012) to measure corruption across states. To construct *CCI*, following Glaeser and Saks (2006) and Alt and Lassen (2012) we deflate the number of convictions by state population. Since the data cover convictions of both private individuals and public officials, deflating the number of convictions by population instead of the number of government employees is more appropriate. Because it takes time for corruption to affect people's level of trust (both interpersonal and government) and level of civic participation, we use *CCI* averaged over the last decade in our empirical analysis.

To investigate if our results are robust to different measures of corruption, we also use an alternative corruption index called the Corruption Reflections Index (*CRI*) constructed by Dincer and Johnston (2017). *CRI* is an index based on the corruption stories covered in Associated Press (AP) news wires which are electronically available online via LexisNexis.

Dincer and Johnston (2017) search for the words “corrupt”, “fraud” and “bribe” (and their variants such as “corruption”, “fraudulent”, or “bribery”) and count the appearance of news articles containing those words. To limit the search for the corruption related stories in each state, they use two levels of geographical identifiers: United States as the country identifier, and the name of the individual state as the state identifier. News based corruption indices like *CRI* have also been used by Dincer (2019) for American states and by Foresta (2020) for Italian provinces. As we did with *CCI*, we deflate the *CRI* with the population in each state and average it over the last decade. As Dincer (2020) argues, *CRI* has several advantages over *CCI*.

> Convictions data from the Justice Department cover public corruption convictions in federal courts only and federal prosecutors have considerable discretion over how much effort to put into investigating public corruption. Second, partisan bias exists in the prosecution of public officials by U.S. Attorneys, who are appointed by the President with the advice and support of home-state partisans (Gordon 2009 and Alt and Lassen 2012). Third, there is an unknown time lag between crimes and convictions and the data give little to no indication as to the seriousness or consequences of a case. Finally, the data cover only those officials who are caught and, of course, convicted. Plea bargains and grants of immunity are not included. Both the face and the construct validity of a convictions-based index are thus dubious (Dincer 2020, 1311).

We also control for several economic and demographic variables in our empirical analysis to minimize the omitted variable bias. If corruption is correlated with any of these control variables, omitting them causes the coefficients of *CCI* and *CRI* to be estimated with a bias. Corruption affects social distancing through two channels: social capital/interpersonal trust and trust in government/legitimacy of government. To control for the mediating effects of social capital we first control for how generous people are and how engaged they are civically in each state in terms of charitable giving and volunteering. These are the most relevant components of social capital in the context of this study. We use the State Generosity Index (*SGI*) constructed by *WalletHub* which ranges from 0 to 100 (see wallethub.com for details). We construct a dummy variable, *SGI*, which is equal to 1 if a state falls into the highest quartile of *WalletHub*'s State Generosity Index. Figure 1 shows how people respond to *shelter in place*/*stay at home* orders in five most/least charitable/corrupt states which fall into the lowest quartile of generosity and the highest quartile of corruption. Measurement of social capital is another robustness issue. According to Kawachi et al. (1997), income inequality is one of the main determinants of social capital and it affects health outcomes mainly through social capital. Following Kawachi et al. (1997), we use income inequality as a measure of social capital instead of SGI. Our measure of income inequality (*Income Inequality*) is the share of households whose income are less than $25,000 a year divided by the share of households whose income are more than $100,000. The data are from the Census Bureau.

Second, we control for the percentage of people tested positive for COVID-19 in each state on four consecutive Thursdays starting from April 9 (*COVID*-19 *Positive*). Since higher positivity rate indicates a higher infection risk, it affects people's behavior towards compliance with social distancing orders. The third control variable is the percentage of votes that Donald Trump received in the 2016 presidential elections (*Trump*). The data are from electproject.org. Donald Trump showed his support loudly and repeatedly over both traditional and social media to people protesting (and violating) the *shelter in place*/*stay at* *home* orders issued by the governors of several states. The variable *Trump* also controls for the political ideology which affects risk perception. According to a recent poll conducted by *Axios/Ipsos*, while 60% of Republicans believe that real number of COVID-19 related deaths is lower than the official count, more than 60% of Democrats believe that the real number is higher. Using data from American states, Hsiehchen et al. (2020) find that Republicans are less likely to comply with social distancing orders. The next two control variables are per capita personal income (*Income*), and unionization (*Union*). Social distancing is costlier for some than others. People living paycheck to paycheck with little to no savings may not comply with social distancing. Regarding unionization, the pandemic resulted in job losses across the country, but many union workers had various protections due to their collective bargaining agreements. As NBC News reports, approximately 150,000 United Auto Workers members at Ford, General Motors, and Fiat Chrysler lost their jobs, but continued to receive supplemental unemployment benefits payments from the automakers. Their contract gives members at least six months of extra pay on top of unemployment insurance that adds up to being 85 percent of their hourly wages. Unionization also affects social capital via political and civic engagement (Nissen 2010 and Kerrisey and Schofer 2013). Our *Income* data are from the Bureau of Economic Analysis and *Union* data are from unionstats.com. Finally, we control for population density. In densely populated urban communities, the risk of infection is higher. The data are from the Census Bureau. All control variables except *Trump* are from last year. Summary statistics are presented in Table 2.

2.2. Estimation method

We estimate a system of four equations with seemingly unrelated regressions (SUR) in which the dependent variables are the *Shelter in Place Indices* for April 11, April 18, April 25, and May 2. Each Saturday forms one fourth of the system. Estimating a system with SUR has several advantages over estimating each equation individually with Ordinary Least Squares (OLS). First, SUR is more efficient because it allows errors to be correlated across the equations. Second, because each equation has the same set of independent variables, it allows us to conduct joint tests which helps us investigate if quarantine fatigue worsens the collective action problem. Quarantine fatigue manifests itself as boredom, anxiety, and stress (Marcus 2020). It becomes more difficult for people to comply with the *stay at home*/*shelter in place* orders when they start feeling the psychological effects of social distancing. If trust/social capital is low in the society, this becomes an even greater problem.

