

## COVID-19 Results Briefing

### Bahrain

January 22, 2021

This document contains summary information on the latest projections from the IHME model on COVID-19 in Bahrain. The model was run on January 21, 2021, with data through January 19, 2021.

#### Current situation

- Daily reported cases in the last week were about 300 per day on average (Figure 1).
- Daily deaths in the last week were less than 1 per day on average (Figure 2). This makes COVID-19 the number 3 cause of death in Bahrain this week (Table 1).
- Effective R, computed using cases, hospitalizations, and deaths, was 1.09 on January 8 (Figure 3).
- We estimated that 10% of people in Bahrain have been infected as of January 19 (Figure 4).
- The daily death rate is less than 1 per million (Figure 6).

#### Trends in drivers of transmission

- In the last week, no new mandates have been imposed and no mandates have been lifted (Table 2).
- Mobility last week was 15% lower than the pre-COVID-19 baseline (Figure 8).
- As of January 19, we estimated that 62% of people always wore a mask when leaving their home (Figure 9).
- There were 631 diagnostic tests per 100,000 people on January 19 (Figure 10).
- In Bahrain, 56.4% of people say they would accept a vaccine for COVID-19 and 23.5% say they are unsure if they would accept one (Figure 12).
- We expect that 359,500 will be vaccinated by May 1 (Figure 13).

#### Projections

- In our **reference scenario**, which represents what we think is most likely to happen, our model projects about 660 cumulative deaths on May 1, 2021 (Figure 14). Daily deaths will peak at about 2 on February 25, 2021 (Figure 15).
- If **universal mask coverage (95%)** were attained in the next week, our model projects about 120 fewer cumulative deaths compared to the reference scenario on May 1, 2021 (Figure 14).

- We estimate that 20.8% of people will be immune on May 1, 2021 (Figure 17).
- The reference scenario assumes that the country will not re-impose mandates by May 1, 2021 (Figure 18).
- Figure 21 compares our reference scenario forecasts to other publicly archived models. Forecasts are widely divergent.
- At some point from January through May 1, Bahrain will have high or extreme stress on hospital and ICU beds (Figures 22 and 23).

## Model updates

This week we have fully revised the way we estimate past daily infections in a modeling framework that leverages data from seroprevalence surveys, daily cases, daily deaths, and, where available, daily hospitalizations. We have not revised the way our projections are being made. The changes introduced affect the part of our model that estimates infections from the beginning of the pandemic to the present day.

This new approach to estimating infections in the past has several advantages. First, it puts more emphasis on the recent trend in cases and hospitalizations than our previous approach. Second, it is more robust to reporting lags in any one of the three main indicators. Third, for locations with small populations, by synthesizing data on all three indicators (cases, deaths, and hospitalizations), the results are less sensitive to fluctuations due to chance or measurement error in any one of the indicators. Fourth, our new approach leverages the information collected through seroprevalence surveys to validate the estimates of daily infections.

### Why did we change our approach?

Our COVID-19 forecast model depends on estimating daily infections and effective R since March 2020 for each location. We estimate the relationship between daily infections to date and covariates (such as mobility, mask use, testing per capita, and social distancing mandates) and use that relationship to forecast effective R in the future. Up until this week's release, our method for estimating daily infections in the past was anchored on daily deaths because in the first months of the pandemic, there was less measurement error in daily deaths than in daily cases. Over the past two months, and particularly over various holiday periods across the world, there has been clear evidence of significant delays in reporting of cases and deaths. These reporting lags result in artificial dips and then artificial surges due to catch-up reporting. In contrast, in places where daily hospital admissions for COVID-19 are reported in a timely manner such as the US HHS, daily hospital admissions have not exhibited large reporting lags. Throughout the pandemic, we have also seen that the trend measured through daily hospitalizations has been much less affected by the availability of testing than the trend observed in cases.

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### More details on the new approach

We use 884 seroprevalence surveys which provide information on the proportion of a population that has SARS-COV2 antibodies in their blood, and we relate them to estimates of cumulative cases, hospitalizations, and deaths for the same time period in these populations to derive measurements of three quantities of interest: 1) the infection detection rate (IDR), 2) the infection hospitalization rate (IHR) and 3) the infection-fatality rate (IFR). Because the IHR and the IFR are strongly related to age, we analyze the age-standardized IHR and IFR. For each of the three measures, we have developed predictive models so that we can have estimates for all locations, not just those that have seroprevalence surveys.

- **IDR:** The key covariate in this model is testing rates per capita. This model also includes location random effects, so the IDR is tuned to the available data for each location. Overall, the data suggest the IDR has increased across all locations from very low levels, as low as 1%, at the beginning of the pandemic to much higher levels, exceeding over 50% in some high-income settings. The model also includes corrections for seroprevalence surveys that may be biased compared to the general population such as blood donors.
- **IHR:** The IHR varies considerably across countries and states or regions within a country, likely reflecting variation in clinical practice. We have tested and found that there isn't a consistent relationship between the IHR and time, indicating that while clinical practice varies across locations, there has not been a substantial shift in the IHR over time within each location. The model also includes corrections for seroprevalence surveys that may be biased compared to the general population such as blood donors.
- **IFR:** As noted in previous briefs, the age-standardized IFR has changed over time and is highly correlated with population levels of obesity. The final model includes time, obesity prevalence, corrections for potentially biased sources of seroprevalence, and location random effects.

Our new approach includes three main steps.

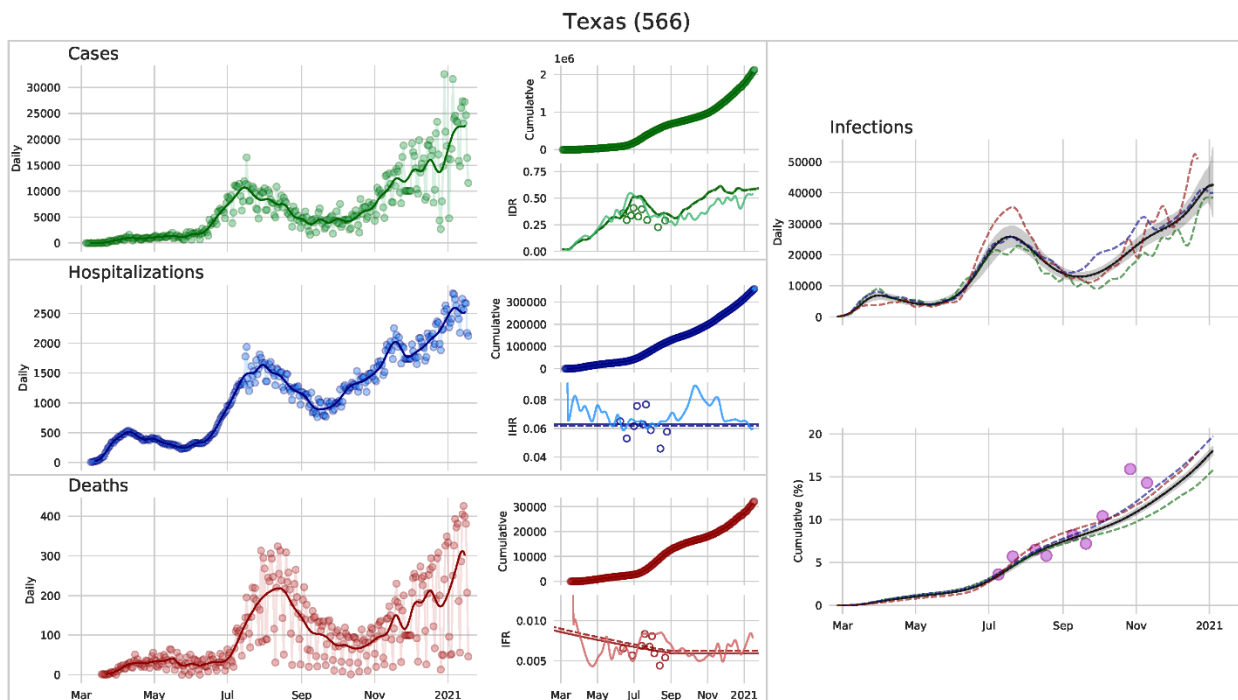
First, we produce three distinct time series of infections per day:

- **Using cases:** To estimate infections per day, we convert the smoothed time series of cases per day by the IDR and shift it back 11 days. This way we capture the lag between the time of infection and being diagnosed as a case.
- **Using hospitalizations:** We divide the smoothed time series of hospitalizations per day by the IHR and shift everything back by 11 days.
- **Using deaths:** We divide the smoothed time series of deaths per day by the IFR. These are shifted back by 24 days.

Second, we pool the three time series to generate our best estimate of the trend in infections per day from March to the present.

