İSTANBUL ÜNİVERSİTESİ YAYINEVİ

SİYASAL: Journal of Political Sciences, 31(1):91–114

DOI: 10.26650/siyasal.2022.31.1049435
http://jps.istanbul.edu.tr

SİYASAL: Journal of Political Sciences

Submitted: 28.12.2021
Revision Requested: 06.02.2022
Last Revision Received: 23.02.2022
Accepted: 02.03.2022

RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

The Reliability of COVID-19 Data in the Shadow of Anti-Pandemic Measures' Cancellation

Pandemi Önlemlerinin Kaldırılması Kararları Işığında Covid-19 Verilerinin Güvenilirliği Sorunu

Evgeny Sedashov[1], Mert Moral[2]

Abstract

COVID-19 pandemic necessitates taking measures that may be very costly from an economic standpoint and likely to make the mass public discontent. If an anti-pandemic regimen does not accomplish its goals, its costs become even harder to justify. We argue that, under such circumstances, cancellation of an anti-pandemic regimen would decrease the reliability of health data because rank-in-file policymakers and bureaucrats have incentives to present more optimistic statistics to signal their competence and politicians would further pressure them to report statistics that appear to agree with the cancellation of restrictions and give legitimacy to taking the measures. Our empirical analyses suggest that closeness to the restrictions' cancellation date is associated with lower reliability of COVID-19 daily cumulative cases and deaths data. Being robust to several sensitivity and robustness checks, this finding is alarming from the perspective of representative democracy and for those who have to survive in these turbulent times.

Keywords

COVID-19 pandemic, Pandemic restrictions, Data manipulation, Populism, Comparative politics

Öz

Covid-19 pandemisi, dünyanın dört bir yanındaki hükümetleri oldukça önemli ekonomik ve sosyal sonuçları olan tedbirler almaya itmiştir. Alınan bu oldukça sert tedbirlerin pandemiyle mücadele hususunda yetersiz kaldığı yahut başarısız olduğu durumlarda, bu tedbirler en başta ekonomik olmak üzere toplumun çeşitli kesimleri üzerindeki ağır maliyetleri kamuoyu nezdinde tepkiyle karşılanabilmektedir. Çalışmamızda bu gibi durumlarda, hükümetler ve ilgili uzmanların aldıkları tedbirlerin başarısını ölçmek için referans aldığımız hasta ve vefat istatistiklerinin güvenilirliğinin önemli ölçüde azaldığı öne sürülmektedir. Zira, alınan bu sert tedbirlerin başarısız olması durumunda, seçilmişler bunların meşruluğunu ve olumlu sonuçlarını gösterecek, daha iyimser istatistikler yayımlanmasını talep etme temayülünde olacak ve ilgili istatistiklerin hazırlanmasından sorumlu uzman ve bürokratlar üzerlerinde çeşitli baskılar kuracaklardır. Nitekim, betimsel ve ampirik tahliller tam kapanma uygulamasının sona ermesinin öncesinde toplam vefat ve hasta sayılarına dair istatistiklerin daha az güvenilir hala geldiğini göstermektedir. Çalışmamızın eklerinde yer verilen alternatif model, ölçüt ve analizler de bu sonuçları destekler niteliktedir. Bu açıdan, çalışmamızın sonuçları gerek temsili demokrasi gerekse de pandemi süresince hayatlarını bu istatistiklere göre idame ettirmeye çalışan vatandaşlar için oldukça kaygı vericidir.

Anahtar Kelimeler

Covid-19, Pandemiyle mücadele önlemleri, Veri manipülasyonu, Popülizm, Karşılaştırmalı siyaset

1 **Corresponding Author:** Evgeny Sedashov (Asst. Prof.), National Research University Higher School of Economics, School of Politics and Governance, Moscow, Russian Federation. E-mail: esedashov@hse.ru ORCID: 0000-0002-1022-6375

2 Mert Moral (Asst. Prof.), Sabanci University, Faculty of Arts and Social Sciences, Istanbul, Turkiye. E-mail: mmoral@sabanciuniv.edu ORCID: 0000-0001-6674-3198

To cite this article: Sedashov, E., & Moral, M. (2022). The Reliability of COVID-19 Data in the Shadow of Anti-Pandemic Measures' Cancellation. *SİYASAL: Journal of Political Sciences, 31*(1), 91–114. http://doi.org/10.26650/siyasal.2022.31.1049435

Introduction

It has been more than a year since the first reports of COVID-19 appeared in media outlets. As the pandemic has unfolded, governments around the globe were forced to make difficult decisions to alleviate major public health crises. The resulting anti-pandemic measures have varied from the cancellation of public events, school closings, and stay-at-home requirements to restrictions on international travel and many other policies constraining our daily lives (Thomas Hale et al., 2020b). One unifying feature of all those measures is their economic cost. Any enterprise that somehow involves in-person interactions was affected, and many people lost their income and jobs as a result. In the US alone, unemployment peaked at 14.7% in April 2020 before returning to a more acceptable, but still higher-than-average 6.7% (Falk, Romero, Nicchitta, & Nyhof, 2020), while the real GDP is projected to contract by 5.6% (Seliski, 2020). In the world, 92.9% of economies are expected to be in a state of recession as of 2020, while the global GDP is expected to shrink by about 4% (World Bank, 2021). In short, governments have been caught between the Scylla of health-related consequences of COVID-19 and the Charybdis of economic downturn brought about by their attempts to constrain the disease. Under such circumstances, the longer a government maintains a strict anti-pandemic regimen, the higher is its potential political cost.

This short paper aims to provide a theoretical discussion and empirical investigation of the relationship between the cancellation of anti-pandemic measures and the manipulation of the pandemic statistics. We propose two main reasons why the cancellation of restrictions may cause less reliable data reporting in the days immediately preceding such cancellation. Firstly, rank-in-file policy administrators have incentives to present more optimistic statistics mainly because they would like to signal their competence and improve their post-pandemic careers. Secondly, politicians would like to give legitimacy to the policy cancellation and, therefore, may induce reporting of statistics that are in agreement with the public's perception that things are getting better.

We test these expectations by employing the Oxford COVID-19 Government Response Tracker data (Thomas Hale et al., 2020a) and find evidence of manipulation in cumulative cases and deaths data in the days preceding the cancellation of restrictions. Because democratic governance and the relationship between the representatives and the represented rest on responsibility, accountability, and congruence, we also assess whether the expected effect of policy cancellation on the reliability of COVID-19 reporting is conditioned by the type of political regime. Finally, we check whether the reliability of COVID-19 reporting in the days preceding the cancellation of restrictions differs across populist and non-populist governments.

Following a discussion of our theoretical framework informed by the social psychology and political science literature in the next section, we present our research design and empirical findings. We conclude by discussing the implications of our findings from the perspective of representative democracy.

Cancellation of Anti-Pandemic Measures and the Reliability of Reporting

Like any other policy decision, the cancellation of anti-pandemic measures creates behavioral incentives for various actors. In this study, we are interested in the behavior of two groups of actors. The first group consists of political elites who make the ultimate decisions of when to introduce an anti-pandemic regimen, how strict the regimen should be, and when to cancel the restrictions. The second group is made up of rank-in-file bureaucrats who are responsible for the implementation of the anti-pandemic regimen introduced by politicians. In the following subsection, we consider how the incentives of both these two groups of actors may lead to disincentives for correctly reporting COVID-19 statistics before the cancellation of restrictions.

Bureaucratic Misreporting

In this subsection, we are going to assume a career-motivated bureaucrat (policy administrator) –i.e., the bureaucrat is always motivated to perform actions that bolster their chances of future promotions. The COVID-19 pandemic presents a unique challenge for rank-in-file policy administrators, but also a unique opportunity. If an administrator can demonstrate their efficiency under such conditions, this efficiency will likely translate into promotion opportunities once the pandemic disappears.

How can such circumstances lead to data manipulations? An administrator would like to signal their competence by showing a reduction in COVID-19 cases and deaths in their area of responsibility because their future promotions significantly depend on these two performance indicators. To give a practical example, one can imagine the head of a certain municipality who would like to rise in ranks by showing that their municipality implemented restrictions more strictly than did the neighboring municipalities. By presenting case and death counts that are more in accordance with the policy expectations, the head of the municipality can bolster their chances of future promotions.

Making matters worse, misreporting itself can become an epidemic-like phenomenon. If an administrator starts to present manipulated statistics with the hope of improving their post-pandemic career prospects, to avoid looking incompetent other administrators may be pushed to "cook" the statistics too. This would remind the reader of the well-known prisoners' dilemma. The outcome when all officials present correct data is preferable for the public, but each administrator has individual incentives to present a more favorable picture as a way of improving their future promotion chances.

