

The Importance of Cultural Tightness and Government Efficiency For Understanding COVID-19
Growth and Death Rates

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We have no known conflict of interest to disclose.

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Abstract

The spread of COVID-19 represents a global public health crisis, yet some nations were more effective than others at limiting the spread of the virus during the early stages of the pandemic. Here we show that institutional and cultural factors combine to partly explain these cross-cultural differences. Nations with tight cultures and efficient governments were the most effective at limiting COVID-19's growth and mortality rates as of early April, and this interaction of cultural tightness and government efficiency is robust to controlling for underreporting of cases, economic development, inequality, median age, population density, climatological variation, and other dimensions of cross-cultural variation (collectivism, power distance, relational mobility). A formal evolutionary model explores the mechanism that may underlie our findings, suggesting that these cross-cultural trends may be associated with group variation in cooperation under conditions of high threat. These analyses shed light on why some nations contained COVID-19 more effectively than others.

Keywords: culture; COVID-19; governance; health; pandemic

Significance Statement: Certain countries have had far more success than others in slowing the growth and mortality rates of COVID-19. Here we show that nations with tight norms and efficient governments were the most successful in dealing with COVID-19 in its early stages. By integrating research in cross-cultural psychology on social norms with government institutions, we can begin to understand variation in how societies respond to collective threat.

The Importance of Cultural Tightness and Government Efficiency For Understanding
COVID-19 Growth and Death Rates

The COVID-19 pandemic represents a global health crisis. In early 2020, the virus quickly spread from its epicenter in Wuhan, China, across the planet. By April 5th 2020, COVID-19 had infected over 1,000,000 people and killed over 60,000 people worldwide. There had been over 300,000 cases and 8,000 deaths in the United States alone, and both figures were growing by the day. Yet certain countries and regions had far more success than others in slowing the growth rate of COVID-19 cases in the early days of infection. For instance, Singapore and Taiwan each were able to effectively contain the virus, whereas Italy, Spain, and the U.S. experienced more pronounced growth in COVID-19 cases. The factors that explain cross-cultural variation in growth rates is of great interest to scientists, policy-makers, journalists, and lay people alike.

Here we present data on how culture and societal institutions interacted to account for cross-cultural variation in the containment of COVID-19 in its early stages. Our analyses are based on the premise that this pandemic is a global threat that requires rapid cooperation and coordination to address. On this basis, we propose that cultural and institutional factors that help nations swiftly distribute resources from the public and private sectors and mobilize the public to adopt cooperative norms should be linked to which nations best handled the virus. Institutionally, nations with efficient governments that are able to quickly allocate resources and coordinate between the public and private sectors may have been able to slow the trajectory of the virus compared with nations with less efficient governments. Government efficiency, however, may have been more effective in *culturally tight nations*—those with strong norms and little tolerance for deviance (Gelfand et al., 2011)—since people in tight cultures may be better prepared to

adhere to cooperative norms (e.g. social distancing, effective handwashing) that contain the virus (Roos et al., 2015). Research in cross-cultural psychology has indeed shown that tight nations tend to have a history of chronic threat—whether from invasions, disasters, or pathogens—and that strict rules can help groups to coordinate to survive in such circumstances (Gelfand et al., 2011; Roos et al., 2015). Accordingly, nations with tight norms and efficient governments could combine swift institutional action with high adherence to new social guidelines for an especially effective response to the pandemic.

Building on this theoretical foundation, we hypothesize that cultural tightness and government efficiency should interact to account for variation in the growth and mortality rates of COVID-19 up to early April, such that nations with both high cultural tightness and high governmental efficiency may have responded most effectively to the COVID-19 pandemic, and significantly better than nations that possess only one (or neither) of these characteristics. Put differently, tight adherence to norms may only be effective when institutions are able to rapidly allocate resources to coordinate between the public and private sectors (e.g. closing down non-essential business to avoid large crowds), and efficient institutional action may only successfully contain the virus when people will adhere to newly introduced cooperative norms that help stop the spread of the disease (e.g. social distancing). We suggest that this interactive dynamic should be robust to other potential covariates, such as potential underreporting of COVID-19 cases, economic development, inequality, median age, population density, and other dimensions of cross-cultural variation such as individualism-collectivism and power distance as well as climate. To our knowledge, this is one of the first studies to examine how research in cross-cultural psychology on social norms can be fruitfully integrated with data on government institutions to understand how societies respond to collective threat.

We test this account with two converging analyses. Our primary analysis uses data on confirmed cases and deaths from COVID-19 around the world to examine how governmental efficiency and cultural tightness together can account for variation in the growth and mortality rates of COVID-19 above and beyond economic and demographic differences between countries. We retrieved these data on April 4th, 2020. Given this time-frame, we emphasize that this analysis is intended to analyze the early stages of the COVID-19 pandemic. Moreover, while our analysis controls for potential confounds, it is still an approximation of how nations have responded to COVID-19, since documented cases and mortalities can be an imprecise measure of actual cases and deaths. For this reason, we urge readers to view our findings with caution.

To complement these correlational data, we also developed a formal evolutionary game-theory simulation of how individuals respond to existential threats such as COVID-19. Since population-level behavioral change and cultural transmission patterns cannot be easily observed, evolutionary game theory models are useful tools for simulating human behaviors at the population level over long periods of time, and testing how different factors might causally impact these behaviors (Axelrod & Hamilton, 1981; Sigmund & Nowak, 1999). Recent research in cross-cultural psychology has used computational modeling to study cultural dynamics (Nowak et al, 2015; Roos et al., 2015). In this case, we developed an evolutionary simulation suggesting that culture-level variation in adherence to cooperative norms can help groups survive during existential threats such as the COVID-19 pandemic. We first present our empirical data, and then our formal model. All data and code associated with these analyses are available from OSF at <https://osf.io/pc4ef/> for reproduction and examination.

Methods

Growth and Mortality Rates

We retrieved data on COVID-19 around the world from “Our World in Data” (OWD) (<https://ourworldindata.org/coronavirus-data>) which provides daily updates of the number of COVID-19 documented cases and deaths using data from the European Center for Disease Control. In order to avoid confounding these COVID-19 data with nations’ population sizes, we downloaded data on cases and deaths per million citizens.

We estimated the country-specific growth rates of COVID-19 cases from the first documented case until April 4th. The growth rate of COVID-19 followed a power-law growth curve, which tends to be typical for the early stages of pandemic and epidemic outbreaks (Chen et al., 2020; Fanelli & Piazza, 2020; Manchein et al., 2020; Stroud et al., 2006). We captured growth rate by fitting regression equations for each nation, using log-transformation to linearize the growth rate of the virus, and—for all countries that provided daily testing data—adjusting based on COVID-19 tests per million people. Because not all infected people were tested, this tests-per-capita adjustment allowed us to correct for within-country daily variation in possible underreporting. For instance, if a country only began testing after COVID-19 became widespread, this would theoretically bias its growth curve, but our testing control helped minimize this potential bias. We note that our growth rate estimates with and without controlling for tests-per-capita were correlated above .99. Our supplemental materials provide more detail for how we estimated growth rates and lists the full set of countries in our sample and their associated growth rate.

Government Efficiency

We measured government efficiency using the government efficiency index from the World Bank, which was originally compiled by the World Economic Forum as part of the Global Competitiveness report. The government efficiency index measures the public sector's performance in managing and regulating the political economy (see <http://reports.weforum.org/global-competitiveness-index-2017-2018/competitiveness-rankings/#series=EOSQ043>). Excessive bureaucracy and regulation, wasteful spending, a lack of transparency, and inadequate legal frameworks all impose transaction costs for institutions, organizations, and individuals in societies (Mohamadi et al., 2017; Schwab et al., 2017), and reduce the nation's efficiency in crisis management. Accordingly, this metric shows that efficient governments score highly on five dimensions: they are efficient in spending public revenue, they do not place strong compliance burdens on the private sector, they are able to efficiently settle legal and judicial disputes in the private sector, they are receptive to challenges from the private sector, and they offer transparent information about changes in government policies and regulations affecting private sector activities. The government efficiency indicators are scored from 1-7, and show high internal consistency ($\alpha = .96$).

In sum, the measure is intended to capture variation in how efficiently governments can distribute public sector funding and coordinate with the private sector. Our supplemental materials discuss this measure in detail and show the same pattern of results with convergent measures of government efficiency from the Economist Intelligence Unit Riskwire and Democracy Index, the Political Risk Services International Country Risk Guide, and the Institute for Management and Development World Competitiveness Yearbook.

Cultural Tightness

We measured cultural tightness using the measure from Gelfand and colleagues (2011), who measured tightness through six items, including “There are many social norms that people are supposed to abide by in this country,” and “In this country, if someone acts in an inappropriate way, others will strongly disapprove.” This measure was originally validated by Gelfand and colleagues (2011) across 33 nations, and then expanded to 57 nations using the same procedure. The measure captures the strength of norms in a nation and the tolerance for people who violate norms. The expanded measure correlates highly with the 33-nation measure ($r = .87$), and our supplemental materials summarize the psychometric properties of this expanded measure and replicate our models with the smaller sample from Gelfand and colleagues’ (2011) original 33-nation measure.

Accounting for Underreporting

Underreporting is an important concern when analyzing COVID-19 growth rates. It is all but certain that the number of COVID-19 cases has been underreported, and this underreporting may vary meaningfully across countries. Many sources have suggested that testing is critically linked to underreporting, such that nations with higher rates of testing have more accurately tracked the virus (Flaxman et al., 2020; Nature Biomedical Engineering, 2020; Onder et al., 2020). In particular, countries such as South Korea that used widespread testing are cited as having lower likely underreporting scores than countries such as the United States that were slow to adopt widespread testing. Given this logic, we used the ratio of tests to cases as our primary proxy for underreporting. If there are similar numbers of tests and cases (a low test-case ratio), this suggests that a country is mostly testing people who are symptomatic (as in the United States), and there is probably a high rate of underreporting. In contrast, there is likely less

underreporting for countries that have a high ratio of tests to cases, since many people receiving tests are asymptomatic (as in South Korea). We downloaded data on COVID-19 test-case ratios from OWD from 38 nations with available testing data that overlapped with our sample. We downloaded testing data from April 4th or the most recent available date to match our growth rate data.

Modeling Approach for Growth Rates

We examined growth rate in a second set of regressions that used the slopes from our first set of models as an outcome variable. This approach allowed us to test whether nations with high cultural tightness and high government efficiency would show slower growth rates. In total, 52 nations had data on cultural tightness, government efficiency, and COVID-19 growth rates, and these were the focus of our analysis. However, some nations had missing data on other variables (e.g. inequality), and so degrees of freedom vary across regression models. We note that general linear models do not account for the error inherent in estimating growth curves—in particular, nations with fewer data-points (i.e. days of documented cases) will have less reliable slope estimates than nations with more data-points. To address this limitation, we weighted cases in these regressions by the number of days that nations had documented COVID-19 cases, so that nations with more reliable estimates of growth rate would be weighted over and above nations with less reliable estimates of growth rate. Results were similar with or without this weighting technique.

Our primary model contained cultural tightness, government efficiency, our focal government efficiency $\times$ cultural tightness interaction, and several other key controls: economic development (GDP per capita, retrieved from the International Monetary Fund's 2019 release), inequality (Gini coefficients, retrieved from the most recent World Bank estimate for each

nation), median age (retrieved from the 2018 CIA World Factbook), and population density (log-transformed people per square kilometer, retrieved from the World Bank). We controlled for these variables because each of them could plausibly relate to cross-cultural variation in how effectively nations have contained COVID-19, and we standardized all covariates prior to analysis. We used a stepwise approach to this model, first controlling only for test-case ratios and then entering all our covariates. We estimated simple slopes in these models at one standard deviation below and above the interaction term to show how the effect of cultural tightness varied based on government efficiency and vice versa. All tests are two-tailed.

After these primary models, a secondary model controlled for two cultural variables correlated with tightness: individualism-collectivism and power distance using estimates from Hofstede and colleagues (Hofstede et al., 2010). Finally, we estimated whether our effects generalized to using healthcare capacity as a proxy for underreporting rather than test-case ratio.

Our supplemental analyses examine a variety of other models focused on ruling out confounding variables and evaluating the robustness of our effects. For example, supplemental models replicate our effects controlling for climate variables, relational mobility, authoritarianism, and spatial interdependence. They also present model diagnostics from our primary models, replicate our results using bootstrapping, and replicate our results with alternative underreporting proxies.

Modeling Approach for Mortality Rates

Following our analysis of growth rate, we performed a nearly identical series of stepwise models to analyze cross-cultural differences in mortality rate, which we measured via the number of deaths from COVID-19 per million people. We used the same covariates as in our growth rate analysis, but added World Bank data on all-cause mortality rate data from 2017, which was the

most recent year prior to the COVID-19 output that had complete data for our sample. All-cause mortality is an important covariate because it is the mortality rate expected from the nations before the onset of COVID-19.

While these models did not estimate change over time, they captured the toll of the COVID-19 pandemic through how many people have died from the infection. Data on COVID-19 related deaths can be influenced by a variety of factors, including underreporting of cases. Controlling for underreporting helped us rule out this confounding variance, and gave us more confidence in our estimations of the COVID-19's death toll. We also note that mortality rate had a skewed distribution across nations, and so we log-transformed it prior to analyses.

Results

How did government efficiency and cultural tightness relate to cross-cultural variation in the COVID-19 growth rate? Results from our multiple regressions, displayed in Table 1, supported our hypotheses. The interaction of cultural tightness and government efficiency was significantly associated with COVID-19 growth rates, such that nations with high (+1 SD) cultural tightness and high (+1 SD) government efficiency had the slowest rates of infection. Surprisingly, cultural tightness was positively associated with higher growth rates at low (-1 SD) levels of government efficiency, a point to which we return in the discussion. These effects replicated when we controlled for just underreporting, and when we entered our full set of covariates.

Our models also found several other significant fixed effects. For example, test-case ratio was associated with lower growth rates, which is not surprising since it is likely harder to comprehensively test when the infection grows. GDP per capita and population density were also associated with faster COVID-19 growth rates, such that the fastest growth rates would be

expected in economically developed nations with dense populations. The R^2 values of our models were consistently high, indicating that our model explained 46% of variation in COVID-19 growth rates across nations when only controlling for test-case ratio, and explained 71% of variation when also controlling for other covariates.

What are the implications of the interaction between cultural tightness and government efficiency? To put this interaction into context, the intercept of Model 1b from Table 1 indicated that nations with high cultural tightness and high government efficiency would have a relatively low log-transformed rate of 1.68 new cases per million per day. However, nations with mean levels of cultural tightness and government efficiency would have a higher log-transformed rate of 2.55 new cases per million people per day, and nations with low cultural tightness and low government efficiency would have a similarly high log-transformed rate of 2.48 new cases per million. Re-converting these log-transformed values through exponentiation (which convert linear slopes back into non-linear slopes) suggests that, in the month (30 days) following the first COVID-19 case per million people, a tight nation with high government efficiency would have 4292.55 fewer cases per million people than a loose nation with low government efficiency. These estimated growth curves are displayed in Figure 1. Figure 2 also displays a heat map that illustrates our growth curves at different levels of cultural tightness and government efficiency.

We next replicated our model while adding other dimensions of cross-cultural variation. In particular, we tested whether the interaction between cultural tightness and government efficiency replicated controlling for cultural collectivism and power distance, which each correlate positively with cultural tightness (Gelfand et al., 2011). We found that the interaction between cultural tightness and government efficiency was robust to these controls (Table 2).

We also tested whether our primary models would replicate with alternative metrics of underreporting. A common approach in past research has been to model underreporting via a proxy such as healthcare capacity, with the assumption that societies with lower healthcare capacities (e.g. fewer doctors per 1,000 people) will face the greatest difficulty tracking cases. Our models showed that healthcare capacity was not significantly associated with growth rate when accounting for differences in economic development and inequality, and our observed interaction between cultural tightness and government efficiency was robust to controlling for healthcare capacity rather than test-case ratio (Table 3).

Our supplemental materials explore these models in greater depth, showing that the interaction between cultural tightness and government efficiency replicated when controlling for relational mobility, climate, authoritarianism, spatial interdependence in the data, and when bootstrapping the model's standard errors across 5,000 samples. Our supplemental materials also summarize model diagnostics that illustrate no problematic heteroscedasticity, no evidence of problematic multicollinearity, and no cases with undue influence on our estimated coefficients (no studentized residuals with significant deviation from the predicted value). We encourage readers to interpret these models with caution since the findings are limited to the early stages of the pandemic—with data collected up to April 4th—but these checks give confidence that these findings were not driven by spurious outliers or violations of model assumptions.

