Cultural and Institutional Factors Predicting the Infection Rate and Mortality Likelihood of the COVID-19 Pandemic

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Author contributions: 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. and J. C. J 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.

Working paper statement. This manuscript is a working paper, and is subject to change prior to publication. 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 many colleagues, including Paul Hanges, Nava Caluori, Moin Syed, Jonas Kunst, Ulrike Schaede, and Kate M. Turetsky for helpful feedback on earlier versions of this manuscript.

Abstract: The spread of COVID-19 represents a global public health crisis, yet some nations have been more effective than others at limiting the spread of the virus and the likelihood that people die from infection. Here we show that institutional and cultural factors combine to partly explain these cross-cultural differences. Nations with efficient governments and tight cultures have been most effective at limiting COVID-19's infection rate and mortality likelihood, and this interaction of cultural tightness and government efficiency is robust to controlling for underreporting of cases, economic development, inequality, median age, population density, and authoritarianism. A formal evolutionary model explores the mechanism that may underlie these findings, and suggests that the observed cross-cultural trends may be driven by variation in how much groups adhere to cooperative norms under conditions of high threat. These analyses shed light on why some nations have contained COVID-19 more effectively than others.

Introduction

The COVID-19 pandemic represents a global health crisis. The virus has quickly spread from its epicenter in Wuhan, China, across the planet. As of April 5th 2020, COVID-19 has infected over 1,000,000 people and killed over 60,000 people worldwide. There have been over 300,000 cases and 8,000 deaths in the United States alone, and both figures have surpassed Chinese rates and are growing by the day. Yet certain countries have had more success than others in slowing the number of COVID-19 cases and the likelihood that infected individuals will die from the virus. Singapore, Hong Kong, Taiwan and South Korea have each been able to effectively contain the virus, and despite controversy around its early handling of the virus, China has recently been able to vastly reduce new infections. By contrast, Italy, Spain, and the U.S., have experienced more pronounced growth in prevalence and death rates than other countries. Scientists, policy makers, journalists and lay people alike are all urgently trying to understand the mechanisms that have produced such national variation in order to learn how to curtail the spread of COVID-19.

Here we present data on how societal institutions and culture may interact to predict cross-cultural variation in the containment of COVID-19. Our analyses are based on the premise that this pandemic is a global threat that requires effective and rapid cooperation and coordination to address. On this basis, we propose that institutional and cultural factors that help nations swiftly adopt cooperative norms should predict which nations are best handling the virus. Institutionally, nations with efficient governments that are able to quickly allocate resources and coordinate with private sector industries may be able to slow the trajectory of the virus compared with nations with less efficient governments. Government efficiency, however, should be especially effective when nations are also culturally tight—with strong norms and little tolerance for deviance (1, 2)—since people in tight cultures may be particularly likely to adopt new norms (e.g. social distancing, effective handwashing) that contain the virus. This pattern would be consistent with models of cultural evolution which show how adoption of cooperative norms are critical for survival in contexts of high existential threat (3).

Building on this theoretical foundation, we predict that cultural tightness and government efficiency should interact to predict the infection rate and mortality likelihood associated with COVID-19, such that nations that have both high cultural tightness *and* high governmental efficiency may be responding most effectively to the COVID-19 pandemic, and significantly more effectively 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 introduce new norms (e.g. closing down non-essential business), and efficient institutional action may only be effective when people will adhere to newly introduced norms. We suggest that this interactive dynamic should be robust to other potential covariates, such as potential under-reporting of COVID-19 cases, economic development, inequality, median age, and population density.

We test this account with two converging analyses. Our primary analysis uses data on confirmed cases of COVID-19 around the world to examine how governmental efficiency and cultural tightness together can predict the (a) infection rate and (b) mortality likelihood of COVID-19 above and beyond economic and demographic differences between countries. We retrieved and updated these data between March 21st and April 5th, 2020. To complement these empirical data, we also developed a formal evolutionary game theory simulation of how individuals respond to existential threats such as COVID-19. All data and code associated with these analyses are available from OSF at https://osf.io/pc4ef/ for reproduction and examination.

Materials and Methods

COVID-19 Data. 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 the number of documented deaths due to COVID-19 using data from a variety of sources, including the European Center for Disease Control. In order to avoid confounding these COVID-19 data with nations' population sizes, we downloaded data on cases per million citizens, and indexed mortality likelihood through the number of mortalities divided by the number of total cases. When calculating infection rate, we adjusted our daily case estimates based on testing data (tests per million citizens). Data analysts at OWD have compiled data on the daily number of tests per million citizens for 55 nations, and we used this information to adjust our case estimates.

Government Efficiency. We measured government efficiency using the World Bank's *Government Efficiency Index,* which assesses the public sector's performance in managing and regulating the political economy (see https://bit.ly/34lXAT9). According to this metric, efficient governments score highly on 5 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.

Cultural Tightness. We measured *cultural tightness* using the index from Gelfand and colleagues (1), who measured tightness through 6 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 gathered by Gelfand (1) across 33 nations, and then expanded to 57 nations by Eriksson and colleagues (4) using the same procedure. The measure captures the strength of norms in a nation and the tolerance for people who violate norms (see supplemental materials for more information).

Analytic Plan

Estimating Infection Rate. The infection rate of COVID-19 followed an exponential growth curve, which is typical for the early stages of pandemic and epidemic outbreaks (5). We captured infection rate by fitting regression equations for each nation, log-transforming the outcome variable (cases per million people) and the predictor variable (days) to account for the exponential growth rate of the virus, and controlling for COVID-19 tests per million people to account for cross-cultural differences in testing prevalence. Log-transformation converts exponential growth rates into linear growth rates, which can be predicted in a general linear model. These linear growth rates for each nation are displayed in Figure 1.

