COVID-19 Results Briefing: Qatar

November 19, 2020

This document contains summary information on the latest projections from the IHME model on COVID-19 in Qatar. The model was run on November 18, 2020.

Current situation

- Daily reported cases in the last week are 200 per day on average (Figure 1).
- Effective R, computed using cases, hospitalizations, and deaths on November 5 was 0.89 suggesting that new cases will decrease in the next few weeks.
- We estimated that 7% of people in Qatar have been infected as of November 16 (Figure 4).
- Approximately 70% of infections were detected on November 16, 2020 (Figure 5).
- The daily death rate is less than 1 per million (Figure 6).

Trends in drivers of transmission

- The number of social distancing and mask mandates has not changed in the past week (Table 2, Figure 7).
- Mobility last week was 11% lower than the baseline mobility (average of the period January 1 – March 1, 2020; Figure 8).
- As of November 16 we estimated that 68% of people always wore a mask when leaving their home (Figure 9). Mask-wearing decreased from a peak of 82% in early June.
- There were about 190 diagnostic tests per 100,000 people on November 16 (Figure 10).

Projections

- In our **reference scenario**, which represents what we think is most likely to happen, our model projects 270 cumulative deaths on March 1, 2021 (Figure 12).
- We expect there to be about 350 infections per day on January 1, 2021 and 1,100 infections per day on March 1, 2021 (Figure 14).
- We estimate that about 7% of people will have been infected by January 1, 2021 and 9% by March 1, 2021.
- We expect no stress on hospital beds and a moderate stress on intensive care unit (ICU) beds based on the percent of total capacity occupied by COVID-19 patients (Figure 19 and 20).
- If universal mask coverage (95%) were attained in the next week, our model projects 20 fewer cumulative deaths compared to the reference scenario on March 1, 2021 (Figure 12).

Model updates

We have substantially revised the infection-fatality rate (IFR) used in the model. To date, we had used an IFR that was derived from an analysis of population-representative antibody surveys where we disaggregated prevalence by age and matched COVID-19 death rates. The age-specific IFR from this analysis was assumed to be the same across locations and time.

We have now accumulated considerable empirical evidence that suggests that 1) the IFR has been declining since March/April due to improvements in the clinical management of patients, and 2) the IFR varies as a function of the level of obesity in a community. The evidence supporting these observations includes:

- An analysis of detailed clinical records of more than 15,000 individuals from a COVID-19 registry organized by the American Heart Association. This registry covers patients in more than 150 hospitals. Our analysis suggests that after controlling for age, sex, comorbidities, and disease severity at admission, the hospital-fatality rate has declined by about 30% since March/April.
- An analysis of more than 250,000 individuals admitted to hospitals in Brazil with COVID-19 shows that after controlling for age, sex, obesity, and oxygenation at admission, the hospital-fatality rate has declined by about 30% since March/April.
- An analysis of age-standardized IFRs from more than 300 surveys also suggests that the population-level trends in the IFR are consistent with a 30% decline since March/April. These data also suggest that the prevalence of obesity at the population level is associated with a higher IFR and that the magnitude of the effect is similar to that found in the individual-level analysis.

Based on these empirical findings, we have switched to a new estimated IFR. The new IFR varies over time (declining since March/April by approximately 0.19% per day until the beginning of September), varies across locations as a function of obesity prevalence, and varies across locations (as before) as a function of the population distribution by age. The implication of lower IFRs over time is that for a given number of observed deaths there are more cumulative infections.

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.