Our supplemental materials also replicate our findings with two additional proxies for underreporting. First, we replicate our models with tests-per-capita as an alternative to test-case ratio. Tests-per-capita can be confounded with number of cases. For example, countries with aggressive testing and small numbers of cases (e.g. Australia) can have the same test-per-capita value as countries with limited testing but large numbers of cases (e.g. Italy), and for this reason

we view test-case ratio as more related to underreporting. Second, we replicate our models using a delay-adjusted case fatality ratio (DA-CFR) which assumes that nations with higher CFRs are underreporting cases compared to those with lower CFRs, after accounting for the delay between hospitalization and mortality for patients who die from COVID-19 (Russell et al., 2020). We are skeptical of this measure because it assumes that there is a fixed CFR rate across nations, and this assumption may not be accurate. Yet replicating our results with these other measures shows that they are robust to multiple potential underreporting proxies.

Mortality Rate Models

We next examined mortality rates. These models, displayed in Table 4, replicated the same interaction between cultural tightness and government efficiency. These models suggest that a lower proportion of COVID-19 patients died in nations with high (+1 SD) cultural tightness and government efficiency (.28 deaths per million people) compared to nations with moderate cultural tightness and government efficiency (1.82 deaths per million people), and with low (-1 SD) cultural tightness and government efficiency (2.12 deaths per million people). Table 5 presents the analyses of mortality rates controlling for collectivism and power distance, and Table 6 presents the analyses of mortality rates using healthcare capacity as a proxy for underreporting. The interaction between cultural tightness and government efficiency remained significant in each of these models. As with growth rate models, our mortality rates model showed no evidence of undue influence, multicollinearity, or heteroscedasticity (see supplemental results), and replicates our models with a variety of other control variables. Figure 2 also displays a heat map that illustrates our growth curves at different levels of cultural tightness and government efficiency.

We emphasize that all of our tests are correlational and must be interpreted with caution. Even though our analyses control for cross-national rates of testing and underreporting, they do not shed light on the individual-level mechanisms by which these factors may be related to how people respond to a threat such as COVID-19. Our theoretical model suggests that nations with tight cultures and efficient governments may be better containing COVID-19 because their citizens are adhering to cooperative norms, but our nation-level analysis cannot address this mechanistic explanation. Our next analyses therefore examined this possibility within an evolutionary model which may illuminate the causal dynamics of group differences in response to an existential threat.

Evolutionary Game Theory Model

Our simulation draws from past game theory models of threat and the evolution of cooperation. These models do not aim to fully explain our observed data, nor are they designed to specifically model pandemics, but they do offer a potential mechanism for how group-based differences may account for cultural variation in response to an existential threat.

Previous evolutionary game theory models have shown that under conditions of high threat—where payoffs are reduced for a population of agents—mutual cooperation becomes essential for the population's survival (Roos et al., 2015). When threat is high and agents are connected in a fixed network (Smaldino et al., 2013), clusters of cooperative agents survive whereas individual defectors quickly die off, and cooperation spreads across the network. In the current geopolitical context, reduced payoff rates may represent the survival pressures of COVID-19, and the demand for cooperation may represent a heightened need for behaviors such as frequent hand-washing or social distancing that may sometimes be costly to the individual but allow the group as a whole to survive (Williams et al., 2015).

We suggest that groups showing high levels of conformity (cultural tightness) should respond faster to threats such as COVID-19 because agents will conform more readily to popular neighboring strategies. When there is no threat, this heightened conformity is not necessarily functional, because cooperative and defective behaviors are similarly effective under low selection pressure from the environment. But in the context of threat, group-based cooperation emerges as essential (Roos et al., 2015), and conformity will allow cooperation to quickly spread across a population of agents

We illustrate this dynamic in an evolutionary model of agents playing a Donation Game, which is a special case of the Prisoner's Dilemma (Hilbe et al., 2013; see Table S8). Agents play in a 20×20 toroidal grid, with agents' payoff determining their fitness (i.e. their likelihood of reproducing). Agents received a standard prisoner's dilemma payoff in this model in addition to a base payoff, but their total payoff was reduced according to a level of threat τ which escalated over time (Roos et al., 2015). One hundred runs represented a loose culture in which agents have a low probability l of conforming to the modal strategy of agents within one grid space ($l = .05$), whereas another 100 runs represented a tight culture in which agents have a higher probability of conforming ($l = .20$).

Figure 3 shows that, in the early stages of the model where threat was low, tight and loose cultures had similar cooperation rates. However, as time passed and threat levels escalated, mutual cooperation became more essential and agents in tight cultures were able to mimic the behavior of cooperative groups more rapidly than agents in loose cultures. Since mutually cooperative agents received higher joint payoffs than defecting agents, agents in tight cultures had higher survival rates than agents in loose cultures. This suggests that strong normative conformity can be an effective evolutionary strategy during periods of intense threat when agents

are facing stronger pressure to adopt more effective strategies. Our supplemental materials summarize this model in more depth and perform additional robustness checks and exploratory runs that support our main findings.

While the above model does not explicitly incorporate government efficiency, it implies that tightness should be most effective when populations can rapidly introduce—and allocate resources to enforce—cooperative norms following a global threat such as COVID-19. In societies where governments are inefficient (e.g., have excessive bureaucracy and regulation, wasteful spending, and a lack of transparency), institutions, organizations, and individuals incur a cost from this inefficiency.

To express this in terms of game-theoretic payoffs, inefficient governments' transaction costs may reduce the benefits produced by individuals' contributions, thus lowering the benefit of cooperation. This can be expressed in our model's donation game (Table S8), in which each individual is interacting with another person and is asked to contribute an amount c to generate a benefit $b = kc$, where $k > 1$. If both individuals *cooperate* (i.e., each contributes c), then each receives the benefit b , hence each individual's net payoff is $b - c$. If one individual cooperates and the other *defects* (refuses to contribute), then the cooperator contributes the cost and the defector gets the benefit, so their net payoffs are $-c$ and b , respectively. If both individuals defect (i.e., neither contributes), then no benefit is generated, so each gets payoff 0. In these equations, the quantity k represents how much each contribution from a cooperator can be effectively transformed to a larger benefit for others. Thus, in terms of game-theoretic payoffs, inefficient governments' transaction costs reduce the benefits produced by individuals' contributions, thereby lowering the value of k ; i.e., the contribution c generates a smaller benefit $b = kc$ to the government's citizens.

In Figure 3, the benefit of cooperation was high ($b = 3$, $c = 1$, $k = 3$) as is typically the case in research on the evolution of cooperation (Roos et al., 2015) and shows support for our theory that both tight norms and efficient governments are important for cooperating under high threat. In Figures S6-S8, we illustrate how different levels of transaction costs incurred to agents affect cooperation and alive rates under increasing threat. Notably, as k decreases, tight cultural groups have even lower levels of cooperation than loose groups, and only start to cooperate at high levels when threat becomes severe. These EGT results illustrate that both tightness and government efficiency are needed to establish cooperation and survival as threat increases.

Discussion

Our empirical data show that, during a global pandemic, cultural and institutional factors are associated with cross-cultural variation in the growth and mortality rates of COVID-19 infection. Nations with high levels of cultural tightness and government efficiency have slower growth and mortality rates compared with nations that have one of these factors or neither. A theoretical model explores mechanistic questions about why some groups may contain threats better than others, and suggests that adherence to cooperative norms may be key for responding effectively to existential threats. More generally, by integrating research in cross-cultural psychology on social norms with government institutions, we can begin to understand societal variation in the early stages of COVID-19.

These findings may contain implications for understanding the spread of COVID-19. As COVID-19 progresses, countries that are in need of flattening the curve may benefit from increasing governmental efficiency—e.g., developing governmental policies that improve coordination between the public and private sectors and provide unambiguous signals about the importance of cooperative behaviors—along with deploying interventions to strengthen social

norms. The nature of social norm interventions, however, will need to be tailored to specific societies. Nudging people to follow norms is particularly important in loose cultures, since people in these cultures have generally experienced fewer historical ecological threats and may therefore be more likely to underestimate the risk of the virus and resist increased constraint (Gelfand et al., 2011). It's also important to note that nations that are both tight and have low government efficiency have also struggled to contain the early spread of COVID-19, suggesting that norm abundance in tight cultures still requires clear signaling and top-down coordination of the government. Indeed, to the extent that people in tight cultures view the government's disorganized response as indicative that the pandemic isn't serious, they may not adopt cooperative norms. These recommendations should complement existing behavioral insights into how people and groups should manage the economic and health impacts of the pandemic (Van Bavel et al., 2020).

These implications notwithstanding, our empirical data are correlational, and therefore are best suited for offering a tentative account for why some nations responded more effectively than others to COVID-19 in the pandemic's early stages of growth. It is our view that research is important even given these barriers to accurately estimating COVID-19 growth and mortality rates. Moreover, we take several precautions to account for the correlational nature of our data, including controlling for important covariates (e.g. societal wealth, inequality, average age, underreporting, and other dimensions of cultural variation). Nevertheless, our results should still be interpreted with caution since there is still a high level of uncertainty concerning reported COVID-19 cases and deaths.

We note additional limitations of our data. First, cultural tightness and government efficiency are not the only factors that are related to COVID-19's growth and mortality rates, and

our own analyses suggest that a variety of other factors are related to these outcomes. For example, more developed nations and nations with higher population density are all at risk for faster growth rates. Second, our data focus on the early spread of COVID-19—our models are based on April 4th data and should be considered an analysis of how cultures respond to the early stages of a pandemic. Since the salience of threat increases cultural tightness, it is possible that traditionally looser cultures (e.g. Spain or Italy) will grow tighter as COVID-19 continues to develop, and begin adopting the cooperative norms that we observe here in tight cultures with efficient governments. On the other hand, since loose cultures have higher creativity than tight cultures (Chua et al., 2015, Harrington & Gelfand, 2014), they may be able to develop more innovative long-term methods of countering the virus. Indeed, it may be that cultural tightness is more effective in the early stages of threats such as the current pandemic whereas cultural looseness is more effective at the later stages of the pandemic, when innovation is needed after threats have been initially contained. We encourage future studies to investigate these potential dynamics and to analyze country-level variation in the latter stages of the pandemic.

We also emphasize that our analysis only partly explains cross-cultural variation in COVID-19 case growth and mortality rates. Other factors such as political leaders' personal beliefs about the seriousness of COVID-19, the nature, extent, and timing of countermeasures such as quarantining, and the quality of governments' communications about the virus may also be associated with responses to COVID-19, and we encourage future research on these factors.

Finally, we emphasize that strong norms to fight COVID-19 do not imply that governments should become autocratic, and our supplemental analyses show that authoritarianism is not linked to reduced growth rates and does not account for our observed interaction between cultural tightness and government efficiency. Indeed, while it may be

important for governments to introduce and regulate beneficial norms (e.g. social distancing, effective handwashing) and coordinate social action (e.g. distribution of testing kits and ventilators), authoritarian responses to COVID-19 may do long-term damage to the autonomy and health of nations' citizens.

COVID-19 has already reshaped our world and we urgently need to understand the factors that are linked to its spread. Here we find that two factors—cultural tightness and government efficiency—are associated with cross-cultural variation in the spread of the COVID-19 virus. While these factors are rooted in cultural evolutionary studies of human history, they could possibly foreshadow how nations handle the COVID-19 pandemic in the months to come.

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Author Contributions and Acknowledgements

All authors conceived the project. C.Y.C., J.C.J., and M.G. analyzed the empirical data, X.P., D.N., and M.G. designed the EGT model, and X.P. performed the simulations. M.G., J.C.J., and C.Y.C. wrote the paper. Competing interests: The authors declare no competing interests. Data and materials availability: All data, codes and materials used in the analysis are available from the authors.

Readers with additional questions about the paper's analytic models, conclusions, or design should refer to our responses to frequently asked questions (<https://osf.io/pc4ef/>) or contact the corresponding authors. We thank our editor and Nava Caluori, Moin Syed, Jonas Kunst, Ulrike Schaede, Kate M. Turetsky, Kimmo Eriksson, Pontus Strimling, Paul Smaldino, and Evert Van de Vliert for helpful feedback on earlier versions of this manuscript. The authors received no funding for this work.

Table 1*COVID-19 Growth Rate Primary Models*

Fixed Effect	DF	R²(Adj.)	b (SE)	t	p	LLCI	ULCI	β
Model 1a	32	.46 (.40)						
Test-Case Ratio			-.28 (.07)	-3.99	< .001	-.43	-.14	-.41
Gov. Efficiency (centered)			-.28 (.10)	-2.81	.009	-.48	-.08	-.36
Tightness (centered)			.05 (.24)	.19	.85	-.44	.54	.03
Gov. Efficiency * Tightness			-1.03 (.30)	-3.43	.002	-1.64	-.42	-.57
Model 1a Simple Slopes								
Tightness (low GE)			.93 (.39)	2.38	.02	.13	1.74	.60
Tightness (high GE)			-.84 (.31)	-2.72	.01	-1.47	-.21	-.54
Gov. Efficiency (low CT)			.17 (.13)	1.31	.20	-.09	.43	.21
Gov. Efficiency (high CT)			-.73 (.19)	-3.76	< .001	-1.12	-.33	0.93
Model 1b	28	.71 (.63)						
Test-Case Ratio			-.24 (.06)	-4.18	< .001	-.36	-.12	-.35
GINI			.14 (.09)	1.51	.14	-.05	.34	.21
GDP Per Capita			.31 (.09)	3.60	.001	.14	.49	.46
Population Density			.14 (.06)	2.37	.03	.02	.26	.20
Median Age			.12 (.09)	1.30	.20	-.07	.31	.18
Gov. Efficiency (centered)			-.53 (.10)	-5.36	< .001	-.73	-.33	-.67
Tightness (centered)			.14 (.21)	.65	.52	-.30	.57	.09
Gov. Efficiency * Tightness			-1.25 (.27)	-4.66	< .001	-1.80	-.70	-.69
Model 1b Simple Slopes								
Tightness (low GE)			1.22 (.12)	3.69	< .001	.54	1.90	.78
Tightness (high GE)			-.94 (.30)	-3.17	.004	-1.55	-.33	-.60
Gov. Efficiency (low CT)			.02 (.12)	.13	.90	-.24	.27	.02
Gov. Efficiency (high CT)			-1.08 (.18)	-6.06	< .001	-1.44	-.71	-1.37

Note. All control variables have been standardized in this analysis. GE stands for “Government

Efficiency.” CT stands for “Cultural Tightness.” Models with these acronyms are depicting

estimates of simple slopes at 1 standard deviation above and below the mean. 95% Confidence

intervals (CI) are calculated for unstandardized estimates (LLCI = Lower Limit; ULCI = Upper

Limit). We note that some standardized betas are greater than 1, which may occur due to the way

regressions are rotated (Deegan, 1978). Our supplemental analyses suggest that these estimates

are not biasing our results and that there is no undue covariation between predictors.

Table 2*COVID-19 Growth Rate Models Incorporating Other Dimensions of Cultural Variation*

Fixed Effect	DF	R²(Adj.)	b (SE)	t	p	LLCI	ULCI	β
Model 2	26	.73 (.62)						
Test-Case Ratio			-.23 (.06)	-3.97	< .001	-.35	-.11	-.34
GINI			.16 (.10)	1.62	.12	-.04	.36	.23
GDP Per Capita			.24 (.12)	2.07	.05	.002	.48	.36
Population Density			.15 (.06)	2.48	.02	.03	.28	.22
Median Age			.11 (.10)	1.14	.27	-.09	.31	.16
Collectivism			-.003 (.004)	-.80	.44	-.01	.005	-.11
Power Distance			-.002 (.005)	-.43	.67	-.01	.008	-.07
Gov. Efficiency (centered)			-.51 (.11)	-4.78	< .001	-.73	-.29	-.64
Tightness (centered)			.17 (.22)	.76	.45	-.28	.62	.11
Gov. Efficiency * Tightness			-1.16 (.30)	-3.85	< .001	-1.78	-.54	-.64
Model 2 Simple Slopes								
Tightness (low GE)			1.17 (.35)	3.33	.003	.45	1.89	.75
Tightness (high GE)			-.84 (.33)	-2.55	.02	-1.51	-.16	-.54
Gov. Efficiency (low CT)			.001 (.13)	.003	.99	-.26	.27	.001
Gov. Efficiency (high CT)			-1.01 (.20)	-5.03	< .001	-1.43	-.60	-1.29

Note. All effects are parametrized and formatted in the same manner as Table 1. Coll. stands for

cultural collectivism. Pow. Dist. stands for power distance.