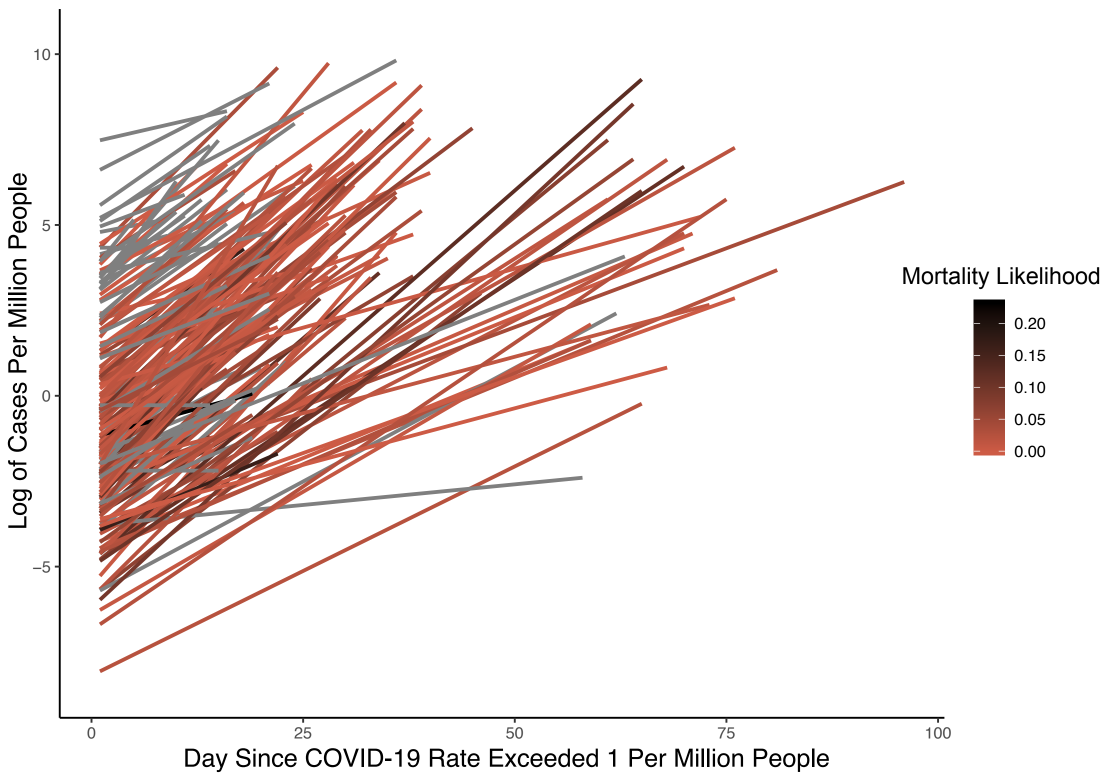

Figure 1. The log-transformed growth curve of COVID-19 cases per million people. Each line is the rate of COVID-19 infection growth over time. The lines are colored based on the mortality likelihood (the probability of mortality for every COVID-19 case). Gray lines represent nations with missing or insufficient data on mortality likelihood. Slopes have been adjusted for COVID-19 testing data (tests per million people) for all nations that have provided public testing data.

Predicting Infection Rate. We predicted infection 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 especially slow infection rate. In total, 49 nations had data on cultural tightness, under-reporting, and government efficiency, and they were the focus of our analysis. We note that general linear models do not account for the error inherent in estimating growth curves. To address this limitation, we weighted cases in these regressions by number of observations across nations, so that nations with high numbers of observations (and more reliable estimates) would be weighted over and above nations with low numbers of observations (and less reliable estimates).

We followed a stepwise procedure in these regressions. In our first model, we only controlled for estimated underreporting. We measured underreporting using Russell and colleagues' estimates for each nation, which they gathered using delay-adjusted case fatality ratios (6). In our next model, we added basic indicators of economic development (GDP per capita, retrieved from the International Monetary Fund's 2019 release) and inequality (Gini coefficients, retrieved from the most recent World Bank estimate for each nation). Then in a final model, we added a series of other control variables that could plausibly relate to the COVID-19 infection rate: median age (retrieved from the 2018 CIA World Factbook), population density (log-transformed people per square kilometer, retrieved from the World Bank), and authoritarianism (dummy-coded based on the Freedom House's annual "Freedom in the World" report). We standardized all covariates prior to analysis.

This stepwise approach allowed us to test whether our observed results were sensitive to other potentially confounding variables. For example, controlling for GDP per capita ensured that our reported results were not driven by differences in economic development across nations, and controlling for authoritarianism ensured that effects of cultural tightness did not reflect effects of authoritarian governments. Using a stepwise approach also allowed us to test whether our effects only reached significance while holding these covariates constant, or whether they were robust to the inclusion or exclusion of these controls.

Predicting Mortality Likelihood. Following our analysis of infection rate, we performed an identical series of stepwise models to analyze cross-cultural differences in mortality likelihood, which we measured via the number of deaths from COVID-19 divided by the number of COVID-19 cases in a nation. While these models did not estimate change over time, they nonetheless captured a critical variable, since it is important to minimize the likelihood that people will die from COVID-19 once they have contracted the illness. Raw mortality likelihood can be influenced by a variety of factors, including underreporting of cases. Nevertheless, controlling for underreporting helped us rule out this confounding variance, and gave us more confidence that we were estimation mortality as influenced by the quality and urgency of care. We also note that mortality likelihood had a skewed distribution across nations, and so we log-transformed it prior to analyses. Our supplemental materials (section 2) show that our findings are similar with or without this log transformation, and that they replicate when we employ generalized linear modeling with non-Gaussian distributions.

Results

Infection Rate Models. How did government efficiency and cultural tightness relate to cross-cultural variation in the COVID-19 infection rate? Results from our multiple regression, displayed in Table 1, suggest that government efficiency and cultural tightness significantly interacted to predict infection rate, and this interaction grew more robust with additional control variables. At low levels of government efficiency (-1 SD), cultural tightness was positively related the COVID-19 infection rate, but at high levels of government efficiency (+1 SD), cultural tightness was negative related the COVID-19 infection rate. Conversely, government efficiency was not significantly related to the COVID-19 infection rate at low levels of cultural tightness, but was significantly and negatively related to the infection rate at high levels of cultural tightness.

