Trust in Government and Lockdown Compliance in Sub-Saharan Africa

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Abstract

In the fight against COVID-19, Sub-Saharan Africa has performed much better (in terms of total cases and deaths) than the U.S. and Europe, where higher trust in national governments has been associated with greater initial compliance with coronavirus-related lockdowns. This investigation fills a gap in the literature by examining that same relationship but in Sub-Saharan Africa. Using an OLS methodology with country fixed effects, this study surprisingly finds that higher trust in government was associated with *lower* initial compliance with such lockdowns in the region, as measured by the percent change in human movement one week before vs. one week after each lockdown began. These findings are robust to different specifications. However, the countries and national subregions in this study's data are not necessarily representative of the entire region.

Keywords: COVID-19, Africa, political trust, compliance, shelter-in-place
JEL codes: E71, I12, H12, I18

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1 Introduction

The COVID-19 pandemic has greatly impacted life on every corner of the planet. As of this writing, there have been over 150 million cases of the virus—20 million of them active—and it has killed 3.1 million people, at a current rate of over 12,000 deaths per day (Worldometers). It has posed not only a tremendous public health burden on the world, but also an economic one: global GDP is estimated to have fallen by 4% in 2020 (Fitch).

Yet despite the region's history of deadly disease outbreaks, Sub-Saharan Africa has been relatively spared by the virus, a pleasant surprise for experts who predicted much worse. As of April 30, 2021, the region has reported 3.2 million cases and 82,000 deaths, both less than 3% of the global total (Worldometers). This is particularly impressive, considering that Sub-Saharan Africa is home to more than 1.1 billion people (14% of the world's population) but currently has case and death totals similar to those of Germany.

Still, there is room for concern. Despite the fact that over 32 million tests have been administered, case numbers in the region are likely underestimated (DW News). For example, Tanzania has not reported case numbers or deaths at all since April 2020, when President John Magufuli declared the country free of the virus (Dahir). Furthermore, the virus has already made life exceptionally difficult for the region's inhabitants—pregnant mothers have been unable to give birth at medical centers, students have been forced to continue their classes online despite many lacking in-home internet, and public health policies implemented in response to the virus have threatened the survival of countless people who are no longer able to earn income.

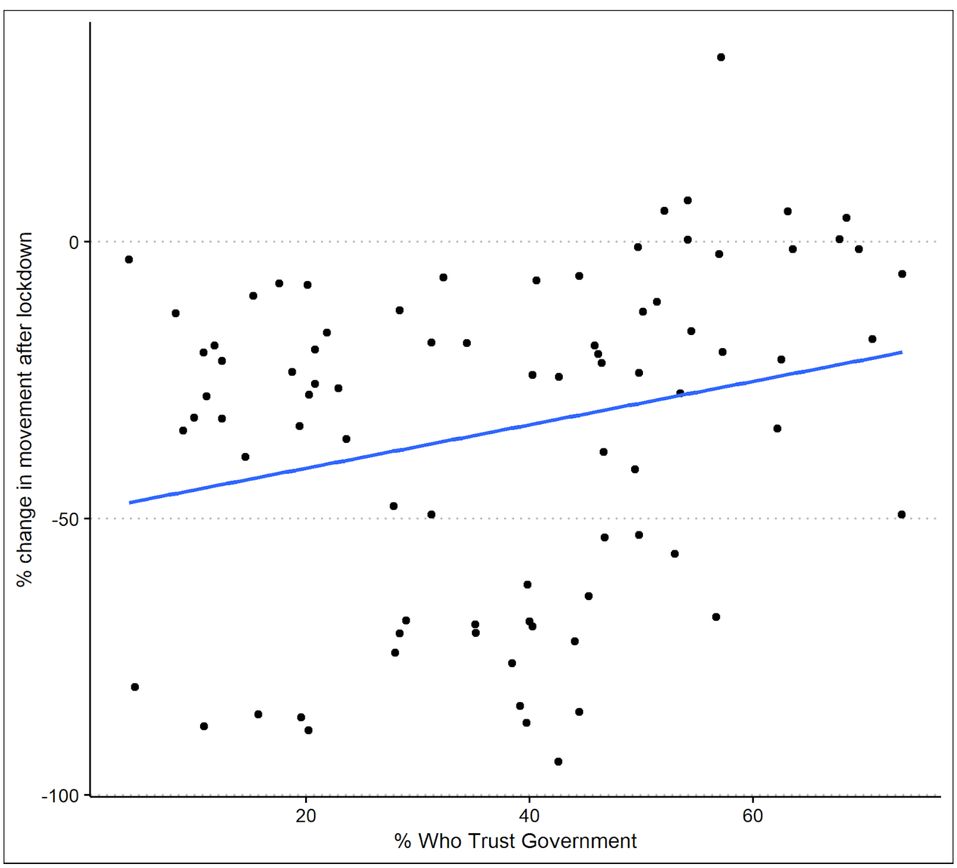
These policies have included border closures, mass testing, contact tracing, mandatory isolation for positive cases, and, most importantly, shelter-in-place orders. When cases of the virus began appearing in Africa in March of 2020, 26 of the region's 47 countries swiftly enacted such lockdowns, outlawing gatherings in public settings and workplaces (France 24). According to the WHO, compliance with lockdowns has been "quite good," and surveys have indicated that people in urban areas have understood the need for such measures, despite the difficulties they impose (France 24).

However, the region has not experienced perfect compliance—there has been immense variation in the extent to which populations wear masks, practice social distancing, and comply with lockdown orders, and many governments have resorted to brutal means of enforcement. For example, Nigerian security forces killed at least 18 civilians during the first month of enforcing lockdowns, sparking massive public protests against the government's COVID-19 measures and its heavy-handed enforcement of them (Mugabi). Similar incidences of police brutality have occurred in South Africa, Kenya, and Uganda. In fact, Ugandan authorities arrested opposition presidential candidate Bobi Wine before a campaign event under the pretext of protecting public health, despite allowing rallies for the ruling National Resistance Party to continue (Human Rights Watch). As these national governments continue using COVID-19 regulations as a justification for violating citizens' rights, public trust in them will continue to fall, further jeopardizing their abilities to effectively enact public policy.

African governments will continue to need maximum compliance with public health regulations as they battle the coronavirus, so understanding which factors impact compliance is essential to helping them better respond to disease outbreaks, both now and in the future. Therefore, this paper will attempt to answer: *Is greater trust in government associated with higher COVID-19 lockdown compliance in Sub-Saharan Africa?*

Since the pandemic is not over, we are unable to measure most of its full impacts on the region yet. We can, however, study the extent to which African citizens complied with the initial shelter-in-place orders, since in most countries, such events already happened in March or April of 2020. Compliance can be quantified in a number of ways, including the percent change in human movement in response to the lockdowns. This can be measured using the COVID-19 Community Mobility Reports created by Google, which track movement trends among those who have enabled Google to collect anonymous location data from their smartphones (Google). Such data therefore is limited to those who have smartphones, but is arguably more accurate than survey data or government statistics, both of which can overestimate compliance. In fact, as will be discussed in the next section of this paper, this Google location data is the primary method through which lockdown compliance has been measured in recent literature on the subject.