Table 3*COVID-19 Growth Rate Models using Healthcare Capacity as an Underreporting Proxy*

Fixed Effect	<i>DF</i>	<i>R²(Adj.)</i>	<i>b (SE)</i>	<i>t</i>	<i>p</i>	<i>LLCI</i>	<i>ULCI</i>	<i>β</i>
Model 3	41	.43 (.31)						
Healthcare Capacity			.14 (.14)	1.01	.32	-.14	.42	.20
GINI			.22 (.12)	1.92	.06	-.01	.46	.33
GDP Per Capita			.31 (.13)	2.47	.02	.06	.56	.46
Population Density			.06 (.08)	.77	.44	-.09	.21	.09
Median Age			.19 (.13)	1.50	.14	-.07	.45	.28
Gov. Efficiency (centered)			-.42 (.13)	-3.24	.002	-.69	-.16	-.54
Tightness (centered)			.15 (.26)	.56	.58	-.38	.68	.10
Gov. Efficiency * Tightness			-.74 (.27)	-2.75	.009	-1.28	-.20	-.41
Model 3 Simple Slopes								
Tightness (low GE)			.79 (.39)	2.05	.04	.01	1.56	.50
Tightness (high GE)			-.49 (.32)	-1.54	.13	-1.13	.15	-.31
Gov. Efficiency (low CT)			-.10 (.16)	-.64	.53	-.43	.22	-.13
Gov. Efficiency (high CT)			-.75 (.19)	-3.93	< .001	-1.13	-.36	-.95

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table 4*COVID-19 Mortality Rate Primary Models*

Fixed Effect	DF	R²(Adj.)	b (SE)	t	p	LLCI	ULCI	β
Model 4a	30	.41 (.33)						
Test-Case Ratio			-2.80 (1.10)	-2.54	.02	-5.06	-.55	-1.31
Gov. Efficiency (centered)			-.12 (.37)	-.33	.75	-.87	.63	-.05
Tightness (centered)			-.97 (.72)	-1.36	.19	-2.43	.49	-.20
Gov. Efficiency * Tightness			-2.49 (1.03)	-2.42	.02	-4.59	-.39	-.44
Model 4a Simple Slopes								
Tightness (low GE)			1.19 (1.22)	.97	.34	-1.30	3.68	.24
Tightness (high GE)			-3.13 (1.06)	-2.95	.006	-5.29	-.96	-.64
Gov. Efficiency (low CT)			.97 (.41)	2.40	.02	.14	1.80	.39
Gov. Efficiency (high CT)			-1.21 (.72)	-1.69	.10	-2.67	.25	-.49
Model 4b	25	.69 (.57)						
Test-Case Ratio			-2.63 (.96)	-2.73	.01	-4.61	-.65	-1.23
2017 Mortality			.12 (.38)	.30	.76	-.67	.90	.05
GINI			.04 (.33)	.12	.91	-.65	.73	.02
GDP Per Capita			1.22 (.32)	3.86	< .001	.57	1.86	.57
Population Density			.21 (.22)	.94	.35	-.24	.66	.10
Median Age			.22 (.37)	.60	.55	-.54	.99	.10
Gov. Efficiency (centered)			-1.07 (.38)	-2.85	.009	-1.84	-.30	-.43
Tightness (centered)			-.20 (.67)	-.29	.77	-1.56	1.18	-.04
Gov. Efficiency * Tightness			-2.28 (.92)	-2.49	.02	-4.17	-.39	-.40
Model 4b Simple Slopes								
Tightness (low GE)			1.78 (1.06)	1.67	.11	-.41	3.96	.36
Tightness (high GE)			-2.17 (1.01)	-2.14	.04	-4.26	-.08	-.44
Gov. Efficiency (low CT)			-.07 (.42)	-.18	.86	-.94	.79	-.03
Gov. Efficiency (high CT)			-2.07 (.65)	-3.16	.004	-3.41	-.72	-.83

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table 5*COVID-19 Mortality Rate Models Incorporating Other Dimensions of Cultural Variation*

Fixed Effect	DF	R²(Adj.)	b (SE)	t	p	ULCI	LLCI	β
Model 5	23	.69 (.55)						
Test-Case Ratio			-2.79 (1.04)	-2.68	.01	-4.94	-.63	-1.31
2017 Mortality			.08 (.44)	.19	.85	-.82	.99	.04
GINI			.04 (.35)	.11	.91	-.68	.76	.02
GDP Per Capita			1.33 (.45)	2.95	.007	.40	2.27	.62
Population Density			.20 (.23)	.88	.39	-.28	.68	.10
Median Age			.24 (.38)	.63	.54	-.56	1.04	.11
Collectivism			-.006 (.02)	-.39	.70	-.04	.03	-.06
Power Distance			.01 (.02)	.69	.50	-.03	.05	.13
Gov. Efficiency (centered)			-1.15 (.41)	-2.83	.009	-1.99	-.31	-.47
Tightness (centered)			-.17 (.70)	-.25	.81	-1.61	1.27	-.04
Gov. Efficiency * Tightness			-2.40 (.98)	-2.46	.02	-4.42	-.38	-.42
Model 5 Simple Slopes								
Tightness (low GE)			1.90 (1.11)	1.71	.10	-.40	4.20	.39
Tightness (high GE)			-2.25 (1.08)	-2.08	.04	-4.48	-.01	-.46
Gov. Efficiency (low CT)			-.10 (.44)	-.24	.81	-1.00	.80	-.04
Gov. Efficiency (high CT)			-2.20 (.71)	-3.10	.005	-3.67	-.73	-.89

Note. All effects are parametrized and formatted in the same manner as Table 1. Coll. stands for cultural collectivism. Pow. Dist. stands for power distance.

Table 6*COVID-19 Mortality Rate Models using Healthcare Capacity as an Underreporting Proxy*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b</i> (<i>SE</i>)	<i>t</i>	<i>p</i>	<i>LLCI</i>	<i>ULCI</i>	<i>β</i>
Model 6	38	.61 (.52)						
Healthcare Capacity			.63 (.36)	1.76	.09	-.09	1.36	.30
2017 Mortality			-1.12 (.31)	-3.62	< .001	-1.75	-.49	-.53
GINI			-.23 (.30)	-.75	.46	-.84	.38	-.11
GDP Per Capita			.73 (.38)	1.95	.06	-.03	1.49	.34
Population Density			.30 (.22)	1.34	.19	-.15	.74	.14
Median Age			.83 (.35)	2.35	.02	.11	1.55	.39
Gov. Efficiency (centered)			-.98 (.40)	-2.48	.02	-1.78	-.18	-.40
Tightness (centered)			-.66 (.63)	-1.04	.30	-1.94	.62	-.13
Gov. Efficiency * Tightness			-1.95 (.64)	-3.03	.004	-3.25	-.64	-.34
Model 6 Simple Slopes								
Tightness (low GE)			1.02 (.90)	1.14	.26	-.80	2.85	.21
Tightness (high GE)			-2.34 (.78)	-3.01	.005	-3.91	-.77	-.48
Gov. Efficiency (low CT)			-.13 (.43)	-.31	.76	-1.00	.74	-.05
Gov. Efficiency (high CT)			-1.83 (.54)	-3.43	.002	-2.91	-.75	-.74

Note. All effects are parametrized and formatted in the same manner as Table 1.

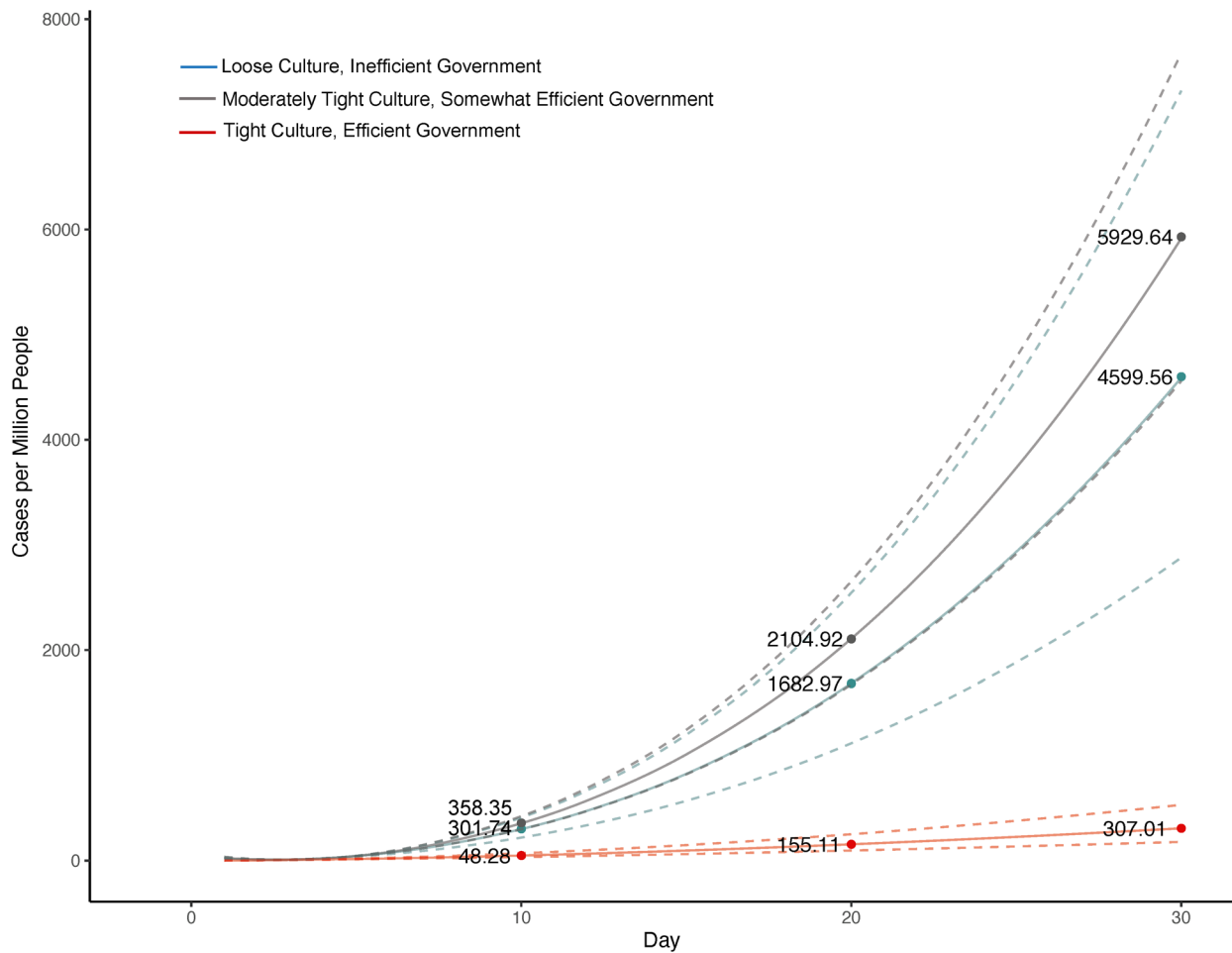
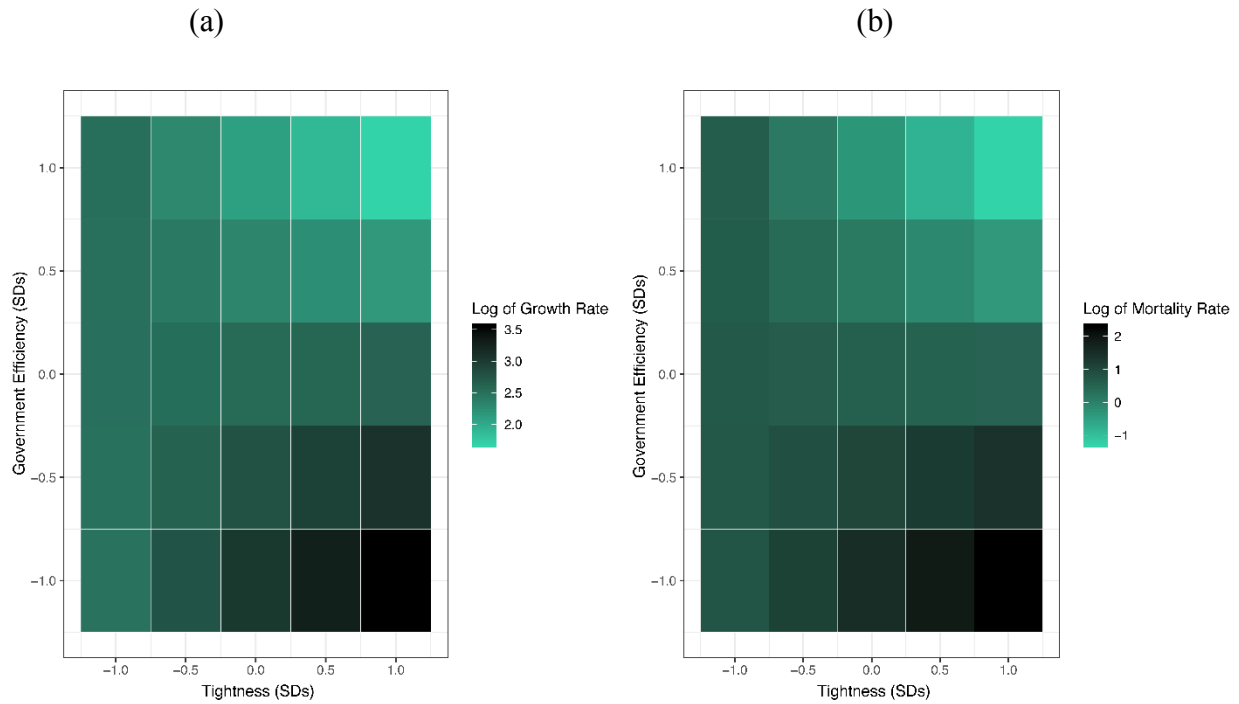
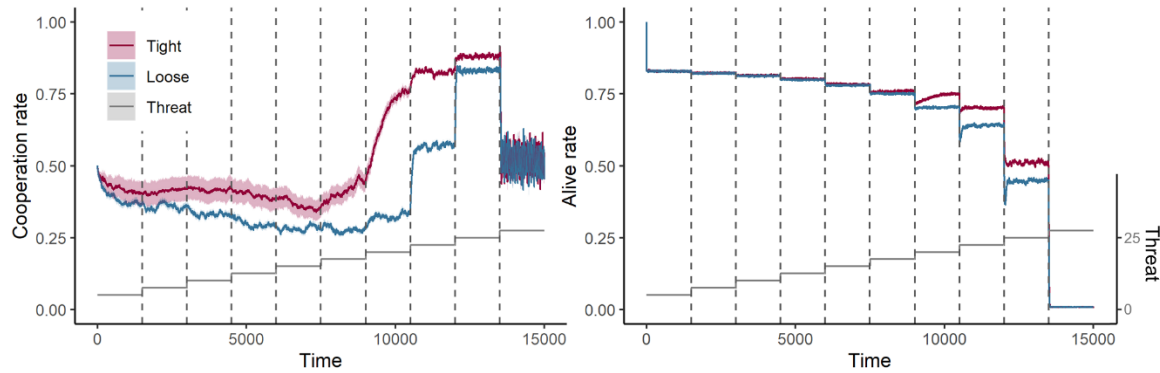
Figure 1*Estimated Growth Rate Curves*

Figure 1. The estimated growth rate curves for nations with loose and inefficient governments (blue) nations with moderately tight cultures and somewhat efficient governments (gray), and nations with tight cultures and efficient governments (red). The estimates are derived from Model 1b in Table 1, through exponentiating the intercepts from these models to account for the initial log transformation. Dashed lines represent upper and lower limits of these curves based on standard errors in Model 1b.

Figure 2*Model-Derived Growth Rates at Different Levels of Cultural Tightness and Government**Efficiency*

Note. A heat map displayed model-derived growth rates (a) and mortality rates (b) at different levels of cultural tightness and government efficiency. The light green panels in the top right show that growth rate and mortality rate are lowest when tightness and efficiency are both high.

Figure 3*Results of Evolutionary Game Theory Model*

Note. The results of an evolutionary game theory model of cooperation in the face of a threat such as COVID-19. The figure depicts 200 runs of the model, with each run containing 15,000 iterations. The shadow shows standard error. In 100 “tight” runs, agents had a high likelihood ($c = .20$) of conforming to the prisoner’s dilemma decisions of the agents within one grid space. In 100 “loose” runs, agents had a lower likelihood ($c = .05$) of conforming to neighbors’ decisions. The model also included a level of threat τ which started at a low level (5) and escalated every 1,500 iterations and reached its maximum value (27.5) in the 13,500th iteration of the model. The left panel of the plot displays cooperation rates over time, and the right side displays survival rates over time. At the highest level of threat, all agents die out, but at moderate-to-severe levels of threat, tightness bolsters agents’ cooperation and survival rates.

Supplemental Materials

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Supplemental Methods

Measurement of Cultural Tightness

Our measure of cultural tightness was adapted from Gelfand and colleagues (2011), who gathered cross-cultural data on cultural tightness using a self-report measure in 33 nations. Since its publication, the scale has been used to predict a wide range of phenomena, including national differences in creativity rates (Chua et al., 2015), CEO discretion (Crossland & Hambrick, 2011), stock price synchrony (Eun et al., 2015), leadership preference (Aktas et al., 2016), expatriate outcomes (Geeraert et al., 2019), global differences in prejudice (Jackson et al., 2019), and other organizational outcomes (Taras et al., 2010).