Legitimacy of Policy Cancellation

Before we consider how the cancellation of anti-pandemic measures influences politicians' incentives regarding health data reporting, let us first consider the cancellation of anti-pandemic measures from the perspective of citizens. We have already mentioned that anti-pandemic measures are often highly costly from an economic standpoint. The key question, therefore, concerns the conditions under which these costs would be perceived by the public as justifiable.

Generally speaking, at the moment of policy cancellation there are three possible scenarios: the epidemiological situation may be worse than that before the introduction of the policy, the epidemiological situation may be the same as before, and the epidemiological situation may be better than before the introduction of the policy. All three scenarios have corresponding counterfactuals that citizens can employ as evaluative tools.

To keep the discussion concise, we assign each counterfactual a label and then refer to the label in the following discussion. If the statistics are worse than those before the introduction of restrictions, there is only one counterfactual (A1) that corresponds to the avoidance of an economic downturn caused by the restrictions. In other words, if the policy did nothing to improve the health statistics (e.g., the numbers of new cases and/or deaths), the associated economic costs would be perceived by the public as unnecessary, therefore increasing the political costs of the policy.

If there was no substantive change in the state of the epidemiology, there are two counterfactuals: the situation would have stayed the same even without the policy (counterfactual B1) or become worse without the policy (counterfactual B2). One may be inclined to think that there is a third plausible counterfactual that corresponds to the epidemiological situation improving without the policy. However, this counterfactual contradicts the very basic logic of pandemic fighting; it also requires a very high degree of optimism which is unlikely to emerge under pandemic circumstances. Due to these reasons, we do not consider the improvement scenario as a plausible counterfactual here.

Finally, if the state of the epidemiology had substantially improved, there are three counterfactuals: the situation would have become worse without the policy (counterfactual C1), the situation would have stayed the same without the policy (counterfactual C2), and the situation would have improved on its own without the policy (counterfactual C3). In this context, the main question of interest is which of those counterfactuals citizens would perceive as the most probable.

Social psychology literature provides us with several useful insights concerning citizens' counterfactual reasoning. Roese (1994) defines two general groups of counterfactuals: *upward* counterfactuals are "those that describe alternatives that are better than what actually happened," while *downward* counterfactuals "describe alternatives that are worse than reality". We employ this framework and divide the counterfactuals accordingly: A1, B1, and C3 are upward counterfactuals because they are centered around the feeling of regret for the policy introduction (i.e., "if the policy had not been introduced, things would have still been the same, but the economy would not have been in shamble") while B2, C1, and C2 are downward counterfactuals because they are focused on how things would have been even worse without the policy. Therefore, our task is to determine which type of counterfactual reasoning, upward or downward, citizens are more likely to employ in the environment shaped by COVID-19.

The most important pandemic-related factor that can affect citizens' counterfactual thinking is distress: people feel anxious due to health concerns and uncertain about their future (Galea, Merchant, & Lurie, 2020; Shevlin et al., 2020; Swami, George Horne, & Furnham, 2021; Tull et al., 2020). Under such conditions, psychological defense mechanisms are activated to avoid other sources of stress. Upward counterfactual reasoning, on the other hand, is well-known to cause greater distress (Epstude & Roese, 2008; Gilbar & Hevroni, 2007; Lecci, Okun, & Karoly, 1994). Therefore, psychological defense mechanisms push people to avoid engaging in upward counterfactual reasoning because it can cause additional distress.

How can this framework help explain politicians' calculus related to policy cancellation? First, upward counterfactuals are known to be associated with harsher evaluations of decisions and decision-makers (Kahneman & Tversky, 1982; Mellers, Schwartz, Ho, &

Ritov, 1997). Politicians, therefore, stand to lose quite a lot if citizens primarily rely on upward counterfactuals in their evaluation of politicians' actions such as the introduction of stay-at-home policies. Second, when the policy does not prevent the worsening of the state of the pandemic, we would observe only an upward counterfactual. Third, the remaining scenarios have both upward and downward counterfactuals, and people under the stress of the pandemic will be more inclined to use downward counterfactual reasoning. However, the upward counterfactual B1 is much more plausible than the upward counterfactual C3 simply because an expectation about the improvement of the situation without any policy interventions requires a very high degree of optimism. Therefore, politicians have multiple incentives to present the outcome of the policy in accordance with the improvement scenario in order to avoid citizens' discontent caused by upward counterfactual reasoning.

To summarize, our arguments point to a high degree of potential for data manipulation before the cancellation of restrictions. On the one hand, career bureaucrats motivated by post-pandemic promotion opportunities have incentives to report optimistic statistics to signal their competence and efficiency. On the other hand, politicians also have incentives to present more optimistic statistics to avoid potential punishment from citizens and to improve their reelection chances. Hence, our main hypothesis is as follows:

The closer the restrictions' cancellation date, the lower the reliability of COVID-19 reported data.

The arguments above rest on the assumption that neither career bureaucrats nor politicians are constrained in their decision-making calculations. In fact, another discipline, political science, provides us with a list of several important factors that are likely to constrain the actions of political and bureaucratic actors: democratic accountability, and checks and balances. Shvetsova et al., (2020) find that a political regime does indeed condition governments' anti-pandemic policies: democratic and decentralized countries show a faster and stronger response to the pandemic. Likewise, Frey, Chen, and Presidente (2020) show that democracies were more successful than autocratic ones at reducing mobility without imposing as stringent lockdowns. In another study examining only the EU-member countries, UK, Switzerland, France, and the UK, Toshkov, Carroll, and Yeşilkağıt (2021), on the other hand, show that countries with higher democracy scores were slower in adopting school closure and national lockdown policies (approximated as the natural log of the number of confirmed cases). Although the findings are contradictory, a similar conditioning mechanism might be in play for policy cancellation, too: as liberal democracies restrict career bureaucrats and politicians in their powers to manipulate health statistics by higher state capacity, well-functioning institutions, a well-informed citizenry, free media, freedom of expression, low levels of press-party parallelism, a strong opposition, and strong civil society organizations. Consequently, we hypothesize that:

The negative effect of the anti-pandemic policy cancellation on the reliability of COVID-19 statistics will be more pronounced in nondemocratic regimes.

A government's level of populism constitutes another important political dimension pertaining to the anti-pandemic response. Populism was famously coined by Mudde as a "thin-centered ideology" (2007, p. 23), which "considers society to be ultimately separated into two homogenous and antagonistic groups, 'the pure people' versus the 'corrupt elite,' and which argues that politics should be an expression of the volonté générale (general will) of the people" (2004, p. 543). Here, we define populist leaders as those who "adopt a certain style of behavior, discursive frame, or [the above mentioned] thin ideology... in which everyday citizens are framed as in need of regaining control over the political institutions that were meant to serve them, institutions which are felt to be corrupted by elites to serve the interests of the opulent minority, the Other, the few hegemons near and far" (Gagnon et al., 2018, pp. xi-xii). Such antagonism between the 'pure people' and 'corrupt elites,' the anti-elitist discourse of populist leaders (also see: Akkerman, Mudde, & Zaslove, 2014; Mudde & Kaltwasser, 2012; Rooduijn, 2019), as well as populist party supporters' higher levels of distrust in elites (including the experts, e.g., Mudde & Kaltwasser, 2017) manifest themselves in how populist leaders have framed the COVID-19 pandemic, and how rapidly they have responded to it. For instance, Kavakli (2020) argues that populist and right-wing governments implemented fewer counter-measures at the onset of the pandemic. Some populist leaders (e.g., Trump and Bolsonaro) even dismissed health and policy experts' recommendations for the 'interest' of the public. Since populist ideology rests on the "people vs. corrupt elite" premise (Mudde, 2007), populist governments must constantly show that they are on the people's side, especially given the high political and economic costs of the anti-pandemic measures we explained above. This, in turn, implies populist leaders' heightened desire to demonstrate the effectiveness of the few -but necessary- policies they make and the legitimacy of their cancellation. Therefore, we expect that:

The negative effect of the anti-pandemic policy cancellation on the reliability of COVID-19 statistics will be more pronounced in countries with populist governments.

Data and Research Design

Dependent Variable

For our dependent variable, we need a good measure of the reliability of COVID-19 data. The so-called Newcomb-Benford Law (Benford, 1938; Newcomb, 1881), or the NBL for short, describes the distribution of the leading digits of numbers that occur in various social and natural phenomena. From an intuitive standpoint, the digits (from 1 to 9) should have the same probability of occupying the leading position in a number. For instance, one can generate a sequence from 1 to 1 billion in any computational software and observe that digits from 1 to 9 indeed come out as equiprobable. However, the NBL demonstrates that many naturally occurring phenomena do not follow this pattern: 1 is the most frequent leading digit with a probability of 0.3, 2 is the second most frequent leading digit with a probability of 0.18, and so on until 9, which is the least frequent leading digit with a probability of 0.04.