3. Results

The maximum likelihood estimates with robust standard errors clustered at the state level are presented in Table 3. To show the mediating effects of social capital we first estimate our regression without *SGI*. The estimated coefficient of *CCI* is negative and statistically significant in all four equations indicating that in corrupt states people are less likely to comply with *shelter in place*/*stay at home* orders. The absolute value of the estimated coefficient decreases when we estimate the regression with *SGI* indicating that one of the channels through which corruption affects social distancing is indeed social capital. The magnitude of the effect is significant as well. Based on the estimated coefficients in Equation 4, a one standard deviation increase in *CCI* causes the *Shelter in Place Index* to decrease by approximately 10 percent. The standardized effect of *COVID-*

19 *Positive* is only slightly greater than 10 percent. Perhaps more interestingly, the magnitude of the effect increases each week. The estimated coefficient of *CCI* in Equation 4 (*Shelter in Place Index* on May 2) is 2.5 times greater than the one in Equation 1 (*Shelter in Place Index* on April 11). The null hypothesis that *CCI* has the same effect on *Shelter in Place Index* on April 11 and on May 2 is rejected at the 1% significance level. As what many call "quarantine fatigue" developed, people stayed home less and less during the time period that our sample covers. Across all states, on average, the *Shelter in Place Index* decreased by 30 percent from April 11 to May 2. On the other hand, in states such as Mississippi, Montana, Oklahoma, and South Dakota which fall into the highest quartile of *CCI*, it decreased more than 50 percent even though the risk of infection was still high, and the percentage of people tested positive for COVID-19 stayed the same or increased. Our results show that "quarantine fatigue" makes the collective action problem even more difficult to solve in states in which corruption is high.

The signs of the estimated coefficients of the control variables are also statistically significant and their signs are consistent with our expectations. People respond to *shelter in place*/*stay at home* orders if more people tested positive for COVID-19. In densely populated charitable states, they stay at home more as well. The estimated coefficient of *Trump* is not only negative, but its magnitude is also greater than that of *CCI*. Based on the estimated coefficients in Equation 4, a one standard deviation increase in *Trump* reduces the *Shelter in Place Index* by 20 percent. Finally, in richer states and the states in which workers are unionized people comply with social distancing policies more.

Several economic and demographic control variables which we think are relevant are omitted in our regressions because of multicollinearity. When we included variables controlling for poverty, race, gender, and age in our regressions, their coefficients were estimated to be statistically insignificant with very high *p* values. Inclusion of these variables in the estimation did not change the estimated coefficient of *CCI* either. We do not report the results for the sake of brevity, but they are available on request.

3.1. Robustness of results

To investigate if our results are robust to different measures of corruption, we first estimate our system of equations with *CRI*. The results which are consistent with the earlier ones are presented in Table 4. A 1 standard deviation increase in *CRI* causes the *Shelter in Place Index* to decrease by approximately 7.5 percent.

The second robustness issue is the measurement of social capital. In a second set of regressions, we estimate our system using income inequality as a measure of social capital instead of *SGI*. *Income Inequality* too, through its negative effects on social capital, reduces the *Shelter in Place Index.* The standardized effect of *Income Inequality* is only slightly greater than those of *CCI* and *CRI*. The results are presented in Table 5 and Table 6.

The third and last robustness issue is the states which did not issue *shelter in place*/*stay at home* orders. Five states, Arkansas, Iowa, Nebraska, North Dakota, and South Dakota did not issue *shelter in place*/*stay at home* orders albeit limiting social gatherings. We estimate our system of equations without these states as well. The results are presented in Table 7 and Table 8. The estimated coefficients of *CCI* and *CRI* are negative and statistically significant again in all four equations. The magnitudes of the estimated coefficients do not change that much either.

3.2. Limitations of Results

Unfortunately, we are not able to control for some important variables in our regressions because state level data are not available. The first two are interpersonal trust and trust in government both of which mediate the effects of corruption on social distancing. Low interpersonal trust in a society may make people self-quarantine because they question others' social distancing behavior. It may also reduce (social) networks. Without networks, staying at home is less of a sacrifice for an individual and less costly. Trust in government is a crucial determinant of government legitimacy. Unfortunately, two frequently used surveys, American National Election Study (ANES) and General Social Survey (GSS) which ask questions regarding trust, are both nationally representative surveys. In other words, sampling is not done at the state level.

The second variable is social and traditional media misinformation which may affect people's behavior towards social distancing. Bursztyn et al. (2020) investigate the effects of misinformation comparing two major cable news shows, *Hannity* and *Tucker Carlson Tonight*. These two shows aired back-to-back on Fox News and had relatively similar content but, differed significantly in their coverage of COVID-19 pandemic. While Carlson warned his viewers about the dangers of COVID-19, Hannity dismissed the risks arguing that it was less concerning than the common flu and that Democrats were using it against Donald Trump. Using survey data (more than 1,000 Fox News viewers aged 55 or older), Bursztyn et al. (2020) find that viewership of Hannity is associated with changing behavior (washing hands, social distancing etc.) four days later than other Fox News viewers, while viewership of Tucker Carlson Tonight is associated with changing behavior three days earlier. Bridgman et al. (2020) conduct a national representative survey covering more than 2,000 Canadians of age 18 or older which includes questions about common misperceptions regarding COVID19, social distancing compliance, and exposure to traditional news and social media. We find that being exposed to traditional news media is associated with fewer misperceptions and more social distancing compliance while conversely, social media exposure is associated with more misperceptions and less social distancing compliance.

4 Conclusion

Studies from across the social sciences have pointed to corruption as corrosive to trust/social capital which are vital to compliance with public health orders. Using data from American states, we show that more corrupt states are likely to have lower compliance with *shelter in place*/*stay at home* orders.

While it would be facile to argue with any conviction that we should expect our results to hold in other countries, the fact that we have evidence for many of the channels motivating our study being salient in a variety of different contexts does suggest that the links between corruption and compliance with public health orders could be fruitfully investigated beyond America. Moreover, examining this link between corruption and compliance in other contexts could also allow for a deeper understanding of the channels. For example, surveys could be designed that would allow for an investigation of the moderating effect of a prior experience with other infectious outbreaks such as Ebola, MERs, and Zika, and the governments' success or failure in fighting the outbreaks. Such prior experience could plausibly strengthen the negative effect of corruption on compliance by reducing the trust in government or weaken it by increasing the perceptions of the risks of noncompliance.

