By Tse Yang Lim, Ran Xu, Nick Ruktanonchai, Omar Saucedo, Lauren M. Childs, Mohammad S. Jalali, Hazhir Rahmandad, and Navid Ghaffarzadegan

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Why Similar Policies Resulted In Different COVID-19 Outcomes: How Responsiveness And Culture Influenced Mortality Rates

ABSTRACT **In the first two years of the COVID-19 pandemic, per capita mortality varied by more than a hundredfold across countries, despite most implementing similar nonpharmaceutical interventions. Factors such as policy stringency, gross domestic product, and age distribution explain only a small fraction of mortality variation. To address this puzzle, we built on a previously validated pandemic model in which perceived risk altered societal responses affecting SARS-CoV-2 transmission. Using data from more than 100 countries, we found that a key factor explaining heterogeneous death rates was not the policy responses themselves but rather variation in responsiveness. Responsiveness measures how sensitive communities are to evolving mortality risks and how readily they adopt nonpharmaceutical interventions in response, to curb transmission. We further found that responsiveness correlated with two cultural constructs across countries: uncertainty avoidance and power distance. Our findings show that more responsive adoption of similar policies saves many lives, with important implications for the design and implementation of responses to future outbreaks.**

Tse Yang Lim, Harvard University, Boston, Massachusetts.

Ran Xu, University of Connecticut, Storrs, Connecticut.

Nick Ruktanonchai, Virginia Tech, Blacksburg, Virginia.

Omar Saucedo, Virginia Tech, Blacksburg, Virginia.

Lauren M. Childs, Virginia Tech, Blacksburg, Virginia.

Mohammad S. Jalali, Harvard University.

Hazhir Rahmandad, Massachusetts Institute of Technology, Cambridge, Massachusetts.

Navid Ghaffarzadegan (navidg@vt.edu), Virginia Tech, Falls Church, Virginia

The COVID-19 pandemic has caused millions of deaths and major health, economic, and social disruptions around the world. But the mortality burden was not distributed evenly. In the first two years of the pandemic, the same SARS-CoV-2 virus (and its variants) led to per capita death rates that varied by more than two orders of magnitude across countries.[1] Importantly, differences in many usual explanatory factors such as demographics, per capita income, pandemic preparedness, and health care capacity do not explain these vastly divergent outcomes, hinting that the differences in fatalities may instead be due to divergent responses of governments and individuals.[2–4]

The pandemic elicited major responses both from governments and from affected communities globally. Governmental policy responses included imposing a range of nonpharmaceutical interventions, such as lockdowns, activity closures, mask mandates, and limits on social gatherings and mobility, as well as pharmaceutical measures, such as novel treatments and vaccination, which started being deployed at scale after the first year and a half.[5,6] Responses from individuals and communities, from voluntary adoption of nonpharmaceutical interventions to adherence to various government mandates, further moderated the spread of the disease.

Whereas studies focused on the short-term impacts (days to weeks) of specific nonpharmaceutical interventions identified some benefits,[7–9] examining the data over longer time horizons points to three unexpected regularities. First, although specific combinations of nonpharmaceutical interventions varied, the average stringency of governmental policies was rather similar across countries.[10] Second, important outcomes (such as mortality) were substantially different in various regions,[11,12] a finding robust to controlling for undercount.[4] Finally, over a horizon of months, there was little correlation between the stringency of policies and mortality outcomes.[13–15] Online appendix S4.a provides a simple demonstration of these regularities across 231 countries and regions.[16] The latter observation extends not just to measures of policy but to individual and community responses, such as reductions in mobility, which are likewise not correlated with longer term mortality outcomes (for example, see appendix S4.b).[16] This policy outcome variation presents a puzzle: How did different countries achieve such vastly different mortality outcomes despite relative similarity in the stringency of their policies and the magnitude of community responses? This variation is especially intriguing as it suggests that more stringent responses are not necessarily required to achieve significantly better outcomes.