The first digits of many physical constants and population statistics are well-approximated by the NBL, as well as many numbers associated with other diseases than COVID-19 (Sambridge, Hrvoje Tkalcic, & Jackson, 2010). Naturally, the NBL has long been used as a fraud and data manipulation detection tool. For example, it has been used to detect election (Mebane, 2006, 2008), scientific and accounting fraud (Grammatikos & Papanikolaou, 2021; Varian, 1972). Not surprisingly, the NBL has also been employed to detect manipulations with COVID-19 statistics in recent research as well (Anran Wei & Vellwock, 2020; Sambridge & Jackson, 2020; Wei & Vellwock, 2020).

Our use of the NBL in this paper is slightly more complicated than it is in previous applications because we would like to track how the reliability of data varies over time and shortly before policy cancellation. With this aim, we generate the appropriate measure in several steps. Firstly, for each country included in the Oxford COVID-19 Government Response Tracker dataset (Thomas Hale et al., 2020a) we check the date when the first case/death was detected. Secondly, we calculate a quality-of-fit statistic to estimate the difference between the observed cases and deaths data and the NBL. In doing so, we exclude the first 30 observations for each country since the probabilities of observing the digits with fewer observations will deviate from those predicted by the NBL to a great extent. Such deviations should however be lower when there are more observations. Hence, in the case of non-fraudulent reporting, we should observe a negative deviation trend over time –i.e., when countries report more daily statistics. After the 30th day since the detection of the first case/death, we start by calculating a quality-of-fit statistic for the first 31 days, then we do the same for the first 32 days, and so on. What this statistic provides us is essentially a time- sensitive measure of the data reliability, which is what we need for testing our hypotheses.

As our reliability measure, we employ a modified version of Pearson's χ^2[1] to measure the deviation of the observed data from the NBL. The statistic is calculated with the following formula:

$$\chi^2 = \frac{\sum_{i=1}^{9}(\tilde{p}_i - p_i)^2}{p_i}$$

, where $\tilde{p}_i$ is the observed proportion of the digit i in the data, and p_i is the proportion of the digit i expected by the NBL.[2] We calculate this quality-of-fit statistic for cumulative daily cases, (Δ) daily cases, cumulative daily deaths, and (Δ) daily deaths, resulting in a total of four dependent variables.

Independent Variables and Control Variables

Our empirical investigation focuses on the cancellation of the stay-at-home policy. The reasons for this choice are twofold. First, the stay-at-home policy is one of the toughest anti-pandemic measures and has been documented to cause extreme stress among citizens (Tull et al., 2020). Hamadani et al. (2020) document the increased level of depression and anxiety among Bangladeshi mothers after the introduction of the stay-at-home policy; the rise in the levels of emotional and physical violence was also reported. Second, the stay-at-home policy is one of the costliest anti-pandemic measures from both political and, as stated above, economic standpoints. Even though scholars now mostly agree that the stay-at-home order is an effective anti-pandemic policy (Doyle et al., 2020), citizens tend to feel its costs more acutely than its effects, especially those who lost jobs and income

1 We report the results for an alternative quality-of-fit statistic, $D = \sum_{i=1}^{9}|\tilde{p}_i - p_i|$, in Table A.9 in the online appendices. The models employing this alternative measure show essentially the same findings.

2 The standard χ^2 formula includes the total number of observations $N: \chi^2 = N\frac{\sum_{i=1}^{9}(\tilde{p}_i - p_i)^2}{p_i}$. Since our independent variable is the number of days before policy cancellation, including N into the quality-of-fit statistic creates a mechanical effect. To avoid this, we removed N from the formula.

as a result. Due to these reasons, we believe that our theoretical arguments are the most applicable to the stay-at-home policy.

To construct our independent variable, we count the number of days until the cancellation of the stay-at-home requirement. In the absence of data manipulation, we would expect a negative relationship between this variable, which, for instance, scores -30 for 30 days before and 0 on the cancellation day of the policy, and the degree of deviation from the NBL. This is because, as noted in the previous section, with the growing number of available data points the distribution of cases/deaths should become closer to the NBL (i.e., we should observe convergence in distribution to the NBL) (Miller & Nigrini, 2008), and an increase in our independent variable corresponds to a larger number of available data points. If we observe a positive relationship, however, our main hypothesis is likely to be true.

Our control variables include the natural logarithm of GDP per capita (Inklaar, de Jong, Bolt, & van Zanden, 2018), log of total population (World Bank, 2019), and the revised autocracy-democracy measure (Polity2) from the Polity project (Marshall & Gurr, 2020). All data are coded from the V-Dem dataset (Coppedge et al., 2020) and we inform the list of control variables by previous research (Adiguzel, Cansunar, & Corekcioglu, 2020) on the reliability of COVID-19 reporting.

Analyses and Results

Descriptive Evidence

We start our analyses by discussing some descriptive evidence for our arguments. Some countries have already started admitting incorrect reporting of COVID-19 statistics. Russia, for example, has recently officially confirmed that reported death tolls were incorrect (Agence France-Press, 2020). However, such admissions cannot conclusively establish the effect of anti-pandemic policy cancellation on COVID-19 data reliability. After all, some countries may always report skewed numbers, and such reporting is not specifically driven by any policy cancellation considerations.

To provide more relevant evidence, we thus turn to our data and demonstrate the basic relationship between days before cancellation of the stay-at-home order and estimated chi-squared statistics for two countries, Saudi Arabia and the United Kingdom. One can see from the scatterplots in Figure 1 that the numbers of cumulative cases reported by the UK appear to be truthful since the chi-squared statistic becomes smaller as the policy cancellation day approaches while the reliability of COVID-19 cumulative cases data in Saudi Arabia appears to diminish as the policy cancellation day becomes closer. The evidence for daily new cases is more mixed. In the UK, the data reliability seems to diminish between the 30 and 11 days preceding the cancellation, but after then the trend reverses and reporting becomes more truthful. In Saudi Arabia, the trend is similar to the one for cumulative cases. This observation points to the possible conditioning effect we discussed earlier: since the UK is an established democracy with well-functioning checks and balances and a free media environment, opportunities for data manipulations are more limited than in Saudi Arabia, one of the most authoritarian countries in the world. We now turn to the regression methods and test our expectations more systematically.

Regression Analyses

Our sample consists of all countries that have introduced and canceled the stay-at-home order at least once and with total cumulative cases of no less than 10,000.[3] Given our measure of data reliability, we restrict our attention to the stay-at-home orders for at least 30 days and discard the window of the first 30 days after the introduction of a policy and examine all other days preceding the cancellation in our empirical analyses. Therefore, for all country-policy pairs, the minimum value of the independent variable is -30 and the maximum value is 0.[4] [5]

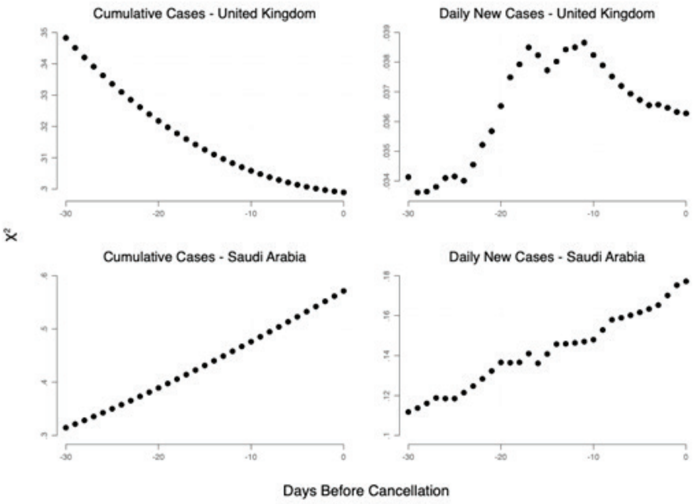

Figure 1. # of Days before Policy Cancellation and the Reliability of COVID-19 Data, UK and Saudi Arabia

Due to the construction of our dependent variable, there is an obvious autocorrelation, which renders OLS inappropriate. Since we have multiple country panels, the most appropriate statistical tool for analyzing the data is Prais-Winsten regression with panel-corrected standard errors (Prais & Winsten, 1954).[6] We also follow the recommendation of Beck and Katz (1995) and employ the AR1 autocorrelation structure to correct our standard errors.[7]

3 We provide the full list of country-policy pairs in Table A.1 of the online appendices.

4 Because the policy duration –i.e., the number of days between the coming into force and cancellation of the stay-at-home policy– varies between 1 (Uruguay, cancelled on August 25, 2020) and 629 days (Canada, cancelled on December 3, 2021) and several other systematic (e.g., seasonality, shorter policies being less effective) and unsystematic factors affect our dependent variable especially for longer policy periods, we focus on policies that were in force for at least 30 days and to the last month of the policy period and country-days with at least 10,000 recorded cumulative cases.