Studying other countries would also help us understand the effects of corruption in healthcare. Corruption in healthcare reduces both access to and satisfaction with healthcare (Habibov 2016; Hsiao et al. 2019) which are important determinants of health behavior and compliance with public health policies (Mohamed and Azizan, 2015; Reime et al, 2019). Unfortunately, we do not have data to explore this additional channel for America but, future work should explore this possibility.

Even with important external validity caveats, we believe that our results have practical implications. Fang et al. (2020) found that lockdown was an effective policy in China while Dave et al. (2020) found that *stay at home*/*shelter in place* orders reduced the number of COVID-19 infections by more than 50% over a span of three weeks in America. Considering how effective social distancing is, our findings show a link between corruption and the spread of COVID-19. Corruption also reduces the quality of healthcare (Mostert et al. 2015; Friedman, 2018) making the problem is even worse. Hence, more corrupt states might need additional resources to fight the pandemic.

Finally, while there is evidence from the recent West African Ebola outbreak that trust in government increases via the provision of public goods (Fluckiger et al, 2019), we also know that corruption reduces the willingness to contribute to pure public goods (Beekman et al, 2014) and the provision of quasi-public goods such as infrastructure (Gillanders, 2014) - though perhaps only once it passes a threshold level (Bose et al. 2008). Compliance with public health policies generates a benefit to society which is both non-rival and non-excludable - the two characteristics of a pure public good. Therefore, one interpretation of our results is that corruption reduces individuals’ willingness to contribute to pure public goods in the health domain. We believe that this is a novel contribution with implications beyond the current COVID-19 crisis. Organizations such as the World Bank view public health in general, and pandemic preparedness in particular, as global public goods (Stein and Sridhar 2017). With over six billion people living in countries that are classified as corrupt by Transparency International (scoring less than 50 on Corruption Perceptions Index) in 2019, our results, subject to the external validity caveats noted above, identify corruption as a significant barrier to the provision of these global public goods.

References

Ali, M., Fjeldstad, O. H., & Sjursen, I. H. (2014). To pay or not to pay? Citizens' attitudes toward taxation in Kenya, Tanzania, Uganda, and South Africa. *World Development*, 64, 828-842.

Alt, J. E., & Lassen, D. D. (2014). Enforcement and public corruption: Evidence from the American States. *Journal of Law, Economics and Organization*, 30, 306–38.

Anderson, C. J., & Tverdova, Y. V. (2003). Corruption, political allegiances, and attitudes toward government in contemporary democracies. *American Journal of Political Science*, 47, 91-109.

Ahnquist, J., Wamala, S. P., & Lindstrom, M. (2012). Social determinants of health–a question of social or economic capital? Interaction effects of socioeconomic factors on health outcomes. *Social Science & Medicine*, 74, 930-939.

Azfar, O., & Gurgur, T. (2008). Does corruption affect health outcomes in the Philippines? *Economics of Governance*, 9, 197-244.

Blair, R. A., Morse, B. S., & Tsai, L. L. (2017). Public health and public trust: Survey evidence from the Ebola Virus Disease epidemic in Liberia. *Social Science & Medicine*, 172, 89-97.

Boly, A., Gillanders, R., & Miettinen, T. (2019). Deterrence, contagion, and legitimacy in anticorruption policy making: An experimental analysis. *Journal of Legal Studies*, 48, 275-305.

Bose, N., Capasso, S., & Murshid, A. P. (2008). Threshold effects of corruption: theory and evidence. *World Development*, 36, 1173-1191.

Brehm, J., & Rahn, W. (1997). Individual level evidence for the causes and consequences of social capital. *American Journal of Political Science*, 41, 999 – 1023.

Bridgman, A., Merkley, E., Loewen, P. Owen, T., Ruths, D., Teichman, L., & Zhilin, O. (2020). The causes and consequences of COVID-19 misperceptions: Understanding the role of news and social media. *Harvard Kennedy School Misinformation Review*, 1, June.

Briggs, R. C. (2014). Aiding and abetting: project aid and ethnic politics in Kenya. *World Development*, 64, 194-205.

Buckman, C., Liu, I., Cortright, L., Tumin, D., & Syed, S. (2020). The influence of local political trends on childhood vaccine completion in North Carolina. *Social Science & Medicine.*, 260: 113187.

Bursztyn, L., Rao, A., Roth, C., & Yanagizawa-Drott, D. (2020). Misinformation during a pandemic. NBER Working Paper 27417.

Chang, E. C., & Chu, Y. H. (2006). Corruption and trust: exceptionalism in Asian democracies? *Journal of Politics*, 68, 259-271.

Christensen, T., Lægreid, P., & Rykkja, L. H. (2020). Organizing for crisis management: Building governance capacity and legitimacy. *Public Administration Review*, 80, 774-779.

Christensen, T. & Lægreid, P. (2020). Balancing governance capacity and legitimacy: How the Norwegian government handled the COVID-19 crisis as a high performer. *Public Administration Review*, 76, 887-897.

Dave, D., Friedson, A. I., Matsuzawa, K., & Sabia, J. J. (2020). When do shelter-in-place orders fight COVID-19 best? Policy heterogeneity across states and adoption time. *Economic Inquiry*.

Dietrich, S. (2011). The politics of public health aid: why corrupt governments have incentives to implement aid effectively. *World Development*, 39, 55-63.

Dincer, O. (2008). Ethnic and religious diversity and corruption. *Economics Letters*, 99, 98–102.

Dincer, O. (2019). Does corruption slow down innovation? Evidence from a cointegrated panel of U.S. states. *European Journal of Political Economy*, 56, 1-10.

Dincer, O. (2020). If you're corrupt, you'd better be free. *Journal of Economic Studies*, 47, 1307-1325.

Dincer, O., & Teoman, O. (2019). Does corruption kill? Evidence from half a century infant mortality data. *Social Science & Medicine*, 232, 332-339.