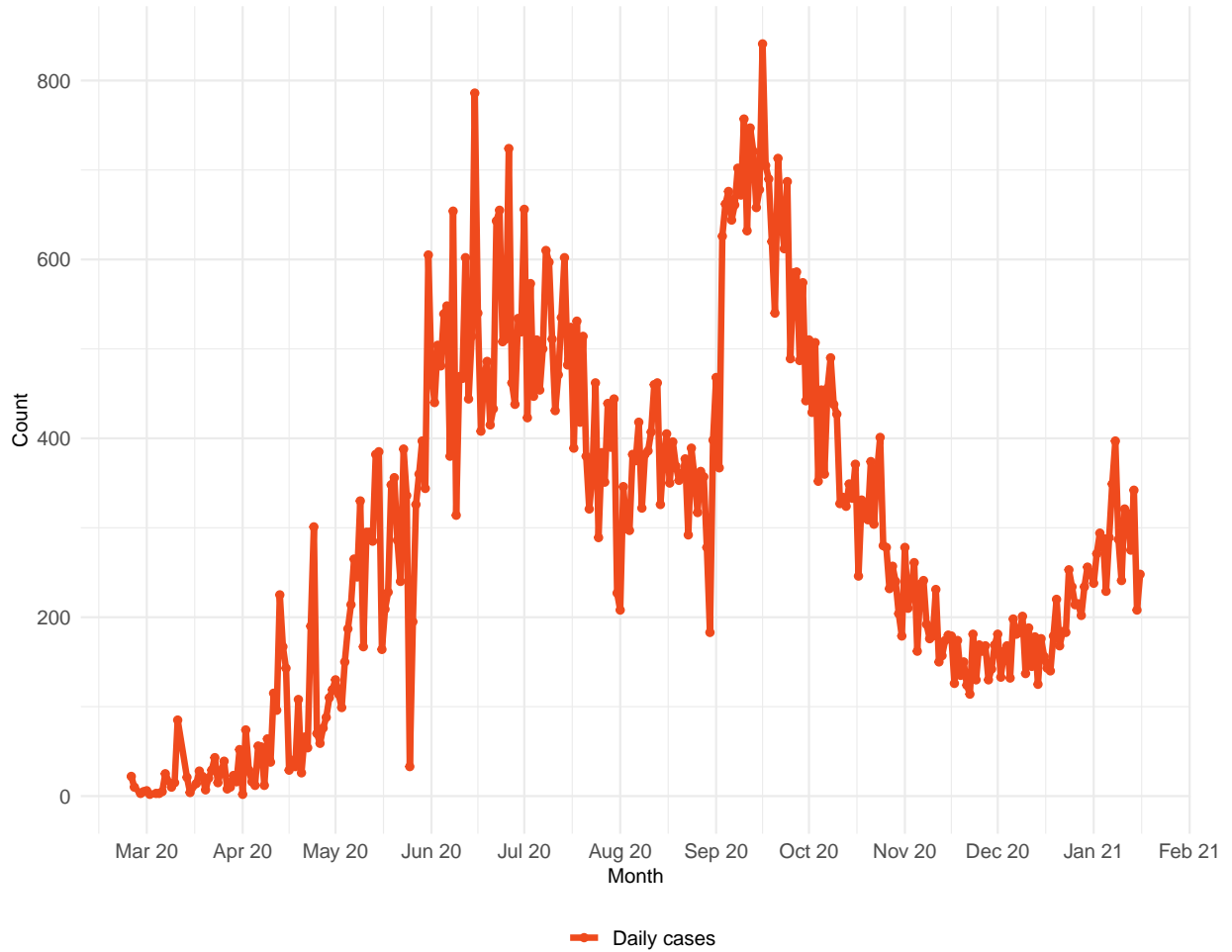
Third, we compare the calculated the cumulative infections from the four series of infections per day (based on cases, hospitalizations, and deaths and the final pooled estimate) to the available seroprevalence data; given the methods employed, on average they match the seroprevalence data.

To explore this visually, the approach is summarized in a plot like the one shown below for each location. The left-hand side shows daily cases in green, hospital admissions in blue, and deaths in red. As mentioned above, a smoothed line is fit to each of these time series. In the middle column of figures, the estimated IDR is shown in green, the IHR in blue, and the IFR in red. The graphs also show data from seroprevalence surveys, when available. The right-hand side graphs show infections. The top right graph shows the three estimated time series of infections per day (based on cases, hospitalizations, and deaths, respectively), and the black line shows the pooled estimate with uncertainty. The bottom right plot shows the estimated cumulative infections based on each time series, and the black line shows the estimated cumulative infections based on the pooled estimate. The purple dots represent the seroprevalence data, where available.



## Current situation

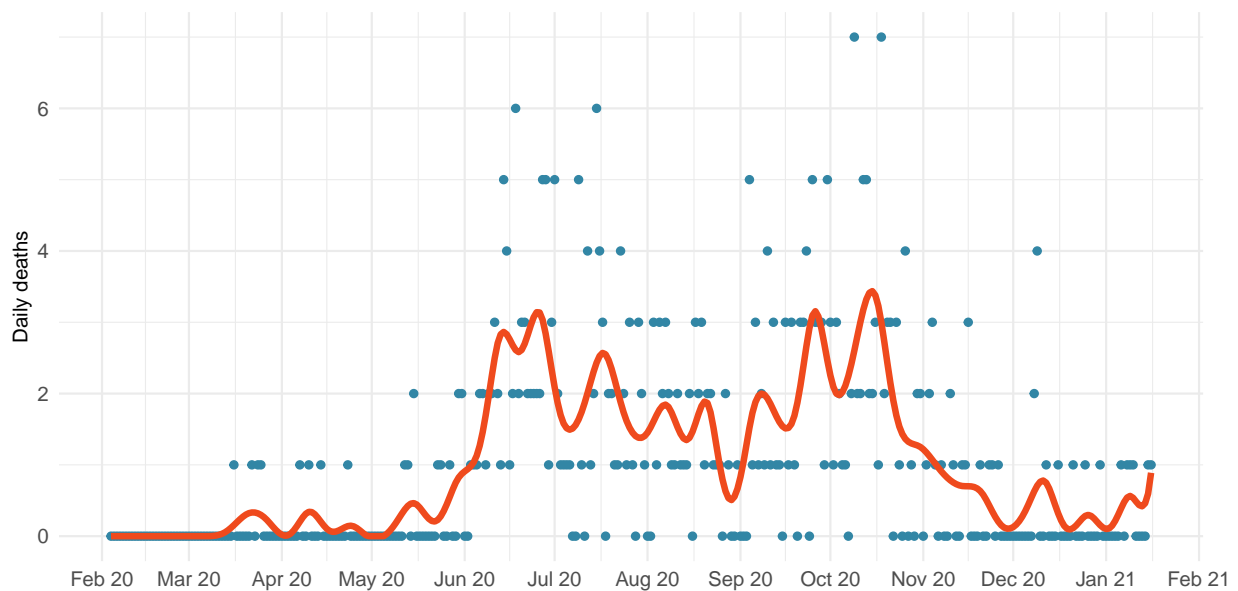
Figure 1. Reported daily COVID-19 cases



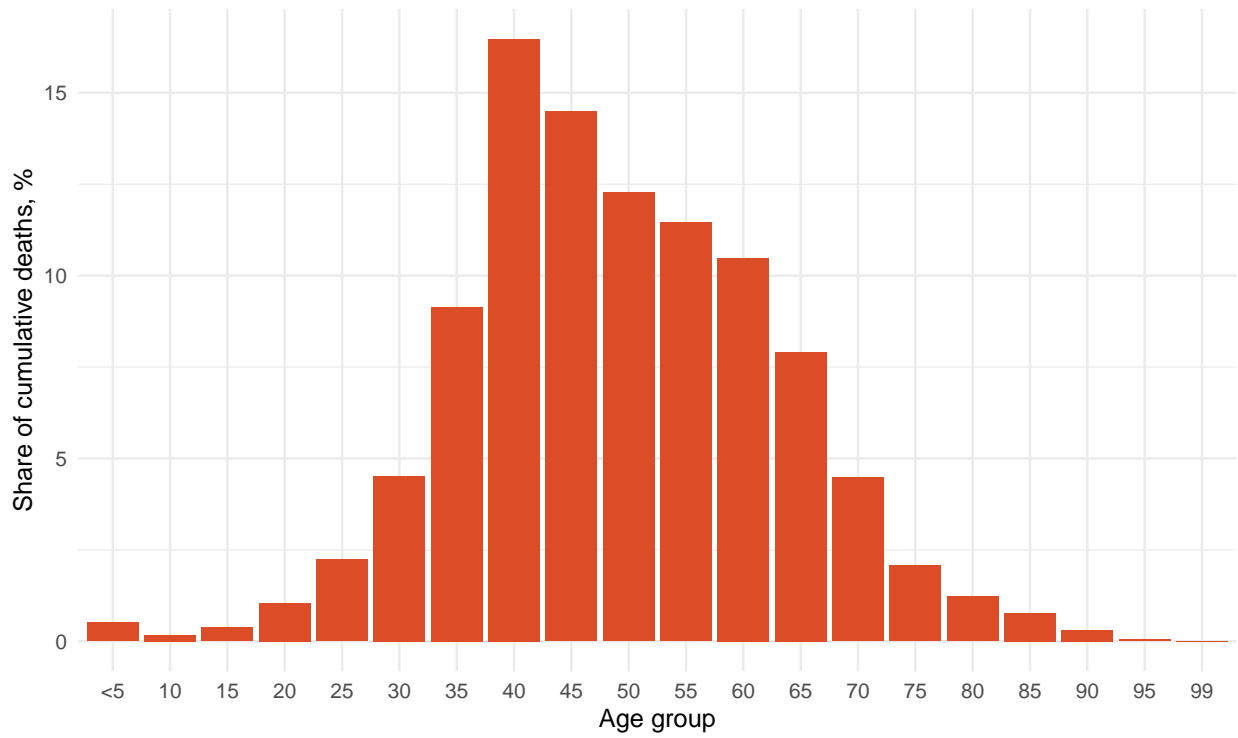
**Table 1.** Ranking of COVID-19 among the leading causes of mortality this week, assuming uniform deaths of non-COVID causes throughout the year

Cause name	Weekly deaths	Ranking
Ischemic heart disease	17	1
Diabetes mellitus	14	2
COVID-19	5	3
Stroke	5	4
Road injuries	3	5
Chronic kidney disease	3	6
Tracheal, bronchus, and lung cancer	3	7
Cirrhosis and other chronic liver diseases	3	8
Chronic obstructive pulmonary disease	2	9
Breast cancer	2	10