5 We also ran our models for an extended set of countries that maintained the policy for at least 15 days and used a 15-day window. The estimates presented in Table A.4 of the online appendices are substantively the same.

6 All models were estimated with Stata's xtpcse command.

7 See Table A.10 in the online appendices for the fixed-effects GLS regression estimates.

Table 1

Days before Policy Cancellation and the COVID-19 Data Reliability

	Cumulative Cases	**Daily New Cases**	**Cumulative Deaths**	**Daily New Deaths**
Days before Cancellation	0.002*** (0.000)	-0.000*** (0.000)	0.001*** (0.000)	-0.002*** (0.000)
Polity2	-0.003*** (0.001)	-0.004*** (0.000)	0.024*** (0.002)	-0.002*** (0.000)
Population (log)	0.116*** (0.002)	-0.004 (0.005)	-0.175*** (0.017)	-0.099*** (0.004)
GDPpc (log)	-0.019*** (0.003)	0.013*** (0.001)	-0.078*** (0.013)	-0.079*** (0.002)
Constant	-1.103*** (0.069)	0.103 (0.090)	4.460*** (0.404)	2.658*** (0.069)
N	4973	4973	4973	4973
R^2	0.171	0.128	0.211	0.201

Standard errors are in parentheses. * p<0.05,** p<0.01,*** p<0.001

We present the results in Table 1. Each of the four columns corresponds to a specific measure of the dependent variable.[8] For the cumulative cases and deaths data we find evidence of data manipulation: as the policy cancellation date approaches, the distribution of reported data becomes more and more dissimilar from the expected NBL distribution. In other words, the relationship becomes positive, whereas it should have been negative in the case of truthful reporting, as we pointed out in the previous section.

We do not find the same statistically significant positive relationship for the daily new cases and the daily new deaths data. We suspect this discrepancy across the models with different dependent variables has something to do with the public's attention to different types of COVID-19 statistics. To assess its plausibility, we compared Google search statistics for the term "total coronavirus cases" against the terms "daily new coronavirus cases" and "daily coronavirus cases." The term "total coronavirus cases" turns out to be a vastly more popular search: between January 3, 2020, and December 19, 2021. Its popularity always exceeds that of the "daily new coronavirus cases" and substantially exceeds the popularity of the "daily coronavirus cases." For deaths, this

8 See Tables A.5-A.8 in the online appendices for the estimates from alternative model specifications.

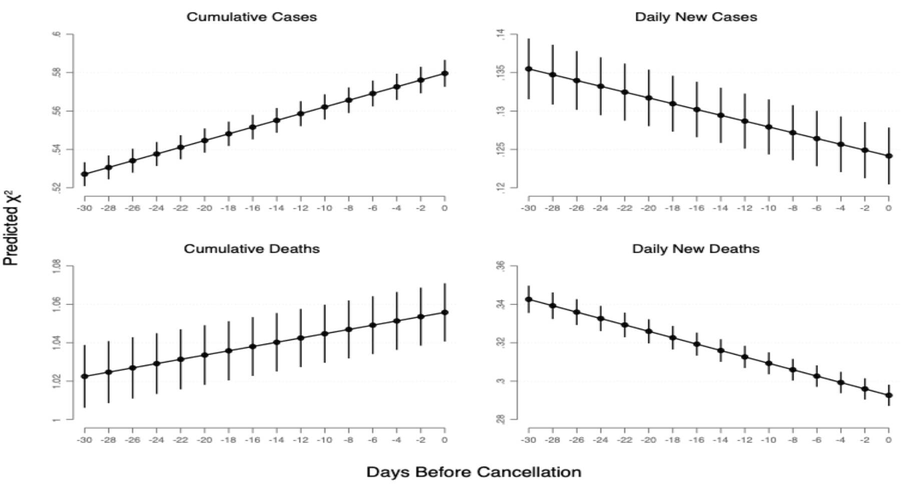

Figure 2. Effect of the # of Days before Policy Cancellation on the Reliability of COVID-19 Data

comparison, however, gives a more mixed result, with terms changing their relative popularity across different periods of the pandemic.

To provide a more substantive illustration of our findings, we plot out-of-sample predictions in Figure 2. For cumulative cases and deaths, we observe a positive relationship between our independent variable and predicted χ^2 scores corroborating the results from Table 1. In reference to Figure 1 presenting descriptive evidence based on a comparison of a democratic and a non-democratic country, the predicted scores in Figure 2 show that cumulative case and death counts significantly depart from what we would expect if there were no data manipulation and misreporting. Moreover, as we expected, the deviation of the observed data from the NBL increases with higher temporal proximity to the cancellation date of the stay-at-home policies.

Table 2

Conditioning Effect of Democracy on COVID-19 Cases Reporting

	Cumulative, Democracies	**Cumulative, Nondemocracies**	**Daily New, Democracies**	**Daily New, Nondemocracies**
Days before Cancellation	0.002*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)	0.000** (0.000)
Population (log)	-0.093*** (0.006)	0.377*** (0.011)	-0.001 (0.003)	-0.012** (0.006)
GDPpc (log)	-0.101*** (0.002)	0.045*** (0.006)	0.011*** (0.002)	0.027*** (0.005)
Constant	3.061*** (0.082)	-6.092*** (0.228)	0.020 (0.048)	0.139 (0.137)
N	3149	1824	3149	1824
R^2	0.337	0.203	0.120	0.155

Standard errors are in parentheses. * p<0.05,** p<0.01,*** p<0.001

We test our first conditional hypothesis for cumulative and daily new cases by splitting our sample into two subsamples:[9] all countries with a Polity score equal to or higher than 6 are considered democracies, and the rest are nondemocracies.[10] The estimates are presented in Table 2, which do not show robust support for our expectations. The positive relationship we would expect to observe in the case of data manipulation holds for cumulative cases in both democracies and nondemocracies. Therefore, we conclude that the political regime does not exhibit any strong conditioning role for this statistical indicator. On the other hand, the findings for the daily new cases reveal the expected conditioning effect, as reporting in nondemocracies appears to be untruthful. In line with our expectations, higher state capacity, better functioning institutions and informed citizenry, higher media freedom and freedom of expression, lower press-party parallelism, and stronger oppositions and civil society seem to contribute to democracies' reporting of truthful data on the number of COVID-19 cases.

Next, we proceed to assess whether the relationship between the restrictions' cancellation and the COVID-19 data reliability is conditioned by populism. Given its larger geographical and temporal scope than other cross-national datasets on populism and that it provides researchers with both party- and country-level measures that are comparable across time and space, we employ the V-Party dataset (Lührmann et al., 2020) to identify the populist parties and create a variable that marks whether a populist party holds the power in a specific country. To code our independent variable, we first identified incumbent parties as those that were either single governing parties or senior partners of governing coalitions in the most recent elections. Then, we coded incumbent parties as populist or not based on their most recent V-Party populism index score. If a party's score exceeds the global (i.e., all countries and parties) mean plus one standard deviation, we coded it as populist.[11]

The findings are presented in Table 3. Relying on the split-sample design once again, we do observe the conditioning effect of populism on the relationship between days before cancellation and data reliability for both cumulative and daily new cases.[12] For cumulative cases, however, the evidence of data manipulation is present for non-populist governments, but not for populist governments. This is quite an intriguing finding. Given their common dismissal of expert recommendations and portrayal of themselves as the champion of the 'pure people,' one would expect populist governments to be the ones "cooking up" the COVID-19 numbers.

Yet, there is a plausible explanation. As noted above, Kavakli (2020) shows that populist governments had introduced fewer counter-measures at the onset of the pandemic. This lagged reaction to the health crisis quickly worsened its scope, so when

9 This is mathematically equivalent to interacting all independent variables in the model equation with the binary variable we use for splitting the sample --i.e., democracy and populist incumbent party indicators in Tables 2 and 3.