Dincer, O. & Johnston, M. (2017). Political culture and corruption issues in state politics: A new measure of corruption issues and a test of relationships to political culture. *Publius*, 47, 131-148.

Estes, C. (2020). Protests against stay-at-home orders are an epidemiological and political headache. *Forbes*. https://www.forbes.com/sites/claryestes/2020/04/26/protests-against-stay-at-home-orders-are-an-epidemiological-and-political-headache.

Fang, H., Wang, L., & Yang, Y. (2020). Human mobility restrictions and the spread of the novel coronavirus (2019-ncov) in China. NBER WP 26906.

Fluckiger, M., Ludwig, M., & Onder, S. (2019). Ebola and state legitimacy. *The Economic Journal*, 129, 2064-2089.

Foresta, A. (2020). The rise of populist parties in the aftermath of a massive corruption scandal. *Public Choice*, 184: 289-306.

Friedman, W. (2018). Corruption and averting AIDS deaths. *World Development*, 110, 13-25.

Fukuyama, F. (1995). Trust: The social virtues and the creation of prosperity. London: Hamish Hamilton

Gillanders, R. (2014). Corruption and infrastructure at the country and regional level. *Journal of Development Studies*, 50, 803-819.

Gilson, L. (2003). Trust and the development of health care as a social institution. *Social Science & Medicine*, 56, 1453-1468.

Glaeser, E.L., & Saks, R.E. (2006). Corruption in America. *Journal of Public Economics*, 90, 1053–1072.

Habibov, N. (2016). Effect of corruption on healthcare satisfaction in post-soviet nations: A cross-country instrumental variable analysis of twelve countries. *Social Science & Medicine*, 152, 119-124.

Hsiao, A., Vogt, V., & Quentin, W. (2019). Effect of corruption on perceived difficulties in healthcare access in sub-Saharan Africa. *PloS one*, 14(8), e0220583.

Hsiechen, D., Espinoza, M., & Slovic, P. (2020). Political partisanship and mobility restriction during the COVID-19 pandemic. *Public Health*, 187, 111-114.

Kawachi I, & Berkman L. (2000) Social cohesion, social capital, and health. In: L. Berkman & I. Kawachi (eds) Social Epidemiology, 174-190, New York: Oxford University Press;

Kawachi, I., Kennedy, B., Lochner, K. & Prothrow-Stith, D. (1997). Social capital, income inequality, and mortality. *American Journal of Public Health*, 87: 1491-1498.

Kerrisey, J, & Schofer, E. (2013). Union membership and political participation in the United States. *Social Forces*, 91, 895-928.

Kuperan, K., & Sutinen, J. G. (1998). Blue water crime: deterrence, legitimacy, and compliance in fisheries. *Law and Society Review*, 32, 309-338.

Levi, M. (1998). A state of trust. In: V. Braithwaite, & M. Levi (eds) Trust and Governance, 77-101, New York: Russell Sage.

Levi, M., & Stoker, L. (2000). Political trust and trustworthiness. *Annual Review of Political Science*, 3, 475-507.

Levi, M., and A. Sacks (2009). Legitimating beliefs: Sources and indicators. *Regulation & Governance*, 3, 311–33.

Lindstrom M. (2008). Social capital and health-related behaviors. In: Kawachi I., Subramanian S., Kim D. (eds) Social Capital and Health, 442-447, New York: Springer.

Lochner, K. A., Kawachi, I., Brennan, R. T., & Buka, S. L. (2003). Social capital and neighborhood mortality rates in Chicago. *Social Science & Medicine*, 56, 1797-1805.

Marcus, J. (2020). Quarantine fatigue is real. The Atlantic. https://www.theatlantic.com/ideas/archive/2020/05/quarantine-fatigue-real-and-shaming-people-wont help/611482/

Mazziotta, J. (2020). From a $25,000 fine to a warning: Here's how states are enforcing coronavirus stay-at-home orders. *People*. https://people.com/health/how-states-are-enforcing-coronavirus-stay-at-home-orders

Mohamed, B., & Azizan, N. A. (2015). Perceived service quality's effect on patient satisfaction and behavioral compliance. *International Journal of Health Care Quality Assurance*, 28, 300-314.

Mostert S., Njuguna F., Olbara G., Sindano, S., Sitaresmi, M., Supriyadi, E., & Kaspers, G. (2015). Corruption in health-care systems and its effect on cancer care in Africa. *Lancet Oncology*, 16, 394–404.

Nissen, B. (2010). Political activism as part of a broader civic engagement: The case of SEIU Florida Healthcare Union. *Labor Studies Journal*, 35, 51-72.

Olson, M. (1971). The Logic of Collective Action: Public Goods and the Theory of Groups. Cambridge: Harvard University Press

Parveen, N. (2020). Piers Corbyn among 19 held in coronavirus lockdown protests. *Guardian*. https://www.theguardian.com/world/2020/may/16/piers-corbyn-among-those-held-in-coronavirus-lockdown-protests

Paternoster, R., Brame, R., Bachman, R., & Sherman, L. W. (1997). Do fair procedures matter? The effect of procedural justice on spouse assault. *Law and Society Review*, 31,163-204.

Radin, D. (2013). Does corruption undermine trust in health care? Results from public opinion polls in Croatia. *Social Science & Medicine*, 98, 46-53.

Reime, B., Tufan, M., Tkachenko, E., Sahbaz, M., Warth, P., & Weidmann, C. (2019).

Illness behavior and health needs in migrants characterized by low satisfaction with healthcare. *European Journal of Public Health*, 29, Supplement 4.

Rodgers, J., Valuev, A., Hswen, Y., & Subramanian, S. (2019). Social capital and physical health: An updated review of the literature for 2007–2018. *Social Science & Medicine*, 236: 112360.

Ronnerstrand, B. (2013). Social capital and immunization against the 2009 A(H1N1) pandemic in Sweden. *Scandinavian Journal of Public Health*, 41: 853–859.

——————— (2005). Social capital and immunization against the 2009 A(H1N1) pandemic in the American States. *Public Health*, 128, 709-715.