In this article we offer a novel explanation for the policy outcome variation puzzle, one with important policy implications. We start with the observation that past analyses have not accounted for the feedback loop between health outcomes and implemented policies (with some exceptions).[17–19] In most policy analyses, policies are treated as independent variables affecting the dependent variable of health outcomes. Less appreciated is the other pathway in the feedback loop: that both government policies and public compliance also change in response to the perceived risk of the disease, as inferred from, for example, recent deaths. This feedback perspective refocuses the analysis on societal sensitivity to a continuously evolving risk situation. In contrast to thinking about the effectiveness of specific policy responses, one needs to consider "collective governmental and societal responsiveness" to risk (for brevity, we refer to this as "collective responsiveness" or "responsiveness"). Greater responsiveness indicates a community's willingness to adopt and adhere to various nonpharmaceutical interventions even at lower levels of perceived risk. As such, collective responsiveness is a social and cultural construct likely related to risk perception; government priorities and agility; and societal preferences for health outcomes, economic performance, and personal freedoms, among others.[20]

Explicitly accounting for the feedback loop between health outcomes and societal responses, in this study we first estimated responsiveness for 136 countries around the world and showed that this single measure could predict a significant proportion of variation in future mortality rates. We then explored some of the cultural constructs that may explain the observed variations in responsiveness across nations.

Risk-Response Feedback And The Policy Outcome Variation Puzzle

The policy outcome variation puzzle asks why responses to COVID-19 had modest variation across nations and barely correlated with the large variations in COVID-19 outcomes (notably mortality). In response, we first observe that although more stringent policies can reduce deaths, the causality can also operate in the opposite direction: More stringent policies are potentially adopted in response to increases in perceived risk as a result of recent deaths. Such a bidirectional relationship constitutes a risk-response feedback loop in which responses reduce deaths, and deaths increase responses. To explore the second part of the relationship further, we correlated, within each country, the weekly policy stringency as a function of recent deaths. A positive correlation emerged where deaths over the previous three weeks predicted current-week stringency (average correlation across all countries and regions in our sample was 0.24 [standard deviation: 0.36]; also see appendix figure S2).[16] The idea that risk perception and change in responses should be incorporated in epidemic modeling is well recognized.[20] However, its full implications emerge only when the mechanism is modeled as an endogenous feedback process in which epidemic and societal behaviors co-evolve.[10] With a few exceptions,[19,21,22] this endogenous feedback mechanism is missing from current models. For example, a recent review of models in the Centers for Disease Control and Prevention's COVID-19 forecast hub found that only one of sixty-one models captured this feedback mechanism.[21]

Transmission reductions in this risk-response feedback result from a combination of official policies and individual behavioral changes, including adherence to those policies; for simplicity, we combined these factors into a single construct of overall response. The feedback from risk levels to this overall response implies that long-term COVID-19 risks (and thus death rates) in each country converged to a threshold that triggered just enough of a response to contain transmission. If perceived COVID-19 risks were below this threshold, responses remained insufficient to contain transmission, allowing increased disease spread and thus, with some lag,

Not only did policies and responses affect the state of the epidemic but also the state of the epidemic regulated those responses via risk perception.

increasing perceived risks. If perceived COVID-19 risks were above that threshold, they triggered responses that brought down transmission and ultimately reduced perceived risk. This feedback framing raises the question of what risk threshold prompts a sufficient response—in other words, how responsive are governments and societies to perceived risks?

This study's central hypothesis is that such collective responsiveness to risk varied across countries, and this variability accounted for a large part of the differences observed in policy outcomes. The subsequent sections of this article elaborate on this hypothesis, providing a formal estimation of responsiveness to COVID-19 risk across nations and its impact on mortality outcomes. Acknowledging that responsiveness is influenced by social and cultural factors, we further delve into the potential for predicting responsiveness by analyzing specific cultural traits across nations. Understanding the role of responsiveness, and the societal factors that shape responsiveness, is key to better adapting policies to mitigate disease transmission.

Study Data And Methods

In this study we used a previously validated model of pandemic dynamics in which governmental policies and behavioral change are a function of the state of the pandemic, operationalized as a response to recent death rates.[21] We first used the model to estimate collective responsiveness across 136 countries and regions by quantifying how recent perceived risk levels drove the societal responses that changed transmission rates. We then examined whether the estimated responsiveness measures predicted future (out-of-sample) death rates, and thus policy outcomes, over long time horizons. We concluded our analysis by exploring the cultural features that predicted responsiveness, and thus death rates, across countries.