10 The findings for deaths are presented in Table A.2 of the online appendices.

11 The values of V-Party indices are comparable over time and across space, which allows us to use the global distribution as the benchmark. Consequently, 19.1% of all and 18.4% of all incumbent governments in dataset are coded as populist. Given the other coding rules explained above, the countries with populist governments in our sample are as follows: Barbados, Cuba, Ecuador, Ethiopia, Hungary, Malta, Mongolia, Palestine, Poland, Serbia, Seychelles, Ukraine, and Venezuela.

12 The estimates for cumulative and daily deaths are presented in Table A.3 of the online appendices.

populist governments finally introduced the necessary restrictions, the situation had already become dire. Under such circumstances, restrictions led to easily observable improvements, and there was no need to "cook up" the numbers to present the measures as effective. Indeed, non-populist governments appear to provide truthful data for daily new cases, as the insignificant coefficient of the days before cancellation variable suggests.

Table 3

Conditioning Effect of Populism on COVID-19 Cases Reporting

	Cumulative, Pop = 0	**Cumulative, Pop = 1**	**Daily New, Pop = 0**	**Daily New, Pop = 1**
Days before Cancellation	0.002*** (0.000)	-0.004*** (0.000)	-0.001*** (0.000)	0.000 (0.001)
Population (log)	0.140*** (0.003)	-0.220*** (0.010)	0.001 (0.004)	-0.072*** (0.011)
GDPpc (log)	-0.028*** (0.007)	0.061*** (0.007)	0.005*** (0.001)	0.062*** (0.021)
Constant	-1.403*** (0.073)	3.451*** (0.196)	0.062 (0.074)	0.799*** (0.355)
N	4320	585	4320	585
R^2	0.171	0.540	0.158	0.128

Standard errors are in parentheses. *p<0.05,** p<0.01,*** p<0.001

Concluding Remarks

In this paper, we examined how the cancellation of anti-pandemic measures affects the reliability of COVID-19 data. We argue that the incentives of both rank-in-file policy administrators and politicians lead to skewed reporting shortly before the cancellation of imposed restrictions on citizens' daily lives. Employing a very comprehensive sample that includes all countries that have introduced a stay-at-home policy between January 2020 and December 2021 and introducing an innovative measure of data reliability that allows for a time-series analysis of the effect of the cancellation of the stay-at-home policy on data manipulation, our empirical analyses suggest that this expectation finds support for cumulative deaths and case statistics, but not for daily new cases and deaths.

We argue that the institutional and social context in which the political and bureaucratic actors operate may condition the way such incentives affect data reliability. To assess this possibility, we estimated two additional sets of regression analyses, where temporal proximity to the cancellation of the examined stay-at-home policies was conditioned by whether the country was a democracy and whether the incumbent was populist. Our expectations were that, thanks to higher state capacity, better functioning institutions and informed citizenry, higher media freedom and freedom of expression, lower press-party parallelism, and stronger oppositions and civil society, democracies would be less likely, whereas, with their delayed policy responses at the early stages and common anti-elitist rhetoric and dismissal of health experts' policy recommendations, populist governments would be more likely to manipulate pandemic data. The empirical analyses, however, show mixed findings. While our expectation about the democracy's mediating effect finds empirical support for daily new cases, populist countries seem to not have manipulated pandemic data. Consequently, the empirical evidence in the previous section as well as in the robustness checks presented in appendices suggests a deleterious effect of anti-pandemic measures' cancellation on the reliability of official COVID-19 data.

Our paper points to several possible directions for future research. Firstly, we discuss the possibility that varying public attention to different types of COVID-19 statistics may induce varying data manipulation strategies. We provide some preliminary evidence for this idea, but a rigorous research design is required to test it. Secondly, one can assess whether the "toughness" of the policy matters for data reliability. For instance, the stay-at-home order is undoubtedly a much harder pill for the public to swallow than the closure of public venues or the cancellation of public events. We have good reasons to suspect that for some easier-to-bear policies the effect of our independent variable will be negative, implying better data reporting practices. Moreover, our examination is limited to data manipulation at a time when all governments experienced significant difficulties in collecting reliable data. Admittedly, our empirical models, however, rely not only on few and dichotomous measures of country-level differences but also lack important potential confounders that are likely to explain a significant portion of the variance in data reporting practices. Consequently, we hope further research will test the validity of our findings by also considering pre-pandemic levels of potential country-level confounders.

Despite such limitations of our study, we believe our findings are quite alarming from the perspective of representative democracy. The evidence presented in this paper suggests that pandemic-related information can be manipulated in order to portray anti-pandemic policies as more effective than they actually are. We do not find that democracies are conclusively better in preventing such misinformation, although democracies seem to report daily new cases and deaths truthfully –the same cannot be said about nondemocracies. Taken together, our findings thus point to the necessity of establishing better domestic and international accountability mechanisms that can prevent such misreporting from occurring in the future.

Peer-review: Externally peer-reviewed.
Conflict of Interest: The author has no conflict of interest to declare.
Grant Support: The author declared that this study has received no financial support.

References

Adiguzel, F. S., Cansunar, A., & Corekcioglu, G. (2020). Truth or Dare? Detecting Systematic Manipulation of COVID-19 Statistics. *Journal of Political Institutions and Political Economy, 1*(4), 543-557.

Agence France-Press. (2020). Russia Admits to World's Third-Worst Covid-19 Death Toll. *Guardian*.

Akkerman, A., Mudde, C., & Zaslove, A. (2014). How Populist Are the People? Measuring Populist Attitudes in Voters. *Comparative Political Studies, 47*(9), 1324-1353.

Anran Wei, & Vellwock, A. E. (2020). Is COVID-19 Data Reliable? A Statistical Analysis with Benford's Law. *Working Paper*.

Beck, N., & Katz, J. N. (1995). What to do (and not to do) with Time-Series Cross-Section Data. *The American Political Science Review, 89*(3), 634-647. Retrieved from http://www.jstor.org/stable/2082979

Benford, F. (1938). The Law of Anomalous Numbers. *Proceedings of the American Philosophical Society, 78*(4), 551-572. Retrieved from http://www.jstor.org/stable/984802

Coppedge, M., John Gerring, Carl Henrik Knutsen, Staffan I. Lindberg, Jan Teorell, D. A., Michael Bernhard, . . . Ziblatt, D. (2020). *V-Dem Country-Year Dataset v10*.

Doyle, A. A., Friedlander, M. S. H., Li, G. D., Marble, W., Smith, C. J., Baronia, N., . . . Srinivasan, M. (2020). The Evidence and Tradeoffs for a 'Stay-at-Home' Pandemic Response: A Multidisciplinary Review Examining the Medical, Psychological, Economic and Political Impact of 'Stay-at-Home' Implementation in America. *Working Paper*.

Epstude, K., & Roese, N. J. (2008). The Functional Theory of Counterfactual Thinking. *Personality and Social*