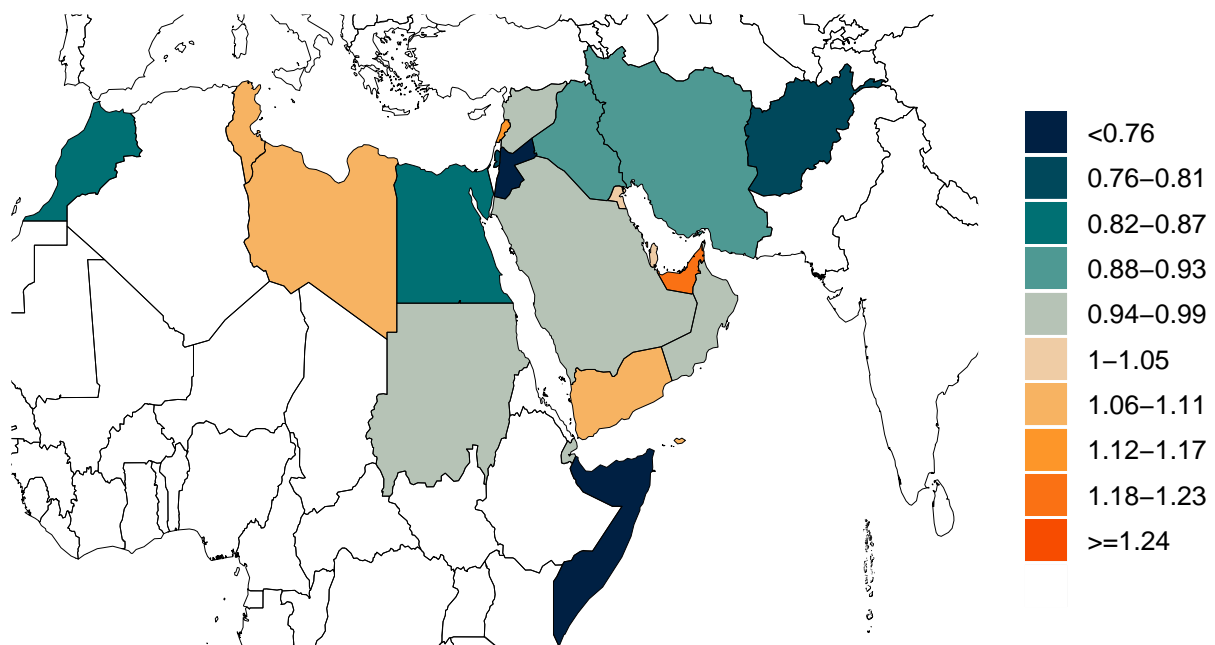
**Figure 2a.** Reported daily COVID-19 deaths



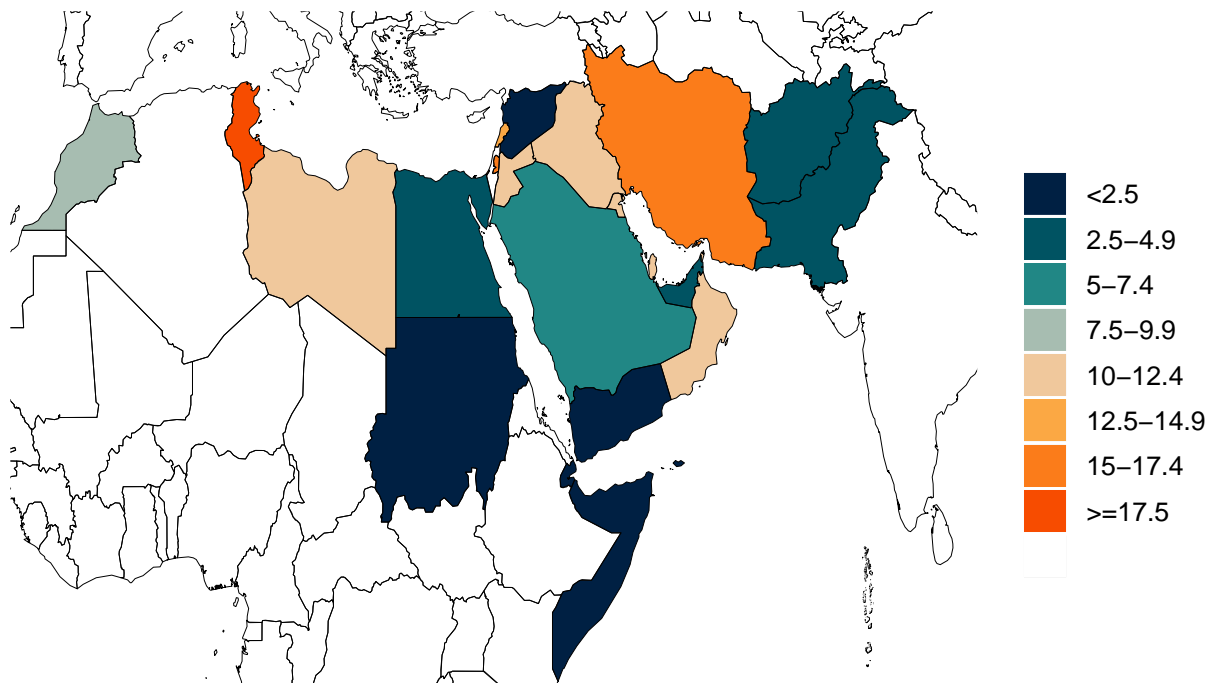
**Figure 2b.** Estimated cumulative deaths by age group



**Figure 3.** Mean effective R on January 08, 2021. The estimate of effective R is based on the combined analysis of deaths, case reporting, and hospitalizations where available. Current reported cases reflect infections 11-13 days prior, so estimates of effective R can only be made for the recent past. Effective R less than 1 means that transmission should decline, all other things being held the same.



**Figure 4.** Estimated percent of the population infected with COVID-19 on January 19, 2021



**Figure 5.** Percent of COVID-19 infections detected. This is estimated as the ratio of reported daily COVID-19 cases to estimated daily COVID-19 infections based on the SEIR disease transmission model.

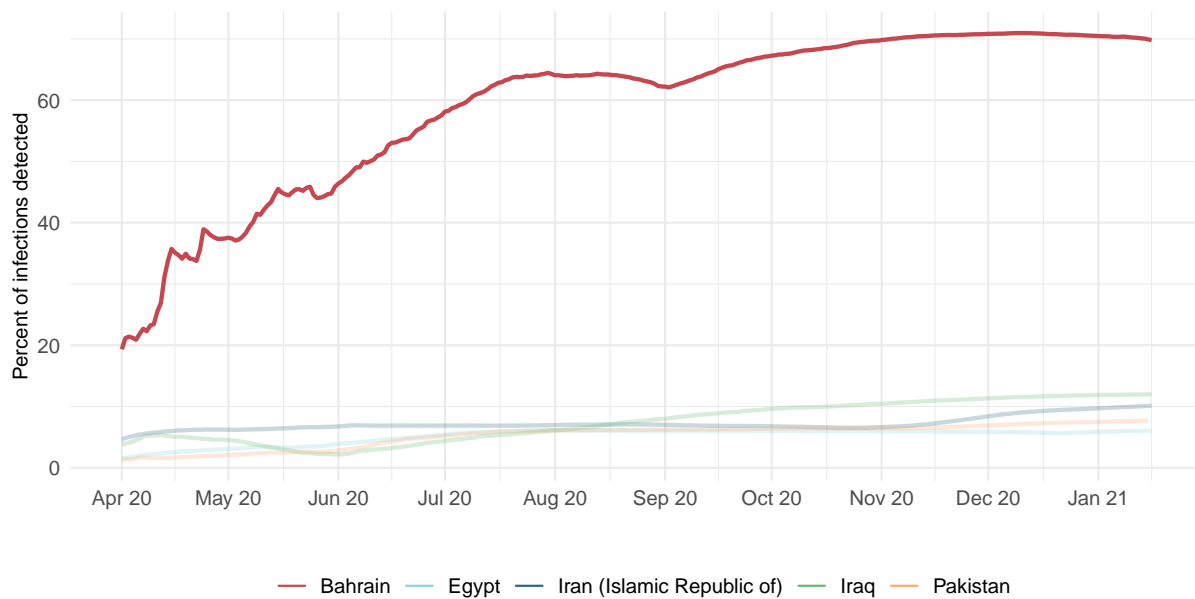
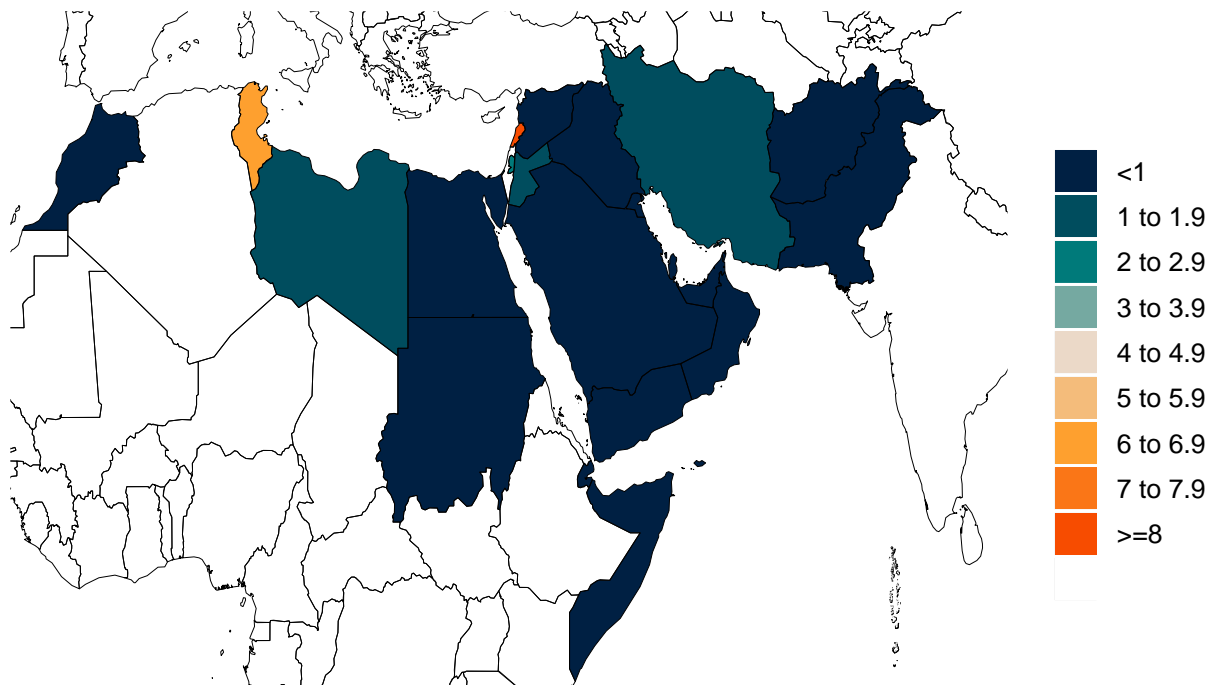