We employed an expanded version of this measure in our analysis, which covered 57 nations. Since the paper that developed this measure is still unpublished, we give a brief summary of the study's procedure here. This project set out to collect data from approximately 200 college students in a major city in each country, which was achieved in almost all countries. To assess the robustness of the country-level measures obtained from these samples, the authors complemented the main sampling strategy in two ways: (a) they collected additional data from non-student samples (or, in two cases, part-time students) in 31 countries; (b) they collected data from two or more student samples located in different cities of each of ten countries. In total, they gathered data from 22,863 participants (students: $n = 18,091$; non-students: $n = 4,772$), after excluding a few participants (1.5%) who reported an age under

18. Participants were recruited using a variety of methods, such as invitations via email, on social media, in class, face to face on campus, using public notices and flyers, and using survey organizations.

The survey was translated into 30 different languages, following the usual practice of independent translation and back-translation. The study was conducted anonymously online using Qualtrics, with a few exceptions. Part of the Estonian non-student sample and the Ghanaian student and non-student samples were collected using pen and paper at the university, with animations shown on a big screen. The study was preregistered when data collection started. The preregistration of this study is available at OSF at <https://osf.io/qg6xy> and the full survey and the data used in the present paper are openly available at our OSF site: <https://osf.io/pc4ef/>. Gelfand and colleagues' (2011) original tightness data overlapped with 25 countries in our study, and we used the same items in our study (e.g., "In this country, if someone acts in an inappropriate way, others will strongly disapprove"). As in the original study, responses were mean-centered within participants. Our measure from the expanded sample correlated very highly ($r = .87$) with the original Gelfand and colleagues (2011) scores. The nation-level reliability was .81 and the individual-level reliability was $\alpha = .70$. A multi-level confirmatory factor analysis (CFA) of showed acceptable SRMR (.04), RMSEA (.09), and CFI (.93) indicators. The Chi Square value of this factor analysis was large ($\chi^2 = 1161.71$), but this is common in CFAs of large samples. Four nations (Algeria, Iran, Slovakia, Armenia) showed alpha values of less than .60. To ensure that our effects were not driven by these unreliable values, we replicated our primary model while excluding these nations. This replication is summarized in Table S1.

Despite the high correlation between our expanded cultural tightness measure and our original measure, readers may be curious about whether our results in this paper generalized to Gelfand and colleagues (2011) 33-nation measure. To this end, Table S2 replicates our primary models using (a) the 33-nation tightness-looseness measure from Gelfand and colleagues (2011), and (b) a combinatory measure that uses the values from Gelfand and colleagues (2011) when available but supplements scores from Eriksson and colleagues (2020) for cases that were not in the original 33-nation sample.

Each of these models replicated the interaction between cultural tightness and government efficiency on growth rate, such that the nations with the slowest growth rates were those with a combination of efficient governments and cultural tightness. Effects sizes and degrees of freedom varied across these models, but the pattern of our findings was similar, indicating that our observed interaction between cultural tightness and government efficiency was robust to the particular measure that we employed in our analysis.

Measurement of Government Efficiency

The World Economic Forum's Government Efficiency Index is one index gathered as part of the "Global Competitiveness Report." We used the most recent data, which was compiled in 2017 as part of the 2017-2018 Global Competitiveness Report. The data collection for this measure came from the "Executive Opinion Survey," which involved 16,658 business executives interviewed between January and April (50.7% online interviews, 49.3% paper interviews) who rated the five key items that make up the government efficiency index from 1 ("Extremely Low") to 7 ("Extremely High"). The items are listed in Table S3, and more details about the report are available from the World Economic Forum at <http://reports.weforum.org/global->

competitiveness-index-2017-2018/competitiveness-rankings/#series=GCI.A.01.01.04. The measure is sometimes named the “Public Sector Performance” measure.

Government efficiency manifests through low wastefulness of public funding, the ability to provide appropriate services for the business sector, and the absence of excessive bureaucracy, red tape, and overregulation in dealing with public contracts (Mohamadi et al., 2017). In this way, it is intended to be a metric for institutional efficiency that transcends economic development. A Cronbach’s alpha analysis revealed high internal consistency in these items across nations ($\alpha = .96$).

We also considered the World Bank’s index of “Government Effectiveness,” which compiles several diverse data sources, including people’s satisfaction with the country’s infrastructure, public transportation, coverage of necessary services (e.g. electricity and drinking water), and political stability. The summary of the particular government effectiveness items and data sources is available here: <https://info.worldbank.org/governance/wgi/pdf/ge.pdf>.

Government effectiveness correlated highly with government efficiency, $r = .70$, $p < .001$, but it was also highly collinear with economic development, especially because many of its items measured the quality of national infrastructure rather than measuring government behavior.

Moreover, government effectiveness correlates very highly with measures of economic and technological development, such as globalization (<https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html>), internet usage

(<https://ourworldindata.org/internet>), and GDP per capita. Indeed, these correlations are

substantially higher than those of government efficiency (see Table S4). Overall, these 3 three indices account for 82.0% of the cross-national variance in the Government Effectiveness Index, but only 19.1% of the cross-national variance in the Government Efficiency Index. This suggests

that the government efficiency measure has high divergent validity since it isn't confounded with economic development, whereas government effectiveness is largely conflated with economic development.

We also ran several analyses involving government efficiency and government effectiveness. In our first analysis, we simply replicated our primary models controlling for government effectiveness, to demonstrate the predictive validity of our government efficiency measure. These models are summarized in Table S5.

We also included an alternative index of government efficiency for additional validity evidence. In particular, we examined the “Institute for Management and Development World Competitiveness Yearbook” 2017 dataset, which had 35 overlapping data-points with our measures of cultural tightness, growth rate, and testing data, and it showed high face validity, such that countries high in this measure score highly on the items “government decisions are effectively implemented,” “bureaucracy does not hinder business activity,” “adaptability of government policy to changes in the economy is high,” and “the distribution infrastructure of goods and services is generally efficient”. As expected, this dataset also interacted with cultural tightness on growth rate in the same way as other measures of government efficiency. These effects are displayed in Table S6.

We also examined two representative datasets that measured bureaucratic quality as an alternative for our government efficiency measure: The Economist Intelligence Unit Riskwire and Democracy Index (“Quality of bureaucracy,” “lack of excessive bureaucracy”) and the Political Risk Services International Country Risk Guide (“bureaucratic quality”) (both of which are included in the larger government effectiveness index). These indices correlated highly ($r = .81$) and assessed institutional efficiency without also conflating infrastructure coverage (e.g.

the coverage of an electricity grid). Table S7 shows that this index of bureaucratic quality (averaged across the two datasets) showed the same pattern of results (though with slightly smaller effect sizes) as our government efficiency analyses.

Estimating the Trajectory of Growth Rate

In the early stages of infection, the number of documented cases typically grows non-linearly according to some power (Chen et al., 2020; Fanelli & Piazza, 2020; Manchein et al., 2020; Stroud et al., 2006). In order to predict these varying growth rates with linear models, it is important to transform the non-linear growth using log transformation. We tested two forms of log-transformation. In one form, we log-transformed the number of cases and estimated this log-transformed value with the raw value of day (i.e. 1, 2, 3, ... n). In another form, we log-transformed the number of cases and also log-transformed the value of day (i.e. $\log(1)$, $\log(2)$, $\log(3)$... $\log(n)$) before estimating the model. Log-transforming both sides of the equation is typical for linearizing power growth, whereas log-transforming only the outcome is typical for linearizing exponential growth, a form of power growth incorporating Euler's number. Both types of equations have been used in past research on growth rates (Chen et al., 2020; Fanelli & Piazza, 2020; Manchein et al., 2020; Stroud et al., 2006). In our case, a multilevel model with random intercepts and slopes, and days nested in countries found that the equation incorporating raw values of days did not converge, whereas the equation incorporating log-transformed values of days converged normally. Therefore, we used the equation incorporating log-transformed values of days to estimate country-specific growth rates.

Not all countries provided daily-testing data, and so we grand-mean imputed values for nations that were missing daily data. Since these imputed values did not vary within countries, they did not influence our growth rate estimates. This allowed us to adjust our growth rate

estimates for countries that provided daily testing data but not for countries that did not provide daily testing data (since the imputed testing value was a constant in the regression equation for these countries) We note that results are substantively identical regardless of whether or not we adjusted our growth rate estimates using daily testing data.

Evolutionary Model Details and Robustness Checks

Agents are embedded in a 20×20 toroidal (i.e., wrap-around) grid. Each location (x, y) has four neighbor locations: $(x + 1, y)$, $(x - 1, y)$, $(x, y + 1)$, and $(x, y - 1)$. Each agent has a strategy, which is either *cooperate* or *defect*. The simulation starts with a grid that is fully occupied by agents whose strategies are chosen randomly, with both strategies being equally likely. Then the simulation repeatedly performs the following sequence of updating steps:

1) *Immigration*: At a randomly chosen empty site, if there is any, a new agent appears whose strategy is equally likely to be *cooperate* or *defect*.

2) *Interaction*: In each iteration, each agent gets a *base payoff* = 30 from the environment, independent of payoffs it gets from interactions. Each agent also plays donation games (Table S8) with all of its alive neighbors, if any, on the grid, and receives *interaction payoffs* from the games. Agents' actions are chosen according to their strategies, which is either *cooperate* or *defect*. All the pairs in the grid play the games in a random order.

In addition, agents are subject to a specific level of threat that is implemented as a deduction of τ from everyone's total payoff. Thus, an agent's final payoff, π , in each iteration is as defined in Eq. 1. These payoffs are not cumulative across iterations.

$$\pi = \text{base payoff} + \text{interaction payoff} - \tau. \quad (1)$$

This final payoff is transformed into an agent's fitness, $f(\pi)$, based on the well-established principle of diminishing marginal utility, as shown in Eq. 2 and Figure S1.

$$f(\pi) = \begin{cases} 1 - e^{-0.1 \cdot \pi}, & \text{if } \pi \geq 0; \\ 0, & \text{if } \pi < 0. \end{cases} \quad (2)$$

3) *Reproduction*: Each agent is chosen in a random order and given a chance to reproduce with a probability equal to its fitness. Reproduction means creating an offspring in a randomly selected adjacent empty site, if there is any. The offspring is a new agent that usually will have the same strategy as its parent, but there is a small probability $\mu = 0.05$ that it will instead have a randomly selected strategy, chosen in the same way as in Step 1 earlier.

4) *Death*: In each iteration, an agent has a probability d to die. The death probability of an agent is a function of its fitness, $f(\pi)$, defined by Eq. 3. As an agent's fitness increases, the death probability of the agent decreases as shown in Figure S2. If an agent dies, it will be removed from the grid.

$$d = e^{-2.3 \cdot f(\pi)} \quad (3)$$

5) *Conform*: In each iteration, after Step 4, each agent has a probability l of adopting the modal strategy in its neighborhood. If the agent's location is (x, y) , the neighborhood locations include $(x + 1, y)$, $(x - 1, y)$, $(x, y + 1)$, $(x, y - 1)$, $(x + 1, y + 1)$, $(x + 1, y - 1)$, $(x - 1, y + 1)$, and $(x - 1, y - 1)$. This is a broader range than the neighbors that an agent interacts with because we assume that people can observe more people than they interact with. If there are multiple modal strategies in the neighborhood (i.e., there are equal number of cooperators and defectors), the agent randomly selects one of the multiple modal strategies.

The key parameters of this model intended to represent ecological threat, manipulated by τ , and cultural tightness, manipulated by l . Consistent with past work (Roos et al., 2015), we operationalized ecological threat via payoff structure, such that highly threatening environments reduced the maximum payoff that agents received. Cultural tightness is operationalized by a probability l of conforming with the local norm. The two outcome variables are cooperation rate,

defined by the proportion of alive agents who have a cooperative strategy, and alive rate, defined by the proportion of grid locations that are occupied by agents.

As shown in Figure S1, when threat is low to medium, the difference between the fitness of different behaviors is small, hence payoff-based selection is weak. In this case, conformity has a greater influence than payoff-based selection, so differences in tightness can make a substantial difference in cooperation rates as threat increases.

We also ran the models under a variety of other levels of tightness. Figure S3 shows the results when $l = [0.1, 0.15, 0.3, 0.4, 0.5]$. In the early stages of the model where threat is low, both tight and loose cultures have relatively low cooperation rates and high alive rates. However, as time passes and threat levels escalate, tightness bolsters cooperation and agents in tight cultures are able to have higher alive rates than agents in loose cultures.

Note that in Figure 3 in the main text and Figure S3, in tight cultures, the standard errors of the cooperation rates are large, especially under low threat. This is because in some of the single runs, most of the population cooperated under low threat while in some other runs, the majority defected (see Figure S4).

We also tested the robustness of the model by using a narrower range of the conforming neighborhood. Figure S5 shows the results from a model in which each agent conforms only to its adjacent four neighbors. 50 runs were run in a tight culture ($l = .20$) and 50 runs were run in a loose culture ($l = .05$). Under moderate-to-severe levels of threat, a tight culture has a higher cooperation rate and thus a higher alive rate.

Finally, while this model does not explicitly incorporate government efficiency, it implies that tightness should be most effective when populations can rapidly introduce—and allocate resources to enforce—cooperative norms following a global threat such as COVID-19. If

institutions do not efficiently supply agents with information about cooperative norms during a pandemic, or do not invest resources to help agents follow these norms, tightness may not be sufficient to counteract the effects of threat.

Here we illustrate this notion with modifications to our Donation Game model. In Table S8, the quantity $k = b / c$ represents how much each contribution from a cooperator can be effectively transformed to a larger benefit for others. In societies where governments are inefficient (e.g., have excessive bureaucracy and regulation, wasteful spending, and a lack of transparency), institutions, organizations, and individuals incur a cost from this inefficiency.

To express this in terms of game-theoretic payoffs, inefficient governments' transaction costs reduce the benefits produced by individuals' contributions, thereby lowering the value of k ; i.e., the contribution c generates a smaller benefit $b = kc$ to the government's citizens.

In Figure 3 in the main text, the benefit of cooperation was high ($b = 3$, $c = 1$, $k = 3$). Figures S6-S8 present the evolutionary dynamics of tight and loose cultures when the benefit of cooperation becomes consecutively lower ($b = 2.5$, 2 , and 1.5). Notably, when b is 1.5 , tight cultural groups have even lower levels of cooperation than loose groups, and only start to cooperate at high levels when threat becomes severe.

Supplemental Results

Alternative Underreporting Metrics

Our primary models used the ratio of tests to cases as the primary measure of underreporting. Here we replicate these results with two additional proxies for underreporting: tests-per-capita and delay-adjusted case-fatality ratio estimates of underreporting. These are imperfect measures of underreporting. Tests-per-capita can be confounded with number of cases. DA-CFR metrics assume that nations with higher CFRs are underreporting cases compared to

those with lower CFRs, after accounting for the delay between hospitalization and mortality for patients who die from COVID-19. This measure is problematic because it assumes that there is a fixed CFR rate across nations, and this assumption may not be accurate. Yet replicating our results with these other measures shows that they are robust to multiple potential underreporting proxies. These results are summarized in Table S9.

In Russell and colleagues' (2020) analysis of underreporting, they supply potential reporting percentages, as well as 95% confidence intervals around these percentage estimates. We also incorporate these confidence intervals into our models using DA-CFR as our underreporting proxy. Specifically, we weighted cases by more precise country estimates. If a nation had a wide confidence band (~60% error), they would be weighted less in this analysis compared to a nation with a narrower confidence band (~10% error). Table S10 shows that our effects replicate with this case weighting strategy.

Replication with Bootstrapping

In analyses with small samples, there is sometimes a concern that regression coefficients are unstable. One way of estimating the possible range of regression coefficients is by applying bootstrapping to the regression models, and estimating the distribution of possible coefficients for these models. Here we illustrate these estimates so that readers can see the mean, standard deviation, and confidence intervals associated with our key interaction between cultural tightness and government efficiency. Figure S9 displays these distributions for the primary models (Models 1a-1b) which we summarized in Table 1 of the main text. Bootstrapping regression objects in R is not compatible with case weights, so we did not weight cases by number of available days in the growth rate analyses while generating these distributions.

Accounting for Spatial Autocorrelation

A common concern for cross-cultural models involves spatial autocorrelation, or “Galton’s problem,” which refers to the possibility that data-points are not truly independent. In analyses of pre-industrial societies, for example, it is common to control for language families in order to properly model the shared phylogenetic history of societies. These sorts of controls are less common for nation-level cross-cultural analyses, but they are sometimes important because spatial autocorrelation can violate the assumption of OLS regression models that datapoints are independent. With respect to our data, datapoints may not have been truly independent because a COVID-19 outbreak in one nation (e.g. Italy) makes it probable that other nations within the same continent (e.g. France, Great Britain) will experience an outbreak.