Table 1. COVID-19 Infection Rate Models

Predictor	***DF***	***R^2(Adj.)***	***b (SE)***	***t***	***p***	***β***	***LLCI***	***ULCI***
Model 1	44	.31 (.25)						
Underreporting			.24 (.08)	3.01	.004	.28	.08	.40
Gov. Efficiency * Tightness			-.18 (.09)	-2.02	.049	-.17	-.36	-.001
Tightness (low GE)			.01 (.12)	.10	.920	.01	-.23	.25
Tightness (high GE)			-.28 (.10)	-2.72	.009	-.32	-.48	-.07
Gov. Efficiency (low CT)			.17 (.14)	1.20	.237	.15	-.11	.45
Gov. Efficiency (high CT)			-.26 (.15)	-1.74	.089	-.23	-.55	.04
Model 2	41	.52 (.45)						
Underreporting			.25 (.07)	3.59	< .001	.29	.11	.39
GINI			.16 (.11)	1.47	.149	.18	-.06	.38
GDP Per Capita			.40 (.10)	4.24	< .001	.46	.21	.59
Gov. Efficiency * Tightness			-.28 (.09)	-3.17	.003	-.25	-.45	-.10
Tightness (low GE)			.24 (.12)	2.02	.050	.27	-.001	.47
Tightness (high GE)			-.20 (.09)	-2.16	.036	-.23	-.39	-.01
Gov. Efficiency (low CT)			-.08 (.14)	-.56	.577	-.07	-.37	.21
Gov. Efficiency (high CT)			-.72 (.17)	-4.29	< .001	-.66	-1.07	-.38
Model 3	38	.61 (.52)						
Underreporting			.24 (.07)	3.63	< .001	.27	.11	.37
GINI			.30 (.12)	2.54	.015	.35	.06	.55
GDP Per Capita			.36 (.09)	3.91	< .001	.41	.17	.55
Population Density			.10 (.07)	1.32	.194	.11	-.05	.25
Median Age			.42 (.18)	2.33	.025	.48	.05	.78
Authoritarianism			-.02 (.07)	-.31	.756	-.02	-.16	.11
Gov. Efficiency * Tightness			-.34 (.09)	-3.82	< .001	-.31	-.51	-.16
Tightness (low GE)			.30 (.12)	2.62	.013	.35	.07	.54
Tightness (high GE)			-.23 (.10)	-2.25	.030	-.26	-.44	-.02
Gov. Efficiency (low CT)			-.02 (.14)	-.12	.906	-.01	-.29	.26
Gov. Efficiency (high CT)			-.80 (.17)	-4.80	< .001	-.73	-1.14	-.46

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. Confidence intervals are calculated for unstandardized estimates.

What are the implications of the interaction between cultural tightness and government efficiency? To put this interaction into context, the intercepts of Model 3 from Table 1 predicted that nations with high cultural tightness and high government efficiency would have a relatively low log-transformed rate of 1.96 new cases per million. However, nations with mean levels of cultural tightness and government efficiency would have higher a log-transformed rate of 2.54 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 2.52 new cases per million. Re-converting these log-transformed values through exponentiation (which convert linear slopes back into exponential 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 4,467.51 fewer cases per million people than a loose nation with low government efficiency. These estimated trajectories are displayed in Figure 2.

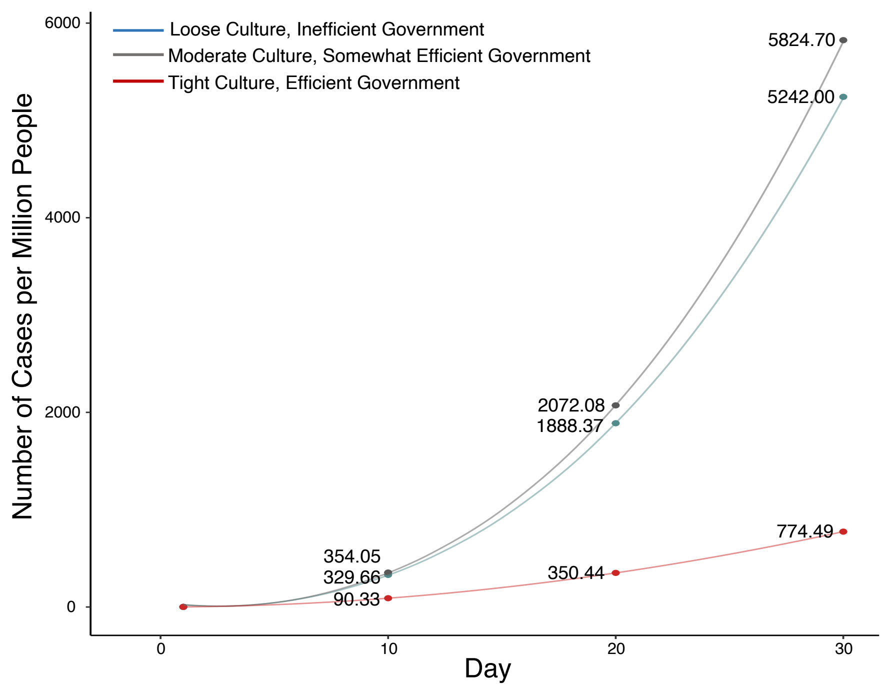

Figure 2. The estimated infection rate curves for nations with loose and inefficient governments (red), nations with moderately tight cultures and somewhat efficient governments (gray), and nations with tight cultures and efficient governments (blue). The estimates are derived from Model 3 in Table 1, through exponentiating the intercepts from these models to account for the initial log transformation.

We note that our models revealed several other predictors of the COVID-19 infection rate. When modeled together, economic development, inequality, and median age all predicted faster COVID-19 infection rates, such that the fastest infection rates would be expected in economically developed nations with high levels of inequality and an older population. Nations with faster COVID-19 infection rates also had higher levels of underreporting, which is unsurprising given that the virus is likely more difficult to track and document as it spreads through larger proportions of a population. As a whole, our final model explained 61% of cross-cultural variation in COVID-19 infection rates, suggesting that these factors are linked to why some nations are experiencing steeper growth rates than others.

Our supplemental materials explore these models in greater depth, and show that the interaction between cultural tightness and government efficiency replicated when controlling for spatial interdependence in the data (approximated via nation continent; $b = -.27$, $p = .004$), 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 COVID-19 pandemic is still progressing, but these checks give confidence that these findings were not driven by spurious outliers or violations of model assumptions.