Psychology Review, 12(2), 168-192.
Falk, G., Romero, P. D., Nicchitta, I. A., & Nyhof, E. C. (2020). Unemployment Rates During the COVID-19 Pandemic: In Brief. *Congressional Research Service*.
Frey, C. B., Chen, C., & Presidente, G. (2020). Democracy, Culture, and Contagion: Political Regimes and Countries Responsiveness to Covid-19. *Covid Economics*(18), 222-238.
Gagnon, J.-P., Beausoleil, E., Son, K.-M., Arguelles, C., Chalaye, P., & Johnston, C. N. (2018). What is Populism? Who is the Populist? *Democratic Theory, 5*(2), vi-xxvi.
Galea, S., Merchant, R. M., & Lurie, N. (2020). The Mental Health Consequences of COVID-19 and Physical Distancing: The Need for Prevention and Early Intervention. *JAMA Internal Medicine, 180*(6), 817-818. Retrieved from https://doi.org/10.1001/jamainternmed.2020.1562
Gilbar, O., & Hevroni, A. (2007). Counterfactuals, Coping Strategies and Psychological Distress Among Breast Cancer Patients. *Anxiety, Stress, & Coping, 20*, 383 - 392.
Grammatikos, T., & Papanikolaou, N. I. (2021). Applying Benford's Law to Detect Accounting Data Manipulation in the Banking Industry. *Journal of Financial Services Research, 59*(1), 115-142.
Hamadani, J. D., Hasan, M. I., Baldi, A. J., Hossain, S. J., Shiraji, S., Bhuiyan, M. S. A., . . . Pasricha, S.-R. (2020). Immediate Impact of Stay-at-home Orders to Control COVID-19 Transmission on Socioeconomic Conditions, Food Insecurity, Mental Health, and Intimate Partner Violence in Bangladeshi Women and Their Families: An Interrupted Time Series. *The Lancet Global Health, 8*(11), e1380-e1389.
Inklaar, R., de Jong, H., Bolt, J., & van Zanden, J. (2018). *Rebasing 'Maddison': New Income Comparisons and the Shape of Long-Run Economic Development*. Retrieved from
Kahneman, D., & Tversky, A. (1982). The Simulation Heuristic. In Daniel Kahneman, Paul Slovic, & A. Tversky (Eds.), *Judgment Under Uncertainty: Heuristics and Biases* (pp. 201-208). New York: Cambridge University Press.
Kavakli, K. C. (2020). Did Populist Leaders Respond to the COVID-19 Pandemic More Slowly? Evidence from a Global Sample. *Working Paper*.
Lecci, L., Okun, M. A., & Karoly, P. (1994). Life Regrets and Current Goals as Predictors of Psychological Adjustment. *Journal of Personality and Social Psychology, 66*(4), 731-741. doi:10.1037/0022-3514.66.4.731
Lührmann, A., Nils Düpont, Masaaki Higashijima, Yaman Berker Kavasoglu, Kyle L. Marquardt, Michael Bernhard, . . . Seim, B. (2020). *Varieties of Party Identity and Organization (V-Party) Dataset V1*.
Marshall, M. G., & Gurr, T. R. (2020). *POLITY5: Political Regime Characteristics and Transitions, 1800-2018*.
Mebane, W. (2006). *Election Forensics: Vote Counts and Benford's Law*. Paper presented at the Summer Meeting of the Political Methodology Society, UC-Davis.
Mebane, W. (2008). Election Forensics: The Second Digit Benford's Law Test and Recent American Presidential Elections. In R. Michael Alvarez, Thad E. Hall, & S. D. Hyde (Eds.), *Election Fraud: Detecting and Deterring Electoral Manipulation* (Vol. 162-181). Washington DC: Brookings.
Mellers, B. A., Schwartz, A., Ho, K., & Ritov, I. (1997). Decision Affect Theory: Emotional Reactions to the Outcomes of Risky Options. *Psychological Science, 8*(6), 423-429.
Miller, S. J., & Nigrini, M. J. (2008). The Modulo 1 Central Limit Theorem and Benford's Law for Products. *International Journal of Algebra, 2*(3), 119-130.
Mudde, C. (2004). The Populist Zeitgeist. *Government and Opposition, 39*(4), 541-563.
Mudde, C. (2007). *Populist Radical Right Parties in Europe*. Cambridge: Cambridge University Press.
Mudde, C., & Kaltwasser, C. R. (2012). *Populism in Europe and the Americas: Threat or Corrective for Democracy?* Cambridge: Cambridge University Press.
Mudde, C., & Kaltwasser, C. R. (2017). *Populism: A Very Short Introduction*. New York: Oxford University Press.
Newcomb, S. (1881). Note on the Frequency of Use of the Different Digits in Natural Numbers. *American Journal of Mathematics, 4*(1), 39-40.
Prais, S., & Winsten, C. (1954). *Trend Estimators and Serial Correlation*. Paper presented at the Cowles Commission Discussion Paper No. 383.
Roese, N. J. (1994). The Functional Basis of Counterfactual Thinking. *Journal of Personality and Social Psychology, 66*(5), 805-818. doi:10.1037/0022-3514.66.5.805
Rooduijn, M. (2019). State of the Field: How to Study Populism and Adjacent Topics? A Please for Both More and Less Focus. *European Journal of Political Research, 58*(1), 362-372.
Sambridge, M., Hrvoje Tkalcic, & Jackson, A. (2010). Benford's Law in the Natural Sciences. *Geophysical Research Letters, 37*(22), 1-5.
Sambridge, M., & Jackson, A. (2020). National COVID Numbers - Benford's Law Looks for Errors. *Nature, 581*(7809), 384.
Seliski, J. (2020). Interim Economic Projections for 2020 and 2021. *Congressional Budget Office*.
Shevlin, M., McBride, O., Murphy, J., Miller, J. G., Hartman, T. K., Levita, L., . . . Bentall, R. P. (2020). Anxiety, Depression, Traumatic Stress and COVID-19-related Anxiety in the UK General Population During the COVID-19 Pandemic. *BJPsychOpen, 6*(6).
Shvetsova, O., Andrei Zhirnov, Julie VanDusky-Allen3, Abdul Basit Adeel, Michael Catalano, Olivia Catalano, . . . Zhao, T. (2020). Institutional Origins of Protective COVID-19 Public Health Policy Responses:

Informational and Authority Redundancies and Policy Stringency. *Journal of Political Institutions and Political Economy, 1*(4), 585-613.
Swami, V., George Horne, & Furnham, A. (2021). COVID-19-related Stress and Anxiety are Associated with Negative Body Image in Adults from the United Kingdom. *Personality and Individual Differences, 170*, 110426.
Thomas Hale, Thomas Boby, Noam Angrist, Emily Cameron-Blake, Laura Hallas, Beatriz Kira, . . . Webster, S. (2020a). Oxford COVID-19 Government Response Tracker. from Blavatnik School of Government
Thomas Hale, Thomas Boby, Noam Angrist, Emily Cameron-Blake, Laura Hallas, Beatriz Kira, . . . Webster, S. (2020b). Variation in Government Responses to COVID-19. *Blavatnik School of Government Working Paper*.
Toshkov, D., Carroll, B., & Yeşilkağıt, K. (2021). Government Capacity, Societal Trust or Party Preferences: What Accounts for the Variety of National Policy Responses to the COVID-19 Pandemic in Europe? *Journal of European Public Policy*. doi:https://doi.org/10.1080/13501763.2021.1928270
Tull, M. T., Keith A. Edmonds, Kayla M. Scamaldo, Julia R.Richmond, Jason P.Rose, & Gratz., K. L. (2020). Psychological Outcomes Associated with Stay-at-Home Orders and the Perceived Impact of COVID-19 on Daily Life. *Psychiatry Research, 289*, 113098.
Varian, H. (1972). Benford's Law (Letters to the Editor). *The American Statistician, 26*(3), 65.
Wei, A., & Vellwock, A. E. (2020). Is COVID-19 Data Reliable? A Statistical Analysis with Benford's Law. *Working Paper*.
World Bank. (2019). *World Bank Development Indicators*.
World Bank. (2021). *Global Economic Prospects*.

Online Appendix

Table A.1

Data Description

Country	Policy Cancellation Date	Days b/f Cancellation	Polit y2	Population (log)	GDPpc (log)
Afghanistan	26aug2020	30	-1	17.43108	7.565
Algeria	20oct2021	30	2	17.5586	9.498
Australia	29may2020	30	10	17.03408	10.71
Australia	11jan2021	30	10	17.03408	10.71
Australia	22oct2021	30	10	17.03408	10.71
Austria	01may2020	16	10	15.99559	10.715
Austria	16may2021	30	10	15.99559	10.715
Azerbaijan	28sep2021	30	-7	16.11231	9.635
Bahrain	23aug2020	30	-10	14.26623	10.591
Bangladesh	15jul2021	30	-6	18.89912	8.086
Belarus	17aug2021	30	-7	16.06526	9.84
Belgium	08jun2020	30	8	16.25106	10.59
Belgium	30jul2021	30	8	16.25106	10.59
Bolivia	05jan2021	30	7	16.245	8.719
Bolivia	28sep2021	30	7	16.245	8.719
Bosnia and Herzegovina	21may2020	30	0	15.01666	9.266
Bosnia and Herzegovina	27may2021	30	0	15.01666	9.266
Botswana	05oct2021	30	8	14.62827	9.617
Bulgaria	31may2020	30	9	15.76487	9.796
Burkina Faso	10sep2020	30	6	16.79874	7.353
Burkina Faso	30may2021	4	6	16.79874	7.353
Cambodia	21dec2020	30	-4	16.60359	8.104
Canada	03dec2021	30	10	17.42802	10.668
Central African Republic	24nov2020	30	6	15.35589	6.428
Central African Republic	20apr2021	30	6	15.35589	6.428
Central African Republic	21sep2021	19	6	15.35589	6.428
Chile	01oct2021	30	10	16.74559	9.973
China	02sep2020	30	-7	21.05453	9.419
Cote d'Ivoire	27jul2020	30	4	17.03715	8.206
Cote d'Ivoire	31aug2021	30	4	17.03715	8.206
Croatia	07sep2020	30	9	15.22391	9.982
Cuba	03jul2020	30	-5	16.24368	8.973
Cuba	01oct2020	21	-5	16.24368	8.973
Cuba	23nov2021	30	-5	16.24368	8.973
Cyprus	27jul2021	30	10	13.98885	10.186
Czech Republic	01jun2020	30	9	16.17879	10.345
Czech Republic	12apr2021	30	9	16.17879	10.345
Democratic Republic of Congo	27oct2020	30	-3	18.24714	6.729