DATA Our estimates of country-level parameters included all 136 countries for which sufficient data were available, covering 7.5 billion people. For simplicity, we limited the estimation period to May 1, 2020–March 31,2021. We excluded the first four months of 2020 to avoid conflating the rise of the first wave of the pandemic with the longer-term dynamics (for example, over multiple waves in the first two years of the pandemic; see appendixes S4.f and S4.h for robustness).[16] To reduce model complexity, we chose an end date that largely excluded vaccination effects (only five countries exceeded 10 percent vaccination by that date)[1] and the Delta and Omicron variants. For death and case data, we used seven-day rolling averages.[1] Unless noted, data for the study came from the Our World in Data global COVID-19 database,[1] which draws on different sources, including the Johns Hopkins University Center for Systems Science and Engineering COVID-19 dashboard for cases and deaths.[23] Recognizing significant underreporting of deaths in many countries, in appendixes S4.g and S4.h[16] we report robustness to using estimates of true infection and death rates from the Institute for Health Metrics and Evaluation.[4] Other data we used included gross domestic product (GDP) per capita, population, age distribution (to calculate country-level age multipliers of mortality), hospital beds per capita, Oxford University government response stringency,[10] and independent estimates of (maximum) effective reproduction number R_e (number of secondary cases from an index infection).[24] In addition, we used Hofstede's cultural dimensions to examine associations between collective responsiveness and cultural constructs,[25] available from Geert Hofstede's online database.[26]

ESTIMATING RESPONSIVENESS We built on a previously validated epidemic model, the SEIRb model, which incorporates the feedback loop between mortality and societal responses.[21] This model is intentionally simple to aid transparency and generalizability of insights. Nevertheless, it has outperformed many more complex alternatives in forecasting mortality on an extensive data set of predictions.[21] The model is structurally similar to the classical SEIR (Susceptible, Exposed, Infectious, Removed) compartmental model and incorporates a behavioral risk-response mechanism (thus the "b" in "SEIRb"), where transmission intensity declines (increases) as recent death rates increase (decline). "Responsiveness" represents the strength of this behavioral response mechanism. Formally, instead of being a constant, transmission intensity is a decreasing function of perceived risk of death, which is operationalized as lagged (per capita) mortality rates. The lag reflects the time it takes for governments and individuals to perceive and respond to changing risks and thus could vary across communities. As the perceived risk of death increases, all else equal, the overall transmission intensity declines with a "response" multiplier, which captures the impact of various governmental and societal risk-driven responses on transmission. We formulated this multiplier to be the inverse of 1 plus the product of two components: the parameter for collective responsiveness, and perceived risk of death. With higher values of the responsiveness parameter, transmission intensity will be more sensitive to changes in perceived risk. In short, the model separates collective responsiveness (a country-specific trait) from changing responses, allowing us to estimate responsiveness (the full model specifications and definitions are in appendix S1).[16]

Using the SEIRb model, for each country we estimated the value for the collective responsiveness parameter (as well as lags in risk perception and response adjustment) that offered the best fit between simulated and observed cases and deaths.

ESTIMATING CONTRIBUTORS TO LONG-TERM DEATH RATES Having estimated country-level collective responsiveness, we assessed its predictive value in explaining future COVID-19 death rates across nations. We used linear regressions to explain (log10) deaths as a function of (log10) responsiveness. We predicted deaths for the period April 1–September 30, 2021, which was excluded from the estimation data. We excluded countries for which responsiveness was not reliably identified (that is, not distinguishable from zero). Moreover, to account for death undercounts, we limited the analysis to countries where cumulative excess mortality by September 30, 2021 (based on the *Economist*'s estimates)[27] did not exceed official COVID-19 deaths by more than 100 percent. In appendixes S4.f–S4.h[16] we assess robustness to other inclusion thresholds (25 percent and 50 percent), exclusion of countries with significant early vaccination, and use of estimates for actual (instead of reported) cases and deaths from the Institute for Health Metrics and Evaluation.