Figure 6. Daily COVID-19 death rate per 1 million on January 19, 2021



## Critical drivers

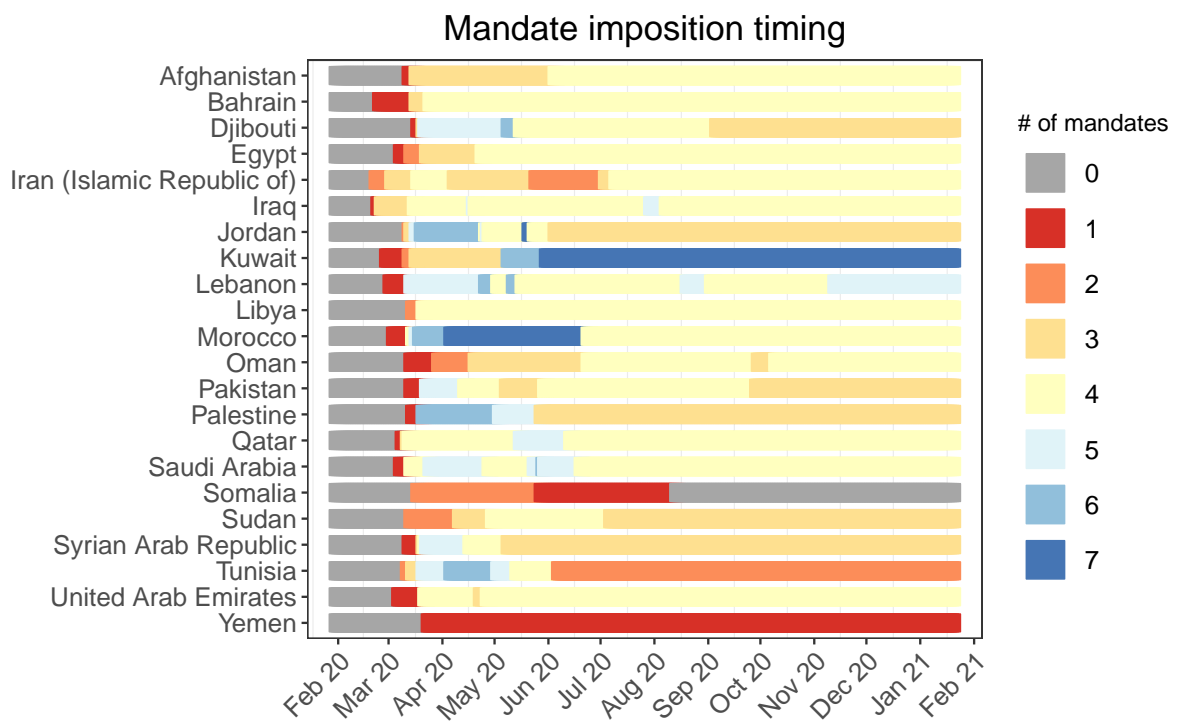
Table 2. Current mandate implementation



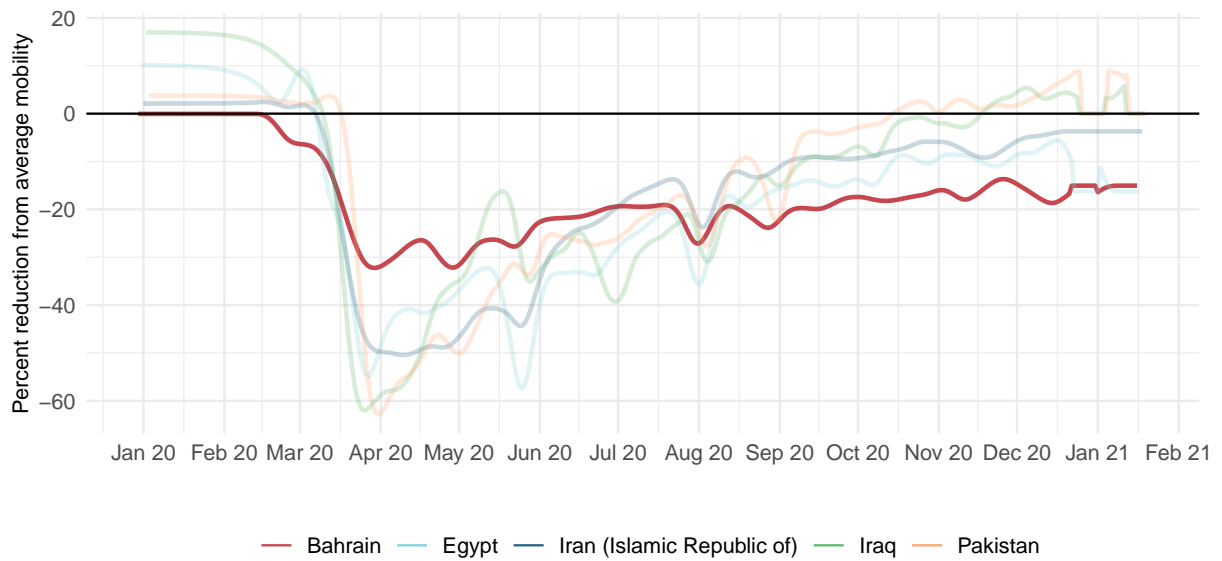
Mandate in place
  No mandate  
 Mandate in place (imposed this week)
  No mandate (lifted this week)

\*Not all locations are measured at the subnational level.

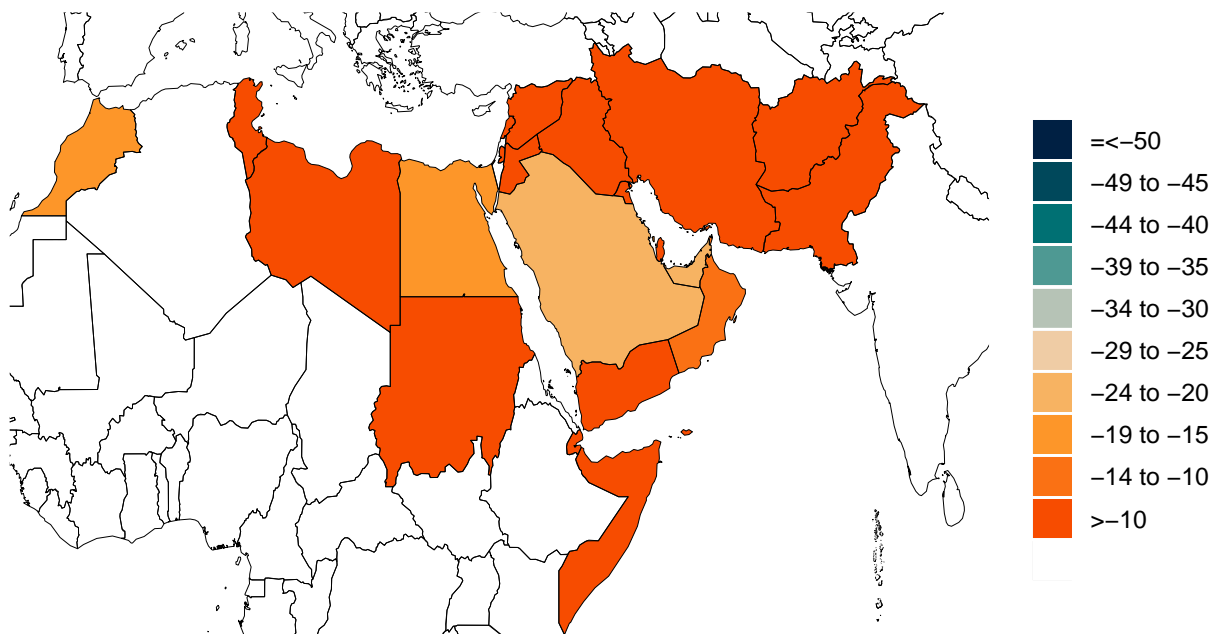
Figure 7. Total number of social distancing mandates (including mask use)