Figure 1: Trust in Government and Lockdown Compliance



As shown in Figure 1 above, there is immense variation in both trust in government (as measured by Afrobarometer survey responses) and lockdown compliance (as measured by Google movement data) in the region. Each dot represents a distinct national subregion, and it is clear that this data is heteroskedastic and contains outliers. The line of best fit has a *positive* slope, and this study argues that a greater reduction in movement signifies greater compliance. Therefore at face value, there appears to be a *negative* relationship between trust and lockdown compliance.

However, this study hypothesizes that the relationship between trust in the national government and lockdown compliance is actually positive after controlling for confounding factors. "Trust" is not defined in the Afrobarometer questionnaire, but it is likely positively correlated with one's perceptions of the legitimacy, competency, effectiveness, and general integrity of their government. Therefore, such positive perceptions of government likely are correlated with greater compliance with laws in general, including shelter-in-place orders. As discussed in Section 2, this hypothesis is thoroughly supported by existing literature. However, it is also possible that higher trust in government has the opposite effect: that if one has greater trust in their government, they may fear lockdown enforcement measures *less*, and thus are less likely to comply if they believe the consequences for non-compliance are not as high. Finally, it is of course entirely possible that there is no significant relationship between trust in government and lockdown compliance, after controlling for confounding factors.

This paper is structured as follows: Section 2 discusses the relevant literature for this topic. Section 3 describes the empirical model and dataset used to answer this study's question. Section 4 presents and discusses the main results and robustness checks. Section 5 concludes the paper, followed by References and Appendices.

2 Literature Review

A region's degree of trust in government is forged over time by countless factors, many of which have been identified in existing literature. With its complex history of colonialism, ethnic tension, and armed conflict, Sub-Saharan Africa has been of great interest to economists studying the determinants (and effects) of trust in government, and this section will discuss three such papers: "The Long-Term Effects of Africa's Slave Trades" by Nathan Nunn (2008); "The Legacy of Colonial Medicine in Central Africa" by Sara Lowes and Eduardo Montero (2018); and "Public Health and Public Trust: Survey Evidence from the Ebola Virus Disease Epidemic in Liberia" by Robert Blair, Benjamin Morse, and Lily Tsai (2017). It will also examine three recent papers which have explored the determinants of compliance with public health orders in other regions of the world: "Poverty and Economic Dislocation Reduce Compliance with COVID-19 Shelter-in-Place Protocols" by Austin Wright, Jesse Driscoll, Konstantin Sonin, and Jarnickae Wilson (2020); "Civic Capital and Social Distancing During the COVID-19 Pandemic" by John Barrios, Efraim Benmelech, Yael Hochberg, Paola Sapienza, and Luigi Zingales; and "Trust and Compliance to Public Health Policies in Times of COVID-19" by Olivier Bargain and Ulugbek Aminjonov (2020).

Nunn (2008) explores the impacts of Africa's slave trades on present-day economic performance by examining country-level variation in the number of slaves exported from 1400-1900. He finds that those countries that were more impacted by the slave trade have lower real GDP per capita today, likely due to slavery's negative impacts on ethnic division, community trust, and the development of political institutions (Nunn, 2008). This paper employs an OLS methodology and its results are confirmed by using each country's distance from sites of slave labor demand (spanning from the Americas to the Indian Ocean) as an instrument for slave exports. Therefore, Nunn (2008) is relevant here, as it establishes a likely determinant of each country's present-day level of trust in government: exposure to the slave trade. Additionally, it demonstrates how regional variation in trust, resulting from the slave trade, explains significant differences in present-day outcomes.

Lowes and Montero (2018) address a similar question that is of even greater relevance to this investigation: the effect of French colonial medical campaigns in the region on present-day trust in medicine. Their study looks at five former French colonies in Central Africa where, from 1921-1956, villagers were forcibly used as test subjects in deadly French research on "sleeping sickness" (trypanosomiasis). The authors use both historical data on French visits to villages for medical testing and present-day data on civilians' willingness to consent to free, non-invasive blood tests—a proxy for trust in medicine. They find that those who live near former sites of French medical campaigns have significantly lower trust in medicine, and that health-related World Bank projects have been less successful in these specific areas (Lowes and Montero, 2018). This provides evidence of intergenerational effects on trust that persist in the region today, especially regarding trust in medicine. Therefore, Lowes and Montero identify a channel that could explain present-day variation in compliance with public health measures, such as shelter-in-place orders.

Blair, More, and Tsai (2017) surveyed thousands of residents in Monrovia, Liberia to examine the relationship between trust in government and compliance with public health measures during the Ebola Virus Disease (EVD) epidemic in 2014-15, which caused over 11,000 deaths in West Africa. In a relatively weak state like Liberia, EVD control measures were seen as an unusual overreach of government authority, and rumors that the national government helped create and spread the disease were popular (Blair et al., 2017). They find that respondents with lower trust in the government were much less likely to have followed or supported such policies (like social distancing mandates), and that experiencing extreme hardship (like unemployment) due to the epidemic fueled such distrust even more. However, they find no correlation between trust and disinformation about the virus. Therefore, much like this analysis, Blair et al. use survey data to study the relationship between trust in government and compliance with disease-related public health guidelines in the region, and their findings support the hypothesis of a positive relationship between the two.

Wright, Driscoll, Sonin, and Wilson (2020) contribute to the emerging research on COVID-19 lockdowns by studying which factors have impacted lockdown compliance in the United States. The authors use cell phone location data from Google to measure changes in population movement (and thus compliance), and they exploit the staggered introduction of local coronavirus shelter-in-place orders in the U.S. to construct treatment and control groups in a difference-in-differences identification strategy. They find that there is lower compliance with shelter-in-place orders among lower-income households, even after controlling for a region's partisanship, population density, unemployment, exposure to recent trade disputes, and other factors (Wright et al., 2020). Although they examine the U.S. rather than Sub-Saharan Africa, their findings are nonetheless highly relevant to this investigation since they identify many factors that could explain lockdown compliance in Sub-Saharan African as well, which therefore should be controlled for in this investigation. Furthermore, their paper is among the first to use cell phone location data to measure COVID-19 lockdown compliance, so it therefore serves as a valuable model for this investigation.

Barrios, Benmelech, Hochberg, Sapienza, and Zingales (2021) study compliance with COVID-19 public health guidelines in the United States and Europe. Like Wright et al. (2020), they use cell phone location data to measure compliance, except they focus on compliance with social distancing orders rather than lockdowns, and they use “civic capital” (measured in a number of ways, including voter participation) as their independent variable of interest rather than trust in government. Their study is based on the premise that people are only likely to comply with such guidelines if they both care about public welfare and believe that their peers will also comply. Barrios et al. find that counties in the U.S. and regions in Europe with higher civic capital exhibited greater social distancing during early phases of COVD-19 and greater mask usage during later stages. Although higher civic capital does not necessarily mean higher trust in government, Barrios et al. (2021) is a valuable model for this investigation as they employ a similar approach: they use survey data to measure the effect of an intangible social factor on compliance with COVID-19 public health guidelines, which they measure using cell phone movement data.