In our model diagnostics, we observed no problematic autocorrelation between model residuals. Nevertheless, we confirmed that our interaction between government efficiency and cultural tightness remained significant controlling for five dummy-coded variables representing continent, which were contrasted against “Australia.” This approach removes autocorrelation between nations within the same continent, and increases our confidence that our results were not driven by spatial autocorrelation. We note that this model had lower degrees of freedom than the models we present in our main text due to the large numbers of model parameters, so effects should be interpreted with caution. However, the model shows a robust interaction between cultural tightness and government efficiency, which mirrored the interaction we found in our main text (see Table S11).

Model Diagnostics

We evaluated the robustness of our models by checking for (a) problematic multicollinearity, (b) heteroscedasticity, and (c) problematic residuals. We estimated

multicollinearity via the variance inflation factors for each of our Fixed Effects in Model 1b, which included our covariates. A variance inflation factor of above 5 generally means that a model has high multicollinearity which is biasing the estimates and standard errors. Table S12 shows that no variables had problematic multicollinearity. We note that some standardized betas in our main text models exceeded 1 when we used test/cases as a control for underreporting (no betas exceeded 1 with the other models), though this does not bias our results. This could have occurred because the interaction between government efficiency and tightness introduced variance inflation. It may have also occurred because of the rotation of the regression, which can result in standardized estimates of greater than 1 even in the absence of multicollinearity (Deegan, 1978). In either case, it does not appear that these large standardized estimates biased our results. Indeed, even in the case of variance inflation due to interaction terms, Allison (2012) notes that inflated estimates do not alter the interpretation of coefficients unless excessively high standard errors lead these coefficients to be non-significant (i.e., type 2 error). Since our observed interaction between government efficiency and cultural tightness consistently reached significance, it appears that this issue did not occur in our data.

We next examined problematic heteroscedasticity. If variation is systematically larger at high or low predicted values in a regression, it can violate OLS model assumptions. To evaluate potential heteroscedasticity, we plotted our model residuals against our model predicted values for our primary model (Model 1b in our main text's Table 1). These plots (see Figure S10) suggested that this model was homoscedastic, with little systematic invariances in the relationship between residuals and predicted values. For example, the relationship between residuals and predicted values was almost zero, $r = -.02$, $p = .93$, indicating no systematic autocorrelation.

Finally, we examined potentially problematic outliers in our analyses of growth rate and mortality likelihood via studentized residuals. An outlier analysis identified Singapore as the case with the highest studentized residual (-3.57). However, this value was not significantly larger than the average studentized residual when we conducted an outlier test with the appropriate Bonferroni correction (Paul & Fung, 1991). Moreover, the significant interaction between government efficiency and cultural tightness replicated even excluding Singapore from the analysis ($p = .02$). The interaction also replicated after removing China from our dataset ($p < .001$), which has a longer COVID-19 growth rate time series than any other country but has faced criticism for its handling of the virus.

Replication Controlling for Relational Mobility

Research on cross-cultural variation in the spread of COVID-19 has linked this variation to relational mobility (the extent to which it is easy to form new relationships and terminate new ones in a society), such that nations with higher levels of relational mobility have had faster growth rates compared to those with lower levels of relational mobility (Salvador et al., 2020). Since relational mobility is correlated with tightness across cultures (Thomson et al., 2018), we sought to test whether relational mobility accounted for cultural tightness's interaction with government efficiency. These analyses are summarized in Table S13, and replicate the effects in the manuscript controlling for relational mobility. We note that only 22 nations had overlapping data with cultural tightness, government efficiency, and growth rate estimates, so these models had less power than our primary and secondary analyses in the main text. For this reason, we suggest that readers interpret these results with caution.

Replication Controlling for Climatological Variables

Past research has linked variation in human culture to temperature and rainfall which could also plausibly predict variation in COVID-19 growth rate. To ensure that our effects were not driven by climatological variables, we replicated our results controlling for Van der Vliert's (2020) measures of heat stress, cold stress, and precipitation stress. Results controlling for these variables are summarized in Table S14.

Replication Controlling for Authoritarianism

We emphasize that our results do not imply that authoritarian governments are better suited to lower growth rates than democratic cultures. To confirm that authoritarianism was not driving our findings, Table S15 replicates our findings controlling for authoritarianism, which we compiled using the Freedom House's measure of authoritarian governments.

Supplementary Results for Mortality Rates

We evaluated the robustness of our models for mortality rates by checking for (a) problematic multicollinearity, (b) heteroscedasticity, and (c) problematic residuals. We estimated multicollinearity via the variance inflation factors for each of our Fixed Effects in Model 4b, which included our covariates. As noted above, a variance inflation factor of above 5 generally means that a model has high multicollinearity which is biasing the estimates and standard errors. Table S16 shows that no variables had problematic multicollinearity.

We next examined problematic heteroscedasticity. If variation is systematically larger at high or low predicted values in a regression, it can violate OLS model assumptions. To evaluate potential heteroscedasticity, we plotted our model residuals against our model predicted values for our primary model (Model 4b in our main text's Table 4). These plots (see Figure S11) suggested that this model was homoscedastic, with little systematic invariances in the

relationship between residuals and predicted values. For example, the relationship between residuals and predicted values was almost zero, $r < .001$, $p = .99$, indicating no systematic autocorrelation.

We examined potentially problematic outliers in our analyses of mortality via studentized residuals. An outlier analysis identified Malaysia as the case with the highest studentized residual (2.50). However, this value was not significantly larger than the average studentized residual when we conducted an outlier test with the appropriate Bonferroni correction (.69). Moreover, the significant interaction between government efficiency and cultural tightness replicated even excluding Malaysia from the analysis ($p = .003$). This interaction also replicated after removing China from analyses ($p = .02$).

Tables S17-S21 present analyses for mortality rates controlling for relational mobility, climate, authoritarianism, and other proxies for underreporting (including a table where we replicate the DA-CFR results weighting based on certainty). Our effects are unchanged by the inclusion of these variables.

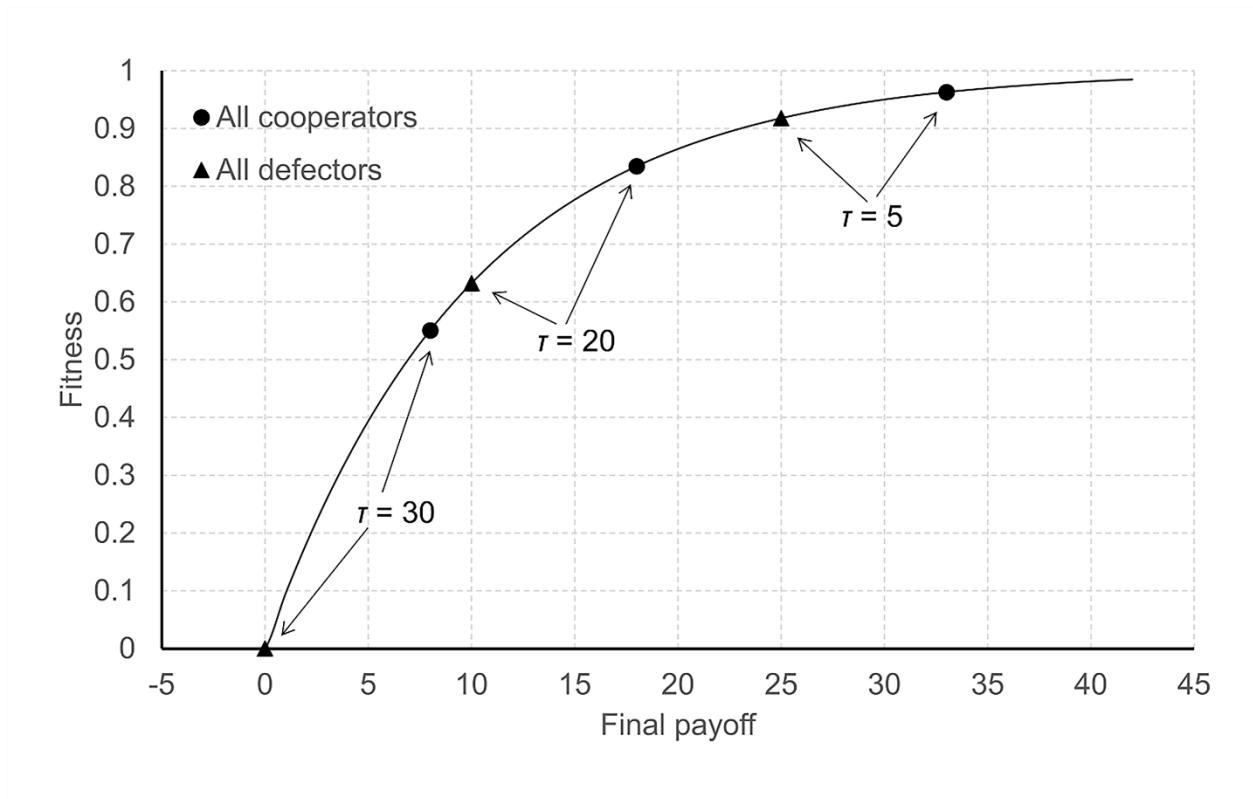
Log-Transforming Mortality Rate Data

Our raw mortality rate data was highly skewed, with some countries showing far greater mortality rates than others. When outcome variables in regression are highly skewed, this can sometimes lead to violations of homoscedasticity, and our initial regression models using raw mortality rate showed a negative association between the residuals and the fitted values. Log-transforming our mortality rate data solved these issues. The log-transformed distribution of mortality rate was normal (see Figure S12, and our model diagnostics (presented in this paper) showed no problematic heteroscedasticity. Table S22 shows that the interaction of cultural tightness and government efficiency replicates when we use the raw (rather than log-

transformed) mortality rate variable.

Supplemental Figures

Figure S1

Fitness as a Function of Final Payoff

Note. Fitness as a function of final payoff. Circles and triangles, respectively, show the final payoff π and fitness $f(\pi)$ for a cooperator surrounded by cooperators and a defector surrounded by defectors, under three threat levels: high ($\tau = 30$), medium ($\tau = 20$), and low ($\tau = 5$), given our payoff matrix and a base payoff of 30.

Figure S2

Death Probability as a Function of an Agent's Fitness

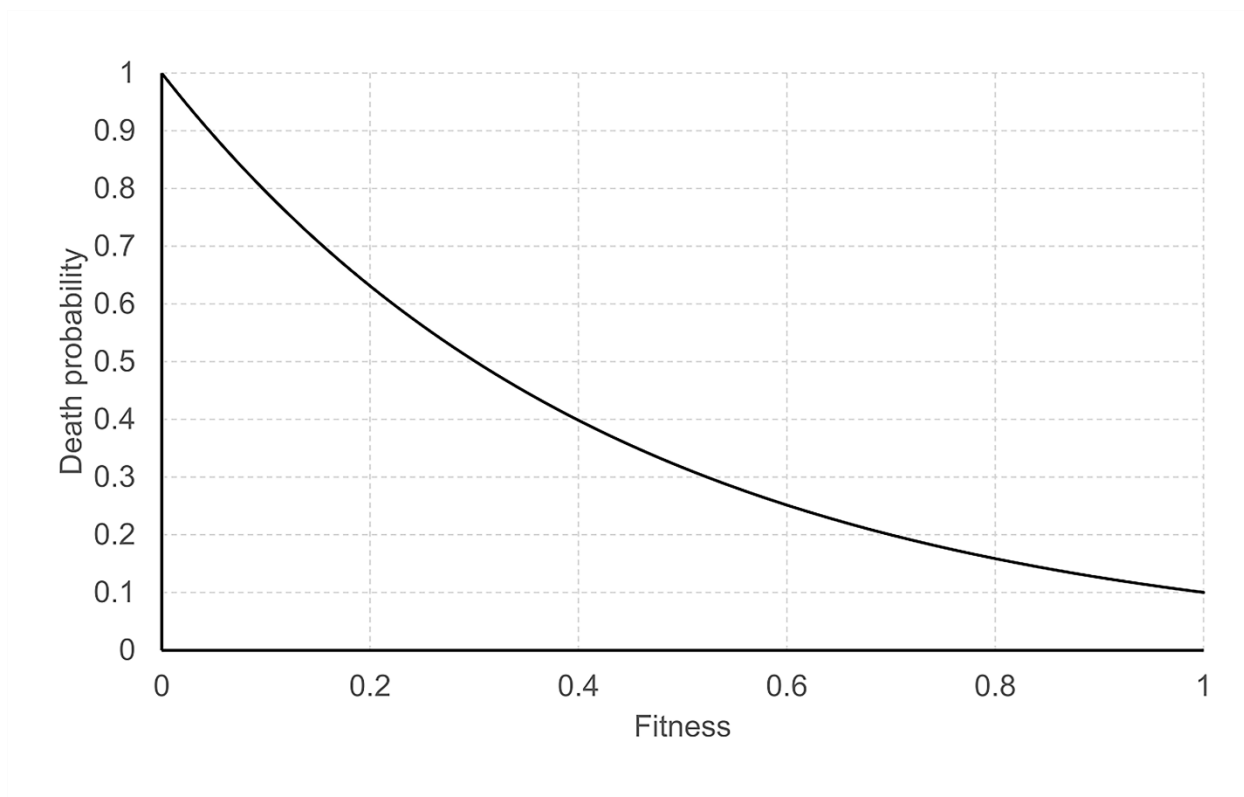
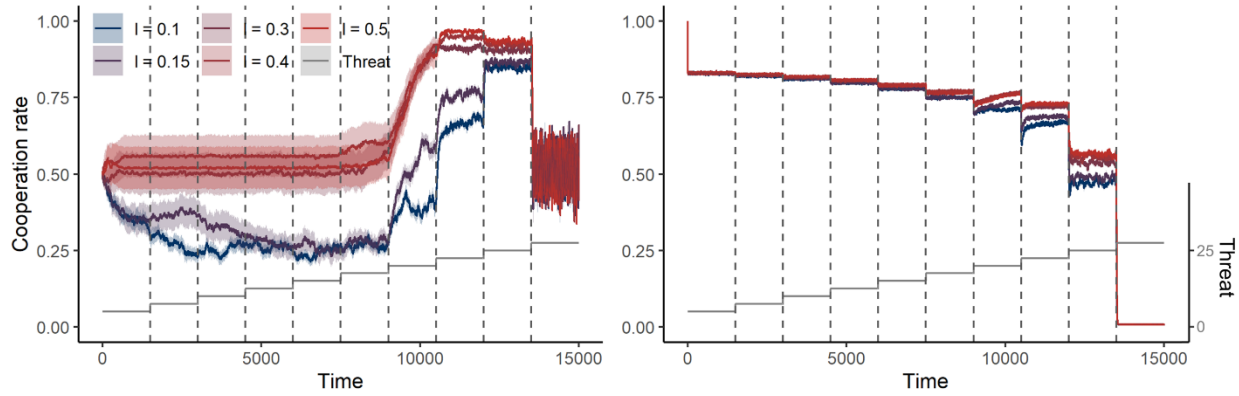
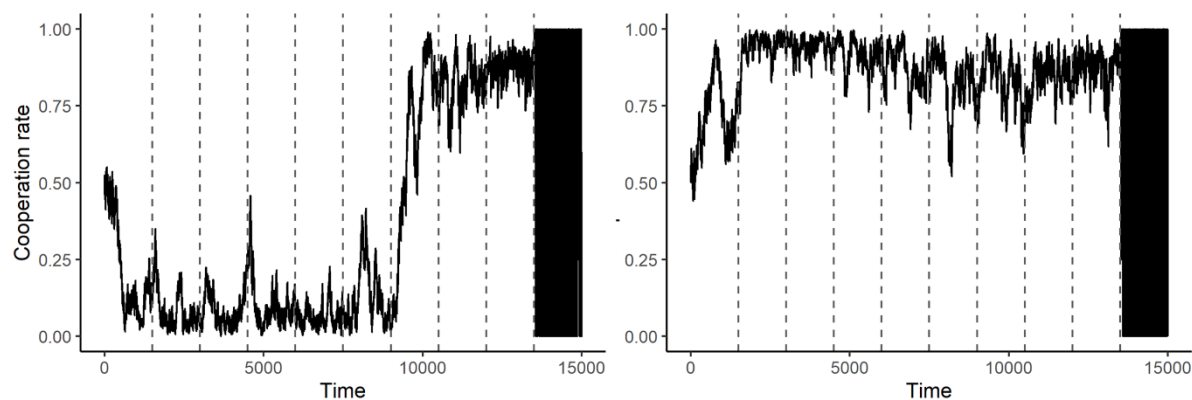