Mortality Likelihood Models. We next replicated these analyses for estimates of mortality likelihood. These models, displayed in Table 2, replicated the same interaction between cultural tightness and government efficiency. These models suggest that a lower proportion of COVID-19 patients would be expected to die in nations with high (+1 SD) cultural tightness and government efficiency (2.18%) compared to nations with moderate cultural tightness and government efficiency (3.61%), and with low (-1 SD) cultural tightness and government efficiency (3.02%). If we combine these estimates with our infection rate estimates for our first set of models, this would suggest that 134.92 fewer people per million will die every month in tight nations with high governmental efficiency than in loose nations with low government efficiency. For a nation the size of the United States (327.2 million people), this translates to approximately 44,145 fewer deaths. As with infection rate models, our mortality likelihood model showed no evidence of undue influence, multicollinearity, or heteroscedasticity (see section 5 in our supplemental materials).

Table 2. COVID-19 Mortality Likelihood Models

Predictor	***DF***	***R^2(Adj.)***	***b (SE)***	***t***	***p***	***β***	***LLCI***	***ULCI***
Model 1	44	.47 (.42)						
Underreporting			.008 (.001)	5.63	< .001	.51	.005	.01
Gov. Efficiency * Tightness			-.003 (.002)	-2.31	.025	-.17	-.006	-.0005
Tightness (low GE)			.004 (.002)	1.97	.055	.23	-.0001	.007
Tightness (high GE)			-.002 (.002)	-1.10	.277	-.12	-.005	.002
Gov. Efficiency (low CT)			.003 (.002)	1.23	.226	.14	-.002	.008
Gov. Efficiency (high CT)			-.005 (.003)	-1.96	.056	-.26	-.01	.0001
Model 2	41	.48 (.41)						
Underreporting			.008 (.002)	5.49	< .001	.51	.005	.01
GINI			.0004 (.002)	.21	.837	.03	-.004	.005
GDP Per Capita			.002 (.002)	.99	.327	.13	-.002	.007

Gov. Efficiency * Tightness			-.004 (.002)	-2.26	.029	-.19	-.007	-.0004
Tightness (low GE)			.005 (.002)	2.11	.041	.29	.00001	.009
Tightness (high GE)			-.002 (.002)	-.80	.426	-.09	-.005	.002
Gov. Efficiency (low CT)			.001 (.003)	.41	.686	.06	-.005	.007
Gov. Efficiency (high CT)			-.008 (.004)	-2.05	.047	-.38	-.02	-.0001
Model 3	38	.51 (.39)						
Underreporting			.008 (.002)	5.33	< .001	.50	.005	.01
GINI			.001 (.003)	.28	.785	.04	-.004	.006
GDP Per Capita			.002 (.002)	1.04	.304	.14	-.002	.007
Population Density			.002 (.002)	1.37	.179	.15	-.001	.006
Median Age			.001 (.004)	.21	.837	.05	-.007	.009
Authoritarianism			.0001 (.004)	.11	.914	.01	-.003	.003
Gov. Efficiency * Tightness			-.005 (.002)	-2.44	.019	-.22	-.008	-.0007
Tightness (low GE)			.005 (.002)	1.93	.061	.29	-.0002	.01
Tightness (high GE)			-.003 (.002)	-1.16	.253	-.16	-.007	.002
Gov. Efficiency (low CT)			.002 (.003)	.48	.634	.07	-.005	.008
Gov. Efficiency (high CT)			-.009 (.004)	-2.24	.031	-.45	-.02	-.009

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. Confidence intervals are calculated for unstandardized estimates.

These models show that governmental efficiency and cultural tightness combine to explain a significant proportion of cross-cultural variation in how rapidly COVID-19 is spreading, and in the likelihood that confirmed cases will result in mortality. These effects combine with other factors, such as economic development, inequality, and median age, to explain a large proportion of why nations vary in their ability to contain the pandemic. Indeed, adjusted R^2 statistics from our models suggest that our predictors explain 61% of cross-cultural variation in infection rate from COVID-19 (52% adjusting for multiple predictors) and 51% of mortality likelihood (39% adjusting for multiple predictors).

Nevertheless, these tests are correlational and must be interpreted with caution. Even though our analyses control for cross-cultural rates of testing and underreporting, they are not sufficient to confirm that tightness and governmental efficiency are causally influencing nations' responses to COVID-19. These analyses also do not shed light on the individual-level mechanisms by which these factors may be related to the infection rate and mortality likelihood of the pandemic. Our predictions suggest that nations with tight cultures and efficient governments may be better containing COVID-19 because their citizens are adhering to cooperative norms such as handwashing and social distancing, but our nation-level analysis cannot address this mechanistic explanation. Our next analyses therefore examined this possibility within an evolutionary model which investigated the causal dynamics of group differences in responses 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, but they do offer a potential mechanism for why both tightness and the efficiency of governments might be related to more adaptive responses to COVID-19.

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 (3). When threat is high and agents are connected in a fixed network (7), 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 represent the survival pressures of COVID-19, and the demand for cooperation represents 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 (8).

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, since agents may conform to successful individual defectors as well as successful groups of cooperators. But in the context of threat, group-based cooperation emerges as essential (3), and conformity will allow cooperation to quickly spread across a population of agents.

We illustrate this dynamic in an evolutionary model of agents playing prisoner's dilemmas in a 20 x 20 toroidal grid, with agents' payoff over time determining their fitness (i.e. their likelihood of dying and reproducing). Agents received a standard prisoner's dilemma payoff in this model (9) in addition to a base payoff, but their total payoff was reduced according to a level of threat τ which escalated over time (3). One hundred runs represented a loose culture in which agents have a low probability c of conforming to their neighbors' strategies ($c = .05$), whereas another 100 runs represented a tight culture in which agents have a higher probability of conforming ($c = .20$).

Figure 3 shows that, in the early stages of the model where threat is low, tight and loose cultures were similarly likely to cooperate. 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 were able to survive for longer than agents in loose cultures. Our supplemental materials summarize this model in more depth and perform additional robustness checks and exploratory runs that suggest that strong normative conformity can be an effective evolutionary strategy during periods of intense threat when agents are able to quickly update their strategies.