To put into perspective the predictive value of responsiveness for understanding mortality, we controlled for a few other explanatory mechanisms, including the impact of age distribution on COVID-19 mortality, GDP per capita, the maximum reproduction number, health care capacity, and average government policy stringency.

EXPLAINING RESPONSIVENESS THROUGH CULTURAL CONSTRUCTS Finally, we explored potential correlates of collective responsiveness across countries. Conceptually, responsiveness relates to distinct social, governance, and cultural factors. For example, sensitivity to risk may be related to a community's tolerance for uncertainty and its emphasis on short- versus long-term outcomes. Hofstede's cultural dimensions offer a common set of measures that inform the hypothesized correlates of responsiveness.[25] These cultural dimensions are uncertainty avoidance (a society's tolerance for ambiguity), power distance (the extent to which less powerful actors accept and expect that power is distributed unequally), individualism (the extent to which people feel independent), masculinity (the extent to which the use of force is endorsed in society), long-term orientation (addressing a focus on time horizons and preparing for the future), and indulgence (the degree of freedom to pursue the "good things in life"). They have been estimated for many countries through representative national surveys and were available for forty-six countries in our sample. As described above, we excluded countries with too much excess mortality compared with reported COVID-19 deaths. The remaining sample consisted of thirty-three countries with data for all of Hofstede's measures (an additional three included only individualism, uncertainty avoidance, and power distance). We used these cultural factors to predict (log10) responsiveness and also as separate predictors of (log10) death rates using linear regressions.

TECHNICAL DOCUMENTATION We followed replicability best practices for model-based analyses,[28] and we report full documentation of our data, model, estimation methods, and supplementary analyses in the appendix[16] and an online repository.[29]

LIMITATIONS The current study focused on three main points: establishing the COVID-19 policy outcome variation puzzle, providing a plausible resolution based on risk-response feedback and variation in collective responsiveness, and exploring cultural determinants of responsiveness. As such, we made many simplifications that should be noted in interpreting the results.

First, by estimating a single "collective" responsiveness measure, we combined nonpharmaceutical interventions, government mandates, and individual behaviors (from adherence to nonpharmaceutical interventions to hygiene and social distancing). Thus, we could not separate the effects of distinct behaviors or offer recommendations for specific nonpharmaceutical interventions; more complex

Communities with higher responsiveness require lower death rates to trigger sufficient policies and adherence to them.

models would be needed for those purposes. Second, to keep the analysis simple, we excluded many relevant factors such as variants, vaccination, adherence fatigue, and loss of immunity. These simplifications increase the model's transparency and help build intuition, but they limit its predictive power and realism. Third, we focused on the role of collective responsiveness in predicting mortality, instead of offering a comprehensive explanation of country-level mortality variation, thus missing potential determinants such as comorbidities.

Fourth, our preliminary exploration of determinants of responsiveness omitted plausible factors such as recent experience of other epidemics or the ideological leaning of governments during the pandemic. Fifth, we assumed that responsiveness was constant, but it likely changed over time as a result of factors such as adherence fatigue. Finally, the data we used in the primary analysis were based on reported cases and deaths. Those may have significantly undercounted true incidences, so we assessed the use of alternative data for cases and deaths, and included only regions with limited undercount, in our robustness checks. With these simplifications, our analysis provides an illustration of, and a lower bound for, the value of incorporating risk-response feedback in understanding pandemic outcomes and designing more effective policies.[30]

Study Results

ESTIMATING COLLECTIVE RESPONSIVENESS Estimated responsiveness values varied widely across nations and indicated that risk perception had robust effects on changing transmission intensity through the adoption of nonpharmaceutical interventions and behavioral changes. For example, at median responsiveness, the number of daily deaths per million that triggered sufficient responses to reduce transmission intensity by 50 percent was 0.09, with substantial between-country variation (90% range: 0.003–2.67). Appendix table S4 provides estimated responsiveness levels for the sample of countries informing baseline regressions.[16] Moreover, the estimated responses correlated positively with the Oxford University measures of policy stringency (mean/median correlation was 0.35/0.37 across nations).[10] This provides evidence that our estimates of changes in responses over time related to measures of policy that were not used in our estimation. Note that we did not expect the correlation to be very strong because the estimated responses included population adherence and behavioral change, beyond formal policy stringency.