Figure S3*Simulations Under Different Levels of Tightness*

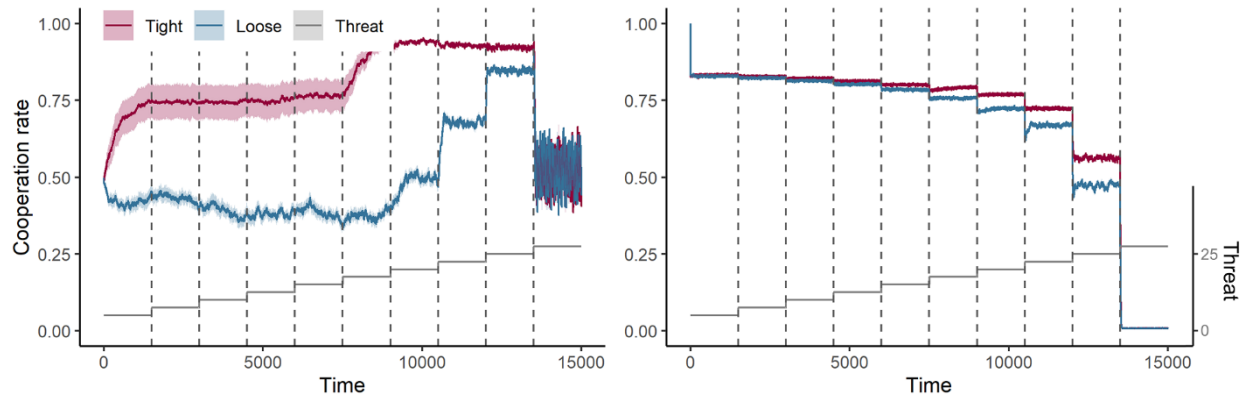
Note. The figure depicts 50 runs at each level of tightness $l = [0.1, 0.15, 0.3, 0.4, 0.5]$, with $b = 3$, $c = 1$, and $k = 3$. Each run contains 15,000 iterations. The shadows show standard errors. The threat τ started at a low level ($\tau = 5$) and escalated every 1,500 iterations, reaching its maximum value ($\tau = 27.5$) in the 13,500th iteration. The left panel shows the results of cooperation rates while the right panel shows the results for alive rates

Figure S4

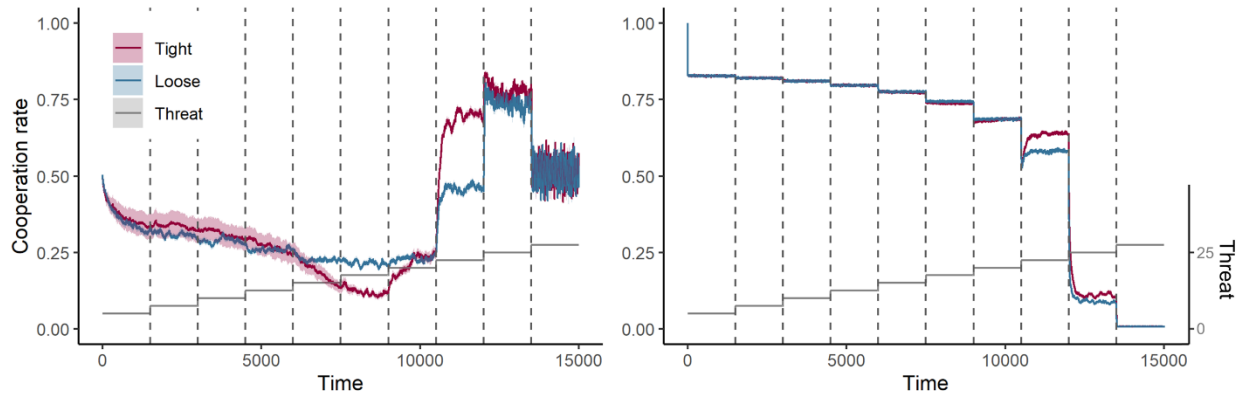
Cooperation Rates in Two Tight Cultures



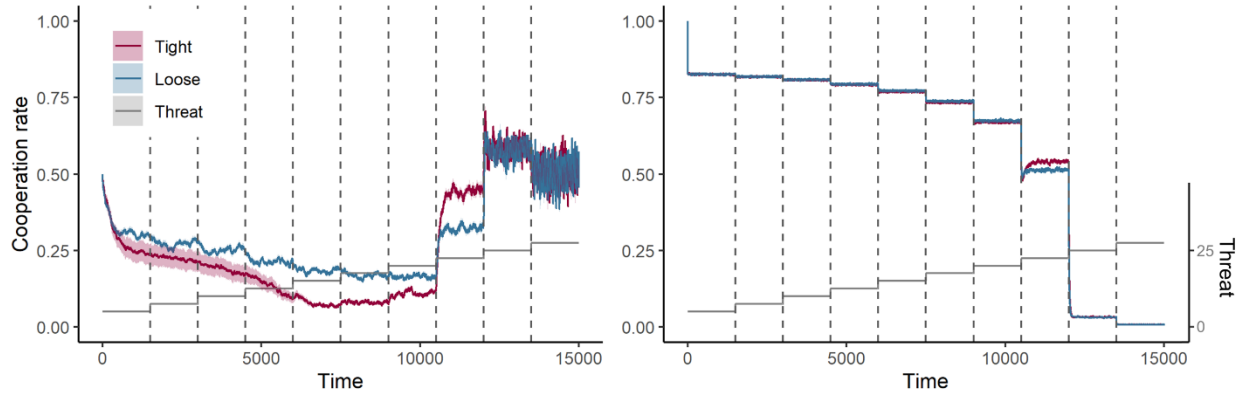
Note. Example of the cooperation rates in two of the tight cultures ($l = .20$) from Figure 3. On the left, the majority defect when threat is low while on the right, the majority cooperate.

Figure S5*Simulation Results With a Smaller Neighborhood*

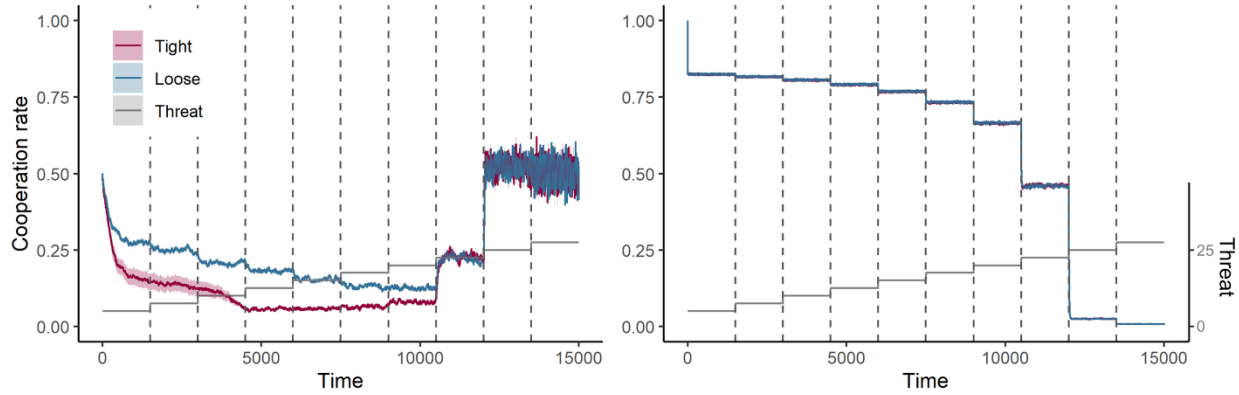
Note. The figure depicts 50 runs in tight ($l = .20$) and loose ($l = .05$) cultures where the conforming neighborhood contains only four adjacent neighbors. In this figure, $b = 3$, $c = 1$, and $k = 3$. Each run contains 15,000 iterations. The shadows show standard errors. The threat τ started at a low level ($\tau = 5$) and escalated every 1,500 iterations, reaching its maximum value ($\tau = 27.5$) in the 13,500th iteration. The left panel shows cooperation rates and the right panel shows alive rates.

Figure S6*Simulation Results With $b = 2.5$* 

Note. The figure depicts 100 runs in tight ($l = .20$) and loose ($l = .05$) cultures where the benefit of cooperation is $b = 2.5$ and the cost of cooperation is $c = 1$. The ratio between the benefit and the cost of cooperation is $k = 2.5$. The shadows show standard errors. The threat τ started at a low level ($\tau = 5$) and escalated every 1,500 iterations, reaching its maximum value ($\tau = 27.5$) in the 13,500th iteration. The left panel shows cooperation rates and the right panel shows alive rates.

Figure S7*Simulation Results With $b = 2$* 

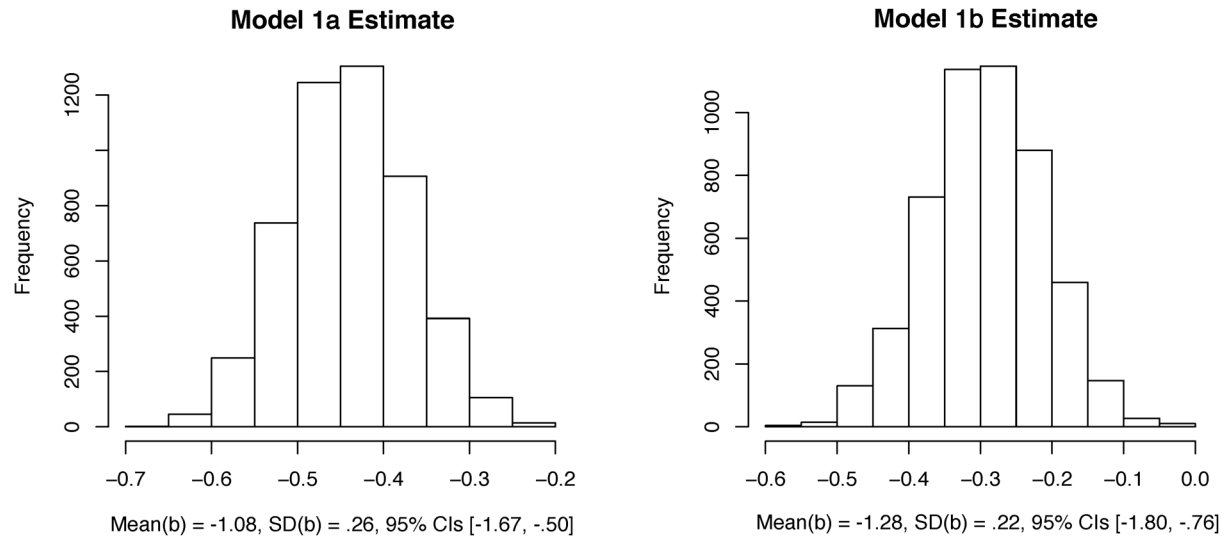
Note. The figure depicts 100 runs in tight ($l = .20$) and loose ($l = .05$) cultures where the benefit of cooperation is $b = 2$ and the cost of cooperation is $c = 1$. The ratio between the benefit and the cost of cooperation is $k = 2$. The shadows show standard errors. The threat τ started at a low level ($\tau = 5$) and escalated every 1,500 iterations, reaching its maximum value ($\tau = 27.5$) in the 13,500th iteration. The left panel shows cooperation rates and the right panel shows alive rates.

Figure S8*Simulation Results With $b = 1.5$* 

Note. The figure depicts 100 runs in tight ($l = .20$) and loose ($l = .05$) cultures where the benefit of cooperation is $b = 1.5$ and the cost of cooperation is $c = 1$. The ratio between the benefit and the cost of cooperation is $k = 1.5$. The shadows show standard errors. The threat τ started at a low level ($\tau = 5$) and escalated every 1,500 iterations, reaching its maximum value ($\tau = 27.5$) in the 13,500th iteration. The left panel shows cooperation rates and the right panel shows alive rates.

Figure S9

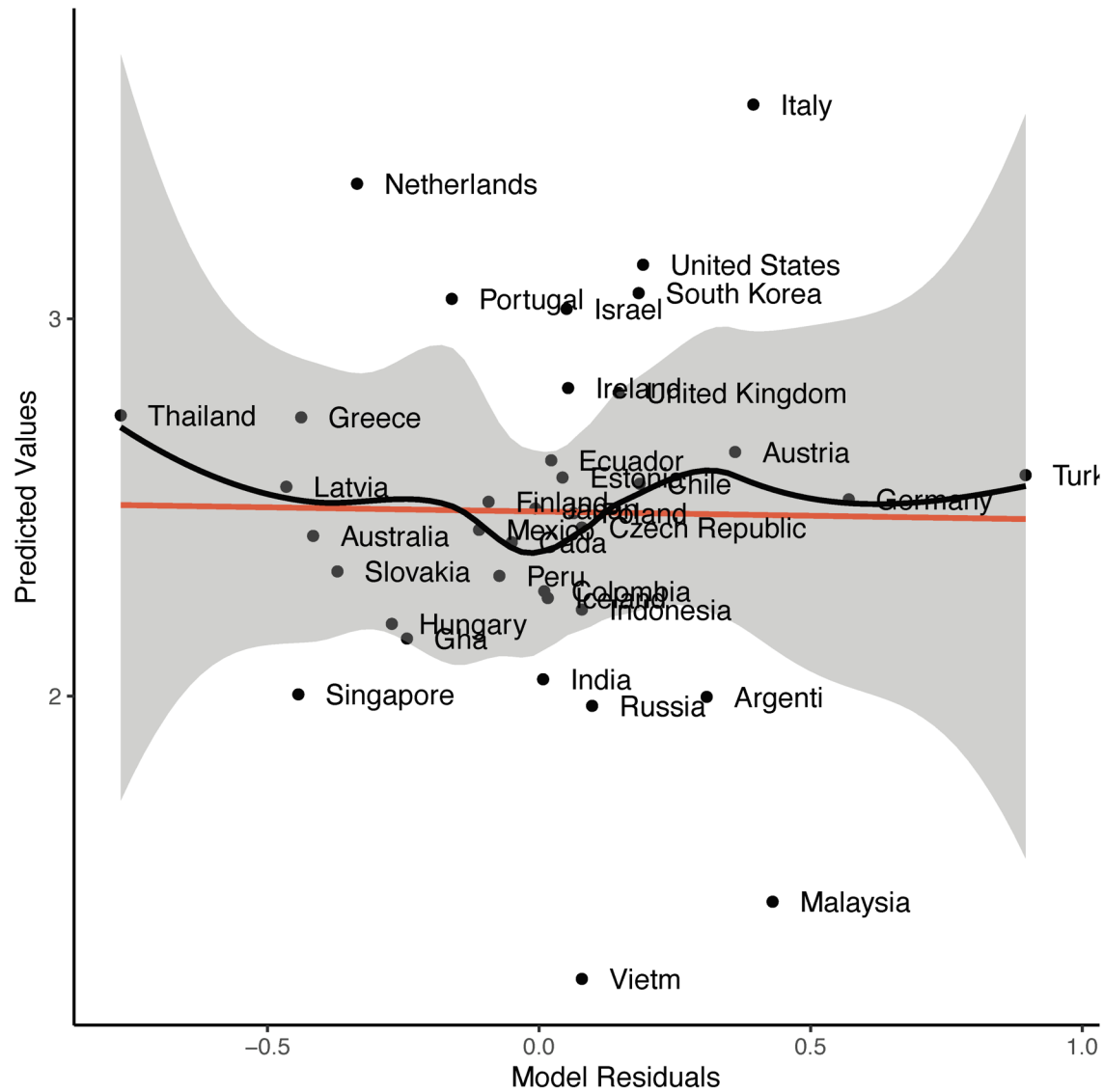
Results From a Bootstrapping Analysis



Note. Results from a bootstrapping analysis of the government efficiency $\times$ cultural tightness interaction on growth rate. These two models represent Model 1a-b from Table 1 in the main text.