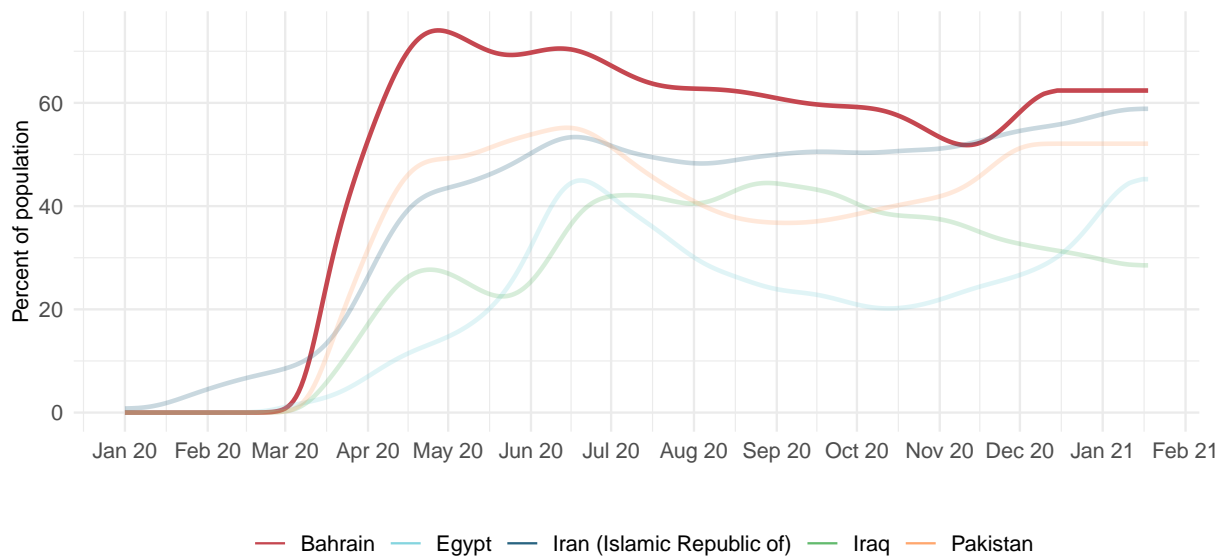
**Figure 8a.** Trend in mobility as measured through smartphone app use compared to January 2020 baseline



**Figure 8b.** Mobility level as measured through smartphone app use compared to January 2020 baseline (percent) on January 19, 2021