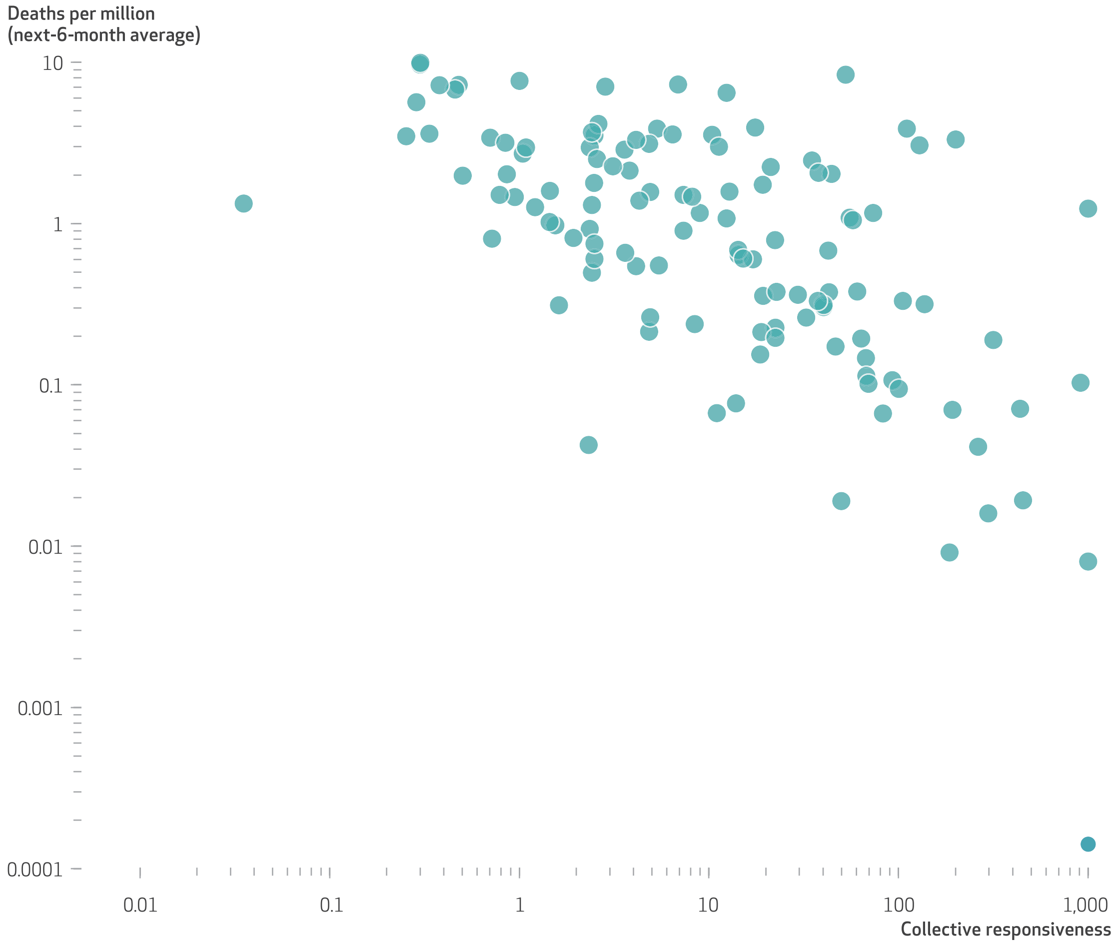
COLLECTIVE RESPONSIVENESS AS A PREDICTOR OF DEATHS Exhibit 1 shows that (log10) responsiveness estimated from May 1, 2020, to March 31, 2021, was strongly and negatively correlated with (log10) death rates ($R = -0.625$) averaged over the subsequent six months (April 1–September 30, 2021).