Rothstein, B. (2000). Trust, social dilemmas, and collective memories. *Journal of Theoretical Politics*, 12,477-503.

——————— (2005). Social traps and the problem of trust. Cambridge: Cambridge University Press.

Rothstein, B., & Eek, D. (2009). Political corruption and social trust: An experimental approach. *Rationality and Society*, 21,81-112.

Seligson, M. A. (2002). The impact of corruption on regime legitimacy: A comparative study of four Latin American countries. *Journal of Politics*, 64, 408-433.

Stein, F., & Sridhar, D. (2017). Health as a “global public good”: Creating a market for pandemic risk. *BMJ*, 358, j3397.

Suryadarma, D., & Yamauchi, C. (2013). Missing public funds and targeting performance: Evidence from an anti-poverty transfer program in Indonesia. *Journal of Development Economics*, 103, 62-76.

Tyler, T.R. (2006). Psychological Perspectives on Legitimacy and Legitimation. *Annual Review of Psychology*, 57, 375–400.

Vinck, P., Pham, P. N., Bindu, K. K., Bedford, J., & Nilles, E. J. (2019). Institutional trust and misinformation in the response to the 2018–19 Ebola outbreak in North Kivu, DR Congo: a population-based survey. *Lancet Infectious Diseases*, 19, 529-536.

Yaqub, O., Castle-Clarke, S., Sevdalis, N., & Chataway, J. (2014). Attitudes to vaccination: A critical review. *Social Science & Medicine*, 112, 1-11.

Yip, W., Subramanian, S. V., Mitchell, A. D., Lee, D. T., Wang, J., & Kawachi, I. (2007). Does social capital enhance health and well-being? Evidence from rural China. *Social Science & Medicine*, 64, 35-49.

Figure 1. Most/Least Charitable/Corrupt States

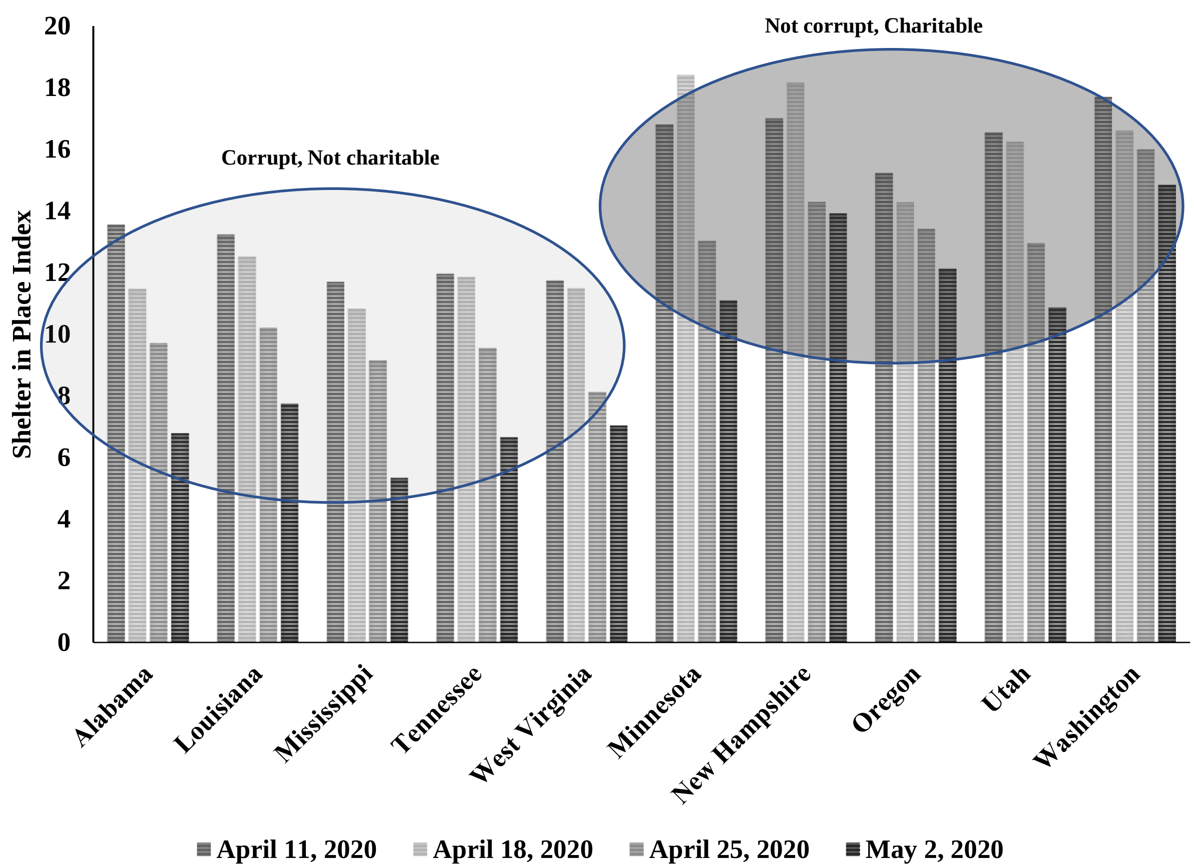

Figure 2

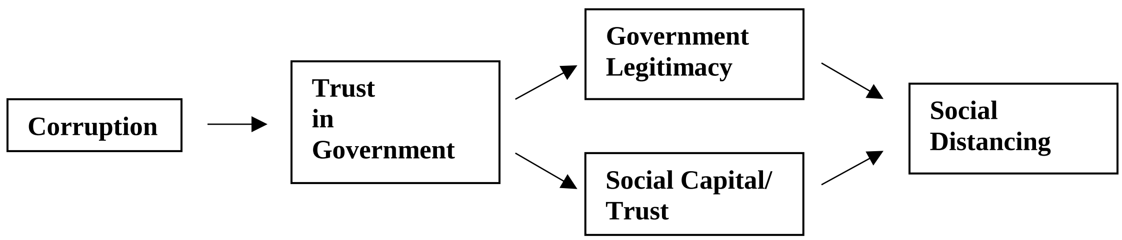
Corruption
Trust in Government
Government Legitimacy
Social Capital/ Trust
Social Distancing