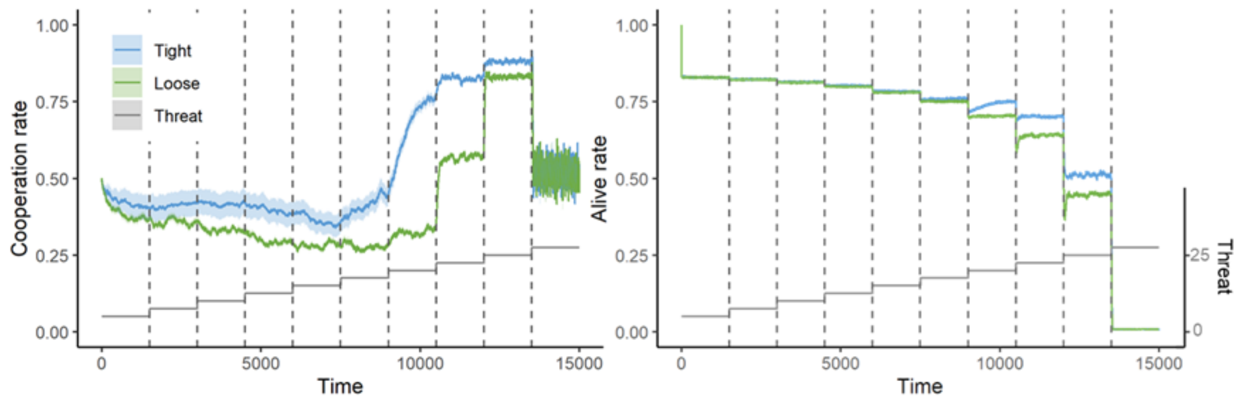

Figure 3. The results of an evolutionary game theory model of cooperation in the face of a threat such as COVID-19. The figure depicts 200 runs of the model, with each run containing 15,000 iterations. The shadow shows standard error. In 100 "tight" runs, agents had a high likelihood (c = .20) of conforming to their neighbors' prisoner's dilemma decisions. 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.

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, conformity may not be sufficient to counteract the effects of threat.

Discussion and Limitations

Our empirical and theoretical data show that, during a global pandemic, cultural and institutional factors can combine to predict nations' responses. Nations with high levels of government efficiency and cultural tightness have slower infection rates and lower mortality likelihoods compared with looser and less institutionally efficient nations. A theoretical model supports these data by suggesting that nations with strict norms and efficient institutions may be able to more readily adopt cooperative norms that increase a population's survival.

These findings may contain implications for effective responses to COVID-19. For example, governmental policies that increase communication between the public and private sectors may be able to put recommendations into action on a widespread scale. It could be an effective strategy for loose cultures such as Spain and the United States to emphasize the importance of complying with social norms in mass communication about COVID-19, since people in these cultures have generally experienced less ecological threat (1) and may therefore be more likely to underestimate the risk of the virus and have reactance to having increased constraint. These recommendations should complement existing behavioral insights into how people and groups should manage the economic and health impacts of the pandemic (10).

These implications notwithstanding, our empirical data are correlational, and therefore are best suited for offering a tentative account for why some nations may be responding to COVID-19 better than others. We do 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 testing), employing a longitudinal design, and building an evolutionary game theory model with causal dynamics. But even with these implications, our models are not designed to make causal claims.

We also note additional limitations of our data. First, government efficiency and cultural tightness are not the only other factors that are related to COVID-19's infection rate and mortality likelihood, and our own analyses suggest that a variety of other factors are related to these outcomes. For example, more developed nations, more unequal nations, and nations with a higher median age are all at risk for faster infection rates. Second, our data focus on the early spread of COVID-19. Since loose cultures have higher creativity than tight cultures (1,11), 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.

Finally, we emphasize that strong norms to fight COVID-19 do not imply that governments should become autocratic, and our models show that authoritarianism does not predict reduced infection rates. 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 due to its impact on well-being (12) and creativity (10).

COVID-19 has already reshaped our world and we urgently need to understand the factors that predict its spread. Here we offer two factors—cultural tightness and government efficiency—that in combination predict the spread of the COVID-19 virus and determine whether the virus has a high mortality rate. While these factors are rooted in cultural evolutionary studies of human history, they make important predictors for how nations will handle a global public health crisis in the months to come.

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Supplemental Materials

1. Measurement of Cultural Tightness

Our measure of cultural tightness was adapted from Gelfand and colleagues (1), who gathered cross-cultural data on cultural tightness using a self-report measure in 33 nations. We employed an expanded version of this measure in our analysis, which covered 57 nations. Since the paper that developed this measure (4) is still unpublished, we give a brief summary of the study's procedure here.

We 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, we complemented the main sampling strategy in two ways: (a) we collected additional data from non-student samples (or, in two cases, part-time students) in 31 countries; (b) we collected data from two or more student samples located in different cities of each of ten countries. In total, we 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, the full survey and the data used in the present paper are openly available at OSF: https://osf.io/jy6q8/.

Gelfand and colleagues' (1) original tightness data overlapped with 25 countries in our study, and we used the same items in our study (e.g., "In this country, there are very clear expectations for how people should act in most situations."). As in the original study, responses were mean-centered within participants. Our expanded measure correlated very highly (r = .84) with the original Gelfand and colleagues (1) measure.

2. Examining and Modeling the Infection Rate and Mortality Likelihood Distributions

Prior to estimating our models, we examined the distributions of infection rate and mortality likelihood. These models found that infection rate was relatively normally distributed, whereas mortality likelihood had an exponential distribution (see Figure S1).