Regressing the six-month-averaged daily death rates against responsiveness and several other predictors (exhibit 2) provided a comparison of these factors in explaining death rates. Responsiveness (log10 of our collective responsiveness parameter) was the most important driver of the variation in death rates ($t = -4.1$, $p = 1.9E-4$), enhancing the model's fit (adjusted R^2) by 0.28 (from 0.00 to 0.28); increasing responsiveness by 1 standard deviation reduced death rates by a factor of about 3 (0.35 [95% confidence interval: 0.15, 0.82]). In comparison, we found no evidence that GDP, initial local transmission intensity (reproduction number), hospital capacity, or policy stringency were significant predictors of deaths. Even age multiplier of mortality (a variable calculating expected fatality rates in each country as a result of the age distribution), which was a statistically significant correlate of deaths during the estimation period, lost its predictive power for cumulative deaths later in the prediction period (April–September 2021).

We assessed the robustness of these results to various assumptions such as including the early pandemic period, excluding countries with early vaccination, excluding countries with less reliable death data, and using Institute for Health Metrics and Evaluation estimates of cases and deaths. Those analyses, detailed in appendixes S4.f–S4.h,[16] show that none of those assumptions changed any of the results qualitatively: In all, responsiveness remained statistically significant and was the primary driver of variation in death rates. Overall, the results support the hypothesis that responsiveness to risk was a bet-

EXHIBIT 1

Reported daily COVID-19 deaths per million people in 119 countries (averaged over the 6-month prediction period, April 1–September 30, 2021) against estimated collective responsiveness (estimated during the period May 1, 2020–March 31, 2021)



SOURCE Authors' analysis of data on daily confirmed cases and deaths from the Our World in Data global COVID-19 database (see note 1 in text). **NOTES** The figure includes data on 119 of the 136 countries in the data source, as we excluded countries where responsiveness was too small to be reliability estimated. The correlation in the figure is −0.625. The scale on both the *x* and *y* axes is log base 10. *Responsiveness* is defined in the text.

ter predictor of mortality variation across countries than many commonly considered factors, from demographics to GDP, transmission potential, health care capacity, and policy stringency.

CULTURAL MEASURES ASSOCIATED WITH RESPONSIVENESS AND DEATH RATES Exhibit 3 reports the regression results of collective responsiveness and six-month-averaged daily death outcomes against Hofstede's cultural dimensions. These analyses were done on only the subset of states that contained data for the relevant Hofstede's cultural dimensions. Regression models M1–M3 with the dependent variable of responsiveness show that uncertainty avoidance and power distance were important predictors of responsiveness. In model M1, these two cultural constructs explained about 28 percent of the variation in responsiveness, and the results were robust after we added other cultural dimensions to the regression in models M2 and M3.

Models M4–M6, with the dependent variable of (log10 of average daily) deaths during the prediction period, show that Hofstede's cultural dimensions could partially explain differences in mortality outcomes. Model M4 shows the predictive value of responsiveness alone for the subset of countries for which cultural measures were available. Model M5 shows that the association between uncertainty avoidance (and, to a lesser extent, long-term orientation) with deaths was statistically significant, and the cultural constructs alone explained about 48 percent of the variation in deaths across different countries. Model M6 adds responsiveness to the predictors

EXHIBIT 2

Predictors of cross-national variation in COVID-19 mortality rates per capita, averaged over 6 months beginning April 1, 2021

Predictors	Coefficient ±SE	*p* value	Marginal adjusted R^2	Effect size	95% CI of effect size
Collective responsiveness (log10)	−0.546 ±0.227	0.000	0.28	0.35	(0.15, 0.82)
Age multiplier of mortality (log10)	−0.357 ±0.361	0.474	−0.008	0.84	(0.59, 1.19)
GDP per capita (log10)	−0.240 ±0.226	0.266	0.005	0.83	(0.59, 1.17)
Initial reproduction number	−0.142 ±0.152	0.299	0.002	0.74	(0.39, 1.40)
Hospital beds per thousand	0.018 ±0.024	0.685	−0.015	1.12	(0.83, 1.50)
Policy stringency (six-month average)	0.016 ±0.009	0.21	0.011	1.44	(0.98, 2.11)

SOURCE Authors' analysis of data from the Our World In Data global COVID-19 database (see note 1 in text). **NOTES** The predictors are defined in the text. Dependent variable: per capita mortality (reported daily deaths per million), averaged over 180 days beginning April 1, 2021. Marginal adjusted R^2 = adjusted R^2 for full model − adjusted R^2 for model excluding this predictor. Effect size is the multiplicative change in 6-month-averaged daily deaths per million per 1-standard-deviation change in predictor. *n* (number of countries) = 46; adjusted $R^2 = 0.277$; F = 3.9 ($p = 0.003$). GDP is gross domestic product.

and shows improved predictive power against model M5. As in model M5, long-term orientation was negatively associated with deaths. Interestingly, when responsiveness was controlled for, power distance also became marginally predictive of deaths.