**Figure 9a.** Trend in the proportion of the population reporting always wearing a mask when leaving home



**Figure 9b.** Proportion of the population reporting always wearing a mask when leaving home on January 19, 2021

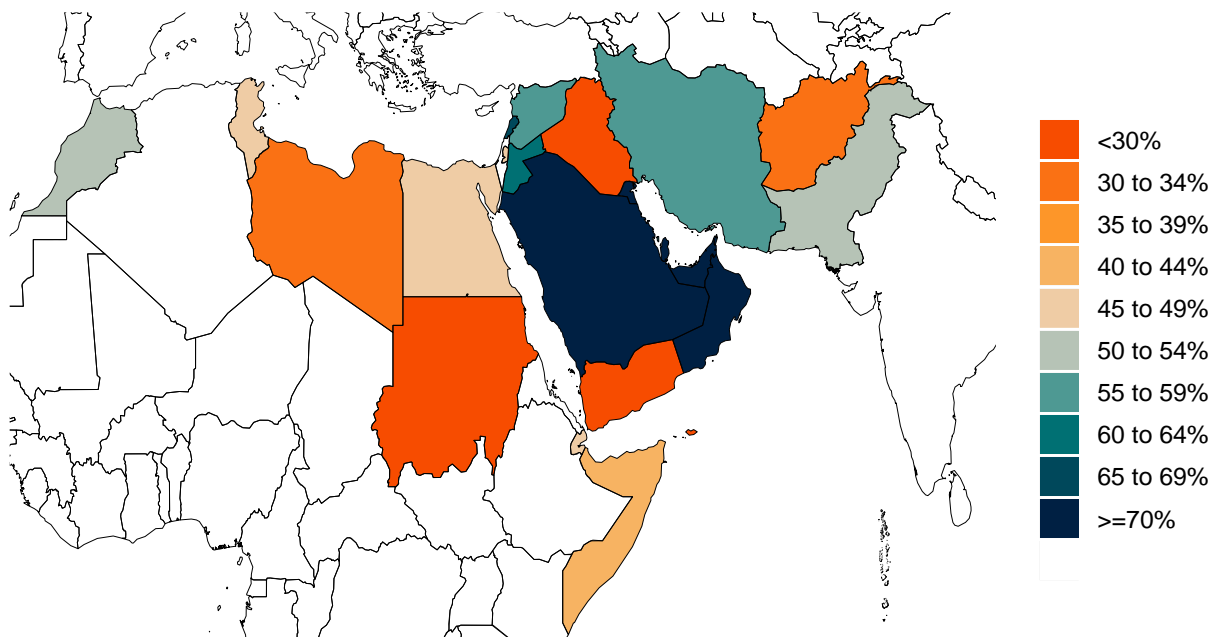


Figure 10a. Trend in COVID-19 diagnostic tests per 100,000 people

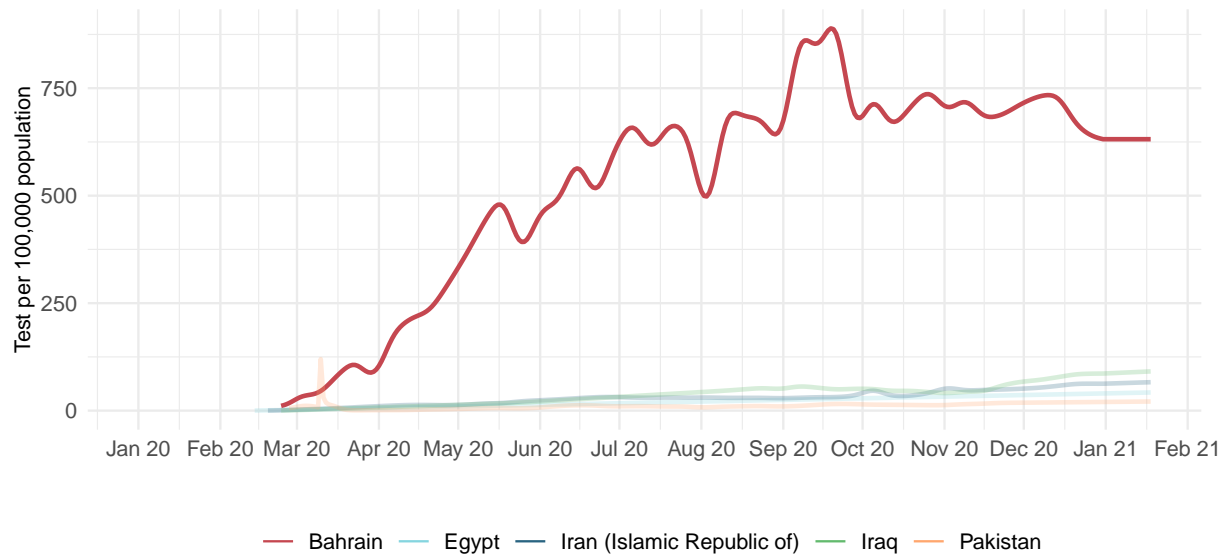


Figure 10b. COVID-19 diagnostic tests per 100,000 people on December 31, 2020

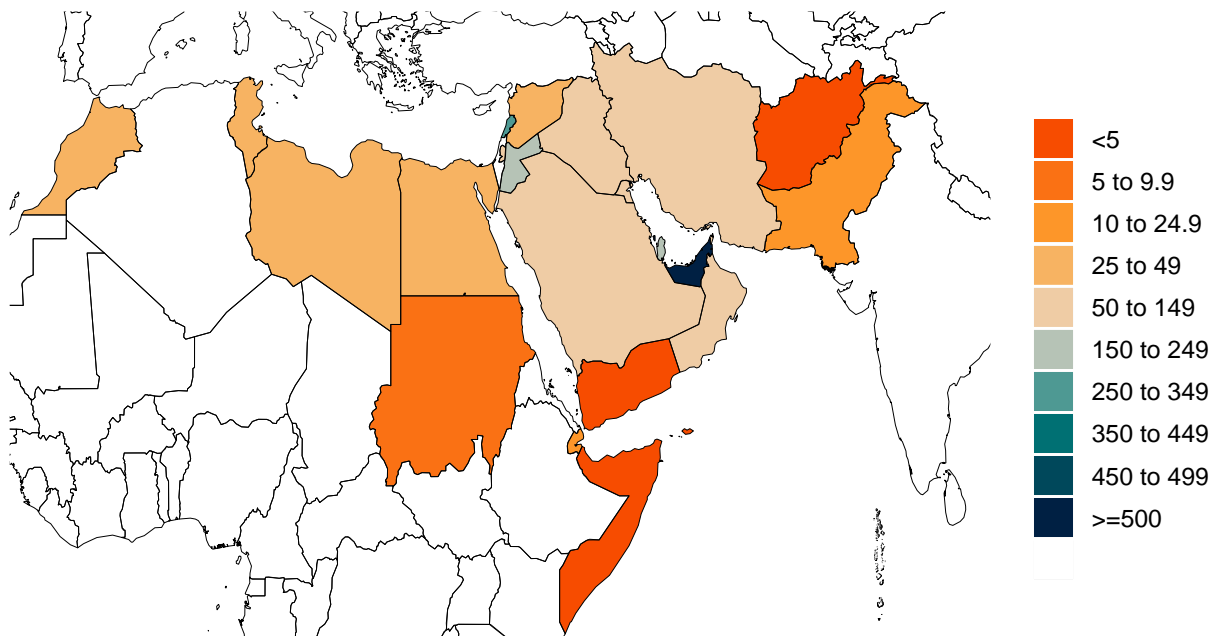
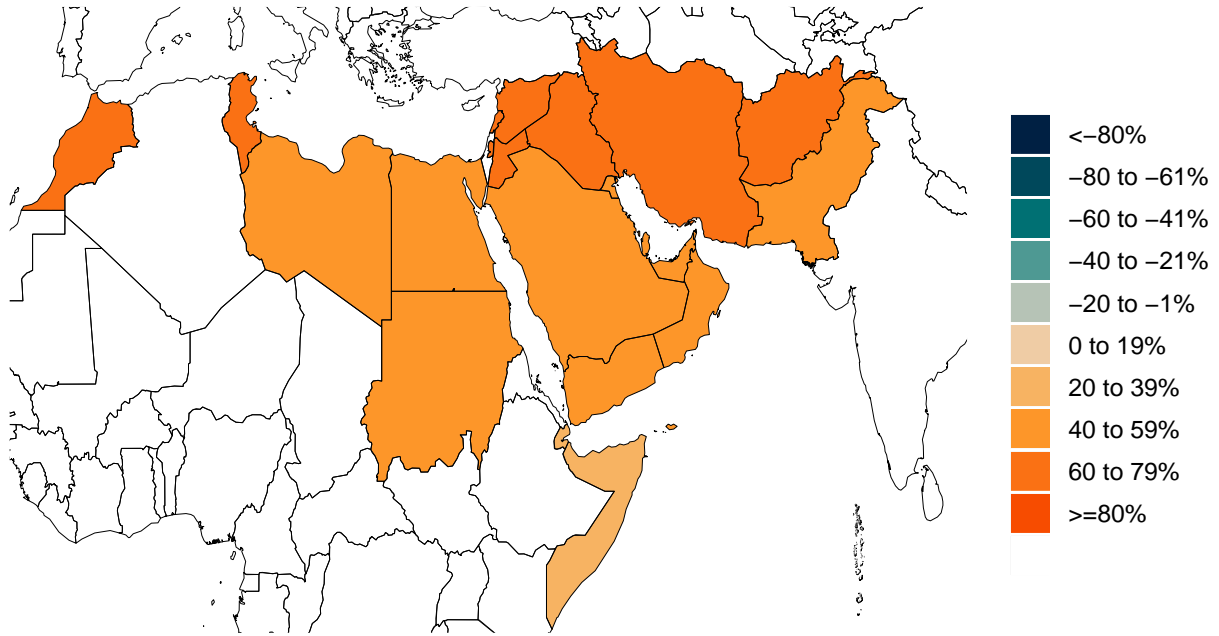
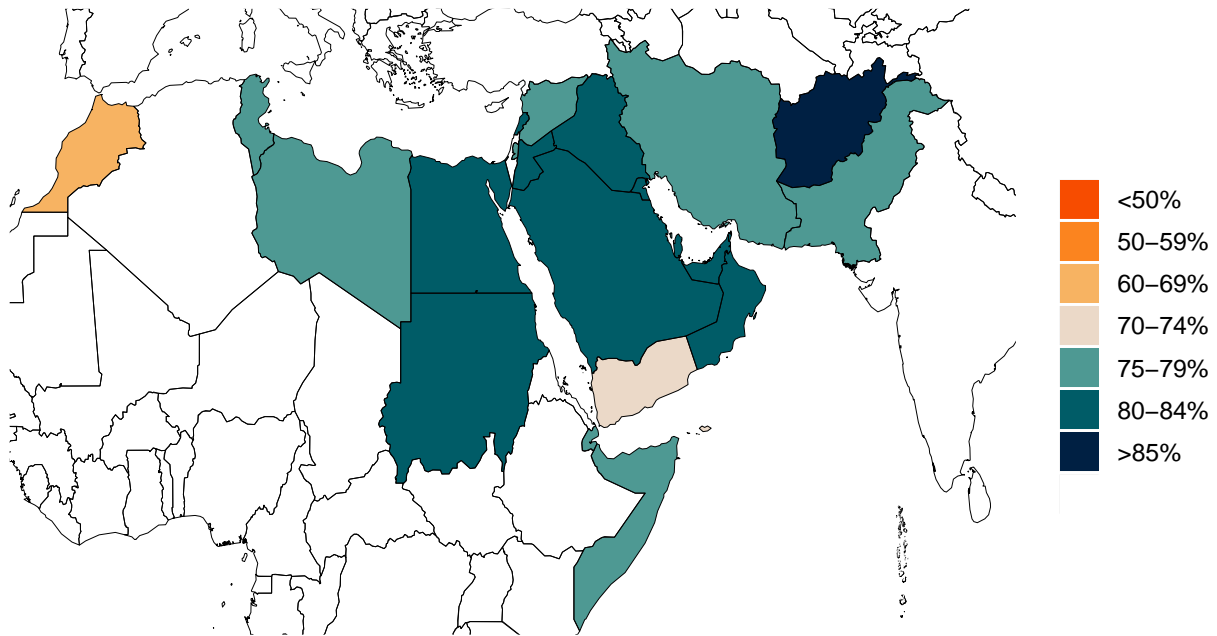


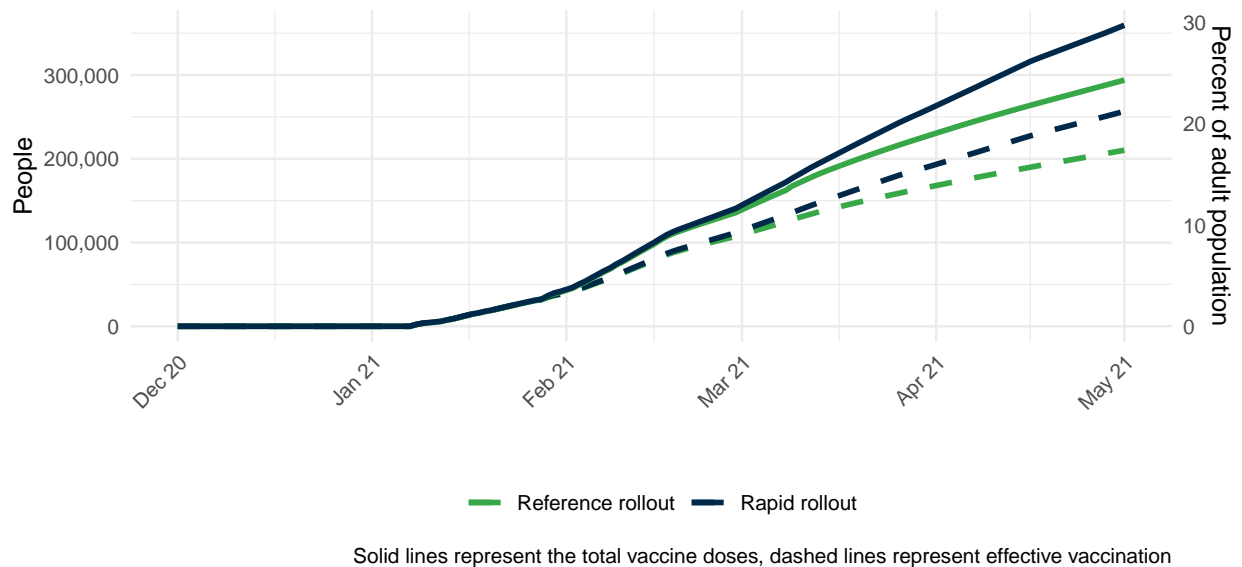
Figure 11. Increase in the risk of death due to pneumonia on February 1 2020 compared to August 1 2020



**Figure 12.** This figure shows the estimated proportion of the adult (18+) population that is open to receiving a COVID-19 vaccine based on Facebook survey responses (yes and unsure).



**Figure 13.** The number of people who receive any vaccine and those who are immune, accounting for efficacy, loss to follow up for two-dose vaccines, partial immunity after one dose, and immunity after two doses.