Country	Policy Cancellation Date	Days b/f Cancellation	Polit y2	Population (log)	GDPpc (log)
Denmark	21oct2020	30	10	15.57293	10.718
Denmark	21may2021	30	10	15.57293	10.718
Djibouti	17may2020	25	3	13.77356	8.13
Ecuador	14sep2020	30	5	16.65367	9.263
Ecuador	01sep2021	30	5	16.65367	9.263
Egypt	22mar2021	30	-4	18.40479	9.344
Egypt	07jun2021	30	-4	18.40479	9.344
El Salvador	09mar2021	30	8	15.67505	9.028
Estonia	18may2020	20	9	14.09381	10.172
Estonia	09may2021	29	9	14.09381	10.172
Eswatini	24nov2020	30	-9	13.94319	8.941
Eswatini	10dec2021	30	-9	13.94319	8.941
Ethiopia	27oct2020	30	1	18.50892	7.414
Finland	01jun2020	30	10	15.52353	10.554
Finland	01nov2021	30	10	15.52353	10.554
France	22jun2020	30	9	18.02001	10.565
France	20jun2021	30	9	18.02001	10.565
Gambia	22jul2020	30	4	14.63973	7.576
Gambia	10nov2020	30	4	14.63973	7.576
Gambia	20sep2021	11	4	14.63973	7.576
Georgia	09oct2020	30	7	15.13219	9.258
Georgia	30jun2021	30	7	15.13219	9.258
Germany	06may2020	28	10	18.23348	10.755
Germany	10oct2021	30	10	18.23348	10.755
Ghana	30mar2021	5	8	17.20891	8.23
Ghana	29aug2021	30	8	17.20891	8.23
Guatemala	01oct2020	30	8	16.66319	8.873
Guatemala	05oct2021	12	8	16.66319	8.873
Haiti	15dec2020	30	5	16.22454	7.4
Hong Kong	11sep2020	30		15.82386	10.759
Hungary	11sep2020	30	10	16.0947	10.088
Hungary	29jun2021	30	10	16.0947	10.088
Iran	30aug2021	30	-7	18.21979	9.65
Ireland	26jun2020	30	10	15.39521	10.927
Ireland	10may2021	30	10	15.39521	10.927
Israel	18jul2020	30	6	15.99974	10.389
Israel	28oct2020	10	6	15.99974	10.389
Israel	07feb2021	30	6	15.99974	10.389
Italy	01jul2021	30	10	17.91702	10.463
Japan	25may2020	18	10	18.65598	10.504
Jordan	01sep2021	30	-3	16.11369	9.371
Kazakhstan	16feb2021	30	-6	16.72113	10.06
Kenya	26oct2021	30	9	17.75501	8.075
Kosovo	25sep2020	30	8	14.42815	
Kosovo	25may2021	30	8	14.42815	
Kuwait	16may2021	30	-7	15.23556	11.124
Kyrgyz Republic	16oct2020	30	8	15.65856	8.71

Country	Policy Cancellation Date	Days b/f Cancellation	Polit y2	Population (log)	GDPpc (log)
Laos	04may2020	5	-7	15.77017	8.752
Latvia	03oct2020	30	8	14.47124	10.059
Lebanon	20jul2020	30	6	15.7396	9.448
Lebanon	27sep2021	30	6	15.7396	9.448
Libya	13jul2021	30	0	15.71441	8.999
Lithuania	17jun2020	30	10	14.84138	10.173
Lithuania	19apr2021	30	10	14.84138	10.173
Luxembourg	20jul2021	30	10	13.31748	11.143
Madagascar	18oct2020	30	6	17.08365	7.175
Madagascar	19oct2021	30	6	17.08365	7.175
Malawi	13oct2020	30	6	16.71381	6.856
Malawi	28apr2021	20	6	16.71381	6.856
Malaysia	10jun2020	30	7	17.26641	10.03
Malaysia	24sep2020	22	7	17.26641	10.03
Mali	10may2020	16	5	16.76403	7.38
Mali	19jul2021	30	5	16.76403	7.38
Mauritania	10jul2020	30	-2	15.29787	8.104
Mauritius	15jun2020	30	10	14.05082	9.844
Mauritius	30jun2021	30	10	14.05082	9.844
Mauritius	21sep2021	30	10	14.05082	9.844
Moldova	10jul2020	30	9	15.0813	8.674
Moldova	12aug2021	30	9	15.0813	8.674
Mongolia	01jun2020	30	10	14.96931	9.315
Morocco	24jun2020	30	-4	17.39984	8.938
Morocco	16nov2021	30	-4	17.39984	8.938
Mozambique	22oct2020	30	5	17.19976	7.161
Namibia	06oct2020	30	6	14.71089	9.371
Namibia	17nov2021	30	6	14.71089	9.371
Nepal	02mar2021	30	7	17.15085	7.858
Nepal	04jul2021	30	7	17.15085	7.858
Nepal	05oct2021	30	7	17.15085	7.858
Netherlands	26jun2021	30	10	16.66222	10.805
New Zealand	14may2020	24	10	15.40178	10.435
Norway	25sep2021	30	10	15.48592	11.244
Oman	23oct2020	30	-8	15.39025	10.516
Oman	13may2021	30	-8	15.39025	10.516
Pakistan	17oct2021	30	7	19.17311	8.566
Papua New Guinea	23jun2020	30	5	15.96801	
Papua New Guinea	29oct2020	4	5	15.96801	
Papua New Guinea	17sep2021	30	5	15.96801	
Paraguay	13oct2021	30	9	15.75513	9.06
Poland	30may2020	30	10	17.45253	10.166
Portugal	01jun2020	30	10	16.14588	10.23
Portugal	01aug2020	1	10	16.14588	10.23

Country	Policy Cancellation Date	Days b/f Cancellation	Polit y2	Population (log)	GDPpc (log)
Portugal	04jan2021	30	10	16.14588	10.23
Portugal	01aug2021	30	10	16.14588	10.23
Romania	01jun2020	30	9	16.78459	9.848
Romania	09oct2020	30	9	16.78459	9.848
Romania	15may2021	30	9	16.78459	9.848
Russia	09jun2020	30	4	18.78864	10.046
Russia	28mar2021	30	4	18.78864	10.046
Russia	10aug2021	27	4	18.78864	10.046
Rwanda	12jan2021	30	-3	16.32527	7.462
Saudi Arabia	30oct2020	30	-10	17.33301	10.768
Senegal	30jun2020	30	7	16.57895	7.841
Senegal	19mar2021	30	7	16.57895	7.841
Serbia	07jun2021	30	8	15.75886	9.547
Serbia	05oct2021	30	8	15.75886	9.547
Slovak Republic	14jun2020	30	10	15.51058	10.193
Slovak Republic	15may2021	30	10	15.51058	10.193
Slovenia	14may2020	30	10	14.54179	10.267
Slovenia	27apr2021	30	10	14.54179	10.267
South Korea	20apr2020	27	8	17.75972	10.495
South Korea	01jul2021	30	8	17.75972	10.495
Spain	21jun2020	30	10	17.65976	10.36
Spain	15sep2021	30	10	17.65976	10.36
Sudan	26sep2020	30	-4	17.54844	8.23
Sudan	15jun2021	30	-4	17.54844	8.23
Sweden	29sep2021	30	10	16.13625	10.7
Switzerland	22jun2020	30	10	15.95752	11.032
Switzerland	26jun2021	30	10	15.95752	11.032
Syria	03aug2020	30	-9	16.6432	8.177
Syria	10jun2021	30	-9	16.6432	8.177
Tajikistan	15jun2020	7	-3	16.02388	8.173
Togo	09jun2020	30	-2	15.88099	7.323
Togo	17nov2020	30	-2	15.88099	7.323
Togo	14sep2021	30	-2	15.88099	7.323
Trinidad and Tobago	22jun2020	30	10	14.14471	10.287
Trinidad and Tobago	26oct2020	30	10	14.14471	10.287
Trinidad and Tobago	17nov2021	30	10	14.14471	10.287
Tunisia	08jun2020	30	7	16.26351	9.271
Tunisia	04oct2021	30	7	16.26351	9.271
Turkey	12aug2021	30	-4	18.22612	9.841
Ukraine	28jun2021	30	4	17.61375	9.179
United Arab Emirates	18may2020	30	-8	16.08049	11.16
United Arab Emirates	19aug2021	2	-8	16.08049	11.16