In summary, we note that two cultural constructs, uncertainty avoidance and power distance, partially predicted the variation in responsiveness, and they were also associated with the variation in mortality outcomes; and cultural constructs partly explained the association between responsiveness and deaths, yet the impact of responsiveness was not limited to the pathways overlapping with cultural precepts.

Discussion

Examining COVID-19 mortality globally points to a puzzling variation in policy outcomes. Specifically, during the acute phase of the pandemic, the stringency of government and societal responses was similar across most countries, yet mortality outcomes varied by more than a hundredfold. While some studies have shown immediate effects of nonpharmaceutical interventions that seem intuitive,[7–9] others have found variability in effects[11,12] or concluded that such policies were ineffective.[15] To resolve this conundrum, we noted that not only did policies and responses affect the state of the epidemic but that also the state of the epidemic regulated those responses

EXHIBIT 3

Cultural constructs as explanatory factors for COVID-19 responsiveness and death outcomes for the prediction period, May 1, 2020–March 31, 2021

	Regression models with dependent variable of collective responsiveness (log)			Regression models with dependent variable of average daily deaths (log)		
	M1	M2	M3	M4	M5	M6
Hofstede's cultural dimensions						
Uncertainty avoidance	−0.035***	−0.030**	−0.030**	—[a]	0.047****	0.032**
Power distance	0.035**	0.051***	0.048**	—[a]	0.015	0.038*
Individualism	—[a]	0.022	0.019	—[a]	0.016	0.025
Masculinity	—[a]	—[a]	−0.001	—[a]	−0.002	−0.003
Long-term orientation	—[a]	—[a]	−0.001	—[a]	−0.026*	−0.027*
Indulgence	—[a]	—[a]	−0.025	—[a]	0.031	0.019
Collective responsiveness (log)	—[a]	—[a]	—[a]	−0.554***	—[a]	−0.488***
Intercept	1.887*	−0.363	1.478	0.654	−5.148*	−4.427*
n	36	36	33	33	33	33
R^2	0.28	0.33	0.34	0.27	0.48	0.62
Adjusted R^2	0.24	0.26	0.18	0.24	0.36	0.51
F-statistic	6.42***	5.17***	2.20*	11.16***	3.98***	5.71****

SOURCE Authors' analysis of data from the Our Word in Data global COVID-19 database (see note 1 in text) and Hofstede's cultural dimensions (see note 26 in text). **NOTES** Dependent variables: Collective responsiveness was estimated during the period May 1, 2020–March 31, 2021, and per capita mortality (reported daily deaths per million), was averaged over the 6 months beginning April 1, 2021. *n* indicates number of countries, reflecting the number of countries in our sample for which data on the relevant Hofstede's cultural dimensions were available, as explained in the text. [a]Variable not included in the regression model of the column. *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$ ****$p < 0.001$

via risk perception. Thus, the primary factor driving variation in COVID-19 mortality rates was not the specific policies implemented, but rather different societies' responsiveness to perceived risk. By explicitly modeling the feedback loop between societal responses and the pandemic's progression, we estimated a measure of responsiveness and correlated it with future deaths. We then explored cultural antecedents of responsiveness.

Three findings emerge. First, the degree of responsiveness to evolving pandemic risks varied markedly among nations. Second, estimated responsiveness was highly predictive of future COVID-19 mortality rates. In fact, responsiveness was a stronger predictor of mortality outcomes than several intuitive predictors, including demographics, health care capacity, the stringency of nonpharmaceutical intervention policies, the maximum reproduction number, and GDP per capita. Responsiveness encapsulates societal and policy-making sensitivity to the pandemic's risks: the number of daily deaths required to compel the adoption of sufficient responses to curb transmission, as well as the speed and effectiveness of policy implementation.