Finally, perhaps the most relevant literature for this investigation is that of Bargain and Aminjonov (2020). Similar to Wright et al. (2020), they examine factors that explain lockdown compliance (measured by cell phone location data), but their research focuses on Europe rather than the U.S. and they focus on trust in government—measured by the European Social Survey—as their key explanatory variable. The authors find that regions (within countries) with higher trust in the national government decreased their mobility significantly more in response to lockdown orders than lower-trust regions (Bargain & Aminjonov, 2020). Furthermore, they find the effect of trust on compliance is non-linear and increases with the “stringency” of the government response, as classified by the Oxford Coronavirus Government Response Tracker (Bargain & Aminjonov, 2020). Their analysis serves as a model for this investigation for many reasons, including that it is at the sub-national level, it uses Google location data to measure compliance, and it controls for the stringency of a government's public health measures. The key difference between their analysis and this one is that they study Europe rather than Sub-Saharan Africa.

Upon examining the six most relevant studies, it is clear that colonialism has had lasting effects on trust in Sub-Saharan Africa, that cross-country variation in trust can explain significant cross-country differences in outcomes today, and that higher trust in government is associated with higher compliance with public health guidelines pertaining to disease outbreaks in the region. It is also clear that trust in government, as well as other factors, can explain variations in compliance with such regulations during the COVID-19 pandemic, at least in the United States and Europe. However, no published research has studied the relationship between trust in government and COVID-19 lockdown compliance in Sub-Saharan Africa, a region with history, culture, and institutions radically different from the United States and Europe.

3 Data and Methodology

3.1 Econometric Model

This analysis uses cross-sectional data, since it studies variation across entities—national subregions—at a single point in time: March and April 2020, when each subregion experienced its first COVID-19 lockdown. To estimate the effect of trust in government on lockdown compliance, this analysis will use an ordinary least squares (OLS) identification strategy. Since there is no unique "treatment" or intervention that a subset of observations experienced, the only other traditional econometric method applicable to this situation is two-stage least squares using an instrumental variable (IV) for trust in government, since trust in government is endogenous.

However, despite the existence of economic literature examining potentially exogenous determinants of—and therefore valid instruments for—trust, this paper will *not* use an IV approach, for multiple reasons: First, the datasets that such papers (those that have discovered potential instruments for trust in government in the region) have constructed and used are nearly impossible to find, and their data is rarely indexed at the subnational level. The second problem is the difficulty of finding an instrument that is a) credibly exogenous, b) only impacts lockdown compliance through trust in government, and c) has easily-attainable data at the sub-national level that would enable the testing of its relevance. Most importantly, neither Wright et al. (2020) nor Bargain & Aminjonov (2020) use instruments for trust in government when studying this relationship in other regions, and they argue—as this analysis does—that the most likely confounding factors can be actually controlled for.

Accordingly, using an OLS methodology with country fixed effects, this analysis will estimate the following relationship for each national subregion i in country j:

$$PctChange_{ij} = \alpha_j + \beta_1 Trust_{ij} + \beta_2 Democracy_{ij} + \beta_3 Stringency_{ij} + \beta_4 In(GDP)_{ij} + \beta_5 Informed_{ij} + \beta_6 Density_{ij} + \beta_7 Urban_{ij} + \beta_8 Cases_{ij} + \beta_9 Response_{ij} + e_{ij} \quad (1)$$

Table 1 below defines these variables and lists the hypothesized sign of their coefficients.

Table 1: Description of Variables

Name	Definition	Hyp. Sign	Source
PctChange	% change in movement in recreational and retail spaces, one week after vs. one week before the lockdown began (usually negative). See Appendix A for an in-depth description of how this was calculated.	N/A	Google Community Mobility Reports (movement data) OxCGRT* (lockdown dates)
Trust	% of respondents who said they trust the national government "Somewhat" or "A lot" (constructed as the average of trust in the president, parliament, and ruling party)	-	Afrobarometer round 7 survey
Democracy	Polity V index, ranging from -10 (strongly autocratic) to 10 (strongly democratic)	+	Center for Systemic Peace
Stringency	OxCGRT* Stringency Index (strictness of lockdown policies that restrict behaviors)	-	Our World in Data
ln(GDP)	Natural logarithm of the subregion's GDP, as estimated by nighttime luminosity data	-	National Oceanic and Atmospheric Administration
Informed	% of residents who access any source of mass communication "every day" (TV, radio, newspaper, internet, and/or social media)	-	Afrobarometer round 7 survey
Density	Population density (persons per km^2)	-	CityPopulation.de
Urban	% of population living in an urban area	-	Afrobarometer round 7 survey
Cases	Total number of confirmed COVID-19 cases in the country on the day the lockdown began	-	Our World in Data
Response	% of residents who say they can get medical care "Right away" or "After a short time"	+	Afrobarometer round 7 survey

*OxCGRT = Oxford Coronavirus Government Response Tracker

The regression model in equation (1) arguably accounts for potential omitted variable bias arising from the endogeneity of trust in government. Likely the strongest covariates with trust in government—democracy and GDP per capita—are included in the model, and the stringency of the lockdown and access to mass communication—both likely correlated with compliance—are as well. Education, proxied by the fraction of residents with college degrees, has surprisingly very little correlation with trust or compliance and its omission from the model has negligible impact on coefficient estimates, therefore it is excluded. Simultaneous causality is likely not an issue since trust in government was measured via surveys from 2016-2018 while lockdown compliance was observed in 2020. Finally, measurement error (from dishonest survey responses about trust in government) is likely not an issue either—respondents were informed their responses are anonymous and confidential, and accordingly, trust in government is neither correlated with fear of political intimidation nor beliefs that "laws must always be followed."

3.2 Summary Statistics

Table 2 below summarizes the variables used to estimate equation (1).

Table 2: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Median	Max
PctChange	82	-34.02	29.64	-93.94	-25.01	33.33
Trust	82	37.51	18.59	4.17	39.92	73.33
Democracy	82	7.28	2.28	-2.00	7.00	10.00
Stringency	82	81.63	6.11	65.28	82.87	93.52
ln(GDP)	82	-0.56	1.23	-1.92	-0.84	2.70
Informed	82	71.96	18.39	33.33	73.25	100.00

Density	82	648.08	1159.04	3.29	276.51	7010.97
Urban	82	50.57	31.92	0.00	48.12	100.00
Cases	82	138.23	204.86	4.00	97.00	709.00
Response	82	31.82	14.41	6.25	29.13	71.15

3.3 Geographical Sample

This analysis matched and merged five distinct datasets into one, and only 15 of Sub-Saharan Africa's 49 countries were represented in all five: Botswana, Burkina Faso, Cape Verde, Gabon, Ghana, Kenya, Mauritius, Namibia, Nigeria, Senegal, South Africa, Togo, Uganda, Zambia, and Zimbabwe. Furthermore, within those 15 countries, only 82 of their 192 first-level national subregions had usable movement data from Google and could therefore be used as observations. As shown in Table 3 below, this creates selection bias since the countries and subregions represented in this study's dataset statistically are more developed, more densely populated, and more urban than those that are absent.