Table 1. State *Stay at Home/Shelter in Place* Orders

State	Time	Type
Alabama	April 4	Mandatory for all
Alaska	March 28	Mandatory for all
Arizona	March 31	Mandatory for all
Arkansas	N/A	N/A
California	March 19	Mandatory for all
Colorado	March 26	Mandatory for all
Connecticut	March 23	Mandatory for all
Delaware	March 24	Mandatory for all
Florida	March 30	Advisory
Georgia	April 13	Mandatory for persons at risk
Hawaii	March 30	Mandatory for all
Idaho	March 25	Mandatory for all
Illinois	March 21	Mandatory for all
Indiana	March 24	Mandatory for all
Iowa	N/A	N/A
Kansas	March 30	Mandatory for all
Kentucky	March 30	Advisory
Louisiana	March 23	Mandatory for all
Maine	April 2	Mandatory for all
Maryland	March 30	Mandatory for all
Massachusetts	March 24	Advisory
Michigan	March 24	Mandatory for all
Minnesota	March 27	Mandatory for all
Mississippi	April 3	Mandatory for all
Missouri	April 6	Mandatory for all
Montana	March 28	Mandatory for all
Nebraska	N/A	N/A
Nevada	March 31	Mandatory for all
New Hampshire	March 27	Mandatory for all
New Jersey	March 21	Mandatory for all
New Mexico	March 24	Advisory order
North Carolina	March 30	Mandatory for all
North Dakota	N/A	N/A
Ohio	March 23	Mandatory for all
Oklahoma	March 24	Mandatory for persons at risk
Oregon	March 23	Mandatory for all
Pennsylvania	March 23	Mandatory for all in certain counties
Rhode Island	March 28	Mandatory for all
South Carolina	April 7	Mandatory for all
South Dakota	N/A	N/A
Tennessee	April 2	Mandatory for all
Texas	April 2	Advisory
Utah	March 27	Advisory

Vermont	March 24	Mandatory for all
Virginia	March 30	Mandatory for all
Washington	March 23	Mandatory for all
West Virginia	March 24	Mandatory for all
Wisconsin	March 30	Mandatory for all
Wyoming	N/A	N/A

Source: CDC MMWR September 4, 2020

Table 2. Summary Statistics

	Mean	**Std. Dev.**	**Min.**	**Max.**
Shelter in Place Index				
***April* 11, 2020**	15.782	4.017	9.06	27.62
***April* 18, 2020**	16.035	4.237	9.89	29.05
***April* 25, 2020**	12.854	4.249	6.48	26.08
***May* 2, 2020**	11.107	4.623	4.22	24.26
COVID*-19 *Positive				
***April* 9, 2020**	0.122	0.093	0.028	0.476
***April* 16, 2020**	0.126	0.094	0.026	0.496
***April* 23, 2020**	0.129	0.093	0.023	0.499
***April* 30, 2020**	0.124	0.088	0.019	0.479
CCI	2.996	2.071	0.301	10.784
SGI	0.260	0.443	0	1
Trump	49.241	10.220	30.030	68.500
Income	83,686	16,537	32,044	124,946
Union	11.274	5.152	3.600	24.400
Population Density	0.202	0.264	0.001	1.197
CRI	3.416	1.892	0.879	8,932
Income Inequality	.791	0.346	0.328	1.811

Table 3. Maximum Likelihood SUR Estimation
Dependent Variable: Log *Shelter in Place Index*

	Equation 1 April 11, 2020		Equation 2 April 18, 2020		Equation 3 April 25, 2020		Equation 4 May 2, 2020	
COVID-19 Positive	0.760 (0.146)***	0.804 (0.147)***	0.801 (0.185)***	0.847 (0.194)***	1.209 (0.182)***	1.248 (0.184)***	1.188 (0.270)***	1.260 (0.274)***
CCI	-0.017 (0.008)**	-0.016 (0.007)**	-0.018 (0.008)**	-0.017 (0.006)***	-0.031 (0.008)***	-0.030 (0.006)***	-0.044 (0.015)***	-0.043 (0.012)***
SGI		0.101 (0.039)**		0.095 (0.038)**		0.090 (0.048)*		0.140 (0.053)***
Trump	-0.010 (0.003)***	-0.009 (0.002)***	-0.008 (0.002)***	-0.007 (0.002)***	-0.013 (0.003)***	-0.012 (0.002)***	-0.019 (0.003)***	-0.018 (0.003)***
Log *Income*	0.101 (0.079)	0.122 (0.065)*	0.115 (0.082)	0.134 (0.068)**	0.087 (0.085)	0.106 (0.073)	0.187 (0.124)**	0.218 (0.105)**
Union	0.009 (0.004)**	0.009 (0.004)**	0.008 (0.004)**	0.007 (0.003)**	0.011 (0.004)**	0.010 (0.004)**	0.012 (0.006)**	0.012 (0.006)**
Population Density	0.032 (0.009)***	0.035 (0.008)***	0.038 (0.009)***	0.041 (0.008)***	0.040 (0.012)***	0.043 (0.011)***	0.041 (0.013)***	0.046 (0.012)***
Constant	1.733 (0.712)**	1.406 (0.712)**	1.513 (0.940)	1.206 (0.779)	1.699 (0.969)*	1.403 (0.853)*	0.797 (1.411)	0.328 (1.221)

Correlation Matrix of Residuals

	April 11	**April 18**	**April 25**	**May 2**
April 11	1, 1			
April 18	0.829, 0.806	1, 1		
April 25	0.882, 0.871	0.814, 0.794	1	
May 2	0.866, 0.847	0.794, 0.763	0.859, 0.846	1, 1

Robust standard errors (clustered at the state level) in parentheses. All models control for region fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4. Maximum Likelihood SUR Estimation
Dependent Variable: Log *Shelter in Place Index*