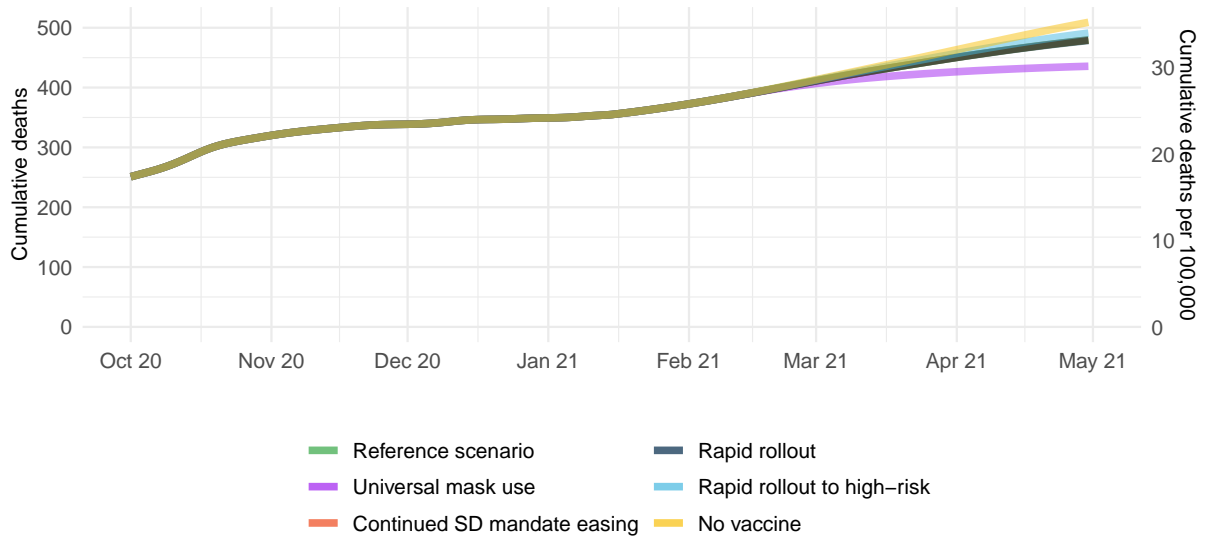


## Projections and scenarios

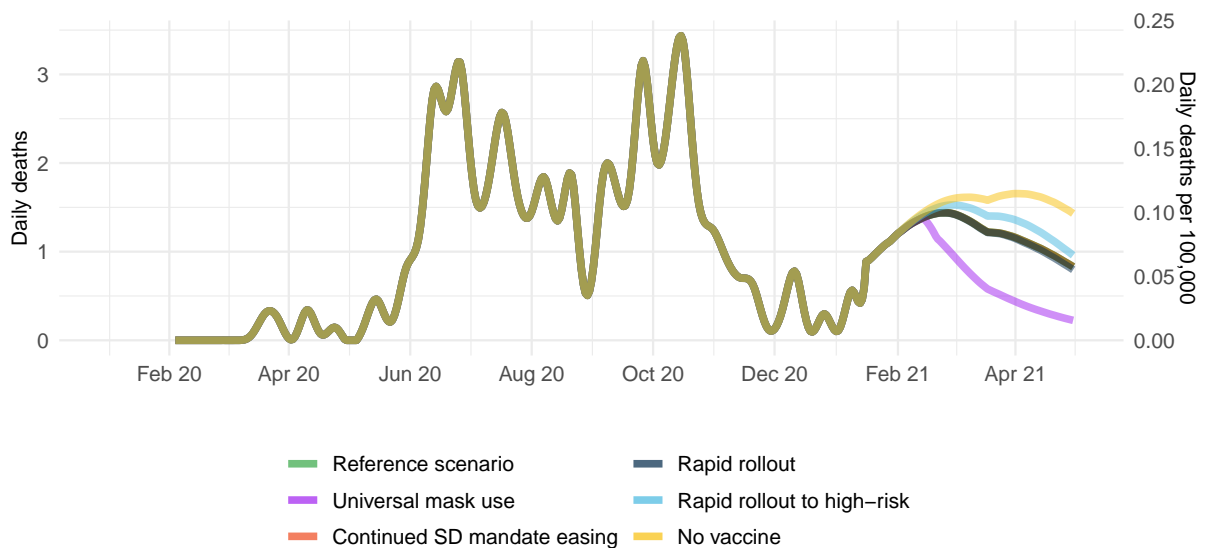
We produce six scenarios when projecting COVID-19. The reference scenario is our forecast of what we think is most likely to happen. We assume that if the daily mortality rate from COVID-19 reaches 8 per million, social distancing (SD) mandates will be re-imposed. The mandate easing scenario is what would happen if governments continue to ease social distancing mandates with no re-imposition. The universal mask mandate scenario is what would happen if mask use increased immediately to 95% and social distancing mandates were re-imposed at 8 deaths per million. These three scenarios assume our reference vaccine delivery scale up where vaccine delivery will scale to full capacity over 90 days.

The rapid vaccine rollout scenario assumes that vaccine distribution will scale up to full delivery capacity in half the time as the reference delivery scenario and that the maximum doses that can be delivered per day is twice as much as the reference delivery scenario. The rapid vaccine rollout to high-risk populations scenario is the same but high-risk populations are vaccinated before essential workers or other adults. The no vaccine scenario is the same as our reference scenario but with no vaccine use.

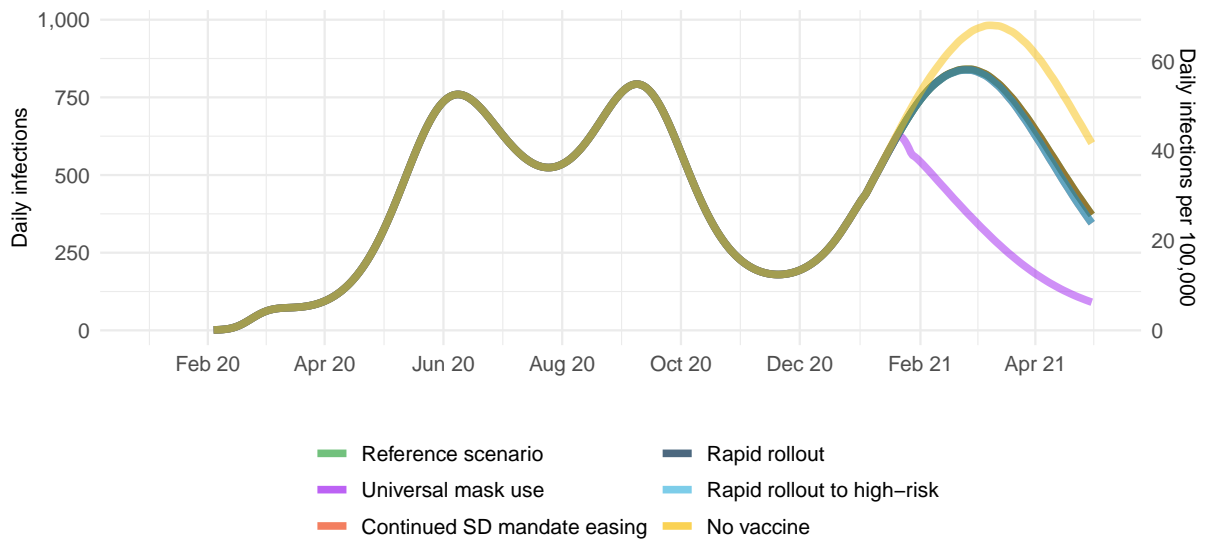
**Figure 14.** Cumulative COVID-19 deaths until May 01, 2021 for six scenarios



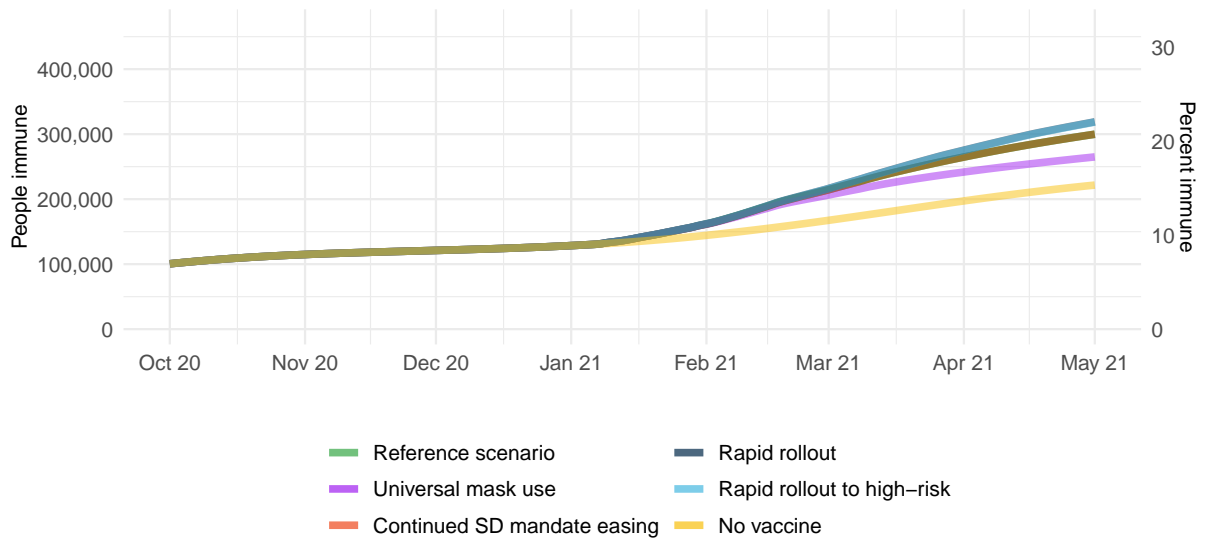
**Figure 15.** Daily COVID-19 deaths until May 01, 2021 for six scenarios



**Figure 16.** Daily COVID-19 infections until May 01, 2021 for six scenarios



**Figure 17.** Estimated percentage immune based on cumulative infections and vaccinations. We assume that vaccine impact on transmission is 50% of the vaccine effectiveness for severe disease



**Figure 18.** Month of assumed mandate re-implementation. (Month when daily death rate passes 8 per million, when reference scenario model assumes mandates will be re-imposed.)