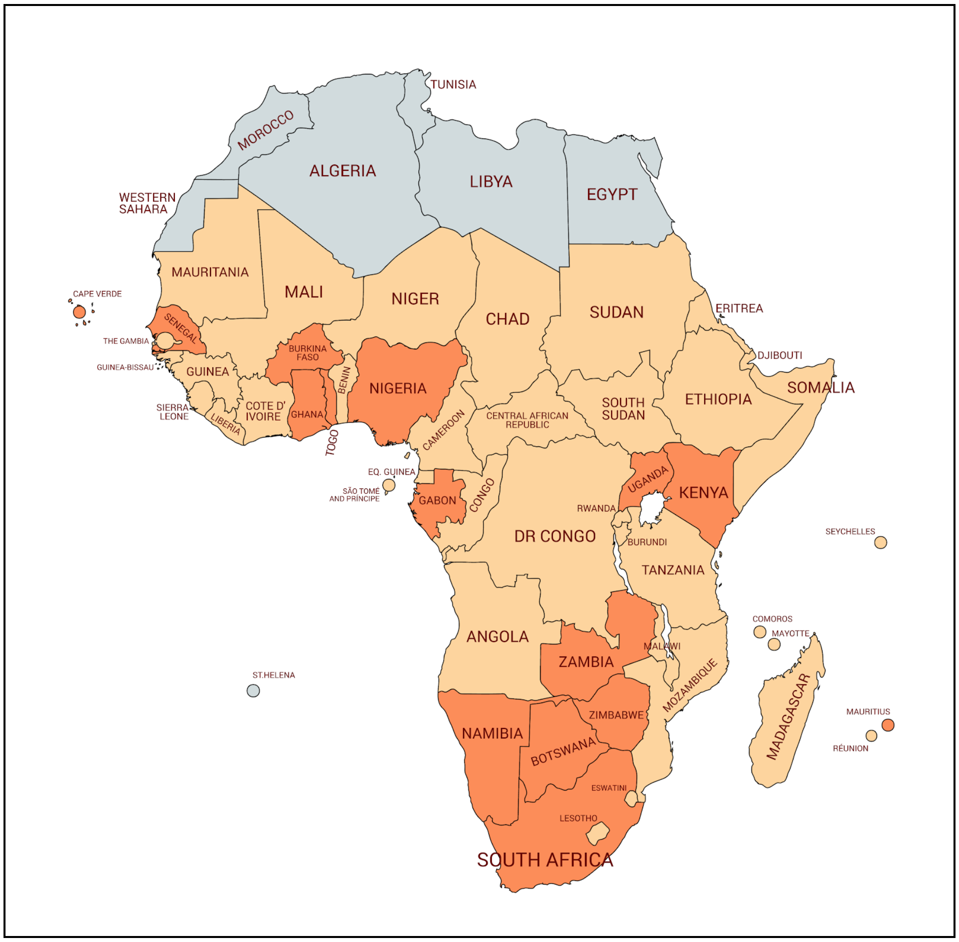
Table 3: Comparing Sample to the Entire Region

Variable	Sub-Saharan Africa	Sample Countries	Sample Subregions
Population	1,107,000,000	484,152,374	342,918,231
HDI	0.50	0.56	0.57
Life expectancy	61.27	60.27	59.07
Median age	19.00	19.66	20.02
Density (people / km^2)	50.76	152.26	637.34
Urban population %	40.71	46.50	48.75

Sources: World Bank, African Development Bank, CityPopulation.de, Our World in Data

Figure 2 below illustrates the geographic distribution of the countries in this study's data, with sample countries in dark orange and the rest of Sub-Saharan Africa in bright orange.

Figure 2: Countries Included in the Sample

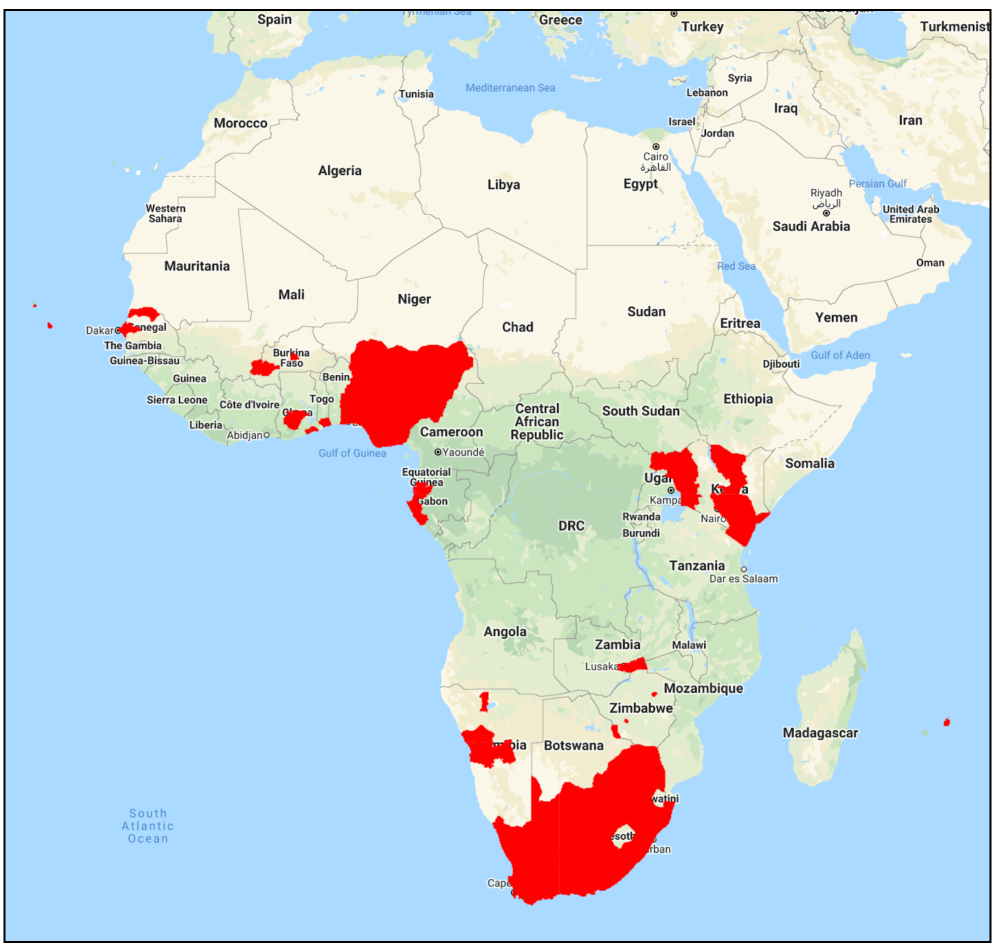


This map reveals a number of interesting patterns: first, most of southern Africa is included. These five countries all border each other, which may be no coincidence as they are all former colonies of—or have been indirectly controlled by—Britain. The same is true for the two in East Africa: Uganda and Kenya. Along the Gulf of Guinea, Gabon, Ghana, Togo, and Nigeria are included, the last of which is by far the most well-represented and populous country in the dataset (Nigeria comprises 37 of the 82 national subregions). Finally, Burkina Faso and Senegal in West Africa are included, as are the island nations of Cape Verde and Mauritius.