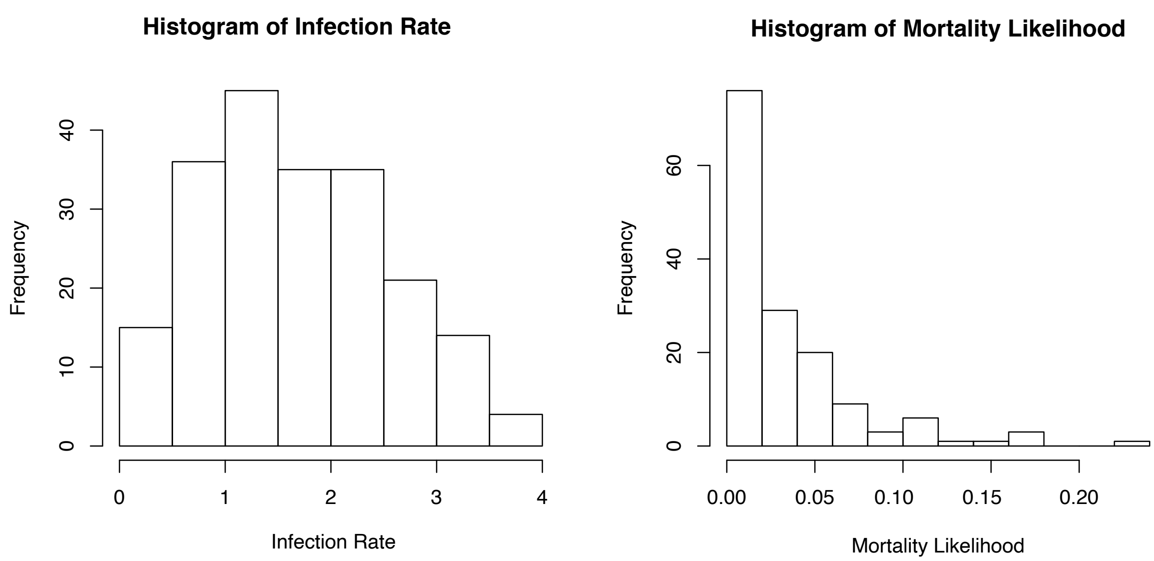

Figure S1. The distributions of infection rate and mortality likelihood across nations. Infection rate was normally distributed, whereas mortality likelihood had a strong positive skew.

To account for Mortality Rate's non-normal distribution, we log-transformed the variable prior to analyses, and our primary results reflect this log-transformation approach. However, another approach would be to fit a generalized linear model with a gamma distribution and a logistical link function, which is appropriate for modeling Mortality Likelihood's exponential distribution. Table S1 reproduces our interaction with this alternative analysis strategy to show that our results are robust to either approach. For the sake of parsimony, we display our "model 3" (i.e. all control variable) results in this supplemental table (and all other supplemental tables). However, our interaction results replicate across all three models (*p*s < .007), and can be reproduced using our script at https://osf.io/qg6xy.

Table S1. COVID-19 Mortality Likelihood Generalized Linear Model

Predictor	***DF (Null)***	***DF (Residual)***	***b (SE)***	***t***	***p***
Model	37	38			
Underreporting			.79 (.09)	8.22	< .001
GINI			.18 (.16)	1.12	.254
GDP Per Capita			.11 (.14)	.80	.428
Population Density			.10 (.12)	.85	.398
Median Age			.10 (.25)	.40	.695
Authoritarianism			-.03 (.10)	-.25	.802
Gov. Efficiency * Tightness			.35 (.12)	-2.94	.006
Tightness (low GE)			.35 (.16)	2.24	.031
Tightness (high GE)			-.21 (.14)	-1.50	.142
Gov. Efficiency (low CT)			.20 (.20)	1.00	.324
Gov. Efficiency (high CT)			-.62 (.26)	-2.38	.022

Note. All control variables have been standardized in this analysis. GE stands for "Government Efficiency." CT stands for "Cultural Tightness." Terms with these acronyms are depicting estimates of simple slopes.

3. 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 S2 displays these distributions for each of our three stepwise models (see Tables 1-2). Model 1 only controls for under-reporting, Model 2 controls for under-reporting, GDP per capita, and GINI, and Model 3 includes our full set of control variables. Bootstrapping regression objects in R is not compatible with case weights, so we did not weight cases by number of available days in the infection rate analyses while generating these distributions.

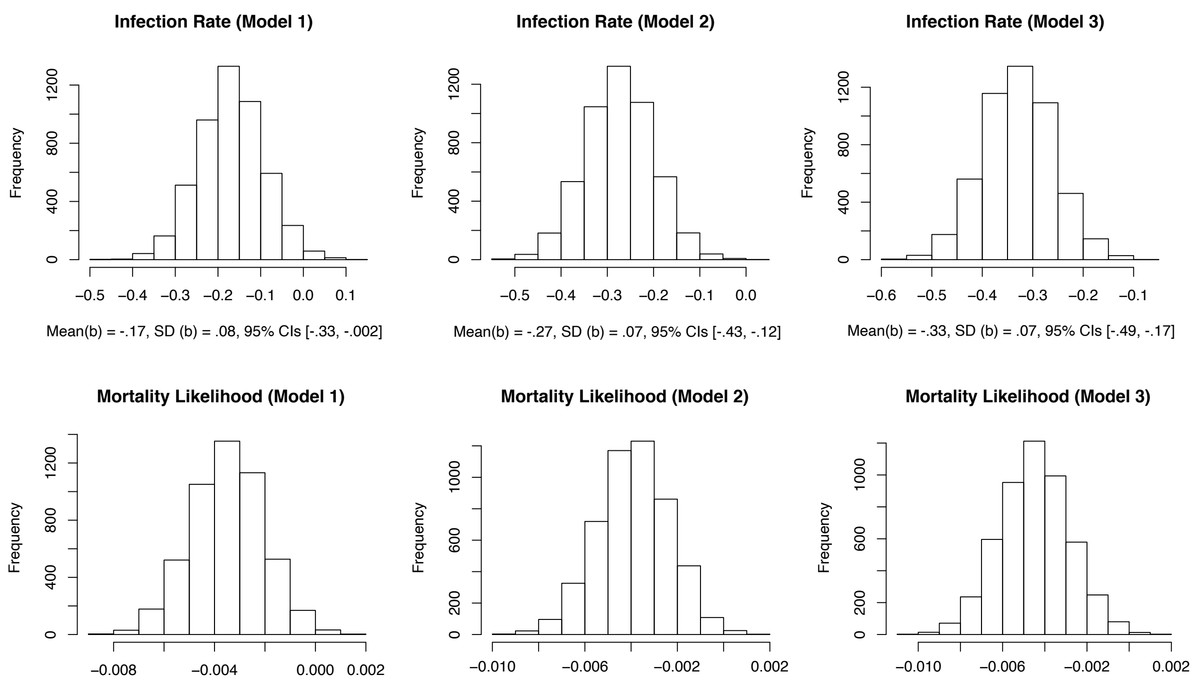

Figure S2. Results from a bootstrapping analysis of the government efficiency x cultural tightness interaction on infection rate (top) and mortality likelihood (bottom). Each column of plots represents a model with increasing numbers of control variables, mirroring the presentation of results in Tables 1-2 in our main text.

4. 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 data-points are independent. With respect to our data, the infection rate slopes 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 (see section 5 of these supplemental materials), we observed no problematic autocorrelation between model residuals. Nevertheless, we confirmed that our interaction between government efficiency and cultural tightness remained significant controlling for 5 dummy-coded variables representing continent, which were contrasted against "Australia." This approach removes any 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 S2).