Figure S10

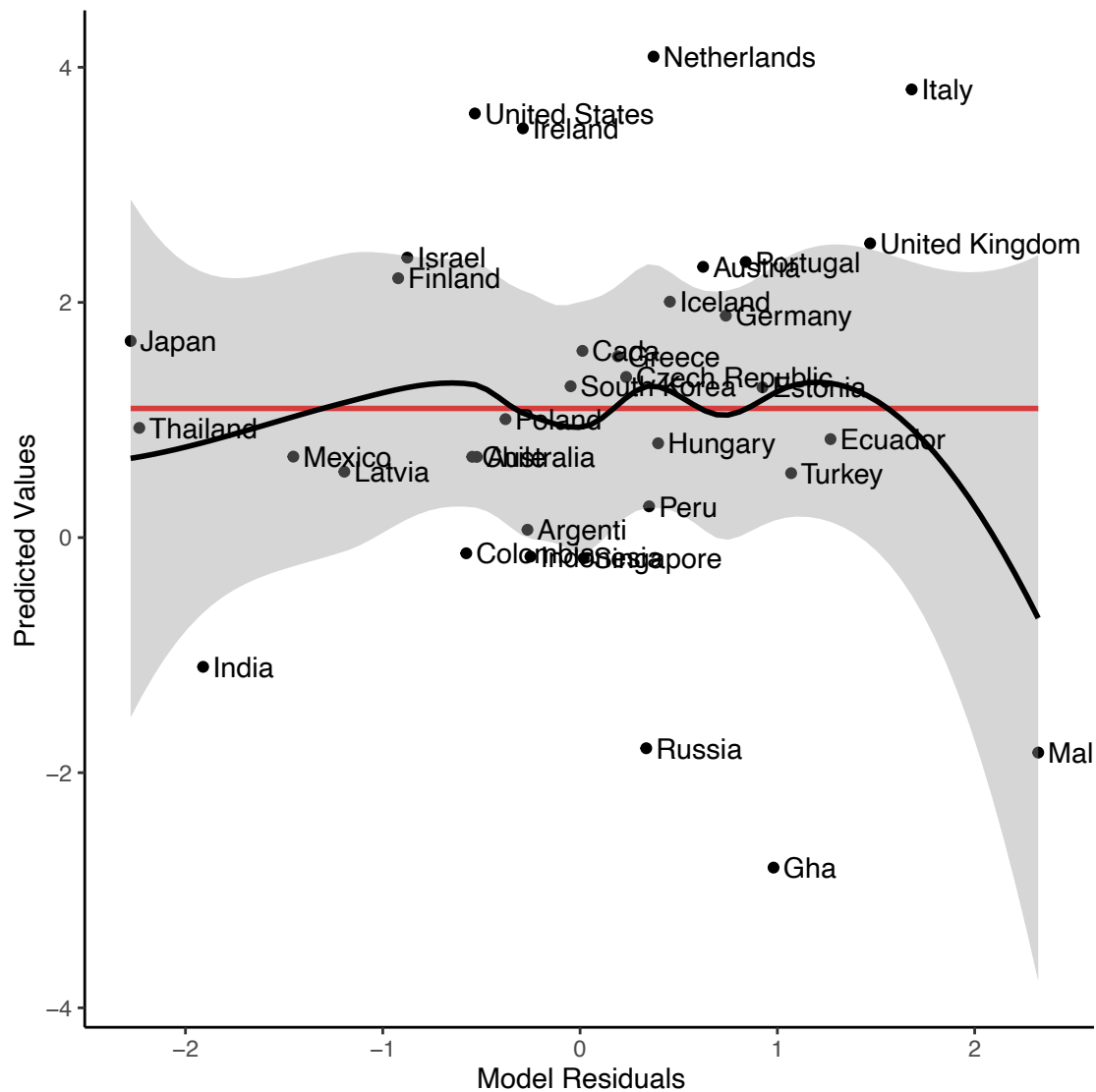
Relationship Between Model Residuals and Predicted Values for Growth Rate



Note. The relationship between our model residuals and predicted values for our analyses of growth rate across Model 1b.

Figure S11

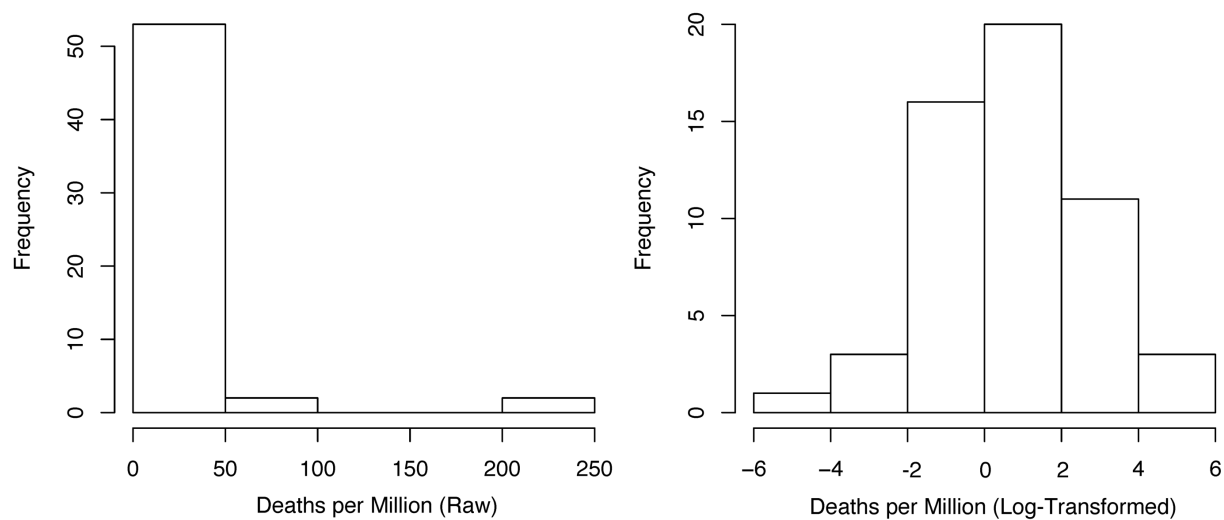
Relationship Between Model Residuals and Predicted Values for Mortality Rate



Note. The relationship between our model residuals and predicted values for our analyses of mortality rate across Model 4b.

Figure S12

Mortality Rate Distributions



Note. The raw (left) and log-transformed (right) mortality rate distributions.

Supplemental Tables

Table S1

COVID-19 Growth Rate Primary Models with Alpha-Adjusted Sample

Fixed Effect	DF	R ² (Adj.)	b (SE)	t	p
Model S1	27	.72 (.64)			
Test-Case Ratio			-.24 (.06)	-4.177	< .001
GINI			.11 (.10)	1.09	.29
GDP Per Capita			.31 (.09)	3.58	.001
Population Density			.14 (.06)	2.42	.02
Median Age			.11 (.10)	1.14	.26
Gov. Efficiency (centered)			-.54 (.10)	-5.38	.001
Tightness (centered)			.11 (.22)	.51	.62
Gov. Efficiency * Tightness			-1.18 (.28)	-4.23	< .001
Simple Slopes					
Cultural Tightness (low GE)			1.13 (.35)	3.27	.003
Cultural Tightness (high GE)			-.92 (.30)	-3.04	.005
Gov. Efficiency (low CT)			-.02 (.13)	-.14	.89
Gov. Efficiency (high CT)			-1.05 (.18)	-5.83	< .001

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table S2*COVID-19 Growth Rate Primary Models with Alternative Tightness Measure*

Fixed Effect	DF	R²(Adj.)	b (SE)	t	P
Model S2	12	.81 (.69)			
Test-Case Ratio			-1.22 (.42)	-2.89	.01
GINI			.18 (.17)	1.10	.29
GDP Per Capita			.22 (.14)	1.64	.13
Population Density			.05 (.08)	.58	.57
Median Age			.20 (.17)	1.23	.24
Gov. Efficiency (centered)			-.29 (.14)	-2.13	.05
33-Nation CT (centered)			.10 (.04)	2.17	.05
Gov. Efficiency * Tightness			-.16 (.04)	-3.56	.004
Simple Slopes					
33-Nation CT (low GE)			.23 (.07)	3.42	.005
33-Nation CT (high GE)			-.04 (.05)	-.82	.43
Gov. Efficiency (low CT)			.15 (.22)	.67	.52
Gov. Efficiency (high CT)			-.73 (.14)	-5.25	< .001
Model S3	28	.66 (.57)			
Test-Case Ratio			-.23 (.06)	-3.82	< .001
GINI			.13 (.10)	1.26	.22
GDP Per Capita			.26 (.10)	2.60	.01
Population Density			.12 (.07)	1.85	.07
Median Age			.10 (.10)	.99	.33
Gov. Efficiency (centered)			-.37 (.11)	-3.47	.002
Combination CT (centered)			.05 (.09)	.62	.54
Gov. Efficiency * Tightness			-.34 (.09)	-3.72	< .001
Simple Slopes					
Combination CT (low GE)			.35 (.16)	3.00	.006
Combination CT (high GE)			-.24 (.12)	-2.03	.05
Gov. Efficiency (low CT)			.03 (.16)	.18	.86
Gov. Efficiency (high CT)			-.77 (.15)	-5.28	< .001

Note. All effects are parametrized and formatted in the same manner as Table 1. Model S2

reflects the original measure of TL in Gelfand et al., (2011). Model S3 reflects the original measure of TL in Gelfand et al. (2011) and additional countries from Eriksson that weren't available in 2011.

Table S3*Government Efficiency Items*

Item	Low Anchor	High Anchor
In your country, how efficient is the government in spending public revenue?	1 – Extremely inefficient	7 – Extremely efficient
In your country, how burdensome is it for companies to comply with public administration requirements (e.g. permits, regulations, reporting)?	1 – Extremely Burdensome	7 – Not burdensome at all
In your country, how efficiently are the legal and judicial systems for companies in settling disputes?	1 – Extremely inefficient	7 – Extremely efficient
In your country, how easy is it for private businesses to challenge government actions and/or regulations through the legal system?	1 – Extremely difficult	7 – Extremely easy
In your country, how easy is it for companies to obtain information about changes in government policies and regulations affecting their activities?	1 – Extremely difficult	7 – Extremely easy

Table S4

The Correlations of Government Efficiency and Government Effectiveness with Key Measures of Technological and Economic Development

	Government Efficiency	Government Effectiveness
GDP per Capita	$r = .67, p < .001$	$r = .83, p < .001$
Internet Users	$r = .41, p < .001$	$r = .75, p < .001$
Globalization Index	$r = .33, p < .001$	$r = .84, p < .001$

Table S5*COVID-19 Growth Rate Models Controlling for Government Effectiveness*

Fixed Effect	DF	R²(Adj.)	b (SE)	t	P
Model S4a	27	.72 (.63)			
Test-Case Ratio			-.24 (.06)	-4.25	< .001
GINI			.14 (.09)	1.52	.14
GDP Per Capita			.41 (.13)	3.05	.005
Population Density			.15 (.06)	2.48	.02
Median Age			.19 (.12)	1.59	.12
Government Effectiveness			-.28 (.31)	-.93	.36
Gov. Efficiency (centered)			-.41 (.16)	-2.60	.02
Tightness (centered)			.13 (.21)	.60	.55
Gov. Efficiency * Tightness			-1.26 (.27)	-4.68	< .001
Simple Slopes					
Tightness (low GE)			1.22 (.33)	3.67	.001
Tightness (high GE)			-.96 (.30)	-3.22	.003
Gov. Efficiency (low CT)			.14 (.18)	.76	.46
Gov. Efficiency (high CT)			-.97 (.21)	-4.50	< .001
Model S4b	26	.73 (.62)			
Test-Case Ratio			-.25 (.06)	-4.20	< .001
GINI			.13 (.10)	1.34	.19
GDP Per Capita			.40 (.14)	2.89	.008
Population Density			.15 (.06)	2.43	.02
Median Age			.17 (.13)	1.31	.20
Gov. Effect * Tightness			.17 (.44)	.38	.71
Gov. Efficiency (centered)			-.43 (.17)	-2.58	.02
Tightness (centered)			.14 (.22)	.65	.52
Gov. Efficiency * Tightness			-1.38 (.43)	-3.25	.003
Simple Slopes					
Tightness (low GE)			1.34 (.46)	2.89	.008
Tightness (high GE)			-1.06 (.39)	-2.69	.01
Gov. Efficiency (low CT)			.18 (.21)	.84	.41
Gov. Efficiency (high CT)			-1.03 (.28)	-3.69	.001

Note. All effects are parametrized and formatted in the same manner as Table 1. Model S3a

controls for just the main effect of government effectiveness. Model S3b controls for the interaction of government effectiveness with cultural tightness. In model S3b, “GE” stands for “government efficiency.”

Table S6*COVID-19 Growth Rate Models Using WCY Measure*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b</i> (<i>SE</i>)	<i>t</i>	<i>P</i>
Model S5	26	.69 (.59)			
Test-Case Ratio			-1.02 (.29)	-3.58	.001
GINI			.13 (.10)	1.28	.21
GDP Per Capita			.34 (.09)	3.89	< .001
Population Density			.08 (.06)	1.37	.18
Median Age			.19 (.10)	1.89	.07
WCY Eff. (centered)			-3.62 (.75)	-4.86	< .001
Tightness (centered)			.07 (.22)	.33	.75
WCY Eff. * Tightness			-4.94 (2.04)	-2.42	.02
Simple Slopes					
Tightness (low GE)			.70 (.33)	2.17	.04
Tightness (high GE)			-.56 (.36)	-1.56	.13
WCY Eff. (low CT)			-1.46 (1.19)	-1.23	.23
WCY Eff. (high CT)			-5.78 (1.13)	-5.11	< .001

Note. All effects are parametrized and formatted in the same manner as Table 1. WYC Eff.

represents the World Competitiveness Yearbook measure.

Table S7*COVID-19 Growth Rate Models Using Bureaucratic Quality*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b (SE)</i>	<i>t</i>	<i>P</i>
Model S6	29	.48 (.33)			
Test-Case Ratio			-.23 (.08)	-2.96	.006
GINI			.03 (.12)	.29	.78
GDP Per Capita			.41 (.76)	2.66	.01
Population Density			.04 (.07)	.49	.63
Median Age			.28 (.14)	2.07	.05
Bur. Quality (centered)			-1.95 (.76)	-2.56	.02
Tightness (centered)			.13 (.28)	.45	.65
Bur. Quality * Tightness			-1.15 (.57)	-2.03	.05
Simple Slopes					
Tightness (low BQ)			.34 (.21)	1.61	.12
Tightness (high BQ)			-.23 (.16)	-1.48	.15
Bur. Quality (low CT)			-.80 (.76)	-1.06	.30
Bur. Quality (high CT)			-3.10 (1.11)	-2.79	.009

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table S8*Payoff Matrix*

Prisoner's Dilemma:

	Cooperate	Defect
Cooperate	(r, r)	(s, t)
Defect	(t, s)	(p, p)

Donation Game:

	Cooperate	Defect
Cooperate	$(b-c, b-c)$	$(-c, b)$
Defect	$(b, -c)$	$(0, 0)$

Note. A symmetric Prisoner's Dilemma game has the form shown at left, subject to the requirements that $t > r > p > s$ and $2r > t + s$. A Donation Game (Hilbe et al., 2013) is a special case of the Prisoner's Dilemma in which r, s, t , and p have the values $b - c, -c, b$, and 0 , respectively. Here, c is the amount each agent is asked to contribute, and $b = kc$ is the benefit the other agent will get from this contribution, where $k > 1$. In our main study, we used $b = 3$ and $c = 1$ (hence $r = 2, s = -1, t = 3$, and $p = 0$).

Table S9*COVID-19 Growth Rate Primary Models with Alternative Underreporting Proxies*

Fixed Effect	DF	R²(Adj.)	b (SE)	t	P
Model S7	29	.53 (.40)			
Tests Per Capita			.04 (.11)	.33	.74
GINI			.18 (.12)	1.51	.14
GDP Per Capita			.34 (.12)	2.76	.01
Population Density			.13 (.08)	1.64	.11
Median Age			.19 (.12)	1.61	.12
Gov. Efficiency (centered)			-.47 (.13)	-3.77	< .001
Tightness (centered)			-.06 (.27)	-.24	.81
Gov. Efficiency * Tightness			-1.04 (.33)	-3.14	.004
Simple Slopes					
Cultural Tightness (low GE)			.83 (.39)	2.13	.04
Cultural Tightness (high GE)			-.96 (.39)	-2.47	.02
Gov. Efficiency (low CT)			-.01 (.16)	-.09	.93
Gov. Efficiency (high CT)			-.92 (.22)	-4.25	< .001
Model S8	39	.55 (.46)			
DA-CFR Underreporting			.22 (.07)	3.15	.003
GINI			.20 (.10)	1.96	.06
GDP Per Capita			.36 (.10)	3.61	< .001
Population Density			.05 (.07)	.66	.51
Median Age			.23 (.11)	2.17	.04
Gov. Efficiency (centered)			-.43 (.12)	-3.73	< .001
Tightness (centered)			.11 (.23)	.49	.63
Gov. Efficiency * Tightness			-.71 (.24)	-3.02	.004
Simple Slopes					
Tightness (low GE)			.73 (.33)	2.24	.03
Tightness (high GE)			-.50(.29)	-1.73	.09
Gov. Efficiency (low CT)			-.12 (.14)	-.87	.39
Gov. Efficiency (high CT)			-.74 (.17)	-4.31	< .001

Note. All effects are parametrized and formatted in the same manner as Table 1. Model S7 presents Tests Per Capital and Model S8 presents Russell, Hellewell, & Abbot's (2020) measure.