	Equation 1 April 11, 2020		**Equation 2 April 18, 2020**		**Equation 3 April 25, 2020**		**Equation 4 May 2, 2020**	
COVID*-19 *Positive	0.670	0.725	0.684	0.737	0.957	1.001	0.836	0.916
	(0.160)***	(0.161)***	(0.193)***	(0.198)***	(0.222)***	(0.219)***	(0.316)***	(0.319)***
CRI	-0.021	-0.018	-0.022	-0.019	-0.036	-0.033	-0.044	-0.041
	(0.010)**	(0.009)**	(0.010)**	(0.009)**	(0.012)***	(0.011)***	(0.015)***	(0.013)***
SGI		0.095		0.089		0.080		0.129
		(0.041)**		(0.037)**		(0.049)*		(0.055)**
Trump	-0.010	0.009	0.008	-0.008	-0.014	-0.013	-0.021	-0.019
	(0.002)***	(0.004)**	(0.002)*	(0.002)***	(0.002)***	(0.002)***	(0.003)***	(0.003)***
Log *Income*	0.092	0.111	0.107	0.124	0.070	0.086	0.156	0.183
	(0.072)	(0.059)*	(0.072)	(0.059)**	(0.069)	(0.059)	(0.101)**	(0.087)**
Union	0.009	0.009	0.007	0.007	0.010	0.009	0.011	0.010
	(0.005)**	(0.004)**	(0.004)*	(0.003)**	(0.004)**	(0.004)**	(0.006)*	(0.006)*
Population Density	0.028	0.032	0.035	0.038	0.037	0.040	0.038	0.043
	(0.008)***	(0.008)***	(0.009)***	(0.008)***	(0.012)***	(0.012)***	(0.013)***	(0.013)***
Constant	1.949	1.635	1.733	1.441	2.107	1.839	1.435	0.992
	(0.786)**	(0.649)**	(0.824)**	(0.681)**	(0.793)***	(0.686)***	(1.445)	(1.002)

Correlation Matrix of Residuals

	April 11	**April 18**	**April 25**	**May 2**
April 11	1, 1			
April 18	0.825, 0.805	1, 1		
April 25	0.880, 0.872	0.815, 0.799	1	
May 2	0.852, 0.837	0.796, 0.771	0.859, 0.849	1, 1

Robust standard errors (clustered at the state level) in parentheses. All models control for region fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 5. Maximum Likelihood SUR Estimation
Dependent Variable: Log *Shelter in Place Index*

	Equation 1 April 11, 2020		**Equation 2 April 18, 2020**		**Equation 3 April 25, 2020**		**Equation 4 May 2, 2020**	
COVID-19 Positive	0.760 (0.146)***	0.742 (0.144)***	0.801 (0.185)***	0.775 (0.154)***	1.209 (0.182)***	1.186 (0.185)***	1.188 (0.270)***	1.164 (0.279)***
CCI	-0.017 (0.008)**	-0.013 (0.007)*	-0.018 (0.008)**	-0.013 (0.006)**	-0.031 (0.008)***	-0.028 (0.007)***	-0.044 (0.015)***	-0.039 (0.014)***
Income Inequality		-0.253 (0.055)***		-0.314 (0.046)***		-0.224 (0.063)***		-0.341 (0.088)***
Trump	-0.010 (0.003)***	-0.006 (0.001)***	-0.008 (0.002)***	-0.003 (0.002)*	-0.013 (0.003)***	-0.009 (0.003)***	-0.019 (0.003)***	-0.014 (0.003)***
Log *Income*	0.101 (0.079)	0.153 (0.057)***	0.115 (0.082)	0.179 (0.053)***	0.087 (0.085)	0.133 (0.069)*	0.187 (0.124)**	0.256 (0.095)***
Union	0.009 (0.004)**	0.010 (0.003)***	0.008 (0.004)**	0.008 (0.003)***	0.011 (0.004)**	0.011 (0.004)***	0.012 (0.006)**	0.013 (0.006)**
Population Density	0.032 (0.009)***	0.021 (0.008)***	0.038 (0.009)***	0.025 (0.008)***	0.040 (0.012)***	0.031 (0.011)***	0.041 (0.013)***	0.027 (0.012)**
Constant	1.733 (0.712)**	1.176 (0.626)*	1.513 (0.940)	0.824 (0.618)	1.699 (0.969)*	1.209 (0.817)	0.797 (1.411)	0.055 (1.123)

Correlation Matrix of Residuals

	April 11	**April 18**	**April 25**	**May 2**
April 11	1, 1			
April 18	0.829, 0.766	1, 1		
April 25	0.882, 0.860	0.814, 0.796	1	
May 2	0.866, 0.823	0.794, 0.723	0.859, 0.830	1, 1

Robust standard errors (clustered at the state level) in parentheses. All models control for region fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 6. Maximum Likelihood SUR Estimation
Dependent Variable: Log *Shelter in Place Index*

	Equation 1 April 11, 2020		Equation 2 April 18, 2020		Equation 3 April 25, 2020		Equation 4 May 2, 2020	
COVID-19 Positive	0.670 (0.160)***	0.662 (0.159)***	0.684 (0.193)***	0.675 (0.171)***	0.957 (0.222)***	0.942 (0.222)***	0.836 (0.316)***	0.828 (0.316)***
CRI	-0.021 (0.010)**	-0.016 (0.008)*	-0.022 (0.010)**	-0.016 (0.009)**	-0.036 (0.012)***	-0.031 (0.011)***	-0.044 (0.015)***	-0.037 (0.013)***
Income Inequality		-0.247 (0.058)***		-0.309 (0.048)***		-0.218 (0.067)***		-0.341 (0.078)***
Trump	-0.010 (0.002)***	0.006 (0.002)**	0.008 (0.002)*	-0.004 (0.002)**	-0.014 (0.002)***	-0.011 (0.002)***	-0.021 (0.003)***	-0.016 (0.003)***
Log *Income*	0.092 (0.072)	0.145 (0.054)***	0.107 (0.072)	0.172 (0.048)***	0.070 (0.069)	0.116 (0.059)*	0.156 (0.101)**	0.228 (0.081)***
Union	0.009 (0.005)**	0.010 (0.003)***	0.007 (0.004)*	0.008 (0.003)***	0.010 (0.004)**	0.011 (0.004)***	0.011 (0.006)*	0.012 (0.005)**
Population Density	0.028 (0.008)***	0.019 (0.007)***	0.035 (0.009)***	0.024 (0.008)***	0.037 (0.012)***	0.029 (0.012)**	0.038 (0.013)***	0.026 (0.014)**
Constant	1.949 (0.786)**	1.363 (0.576)**	1.733 (0.824)**	0.999 (0.552)*	2.107 (0.793)***	1.591 (0.691)**	1.435 (1.445)	0.629 (0.945)