Table S2. COVID-19 Infection Rate Controlling for Continent

Predictor	*DF*	*R^2(Adjusted R^2)*	*b (SE)*	*t*	*p*
Model	33	.68 (.55)			
Underreporting			.21 (.07)	2.86	.007
GINI			.33 (.15)	2.29	.028
GDP Per Capita			.45 (.11)	4.27	< .001
Population Density			.03 (.10)	.35	.730
Median Age			.42 (.19)	2.24	.032
Authoritarianism			-.14 (.18)	-.78	.442
Europe			.71 (.46)	1.53	.136
Africa			.33 (.62)	.53	.601
Asia			.46 (.50)	.91	.371
South America			.97 (.50)	1.94	.061
North America			.20 (.47)	.43	.672
Gov. Efficiency * Tightness			-.35 (.09)	-3.91	< .001
Tightness (low GE)			.47 (.14)	3.40	.002
Tightness (high GE)			-.09 (.14)	-.65	.519
Gov. Efficiency (low CT)			-.05 (.14)	-.33	.742
Gov. Efficiency (high CT)			-.87 (.17)	-5.04	< .001

Note. All control variables have been standardized in this analysis. GE stands for "Government Efficiency." CT stands for "Cultural Tightness." Terms with these acronyms are depicting estimates of simple slopes.

5. 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 predictors in Model 3, our most saturated model. A variance inflation factor of above 5 generally means that a model has high multicollinearity which is biasing the estimates and standard errors. Table S3 shows that neither our analysis of infection rate or mortality likelihood appeared to have problematic multicollinearity.

Table S3. Variance Inflation Factors for Infection Rate and Mortality Likelihood Models

Predictor	Infection Rate *VIF*	Mortality Likelihood *VIF*
Underreporting	1.08	1.08
GINI	1.54	1.54
GDP Per Capita	2.18	2.18

Population Density	1.33	1.33
Median Age	1.75	1.75
Authoritarianism	1.15	1.15
Cultural Tightness	1.80	1.80
Government Efficiency	2.31	2.31

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 3 residuals against our Model 3 predicted values for both infection rate and mortality likelihood. These plots (see Figure S3) suggested that each model was homoscedastic, with little systematic invariances in the relationship between residuals and predicted values.

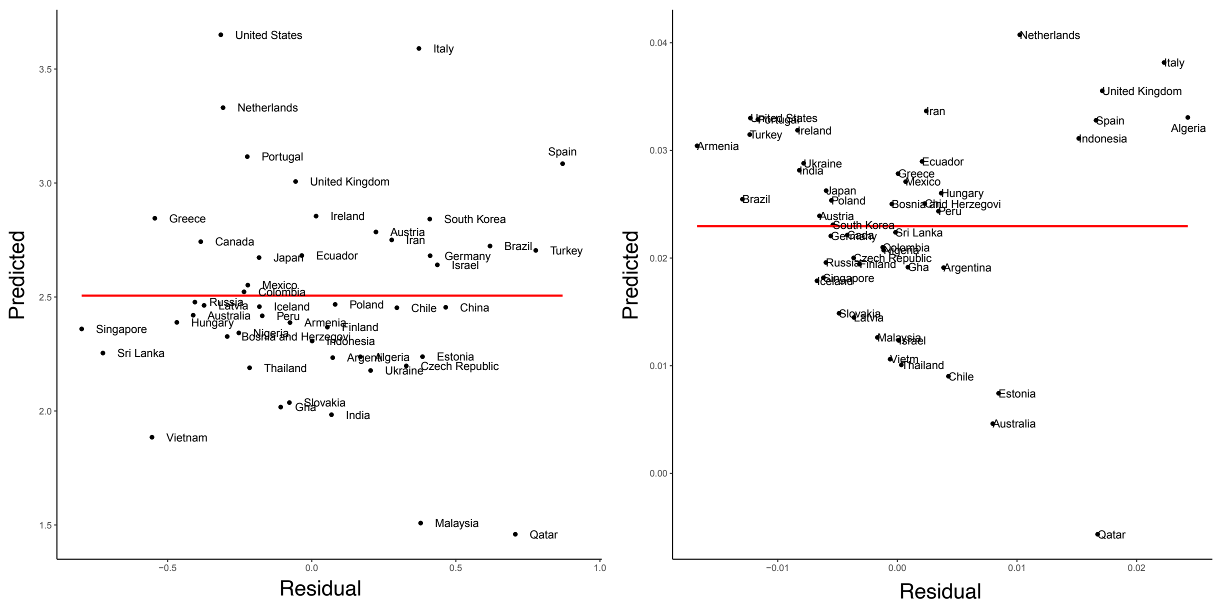

Figure S3. The relationship between our model residuals and predicted values for our analyses of infection rate and mortality likelihood across nations (see Model 3 in Tables 1-2).

Finally, we examined potentially problematic outliers in our analyses of infection rate and mortality likelihood via studentized residuals. An outlier analysis identified Singapore as the case with the highest studentized residual (-2.75) in the analysis of infection rate and Algeria as the case with the highest studentized residual (3.05) in the analysis of mortality likelihood. However, neither Singapore (p = .45) nor Algeria (p = .20) was significantly larger than the average studentized residual when we conducted an outlier test with the appropriate Bonferroni correction (13). Moreover, the interaction between cultural tightness and government efficiency replicated predicting infection rate while excluding Singapore, b = -.25, SE = .08, t = -2.97, p = .005, and predicting mortality rate while excluding Algeria, b = -.17, SE = .06, t = -2.59, p = .01. The effects we observed therefore did not seem driven by any extreme outliers exerting undue influence on our model.

6. Evolutionary Model Details and Robustness Checks.

Agents are embedded in a 20 × 20 toroidal (i.e., wrap-around) grid. 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, 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 typical cooperation games (Table S1) with all of its alive neighbors on the grid, and receives *interaction payoffs* from the games. Agents' actions are chosen according to their strategies, which is either cooperate of defect. All the pairs in the grid play the games in a random order.

Table S4. Payoff of matrix of the cooperation game.