Figure 19. Forecasted percent infected with COVID-19 on May 01, 2021

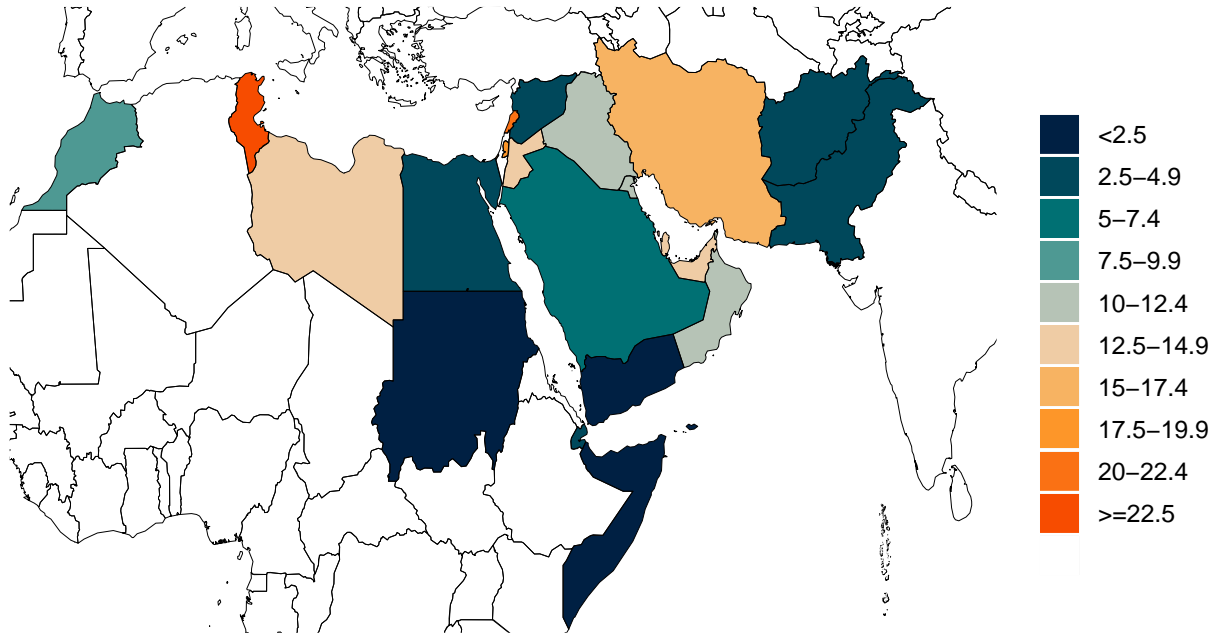
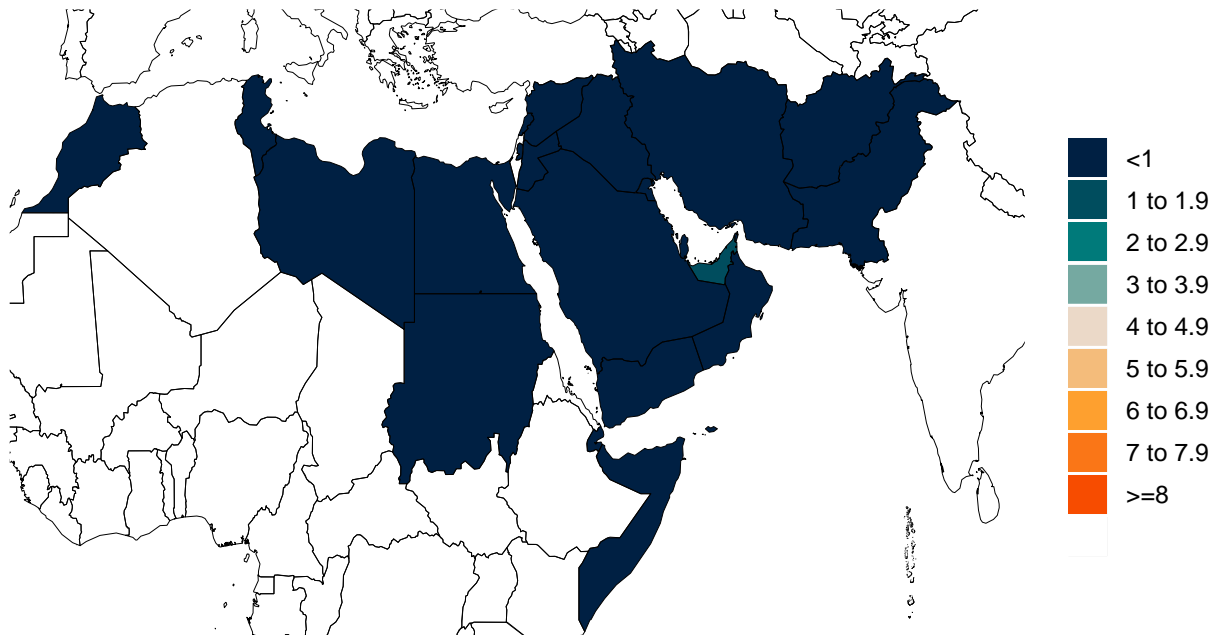
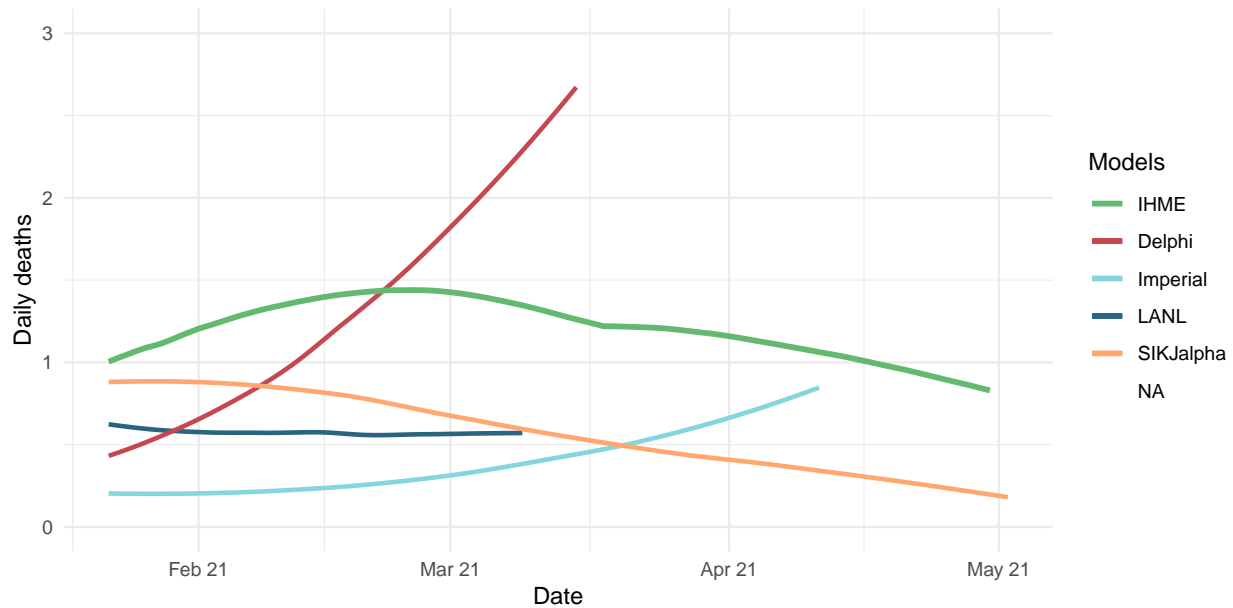


Figure 20. Daily COVID-19 deaths per million forecasted on May 01, 2021 in the reference scenario



**Figure 21.** Comparison of reference model projections with other COVID modeling groups. For this comparison, we are including projections of daily COVID-19 deaths from other modeling groups when available: Delphi from the Massachusetts Institute of Technology (Delphi; <https://www.covidanalytics.io/home>), Imperial College London (Imperial; <https://www.covidsim.org>), The Los Alamos National Laboratory (LANL; <https://covid-19.bsvgateway.org/>), and the SI-KJalpha model from the University of Southern California (SIKJalpha; <https://github.com/scc-usc/ReCOVER-COVID-19>). Daily deaths from other modeling groups are smoothed to remove inconsistencies with rounding. Regional values are aggregates from available locations in that region.



**Figure 22.** The estimated inpatient hospital usage is shown over time. The percent of hospital beds occupied by COVID-19 patients is color coded based on observed quantiles of the maximum proportion of beds occupied by COVID-19 patients. Less than 5% is considered *low stress*, 5-9% is considered *moderate stress*, 10-19% is considered *high stress*, and greater than 20% is considered *extreme stress*.



**Figure 23.** The estimated intensive care unit (ICU) usage is shown over time. The percent of ICU beds occupied by COVID-19 patients is color coded based on observed quantiles of the maximum proportion of ICU beds occupied by COVID-19 patients. Less than 10% is considered *low stress*, 10-29% is considered *moderate stress*, 30-59% is considered *high stress*, and greater than 60% is considered *extreme stress*.





**Table 3.** Ranking of COVID-19 among the leading causes of mortality in the full year 2020. Deaths from COVID-19 are projections of cumulative deaths on Jan 1, 2021 from the reference scenario. Deaths from other causes are from the Global Burden of Disease study 2019 (rounded to the nearest 100).

Cause name	Annual deaths	Ranking
Ischemic heart disease	900	1
Diabetes mellitus	700	2
COVID-19	349	3
Stroke	200	4
Road injuries	200	5
Chronic kidney disease	200	6
Tracheal, bronchus, and lung cancer	100	7
Cirrhosis and other chronic liver diseases	100	8
Chronic obstructive pulmonary disease	100	9
Breast cancer	100	10

## More information

### Data sources:

Mask use data sources include PREMISE; Facebook Global symptom survey (This research is based on survey results from University of Maryland Social Data Science Center) and the Facebook United States symptom survey (in collaboration with Carnegie Mellon University); Kaiser Family Foundation; YouGov COVID-19 Behaviour Tracker survey.

Vaccine hesitancy data are from the COVID-19 Beliefs, Behaviors, and Norms Study, a survey conducted on Facebook by the Massachusetts Institute of Technology (<https://covidsurvey.mit.edu/>).

Data on vaccine candidates, stages of development, manufacturing capacity, and pre-purchasing agreements are primarily from Linksbridge and supplemented by Duke University.

### A note of thanks:

We wish to warmly acknowledge the support of [these](#) and others who have made our covid-19 estimation efforts possible.

### More information:

For all COVID-19 resources at IHME, visit <http://www.healthdata.org/covid>.

Questions? Requests? Feedback? Please contact us at <https://www.healthdata.org/covid/contact-us>.