Perhaps more relevant, though, is which countries are *not* included in the sample. There are noticeable gaps along the coast in West and East Africa. More importantly, Central Africa—aside from Gabon—and the Sahel region straddling the Sahara Desert—aside from Burkina Faso—are not represented in this dataset at all. This makes a considerable difference as Central Africa and the Sahel are among the poorest and most sparsely-populated regions on the continent. Their omission may explain why the sample countries are more developed and densely populated than Sub-Saharan Africa as a whole.

Figure 3 displays the national subregions represented in this study's dataset in red.

Figure 3: Subregions Included in the Sample



The selection bias that occurs at the country level is further compounded at the national subregion level: as shown in Table 3, the 82 subregions with usable movement data are also more developed, more urban, and more densely-populated than the 15 countries as whole. Furthermore, as shown in the map above, in-country representation varies wildly: some countries (like Nigeria and South Africa) have every first-level national subregion represented in the dataset, while some (like Kenya and Uganda) only have about half included, and others (like Zimbabwe and Botswana) are limited to only a few select cities.

Therefore, the following question arises: are the countries and subregions included in this study's dataset representative of Sub-Saharan Africa as whole? This question has no simple answer. Ultimately, whether or not an area is included in this dataset was determined by whether or not both Afrobarometer *and* Google were able to collect data there. This explains the clear bias towards countries and subregions that are more developed and urban, both factors which are likely correlated with lockdown compliance. Additionally, there are key geographical patterns in the countries represented: they tend to be clustered together rather than being randomly spread out across the continent, and more than half were former British colonies.

Nonetheless, these 15 countries represent nearly half (44%) of Sub-Saharan Africa's population. The 82 subregions represent 71% of those countries' populations and encompass immense variation in geography, history, and culture. Therefore, while selection bias may limit this study's findings to *local* effects for the more developed, urban, and densely- populated areas sampled, this analysis can still provide useful insight on the relationship between trust in government and lockdown compliance in Sub-Saharan Africa.

3.4 Afrobarometer Survey Data

Data for many of this study's key variables (including trust in government) comes from surveys conducted by Afrobarometer, a non-partisan research institution that regularly collects high-quality data on what Africans think about their governments, economies, and societies. Specifically, this study uses data from the most recently-completed round of surveys (round 7), which began in 2016 and ended in 2018 (see Appendix B for the specific year each country was surveyed). This means that for every country in the sample, public opinion on trust in government was collected multiple years before lockdown compliance was measured in 2020, which begs the question: does the trust data used in this analysis accurately reflect what Africans thought of their governments when the lockdowns began?

Fortunately, almost none of these countries experienced a major government change (i.e. any change in the party of the president and/or the ruling party in parliament) between the survey data collection and the onset of COVID-19. For example, some countries (like Kenya) had national elections during that period but the incumbent president and party retained their seats, while others (like Burkina Faso) had no national elections at all. Therefore the survey data likely still represents what African citizens thought of their national governments on the eve of the lockdowns. In fact, the only country that experienced a noteworthy government change during this period is Zimbabwe: the surveys took place there in early 2017, but a coup d'état deposed longtime president Robert Mugabe (and replaced him with Emmerson Mnangagwa) later that year in November. However, it is reasonable to assume Zimbabweans' opinions of their national government have not radically shifted since the survey, since Mugabe's ZANU-PF party and Mnangagwa (also of the ZANU-PF party) have remained in power ever since the coup.

3.5 Estimation of Regional GDP

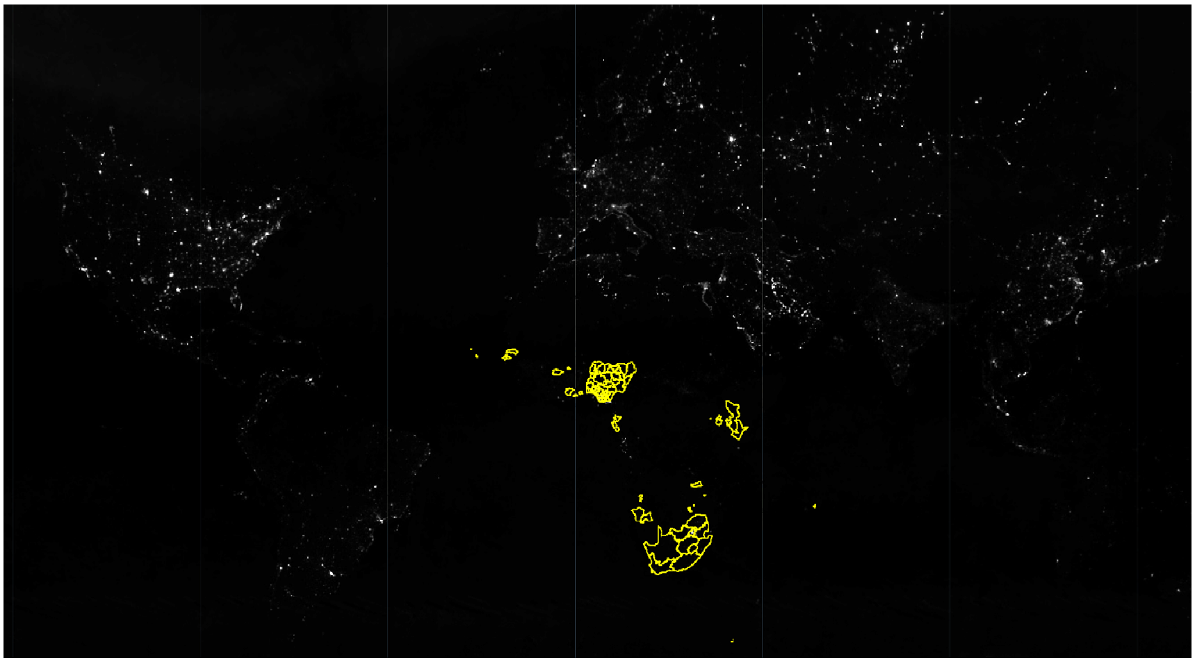
It is essential to control for each region's level of wealth in this analysis, as Wright et al. (2020) found lower-income households complied less with COVID-19 lockdowns. However, this study's units of observation are national subregions, and reliable GDP data cannot be found at the subnational level for countries in Sub-Saharan Africa.

Fortunately, existing literature has shown that nighttime light intensity can be used to estimate regional GDP, since it is a useful proxy for economic activity. After all, consumption, commerce, production, and infrastructure usage at night generally require light, which can be detected by the U.S. Air Force's weather satellites as they circle the planet 14 times a day (Hodler and Raschky, 2014). Accordingly, Henderson, Storeygard, and Weil (2012) find a strong correlation between national GDP growth rates and changes in nighttime light intensity. Hodler and Raschky (2014) build upon those findings by using nighttime light intensity to estimate GDP at the subnational level. Compared to other means of estimating subnational GDP, this method uses unbiased data which can be found for every region of the world (at roughly equal quality) and for every day since 1992.