	Action of Agent Y	
	Cooperate	Defect
Action of Agent X		
Cooperate	(X: 2, Y: 2)	(X: -1, Y: 3)
Defect	(X: 3, Y: -1)	(X: 0, Y: 0)

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.

$$\pi = \textit{base payoff} + \textit{interaction payoff} - \tau. \tag{1}$$

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.

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

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 and group tag 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 S4. If an agent dies, it will be removed from the grid.

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

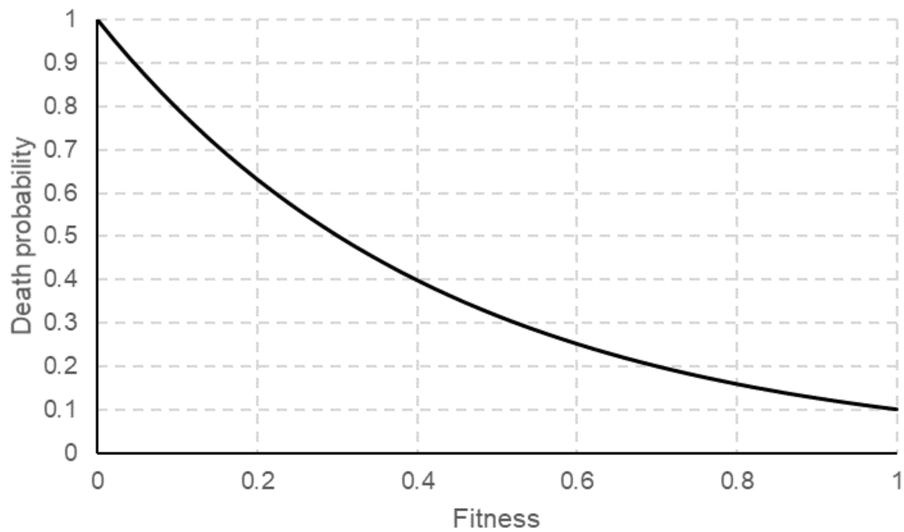

Figure S4. Death probability as a function of an agent's fitness.

5) *Conform*: In each iteration, after Step 4, each agent has a conforming rate of *c* to adopt the mode strategy among all of its alive neighbors. If there are multiple mode strategies among the neighbors (i.e., there are equal number of cooperators and defectors among all the alive neighbors), the agent randomly selects one of the multiple mode strategies.

The key parameters of this model intended to represent ecological threat, manipulated by τ, and cultural tightness, manipulated by c. Consistent with past work (3), we operationalized ecological threat via payoff structure, such that highly threatening environments reduced the maximum payoff that agents received. Culture tightness is operationalized by conforming rate c, which denotes the pressure to conform with the local norm.

Note that in Figure 4, in the tight culture, the standard error on the left panel is high. This is because in some of the single runs, most of the population cooperate while in some other runs, the majority defect (see Figure S5).

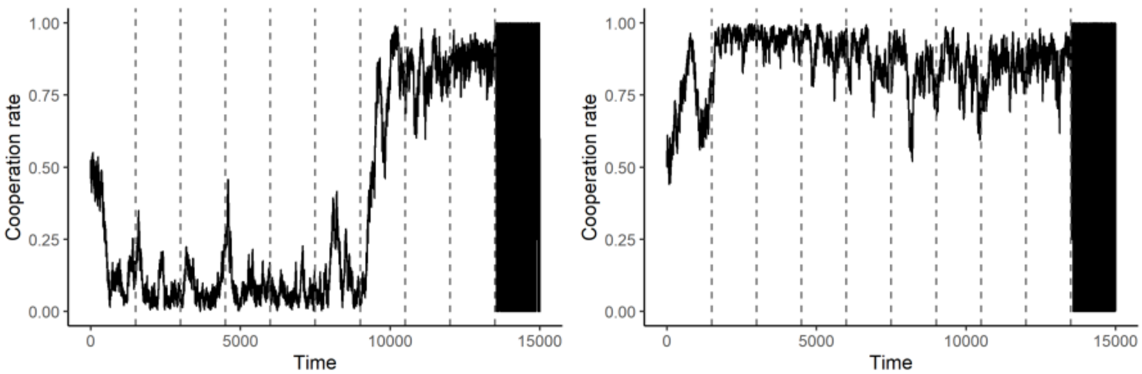

Figure S5. Example of the cooperation rate in two different single runs in tight culture. On the left, the majority defect when threat is low while on the right, the majority cooperate.

We also ran the models under a variety of other levels of tightness. Figure S6 shows the results when $c = [0.1, 0.15, 0.3, 0.4, 0.5]$. The results are replicated. At moderate-to-severe levels of threat, tightness bolsters agents' cooperation and survival rates.

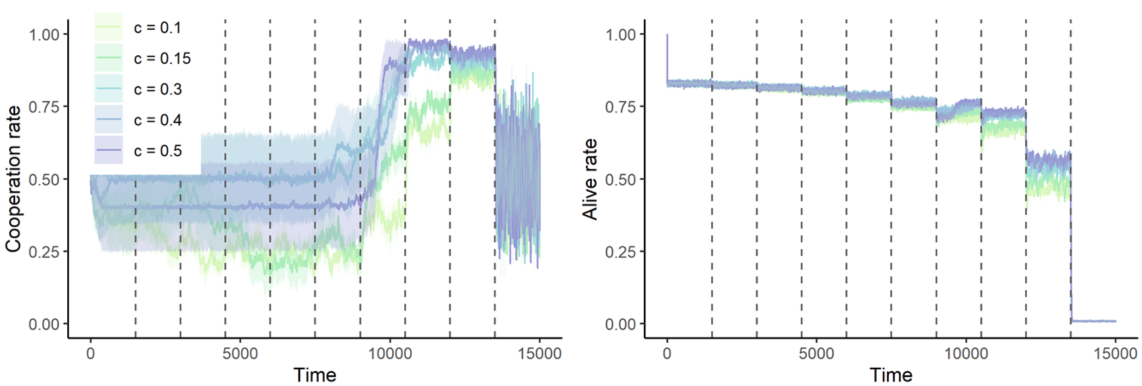

Figure S6. The figure depicts 10 runs under each level of tightness c. Each run containing 15,000 iterations. The shadow shows standard errors. Threat τ started from a low level ($\tau = 5$) and escalated every 1,500 iterations and reached its maximum value ($c = 27.5$) in the 13,500th iteration.