Correlation Matrix of Residuals

	April 11	April 18	April 25	May 2
April 11	1, 1			
April 18	0.825, 0.763	1, 1		
April 25	0.880, 0.858	0.815, 0.800	1	
May 2	0.852, 0.808	0.796, 0.729	0.859, 0.832	1, 1

Robust standard errors (clustered at the state level) in parentheses. All models control for region fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 7. Maximum Likelihood SUR Estimation
Dependent Variable: Log *Shelter in Place Index*
(No AR, ND, NE, IA, and SD)

	Equation 1 April 11, 2020		**Equation 2 April 18, 2020**		**Equation 3 April 25, 2020**		**Equation 4 May 2, 2020**	
COVID*-19 *Positive	0.771 (0.165)***	0.876 (0.155)***	0.799 (0.193)***	0.936 (0.182)***	1.092 (0.221)***	1.327 (0.195)***	1.035 (0.324)***	1.362 (0.286)***
CRI	-0.021 (0.010)**		-0.022 (0.010)**		-0.033 (0.011)***		-0.040 (0.015)***	
CCI		-0.017 (0.008)**		-0.017 (0.006)***		-0.028 (0.008)***		-0.042 (0.014)***
SGI	0.072 (0.039)*	0.084 (0.040)**	0.070 (0.037)*	0.082 (0.039)**	0.060 (0.037)*	0.078 (0.051)	0.106 (0.053)**	0.126 (0.055)**
Trump	-0.010 (0.002)***	0.009 (0.002)***	-0.009 (0.001)***	-0.008 (0.002)***	-0.014 (0.001)***	-0.013 (0.002)***	-0.020 (0.003)***	-0.018 (0.003)***
Log *Income*	0.113 (0.060)*	0.116 (0.068)*	0.132 (0.058)**	0.135 (0.069)*	0.093 (0.058)	0.101 (0.075)	0.193 (0.087)**	0.209 (0.111)*
Union	0.010 (0.004)**	0.009 (0.004)**	0.008 (0.004)**	0.008 (0.004)**	0.010 (0.004)**	0.010 (0.004)**	0.011 (0.006)*	0.012 (0.006)**
Population Density	0.027 (0.008)***	0.031 (0.008)***	0.034 (0.008)***	0.037 (0.008)***	0.036 (0.012)***	0.039 (0.011)***	0.037 (0.013)***	0.041 (0.013)***
Constant	1.674 (0.669)**	1.509 (0.756)**	1.392 (0.668)**	1.225 (0.797)*	1.789 (0.663)***	1.499 (0.868)*	0.910 (0.997)	0.451 (1.288)

Correlation Matrix of Residuals

	April 11	**April 18**	**April 25**	**May 2**
April 11	1, 1			
April 18	0.808, 0.815	1, 1		
April 25	0.876, 0.881	0.811, 0.812	1	
May 2	0.839, 0.855	0.750, 0.751	0.843, 0.844	1, 1

Robust standard errors (clustered at the state level) in parentheses. All models control for region fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 8. Maximum Likelihood SUR Estimation
Dependent Variable: Log *Shelter in Place Index*
(No AR, ND, NE, IA, and SD)

	Equation 1 April 11, 2020		**Equation 2 April 18, 2020**		**Equation 3 April 25, 2020**		**Equation 4 May 2, 2020**	
COVID-19 Positive	0.715	0.808	0.738	0.846	1.038	1.257	0.953	1.255
	(0.163)***	(0.153)***	(0.171)***	(0.152)***	(0.227)***	(0.196)***	(0.325)***	(0.299)***
CRI	-0.018		-0.017		-0.029		-0.035	
	(0.008)**		(0.009)*		(0.012)**		(0.014)**	
CCI		-0.012		-0.011		-0.023		-0.035
		(0.009)		(0.007)		(0.008)***		(0.017)***
Income Inequality	-0.223	-0.235	-0.281	-0.291	-0.205	-0.217	-0.316	-0.321
	(0.059)***	(0.058)***	(0.047)***	(0.046)***	(0.072)***	(0.069)***	(0.085)***	(0.099)***
Trump	-0.007	0.007	-0.005	-0.004	-0.011	-0.010	-0.016	-0.015
	(0.002)***	(0.003)**	(0.002)***	(0.002)**	(0.002)***	(0.003)***	(0.003)***	(0.004)***
Log *Income*	0.146	0.147	0.178	0.179	0.125	0.129	0.238	0.248
	(0.053)***	(0.056)***	(0.045)***	(0.050)***	(0.057)**	(0.068)*	(0.079)***	(0.095)***
Union	0.010	0.010	0.009	0.008	0.011	0.011	0.012	0.012
	(0.004)**	(0.004)***	(0.003)***	(0.003)***	(0.002)***	(0.004)***	(0.005)**	(0.006)**
Population Density	0.017	0.019	0.022	0.024	0.027	0.029	0.023	0.025
	(0.008)**	(0.008)**	(0.008)***	(0.008)***	(0.013)**	(0.012)**	(0.014)	(0.013)*
Constant	1.371	1.259	0.939	0.841	1.494	1.274	0.509	0.168
	(0.568)**	(0.619)**	(0.518)*	(0.593)	(0.659)**	(0.797)	(0.906)	(1.125)

Correlation Matrix of Residuals

	April 11	**April 18**	**April 25**	**May 2**
April 11	1, 1			
April 18	0.769, 0.781	1, 1		
April 25	0.859, 0.869	0.806, 0.813	1	
May 2	0.810, 0.832	0.701, 0.711	0.822, 0.826	1, 1

Robust standard errors (clustered at the state level) in parentheses. All models control for region fixed effects. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.