Country	Policy Cancellation Date	Days b/f Cancellation	Polit y2	Population (log)	GDPpc (log)
United Kingdom	03dec2020	30	8	18.01255	10.575
United Kingdom	12apr2021	30	8	18.01255	10.575
Uruguay	10jul2020	30	10	15.05368	9.898
Uruguay	18oct2021	30	10	15.05368	9.898
Uzbekistan	04jan2021	30	-9	17.31067	9.183
Venezuela	07nov2021	30	-3	17.17832	9.485
Vietnam	01oct2020	30	-7	18.37506	8.705
Vietnam	28sep2021	30	-7	18.37506	8.705
Yemen	13jul2020	30	0	17.16537	7.696
Yemen	25sep2021	30	0	17.16537	7.696
Zambia	31jan2021	30	6	16.66921	8.171
Zambia	16may2021	14	6	16.66921	8.171

Table A.2

Conditioning Effect of Democracy on COVID-19 Deaths Reporting

	Cumulative, Dem	Cumulative, Non-dem	Daily New, Dem	Daily New, Nondem
Days b/f Cancellation	0.002*** (0.000)	-0.001 (0.000)	-0.001*** (0.000)	-0.002*** (0.000)
Population (log)	-0.305*** (0.011)	-0.000 (0.029)	-0.105*** (0.007)	-0.096*** (0.003)
GDPpc (log)	-0.130*** (0.007)	-0.067*** (0.017)	-0.027*** (0.003)	-0.151*** (0.006)
Constant	7.344*** (0.241)	1.285** (0.610)	2.228*** (0.121)	3.281*** (0.069)
N	3149	1824	3149	1824
R^2	0.226	0.208	0.198	0.232

Standard errors are in parentheses. $*$ p<0.05,$**$ p<0.01,$***$ p<0.001

Table A.3

Conditioning Effect of Populism on COVID-19 Deaths Reporting

	Cumulative, Pop = 0	Cumulative, Pop = 1	Daily New, Pop = 0	Daily New, Pop = 1
Days b/f Cancellation	0.001*** (0.000)	0.001* (0.001)	-0.002*** (0.000)	-0.001 (0.001)
Population (log)	-0.207*** (0.021)	-0.783*** (0.029)	-0.109*** (0.005)	-0.204*** (0.029)
GDPpc (log)	-0.027* (0.016)	-0.919 *** (0.091)	-0.087*** (0.003)	-0.072 (0.071)
Constant	4.672*** (0.482)	22.523*** (1.056)	2.902*** (0.079)	4.294*** (0.279)
N	4320	585	4320	585
R^2	0.211	0.354	0.204	0.177
Observations	2914	372	2914	372
R^2	0.216	0.142	0.127	0.017

Standard errors are in parentheses. $*$ p<0.05,$**$ p<0.01,$***$p<0.001

Table A.4

Days before Policy Cancellation and the COVID-19 Data Quality, 15-days Window

	Cumulative Cases	**Daily New Cases**	**Cumulative Deaths**	**Daily New Deaths**
Days b/f Cancellation	0.002*** (0.000)	-0.000*** (0.000)	0.001*** (0.000)	-0.002*** (0.000)
Polity2	-0.003*** (0.001)	-0.005*** (0.000)	0.026*** (0.001)	-0.001 (0.000)
Population (log)	0.117*** (0.002)	-0.002 (0.004)	-0.169*** (0.024)	-0.094*** (0.002)
GDPpc (log)	-0.014*** (0.002)	0.014*** (0.001)	-0.076*** (0.018)	-0.075*** (0.002)
Constant	-1.179*** (0.035)	0.055 (0.079)	4.347*** (0.558)	2.540*** (0.009)
N	2576	2576	2576	2576
R^2	0.193	0.230	0.233	0.345

Standard errors are in parentheses. $* p<0.05, ** p<0.01, *** p<0.001$

Table A.5

Days before Policy Cancellation and the COVID-19 Data Quality, Cumulative Cases

	Model 1	**Model 2**	**Model 3**	**Model 4**
Days b/f Cancellation	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Polity2		-0.008*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)
Population (log)			0.094*** (0.003)	0.116*** (0.002)
GDPpc (log)				-0.019*** (0.003)
Constant	0.649*** (0.008)	0.675*** (0.013)	-0.876*** (0.054)	-1.103*** (0.069)
N	5481	5307	5277	4973
R^2	0.155	0.148	0.153	0.171

Standard errors are in parentheses. $* p<0.05, ** p<0.01, *** p<0.001$

Table A.6

Days before Policy Cancellation and the COVID-19 Data Quality, Daily New Cases

	Model 1	**Model 2**	**Model 3**	**Model 4**
Days b/f Cancellation	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Polity2		-0.003*** (0.000)	-0.003*** (0.000)	-0.004*** (0.000)
Population (log)			-0.013*** (0.004)	-0.004 (0.005)
GDPpc (log)				0.013*** (0.001)
Constant	0.152*** (0.002)	0.160*** (0.003)	0.377*** (0.071)	0.103 (0.090)
N	5481	5307	5277	4973
R^2	0.126	0.130	0.139	0.128

Standard errors are in parentheses. $* \boldsymbol{p}<0.05, ** \boldsymbol{p}<0.01, *** \boldsymbol{p}<0.001$

Table A.7

Days before Policy Cancellation and the COVID-19 Data Quality, Cumulative Deaths

	Model 1	Model 2	Model 3	Model 4
Days b/f Cancellation	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Polity2		0.028*** (0.001)	0.019*** (0.002)	0.024*** (0.002)
Population (log)			-0.135*** (0.016)	-0.175*** (0.017)
GDPpc (log)				-0.078*** (0.013)
Constant	1.087*** (0.012)	0.889*** (0.015)	3.113*** (0.266)	4.460*** (0.404)
N	5481	5307	5277	4973
R^2	0.192	0.206	0.208	0.211

Standard errors are in parentheses. $* \, p<0.05, ** \, p<0.01, *** \, p<0.001$

Table A.8

Days before Policy Cancellation and the COVID-19 Data Quality, Daily New Deaths

	Model 1	Model 2	Model 3	Model 4
Days b/f Cancellation	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)
Polity2		-0.003*** (0.001)	-0.007*** (0.001)	-0.002*** (0.000)
Population (log)			-0.085*** (0.005)	-0.099*** (0.004)
GDPpc (log)				-0.079*** (0.002)
Constant	0.325*** (0.003)	0.319*** (0.004)	1.712*** (0.073)	2.658*** (0.069)
N	5481	5307	5277	4973
R^2	0.142	0.149	0.153	0.201

Standard errors are in parentheses. $* \, p<0.05, ** \, p<0.01, *** \, p<0.001$

Table A.9

Days before Policy Cancellation and the COVID-19 Data Quality, Alternative Measure

	Cumulative Cases	Daily New Cases	Cumulative Deaths	Daily New Deaths
Days b/f Cancellation	0.001*** (0.000)	-0.000*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)
Polity2	0.002** (0.001)	-0.005*** (0.001)	0.007*** (0.000)	-0.001 (0.001)
Population (log)	-0.006*** (0.001)	-0.000 (0.002)	-0.043*** (0.005)	-0.063*** (0.004)
GDPpc (log)	-0.004** (0.001)	0.015*** (0.002)	-0.015** (0.005)	-0.058*** (0.002)
Constant	0.658*** (0.031)	0.152*** (0.033)	1.437*** (0.121)	1.978*** (0.077)
N	4973	4973	4973	4973
R^2	0.709	0.462	0.644	0.454

Standard errors are in parentheses. $* \, p<0.05, ** \, p<0.01, *** \, p<0.001$

Table A.10

Days before Policy Cancellation and the COVID-19 Data Quality, Fixed-Effects GLS Regressions

	Cumulative Cases	**Daily New Cases**	**Cumulative Deaths**	**Daily New Deaths**
Days b/f Cancellation	0.002** (0.001)	-0.001** (0.000)	0.001 (0.001)	-0.002*** (0.001)
Polity2	-0.003 (0.015)	-0.005** (0.002)	0.025* (0.014)	-0.001 (0.004)
Population (log)	0.116 (0.170)	-0.006 (0.010)	-0.181 (0.118)	-0.097*** (0.027)
GDPpc (log)	-0.018 (0.065)	0.013 (0.008)	-0.084 (0.113)	-0.078*** (0.024)
Constant	-1.132 (3.111)	0.126 (0.198)	4.622** (2.312)	2.617*** (0.594)
N	4973	4973	4973	4973

Standard errors are in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$