To construct estimates of subnational GDP, this study employs a methodology similar to that of Hodler and Raschky: the average light intensity (on a scale from 0 to 63) of the pixels within each national subregion's borders is calculated, averaged across every night from January 1st, 2019 to December 31st, 2019. Then, following the protocol of Henderson et al. and Hodler and Raschky, this "average luminosity" for each national subregion is log-transformed. Although this study uses the natural logarithm of estimated GDP as a control rather than the natural logarithm of estimated GDP *per capita*, the latter is used instead of the former as a robustness check in Table 5 of Section 4 and it has very little difference on the overall results.

Figure 4 below is a satellite imaging of the world at night provided by the National Oceanic and Atmospheric Administration (NOAA), and the yellow borders represent the national subregions found in this study's dataset.

Figure 4: Global Nighttime Light Projection



3.6 Code and Data

This study used R and Google Earth Engine to compile, clean, merge, and analyze various sources of data. All of the R scripts, Google Earth Engine scripts, and external datasets used to build this analysis can be find on this public GitHub repository:

https://github.com/charlesmcmurry/McMurry-2021

4 Results and Discussion

4.1 Main Results

Table 4: Main Regression Results

	Dependent variable:		
	Percent Change in Movement		
	OLS		*panel linear*
	(1)	(2)	(3)
Trust government	0.393**	0.103	0.290**
	(0.173)	(0.133)	(0.114)
Democracy		0.981	0.939
		(1.182)	(2.129)
Stringency		0.648	-0.917***
		(0.454)	(0.185)
ln(GDP)		-11.014***	-4.529**
		(2.673)	(2.095)
Informed		-0.628***	-0.133
		(0.167)	(0.167)
Density		0.004	0.001
		(0.003)	(0.002)
Urban		0.124	-0.011
		(0.091)	(0.082)
Cases		-0.054***	1.057***
		(0.014)	(0.362)
Response		-0.278	-0.038
		(0.194)	(0.144)
Constant	-48.757***	-51.440	
	(7.225)	(42.294)	
Country fixed effects	No	No	Yes
Clustered SEs	No	No	Yes
Observations	82	82	82
R^2	0.061	0.610	0.855
Adjusted R^2	0.049	0.562	0.807
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 4 above contains the main regression results of this study. As shown in column 1, the basic relationship between trust in government and change in movement is positive before adding any controls. The coefficient of 0.393 means that a one percentage-point increase in the fraction of a region's population that trusts the national government "somewhat" or "a lot" was associated with a 0.393 percentage-point *increase* in the percent change in movement after a lockdown began. After adding controls in column 2, the coefficient remains positive at 0.103.

However, to properly estimate equation (1), it is essential to include country-level fixed effects and cluster standard errors at the country level to control for unobservable characteristics that vary by country. As shown in column 3, doing so has an immense impact: the coefficient for trust in government becomes significant at the 5% level and increases to 0.290, meaning a one percentage-point increase in trust in government was associated with a 0.290 percentage-point *increase* in the percent change in movement. In other words, higher trust was associated with *lower* compliance, which is the opposite of what this analysis expected. Higher population density and more confirmed COVID-19 cases were surprisingly associated with less compliance too. However, the signs on all the other variables are as expected, while stringency, GDP, and confirmed COVID-19 cases are the only statistically-significant controls in this specification.

4.2 Robustness Checks

Nonetheless, it is possible that the results in Table 4 are highly sensitive to *how* the relationship between trust in government and lockdown compliance is defined, as well as how the data is treated. Therefore, numerous robustness checks are conducted to test if these findings hold for different specifications. Table 5 below contains the results of these robustness checks, with column 1 displaying the results of column 3 in Table 4 for comparison.

Table 5: Robustness Checks

	Dependent variable:											
	Percent Change in Movement											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trust government	0.290**	0.345**				0.186	0.240	0.247**	0.308**	-0.477	0.308**	0.320**
	(0.114)	(0.131)				(0.215)	(0.151)	(0.123)	(0.121)	(0.370)	(0.131)	(0.134)
Trust president			0.212**									
			(0.086)									
Trust parliament				0.295*								
				(0.148)								
Trust ruling party					0.261**							
					(0.105)							
Trust × Nigeria						0.144						
						(0.252)						
Trust × Populous							0.061					
							(0.120)					
Trust × Bantu %								0.320				
								(0.337)				
ln(GDP p/c)									-1.803			
									(2.030)			
Democracy	0.939	1.120	1.132	1.116	0.979	1.006	1.400	0.825	0.145	-3.514	2.448	3.105
	(2.129)	(2.290)	(2.121)	(2.172)	(2.132)	(2.144)	(2.323)	(2.134)	(2.170)	(7.683)	(2.441)	(2.494)
Stringency	-0.917***	-0.959***	-0.875***	-0.898***	-0.890***	-0.869***	-0.926***	-1.045***	-1.155***	-1.076*	-0.941***	-0.860***
	(0.185)	(0.197)	(0.178)	(0.195)	(0.181)	(0.204)	(0.187)	(0.228)	(0.337)	(0.587)	(0.212)	(0.216)
ln(GDP)	-4.529**	-3.950*	-4.787**	-4.868**	-4.360**	-4.319**	-4.660**	-4.685**		-3.183	-3.999	-2.204
	(2.095)	(2.297)	(2.082)	(2.122)	(2.117)	(2.138)	(2.123)	(2.103)		(6.592)	(2.402)	(2.444)
Informed	-0.133	-0.053	-0.155	-0.179	-0.140	-0.105	-0.114	-0.165	-0.126	0.688	-0.127	-0.119
	(0.167)	(0.189)	(0.164)	(0.168)	(0.166)	(0.174)	(0.172)	(0.170)	(0.172)	(0.518)	(0.191)	(0.195)
Density	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	-0.001	0.003	-0.00003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.003)
Urban	-0.011	-0.060	-0.020	-0.017	-0.007	-0.020	-0.010	-0.009	-0.027	-0.345	-0.035	-0.080
	(0.082)	(0.107)	(0.082)	(0.084)	(0.083)	(0.084)	(0.083)	(0.082)	(0.084)	(0.258)	(0.094)	(0.096)
Cases	1.057***	1.015**	1.064***	1.137***	1.019***	1.083***	1.021***	0.982**	0.927**	1.102	0.925**	0.719*
	(0.362)	(0.383)	(0.362)	(0.366)	(0.365)	(0.366)	(0.371)	(0.370)	(0.446)	(1.148)	(0.415)	(0.424)
Response	-0.038	-0.040	-0.041	-0.039	-0.002	-0.054	-0.021	-0.023	-0.016	1.379***	-0.065	-0.078
	(0.144)	(0.168)	(0.144)	(0.148)	(0.141)	(0.147)	(0.148)	(0.145)	(0.147)	(0.469)	(0.165)	(0.167)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Excludes Mauritius	No	Yes	No	No	No	No	No	No	No	No	No	No
Timeframe	1 week	1 week	1 week	1 week	1 week	1 week	1 week	1 week	1 week	1 day	2 weeks	1 month
Observations	82	73	82	82	82	82	82	82	82	78	82	83
R^2	0.855	0.771	0.854	0.849	0.854	0.856	0.856	0.857	0.846	0.627	0.786	0.755
Adjusted R^2	0.807	0.689	0.806	0.800	0.806	0.805	0.805	0.807	0.795	0.496	0.716	0.676

Note: *p<0.1; **p<0.05; ***p<0.01

Nigeria = 1 for subregions in Nigeria. Populous = 1 for the top 50% most populous subregions in the dataset.