To understand the importance of responsiveness, consider a typical outbreak wave in a community. Initially the epidemic grows, with increases in cases, deaths, and hence perceived risk. As the toll escalates, policy makers and the community are compelled to respond, adopting nonpharmaceutical interventions and other measures to reduce transmission and ultimately slowing the spread of the disease. This shift results in declining transmission rates, with mortality rates soon following suit. Over time, as the memory of the wave fades and perceived risk lessens, responses are relaxed, allowing renewed transmission. Eventually, the laxness of policy in the presence of infection seeds the start of a new wave. In essence, the mix of responses converges to those required to keep the epidemic from growing exponentially or subsiding fully, keeping perceived risks at levels just tolerable for the community. Analytically, these response levels are those needed to keep the effective reproduction numbers near 1. The specific death rates that trigger this strength of response, however, depend heavily on the community's responsiveness. Communities with higher responsiveness require lower death rates to trigger sufficient policies and adherence to them. This mechanism is fundamental in explaining how variation in responsiveness predicts observed death rates across communities. The oscillations in response due to this feedback loop also provide a mechanism for the endogenous emergence of pandemic waves that complements other triggers such as new variants, loss of immunity, and seasonality.

Our findings challenge the perceived trade-off between saving lives and minimizing disruptions during the critical phase of a pandemic.

Third, cultural attitudes partially accounted for variations in responsiveness. We found that Hofstede's measures of uncertainty avoidance and power distance were associated with responsiveness. The association of power distance with responsiveness indicates that communities that are more willing to follow the mandates of a centralized government may be more responsive to a fast-changing public health threat. The inverse relationship between uncertainty avoidance and responsiveness may seem unexpected. However, this relationship may underscore the value of societal tolerance toward change and novelty in facilitating rapid policy responses and the adoption of potentially disruptive nonpharmaceutical interventions. We also note that combining responsiveness and Hofstede's cultural constructs provides a more accurate prediction for mortality than either alone.

Our findings have significant policy implications. First, they challenge the perceived trade-off between saving lives and minimizing disruptions during the critical phase of a pandemic. When infection fatality rates are sufficiently high, the implementation of nonpharmaceutical interventions becomes inevitable as the threat of an exponential outbreak compels communities to control transmission. Regardless of timing, every community will need to adopt a mix of nonpharmaceutical interventions sufficient to curtail exponential growth in deaths. Thus, the limited correlation between policy responses and deaths does not imply that nonpharmaceutical interventions against COVID-19 are ineffective, contrary to arguments raised by some.[15] Rather, the correlation with mortality vanishes because all communities ultimately needed to adopt stringent enough responses to curb exponential transmission. Communities that enacted the requisite policies earlier (that is, not waiting for high levels of mortality) achieved life-saving results without imposing additional societal costs.

Second, policy makers would benefit from focusing their attention on responsiveness. Whereas all communities adopted comparable response levels, their responsiveness varied by two orders of magnitude. From protocols for rapid response to having tighter response thresholds and openly communicating with the public about the importance of responsiveness, policy makers can take actions that enhance responsiveness and thus could contribute significantly to reducing the burden of an epidemic. In fact, it is critical for policy makers to articulate the insight that heightened responsiveness and swifter action would preserve lives without requiring the implementation of more stringent policies. This could help secure public backing for more agile, responsive policies in managing future pandemics with major life-saving benefits. If all countries had the responsiveness of the top ten percentile, the COVID-19 death toll in the first two years could have been reduced by nearly an order of magnitude.

Conclusion

The findings of this global-scale study point to the importance of policy responsiveness rather than policy response in reducing mortality during a deadly pandemic. Responsiveness varies widely across nations. While cultural factors significantly influenced responsiveness in our study, they accounted for only about one-third of the variation in estimated responsiveness, indicating that policy makers and communities have scope to enhance responsiveness. Understanding the social mechanisms and organizational structures that enabled governments in certain countries to adopt more responsive policy stances, implement coherent sets of nonpharmaceutical interventions at lower risk levels, and encourage public adherence to these policies is crucial in preparing for future pandemics. ■

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16 To access the appendix, click on the Details tab of the article online.

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