Table S10*COVID-19 Growth Rate Models Incorporating Underreporting Uncertainty*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b (SE)</i>	<i>t</i>	<i>P</i>
Model S9	33	.58 (.48)			
DA-CFR Underreporting			.18 (.07)	2.46	.02
GINI			.29 (.08)	3.48	.001
GDP Per Capita			.38 (.10)	3.85	< .001
Population Density			.15 (.08)	1.96	.06
Median Age			.25 (.09)	2.85	.007
Gov. Efficiency (centered)			-.39 (.12)	-3.26	.003
Tightness (centered)			.29 (.20)	1.41	.17
Gov. Efficiency * Tightness			-.78 (.29)	-2.70	.01
Simple Slopes					
Cul. Tightness (low GE)			.96 (.28)	3.38	.002
Cul. Tightness (high GE)			-.39 (.36)	-1.09	.28
Gov. Efficiency (low CT)			-.05 (.13)	-.39	.70
Gov. Efficiency (high CT)			-.73 (.21)	-3.47	.001

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table S11*COVID-19 Growth Rate Primary Models Controlling for Spatial Autocorrelation*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b</i> (<i>SE</i>)	<i>t</i>	<i>P</i>
Model S10	23	.78 (.66)			
Test-Case Ratio			-.21 (.06)	-3.66	.001
GINI			.14 (.12)	1.18	.25
GDP Per Capita			.30 (.11)	2.82	.01
Population Density			.13 (.08)	1.52	.14
Median Age			.13 (.09)	1.34	.19
Europe			.59 (.39)	1.51	.15
Asia			.13 (.48)	.28	.78
Africa			-.49 (.79)	-.63	.54
South America			.71 (.44)	1.61	.12
North America			.54 (.36)	1.51	.14
Gov. Efficiency (centered)			-.49 (.11)	-4.63	< .001
Tightness (centered)			.65 (.30)	2.16	.04
Gov. Efficiency * Tightness			-1.19 (.27)	-4.44	< .001
Simple Slopes					
Cultural Tightness (low GE)			1.67 (.39)	4.34	< .001
Cultural Tightness (high GE)			-.38 (.27)	-1.02	.32
Gov. Efficiency (low CT)			.03 (.12)	.27	.79
Gov. Efficiency (high CT)			-1.00 (.18)	-5.44	< .001

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table S12*Growth Rate Multicollinearity Analysis*

Fixed Effect	Model <i>VIF</i>
Test-Case Ratio	1.20
GINI	1.60
GDP Per Capita	2.01
Population Density	1.28
Median Age	1.75
Cultural Tightness	1.53
Government Efficiency	1.86

Note. These VIFs are fitted for all of the variables in Model 1b, which included our primary control variables.

Table S13*COVID-19 Growth Rate Primary Models Controlling for Relational Mobility*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b</i> (<i>SE</i>)	<i>t</i>	<i>P</i>
Model S11	9	.85 (.69)			
Test-Case Ratio			-.98 (.44)	-2.25	.05
GINI			.12 (.18)	.64	.54
GDP Per Capita			.17 (.14)	1.20	.26
Population Density			.12 (.06)	1.88	.09
Median Age			.09 (.20)	.44	.67
Relational Mobility			.02 (.12)	.16	.88
Gov. Efficiency (centered)			-.59 (.15)	-3.89	.004
Tightness (centered)			.86 (.35)	2.43	.04
Gov. Efficiency * Tightness			-1.52 (.43)	-3.56	.006
Simple Slopes					
Cultural Tightness (low GE)			2.18 (.53)	4.07	.003
Cultural Tightness (high GE)			-.45 (.49)	-.92	.38
Gov. Efficiency (low CT)			.07 (.19)	.35	.73
Gov. Efficiency (high CT)			-1.26 (.28)	-4.50	.002

Note. All effects are parametrized and formatted in the same manner as Table 1. “Rel Mob.”

stands for “Relational Mobility.”

Table S14*COVID-19 Growth Rate Primary Models Controlling for Climatological Variables*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b</i> (<i>SE</i>)	<i>t</i>	<i>P</i>
Model S12	25	.76 (.66)			
Test-Case Ratio			-.21 (.06)	-3.68	.001
GINI			.23 (.10)	2.28	.03
GDP Per Capita			.31 (.10)	3.11	.005
Population Density			.17 (.07)	2.51	.02
Median Age			.10 (.10)	1.02	.32
Heat Stress			-.08 (.11)	-.80	.43
Cold Stress			.17 (.13)	1.35	.19
Rain Stress			.08 (.11)	.68	.50
Gov. Efficiency (centered)			-.47 (.12)	-3.88	< .001
Tightness (centered)			.35 (.25)	1.43	.17
Gov. Efficiency * Tightness			-1.13 (.30)	-3.79	< .001
Simple Slopes					
Cultural Tightness (low GE)			1.33 (.39)	3.41	.002
Cultural Tightness (high GE)			-.63 (.32)	-1.95	.06
Gov. Efficiency (low CT)			.02 (.12)	.16	.88
Gov. Efficiency (high CT)			-.97 (.22)	-4.37	< .001

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table S15*COVID-19 Growth Rate Primary Models Controlling for Authoritarianism*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b (SE)</i>	<i>t</i>	<i>P</i>
Model S13	27	.72 (.62)			
Test-Case Ratio			-.22 (.08)	-2.73	.01
GINI			.15 (.10)	1.53	.14
GDP Per Capita			.31 (.09)	3.54	.001
Population Density			.14 (.06)	2.36	.03
Median Age			.13 (.10)	1.31	.20
Authoritarianism			-.03 (.10)	-.37	.71
Gov. Efficiency (centered)			-.52 (.11)	-4.92	< .001
Tightness (centered)			.12 (.22)	.51	.61
Gov. Efficiency * Tightness			-1.20 (.31)	-3.91	< .001
Simple Slopes					
Cultural Tightness (low GE)			1.15 (.38)	3.01	.006
Cultural Tightness (high GE)			-.92 (.31)	-2.99	.006
Gov. Efficiency (low CT)			.006 (.13)	.04	.97
Gov. Efficiency (high CT)			-1.04 (.20)	-5.14	< .001

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table S16*Multicollinearity Analysis for Mortality Rates*

Fixed Effect	Model <i>VIF</i>
Test-Case Ratio	1.11
GINI	1.76
GDP Per Capita	1.99
Population Density	1.38
Median Age	2.63
Cultural Tightness	1.55
Government Efficiency	1.82

Note. These VIFs are fitted for all of the variables in Model 4b, which included our primary control variables.

Table S17*COVID-19 Mortality Rate Primary Model Controlling for Relational Mobility*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b</i> (<i>SE</i>)	<i>t</i>	<i>P</i>
Model S14	8	.76 (.46)			
Test-Case Ratio			-.84 (2.17)	-.39	.71
Mortality			1.26 (.87)	1.45	.19
GINI			-.25 (.58)	-.43	.68
GDP Per Capita			.62 (.53)	1.17	.27
Population Density			.30 (.27)	1.10	.30
Median Age			-1.28 (1.03)	-1.24	.25
Relational Mobility			.13 (.45)	.28	.79
Gov. Efficiency (centered)			-.31 (.58)	-.52	.62
Tightness (centered)			1.24 (1.33)	.93	.38
Gov. Efficiency * Tightness			-3.67 (1.56)	-2.36	.046
Simple Slopes					
Cultural Tightness (low GE)			4.42 (2.15)	2.05	.07
Cultural Tightness (high GE)			-1.94 (1.59)	-1.22	.26
Gov. Efficiency (low CT)			1.30 (.70)	1.86	.10
Gov. Efficiency (high CT)			-1.91 (1.05)	-1.81	.11

Note. All effects are parametrized and formatted in the same manner as Table 1. Note the number

of overlapping countries was very small, making the degrees of freedom very low in this analysis.

Table S18*COVID-19 Mortality Rate Primary Model Controlling for Climatological Variables*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b (SE)</i>	<i>t</i>	<i>P</i>
Model S15	22	.72 (.57)			
Mortality			-.10 (.42)	-.24	.81
Test-Case Ratio			-2.78 (1.02)	-2.73	.01
GINI			.0001 (.41)	.00	.99
GDP Per Capita			.00004 (.35)	2.50	.02
Population Density			.35 (.25)	1.42	.17
Median Age			.37 (.39)	.94	.36
Heat Stress			-.33 (.35)	-.93	.36
Cold Stress			-.16 (.46)	-.36	.73
Rain Stress			-.54 (.39)	-1.38	.18
Gov. Efficiency (centered)			-1.44 (.47)	-3.05	.006
Tightness (centered)			.34 (.80)	.43	.67
Gov. Efficiency * Tightness			-2.88 (1.08)	-2.66	.01
Simple Slopes					
Cultural Tightness (low GE)			2.83 (1.25)	2.27	.03
Cultural Tightness (high GE)			-2.15 (1.21)	-1.77	.09
Gov. Efficiency (low CT)			-.18 (.44)	-.41	.69
Gov. Efficiency (high CT)			-2.69 (.83)	-3.23	.004

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table S19*COVID-19 Mortality Rate Primary Model Controlling for Authoritarianism*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b</i> (<i>SE</i>)	<i>t</i>	<i>P</i>
Model S16	24	.70 (.57)			
Test-Case Ratio			-2.97 (1.03)	-2.89	.008
Mortality			.08 (.38)	.20	.84
GINI			.02 (.34)	.05	.96
GDP Per Capita			1.22 (.32)	3.87	< .001
Population Density			.15 (.23)	.68	.50
Median Age			.23 (.37)	.63	.53
Authoritarianism			.30 (.32)	.95	.35
Gov. Efficiency (centered)			-1.16 (.39)	-3.00	.006
Tightness (centered)			-.03 (.69)	-.05	.96
Gov. Efficiency * Tightness			-2.60 (.98)	-2.66	.01
Simple Slopes					
Cultural Tightness (low GE)			2.21 (1.16)	1.91	.07
Cultural Tightness (high GE)			-2.28 (1.02)	-2.23	.04
Gov. Efficiency (low CT)			-.02 (.42)	-.05	.96
Gov. Efficiency (high CT)			-2.29 (.69)	-3.29	.003

Table S20*COVID-19 Mortality Rate Primary Models with Alternative Underreporting Proxies*

Fixed Effect	DF	R²(Adj.)	b (SE)	t	P
Model S17	26	.61 (.48)			
Tests Per Capita			.27 (.31)	.90	.38
GINI			.15 (.37)	.42	.68
GDP Per Capita			1.11 (.37)	2.99	.006
Population Density			.47 (.26)	1.82	.08
Median Age			.31 (.40)	.79	.44
Gov. Efficiency (centered)			-1.13 (.41)	-2.73	.01
Tightness (centered)			-.92 (.70)	-1.31	.20
Gov. Efficiency * Tightness			-2.90 (.99)	-2.93	.007
Simple Slopes					
Cultural Tightness (low GE)			1.60 (1.12)	1.43	.16
Cultural Tightness (high GE)			-3.43 (1.10)	-3.12	.004
Gov. Efficiency (low CT)			.14 (.47)	.31	.76
Gov. Efficiency (high CT)			-2.40 (.70)	-3.40	.002
Model S18	36	.68 (.60)			
DA-CFR Underreporting			.72 (.22)	3.35	.002
2017 Mortality			-.91 (.28)	-3.21	.003
GINI			-.07 (.29)	-.24	.81
GDP Per Capita			1.12 (.30)	3.74	< .001
Population Density			.12 (.22)	.57	.57
Median Age			1.09 (.31)	3.47	.001
Gov. Efficiency (centered)			-.90 (.37)	-2.47	.02
Tightness (centered)			-.57 (.60)	-.96	.34
Gov. Efficiency * Tightness			-1.82 (.60)	-3.05	.004
Model 7 Simple Slopes					
Tightness (low GE)			1.00 (.83)	1.20	.24
Tightness (high GE)			-2.15 (.75)	-2.88	.007
Gov. Efficiency (low CT)			-.11 (.39)	-.29	.78
Gov. Efficiency (high CT)			-1.70 (.51)	-3.36	.002

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table S21*COVID-19 Mortality Rate Model Incorporating Underreporting Uncertainty*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b</i> (<i>SE</i>)	<i>t</i>	<i>P</i>
Model S19	31	.73 (.65)			
DA-CFR Underreporting			.88 (.25)	3.57	.001
Mortality			-.94 (.32)	-3.00	.005
GINI			.001 (.31)	.02	.98
GDP Per Capita			1.19 (.32)	3.76	< .001
Population Density			.28 (.26)	1.07	.30
Median Age			1.27 (.31)	4.16	< .001
Gov. Efficiency (centered)			-1.27 (.40)	-3.21	.003
Tightness (centered)			-.88 (.68)	-1.30	.20
Gov. Efficiency * Tightness			-2.85 (.94)	-3.01	.005
Simple Slopes					
Cultural Tightness (low GE)			1.58 (.95)	1.66	.11
Cultural Tightness (high GE)			-3.34 (1.16)	-2.89	.007
Gov. Efficiency (low CT)			-.02 (.43)	-.06	.96
Gov. Efficiency (high CT)			-2.51 (.69)	-3.68	< .001

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table S22*COVID-19 Mortality Rate Primary Model with Raw Mortality Rate*

Fixed Effect	<i>DF</i>	<i>R</i>²(<i>Adj.</i>)	<i>b</i> (<i>SE</i>)	<i>t</i>	<i>P</i>
Model S20	27	.39 (.19)			
Test-Case Ratio			-5.31 (6.77)	-.78	.44
Mortality			2.50 (11.22)	.22	.83
GINI			8.03 (9.31)	.86	.40
GDP Per Capita			22.97 (9.64)	2.38	.02
Population Density			10.85 (6.37)	1.70	.10
Median Age			8.24 (11.36)	.73	.48
Gov. Efficiency (centered)			-37.41 (11.44)	-3.27	.003
Tightness (centered)			15.71 (19.37)	.81	.42
Gov. Efficiency * Tightness			-61.56 (26.78)	-2.30	.03
Simple Slopes					
Cultural Tightness (low GE)			68.98 (31.36)	2.20	.04
Cultural Tightness (high GE)			-37.56 (28.99)	-1.30	.21
Gov. Efficiency (low CT)			-10.50 (12.15)	-.86	.40
Gov. Efficiency (high CT)			-64.31 (19.70)	-3.27	.003

Note. All effects are parametrized and formatted in the same manner as Table 1.

Table S23*Sample and Key Values*

Country	Cultural Tightness	Gov. Efficiency	Growth Rate	Deaths per Million	Test-Case Ratio
Algeria	0.69	3.27	2.41	2.39	
Argentina	-0.53	2.34	2.31	0.82	10.02
Armenia	0.21	3.4	2.31	2.36	
Australia	-0.05	4.26	2.01	1.18	57.88
Austria	0.21	4.31	3.01	18.65	11.02
Bosnia and Herzegovina	-0.43	2.54	2.03	5.49	
Brazil	-0.38	2.5	3.34	1.69	
Canada	-0.14	4.7	2.36	4.95	17.6
Chile	-0.34	4.15	2.75	2.31	11.79
China	0.19	4.01	2.92	1.15	
Colombia	-0.58	3.04	2.29	0.49	15.87
Czech Republic	-0.46	3.68	2.53	4.95	22.72
Ecuador	-0.18	2.88	2.65	8.22	3.43
Estonia	-0.47	4.4	2.62	9.05	25.5
Finland	-0.28	5.32	2.42	3.61	15.94
Germany	0.13	4.73	3.09	13.82	14.35
Ghana	1.24	3.77	1.91	0.16	78.48
Greece	-0.28	2.76	2.3	5.66	22.75
Hungary	-0.6	2.9	1.92	3.31	23.78
Iceland	0.04	4.61	2.28	11.72	21.74
India	0.73	3.99	2.05	0.05	24.01
Indonesia	0.5	3.92	2.31	0.66	5.63
Iran	0.38	3.15	3.03	37.62	
Ireland	-0.18	4.72	2.87	24.30	8.51
Israel	-0.4	3.75	3.08	4.51	16.16
Italy	-0.06	2.2	3.96	242.81	6.88
Japan	0.19	4.63	2.49	0.55	11.71
Kenya	0.53	3.83	1.65	0.07	
Latvia	-0.04	3.46	2.09	0.53	44.3
Malaysia	0.22	5.1	1.89	1.64	17.48
Mexico	-0.35	3.11	2.33	0.47	5.84

Mozambique	0.53	3.15	1.11	0	
Netherlands	-0.54	4.94	3.02	86.78	5.4
Nigeria	0.54	3.02	2.09	0.01	
Peru	-0.34	2.81	2.25	1.85	10.62
Poland	-0.32	3.2	2.55	1.88	21.52
Portugal	0.1	3.23	2.89	24.13	8.41
Qatar	0.85	5.66	2.17	1.04	
Russia	-0.47	3.16	2.07	0.23	86.24
Saudi Arabia	0.62	4.42	2.37	0.60	
Singapore	0.36	5.77	1.56	0.85	34.54
Slovakia	-0.36	2.64	1.96	0	40.95
South Korea	0.19	3.38	3.25	3.45	50.47
Spain	-0.3	3.22	3.96	233.88	
Sri Lanka	0.65	3.87	1.53	0.19	
Thailand	0.25	3.43	1.97	0.27	13.49
Trinidad and Tobago	-0.2	3.21	1.74	4.29	
Turkey	0.29	3.68	3.48	5.04	7.34
Ukraine	-0.44	2.87	2.38	0.53	
United Kingdom	-0.21	4.82	2.95	53.10	3.34
United States	-0.13	4.26	3.33	21.62	5.29
Vietnam	0.39	3.41	1.33	0	496.12

Note. Cultural Tightness Values have been standardized in this table.

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