Column 2 shows the effects of removing the subregions in Mauritius from this analysis. With by far the largest per capita GDP among the 15 countries, Mauritius is an outlier. However, excluding it from the model has very little effect: the coefficient on trust increases slightly but retains its significance, and the signs and significance of all other variables are unchanged.

Columns 3–5 test if measuring trust in specific entities of the national government (the president, parliament, and ruling political party) rather than averaging them all together makes a difference. The results show it does not: all three methods of measuring a subregion's trust in the national government have positive and significant signs, ranging in magnitude from 0.212 to 0.295. The rest of the coefficients retain their signs and significance, illustrating that *how* trust in government is measured does not meaningfully impact this study's findings. This makes sense because levels of trust in all of these entities are positively correlated with each other, as well as with the original trust in government variable (which is simply the average of the three).

Column 6 includes an interaction term which multiplies trust in government by a dummy for if a subregion is in Nigeria (whose subregions comprise 44% of the sample and nearly 60% of its total population). This interaction term is not significant, meaning trust in government has no meaningfully differential impact on compliance in Nigeria compared to the other 15 countries in the sample. Interestingly however, the coefficient on trust in government noticeably declines and loses all of its significance after including this interaction term, meaning the findings of this study are largely driven by Nigeria.

Column 7 checks if the relationship of interest varies between larger and smaller national subregions by interacting trust in government with a dummy for if a subregion is among the top 41 (out 82) subregions by population. This interaction term's coefficient is not significant either, meaning the effect of trust in government on lockdown compliance does not meaningfully differ between more vs. less populous subregions. However, including this interaction term eliminates the significance of trust in government as well.

Column 8 tests if the relationship between trust in government and lockdown compliance varies by ethnolinguistic group. Sub-Saharan Africa is perhaps the most ethno-linguistically diverse region of the world, with thousands of native languages spoken. These languages can be grouped into several major language families, and the Bantu peoples in Central, Eastern, and Southern Africa form one such family. Since Bantu peoples are the majority ethnolinguistic group for much of the countries and subregions in this study's sample, trust in government is interacted with the percentage of each region's population that speaks a Bantu language (based on Afrobarometer survey responses) to test if the relationship of interest varies along broad cultural lines. Column 8 shows that there is no significant differential effect in this regard.

Column 9 uses the natural logarithm of each subregion's estimated GDP *per capita* as a control variable rather than the natural logarithm of estimated GDP. As previously mentioned, this has practically no impact on the results. However, although both have negative signs, it is worth noting that unlike the latter, the former has no statistical significance as a control.

Column 11 demonstrates how using a two-week (i.e., comparing movement two weeks before vs. two weeks after each lockdown began) rather than a one-week timeframe makes very little difference: it increases the magnitude of the coefficient of interest slightly, but it changes neither the sign nor significance of the other coefficients. The same can be said when using a one-month timeframe in column 12. However, column 10 shows the immense impact using only a one-day timeframe has on the results: the coefficient on trust in government becomes negative and loses its significance. Additionally, the coefficients on democracy score and medical response time flip signs, and the latter becomes highly significant at the 1% level.

4.3 Interpretation and Discussion of Results

Column 3 in Table 4 (which is also column 1 in Table 5) should be interpreted as the primary findings of this investigation, because by including controls, country fixed effects, and clustered standard errors, it estimates the relationship in equation (1) exactly as intended. Every robustness check (except those in columns 6, 7, and 10 of Table 5) support that specification's findings: the coefficient on trust in government is consistently positive and significant at the 5% level, ranging from 0.212 to 0.345. This means a one-percentage point increase in the fraction of a subregion that trusts the national government was associated with a 0.212–0.345 percentage-point increase in the percent change in movement after a lockdown began. However, since nearly every subregion actually experienced a decline in movement after its lockdown, this marginal effect can also be thought of as a decrease in the percent change in movement that is 0.212–0.345 percentage points *smaller* than the average total decrease.

Since compliance was lower in areas that trusted their national governments more, these findings are contradictory to the relationship hypothesized. This may be evidence that higher trust in government results in less compliance with shelter-in-place orders because fewer citizens fear government enforcement of them. Nonetheless, this effect is still fairly small in magnitude—a *ten* percentage-point increase in a region's trust in government is quite large, yet according to this study's findings, that would only increase the percent change in movement by 2.12–3.45 percentage points, and there is little meaningful difference between a 50% reduction in movement and a 46.55%–47.88% reduction.

As hypothesized, the coefficient on stringency is always negative and significant, ranging from -0.860 to -1.155. This means a one-unit increase in the OxCGRT Stringency Index for a country (out of 100) was associated with a 0.860–1.155 percentage-point decrease in the percent change in movement. This intuitively makes sense, as the Stringency Index measures the extent to which each country's lockdown limited movement and interaction, so higher values likely mean that the national government was perceived as taking COVID-19 more seriously. This logically would result in greater compliance with related public health regulations.

The coefficient on the number of confirmed cases is always significant and positive, ranging from 0.719 to 1.137. This means each additional confirmed case of COVID-19 a country had on the day its lockdown began was associated with a 0.719–1.137 percentage-point increase in the percent change in movement. This study initially predicted the opposite, assuming people would be more likely to comply with lockdowns if the scale and threat of COVID-19 in their country was greater. The consistently positive coefficient on this variable is particularly puzzling because confirmed cases is positively correlated with the stringency index, which makes sense since most governments would impose stricter measures if the presence of COVID-19 were greater. However, as previously discussed, the stringency of the government response had the opposite relationship with compliance.

In every specification except columns 10–12 of table 5, the coefficient on the natural logarithm of estimated regional GDP is negative and significant at the 5% level. This means greater wealth was associated with greater lockdown compliance, which is in line with existing literature (Wright et al., 2020). This also makes intuitive sense, since inhabitants of poorer regions are less able to comply with stay-at-home orders—doing so could mean forgoing basic food and supplies necessary to survive. The coefficients on ln(GDP) in columns 1–8 range from -3.950 to -4.868, meaning a one percent increase in regional GDP was associated with a 3.950–4.868 percentage-point *decrease* in the percent change in movement.

The question remains: why did using a one-day timeframe alter the results so much, and how should this be interpreted? One possibility is that this specification (found in column 10 of Table 5) actually estimated the *true* desired effect of this study, since one could argue that using a one-day (rather than a one- or two-week) timeframe better isolates the change in human movement that can be directly attributable to the imposition of a lockdown. However, this specification's findings should be largely disregarded since, by not aggregating across seven-day periods, the calculated changes in movement from each lockdown are misleadingly dramatic—they are at least in-part driven by natural fluctuations in human movement by day of the week. This explains why the data is incredibly noisy when using a one-day timeframe compared to one week, two weeks, or a month.

Finally, it is important to restate a primary limitation of this study's findings: selection bias. As previously mentioned, due to data limitations, the countries and subregions represented in this study's dataset are more developed, densely-populated, and urbanized on average than those of Sub-Saharan Africa as a whole. Therefore, this study's findings can only necessarily be applied to such areas.

5 Conclusion

Although Sub-Saharan Africa has performed relatively well to date in the fight against COVID-19, the effectiveness of countries' efforts to contain the spread of the virus varies greatly. A review of the literature reveals that colonialism has had long-term effects on trust in political institutions and medicine in the region, which can explain present-day disparities in outcomes. The literature also provides evidence that many social and economic factors—including trust in government—have impacted compliance with public health guidelines during disease outbreaks in the region, as well as in the United States and Europe. This investigation adds to the literature by examining the relationship between trust in the national government and initial compliance with COVID-19 lockdowns in Sub-Saharan Africa.

This study's findings indicate that a one-percentage point increase in the fraction of a subregion that trusts the national government was associated with a 0.212–0.345 percentage-point increase in the percent change in movement after a lockdown, indicating higher trust was associated with *less* compliance with lockdowns in the region. Additionally, each subregion's GDP and the stringency of the country's lockdown measures were associated with higher compliance, while the number of confirmed cases in each country on the day its lockdown began was associated with lower compliance. These findings are robust to nearly every specification used. However, these results are somewhat driven by the outsized representation of Nigeria in the dataset and they may lack external validity, since the 15 countries and 82 national subregions represented in this study's dataset are more developed, densely-populated, and urbanized than Sub-Saharan Africa as a whole.

Further research on COVID-19 in the region could use empirical data on mask usage and social distancing as alternative ways of measuring compliance with public health regulations.

Additionally, the methodology of this study could be applied to study the effect of trust in government on lockdown compliance in other developing regions of the world, such as Latin America and South Asia. Finally, once more recent survey data is available, it might be useful for research to measure the reverse effect: how the efficacy of a country's COVID-19 response has impacted how much its citizens trust the national government.

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Appendix A: Change in Movement Calculation

For each subregion i of country j, we want to compare the average level of movement before and after the imposition of its lockdown. Specifically, we want to calculate the percentage change in movement resulting from the lockdown. Therefore, we want to calculate Y_{ij} for each subregion:

$$Y_{ij} = \frac{M_2 - M_1}{M_1}$$

where M_1 is the average amount of human movement in the week *before* the lockdown, and M_2 is the average amount of human movement in the week *after* the lockdown. However, Google Community Mobility Reports do not directly provide M_1 or M_2. Instead, they provide us with the values of A and B:

$$A = 100\left(\frac{M_1 - M_0}{M_0}\right)$$

$$B = 100\left(\frac{M_2 - M_0}{M_0}\right)$$

where M_0 is some "baseline" level of movement according to Google, based on movement trends in January and February 2020. In other words, for each subregion, the amount of "movement" during that period is expressed as the percent difference (multiplied by 100) between the amount of movement during that period and a baseline period in early 2020. Therefore, if a subregion has a value of A = 2, that means that in the week before the lockdown, the average amount of human movement was 2% higher than that of the baseline period.

Since we do not know M_0, M_1, or M_2, we must calculate Y_{ij} using the given values of A and B. Luckily, this problem can be solved algebraically, as shown in Proof 1A and 1B on the following pages. We ultimately find that our outcome variable of interest Y_{ij} should be calculated as:

$$Y_{ij} = \frac{B - A}{100 + A}$$

Proof 1A

To begin, we know that:

$$
\begin{aligned}
B - A &= 100\left(\frac{M_2 - M_0}{M_0}\right) - 100\left(\frac{M_1 - M_0}{M_0}\right) \\
&= 100\left(\frac{M_2 - M_1}{M_0}\right)
\end{aligned}
$$

Rearranging the relationship above, we get our desired quantity Y_{ij}:

$$
\begin{aligned}
\frac{B - A}{100} &= \frac{M_2 - M_1}{M_0} \\
\left(\frac{B - A}{100}\right)\left(\frac{M_0}{M_1}\right) &= \left(\frac{M_2 - M_1}{M_0}\right)\left(\frac{M_0}{M_1}\right) \\
&= \left(\frac{M_2 - M_1}{M_1}\right) \\
&= Y_{ij}
\end{aligned}
$$

Based on proof 1B (below), we know that:

$$
\frac{M_0}{M_1} = \frac{100}{100 + A}
$$

We can use this to express Y_{ij} using the known quantities A and B:

$$
\begin{aligned}
Y_{ij} &= \left(\frac{B - A}{100}\right)\left(\frac{M_0}{M_1}\right) \\
&= \left(\frac{B - A}{100}\right)\left(\frac{100}{100 + A}\right) \\
&= \frac{\mathrm{B} - \mathrm{A}}{100 + \mathrm{A}}
\end{aligned}
$$

Proof 1B

Our goal in this proof is to be able to express (M_0 / M_1) as a function of A and B. To begin, we rearrange the formula for A:

$$A = 100\left(\frac{M_1 - M_0}{M_0}\right)$$

$$\frac{A \cdot M_0}{100} = M_1 - M_0$$

$$-\frac{A \cdot M_0}{100} = M_0 - M_1$$

$$M_1 - \frac{A \cdot M_0}{100} = M_0$$

$$\left(M_1 - \frac{A \cdot M_0}{100}\right)\left(\frac{1}{M_1}\right) = M_0\left(\frac{1}{M_1}\right)$$

$$1 - \left(\frac{A}{100}\right)\left(\frac{M_0}{M_1}\right) = \frac{M_0}{M_1}$$

We can then express (M_0 / M_1) as a function of A and B by rearranging that relationship:

$$1 = \frac{M_0}{M_1} + \left(\frac{A}{100}\right)\left(\frac{M_0}{M_1}\right)$$

$$= \frac{100M_0}{100M_1} + \frac{A \cdot M_0}{100M_1}$$

$$= \frac{100M_0 + A \cdot M_0}{100M_1}$$

$$= \frac{M_0(100 + A)}{100M_1}$$

$$= \left(\frac{M_0}{M_1}\right)\left(\frac{100 + A}{100}\right)$$

Therefore:

$$\frac{M_0}{M_1} = 1 \div \left(\frac{100 + A}{100}\right)$$

$$= \frac{100}{100 + A}$$

Appendix B: Afrobarometer Survey Dates

Table 6: Afrobarometer Round 7 Survey Dates

Country	Year
Botswana	2017
Burkina Faso	2017
Cape Verde	2017
Gabon	2017
Ghana	2017
Kenya	2016
Mauritius	2017
Namibia	2017
Nigeria	2017
Senegal	2017
South Africa	2018
Togo	2017
Uganda	2017
Zambia	2017
Zimbabwe	2017

Source: Afrobarometer