Current situation

Figure 1. Reported daily COVID-19 cases

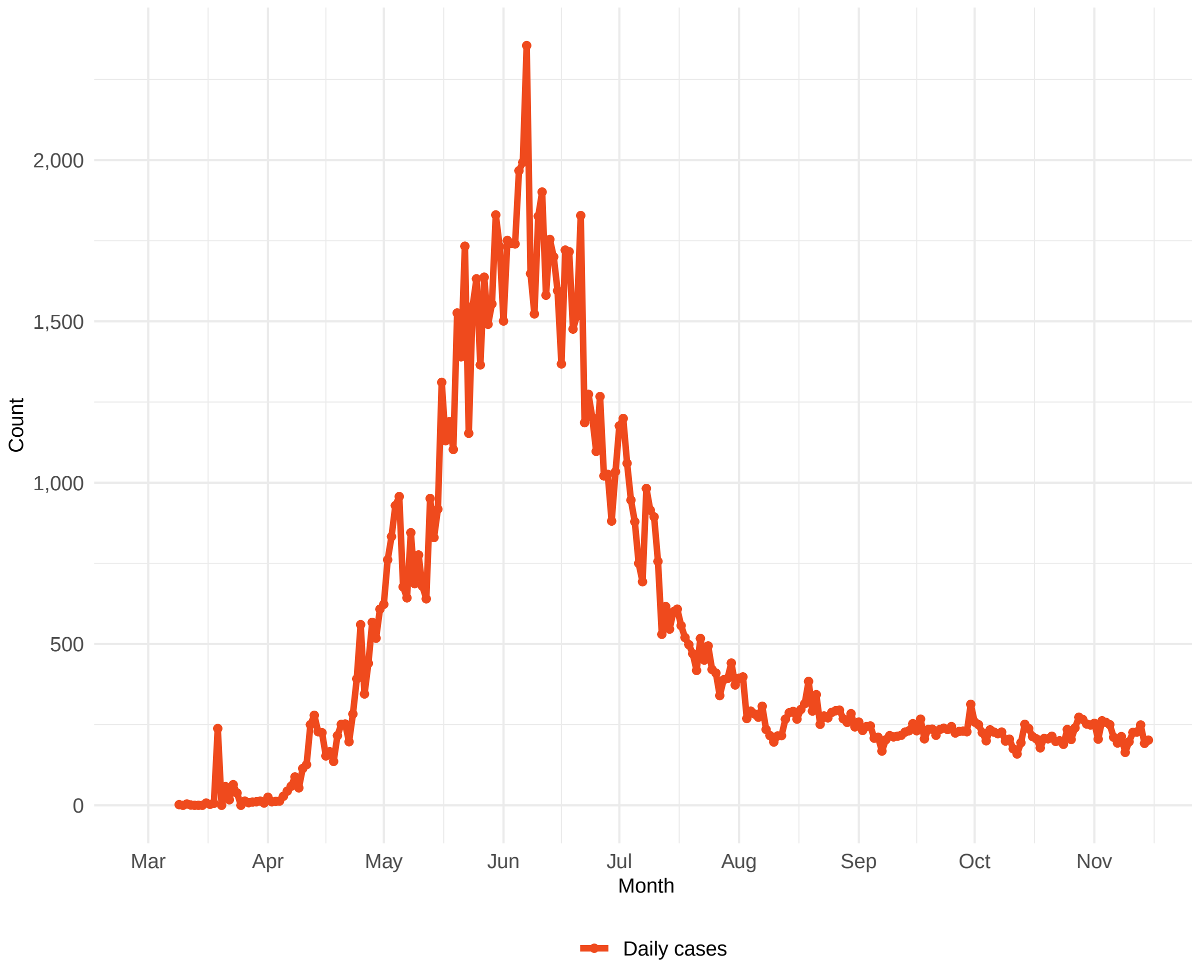


Table 1. Ranking of COVID-19 among the leading causes of mortality this week, assuming uniform deaths of non-COVID causes throughout the year

Cause name	Weekly deaths	Ranking
Ischemic heart disease	16	1
Road injuries	14	2
Diabetes mellitus	7	3
Stroke	3	4
Cirrhosis and other chronic liver diseases	3	5
Chronic kidney disease	3	6
Self-harm	3	7
Tracheal, bronchus, and lung cancer	2	8
Falls	2	9
Congenital birth defects	2	10
COVID-19	1	18

Figure 2a. Reported daily COVID-19 deaths.

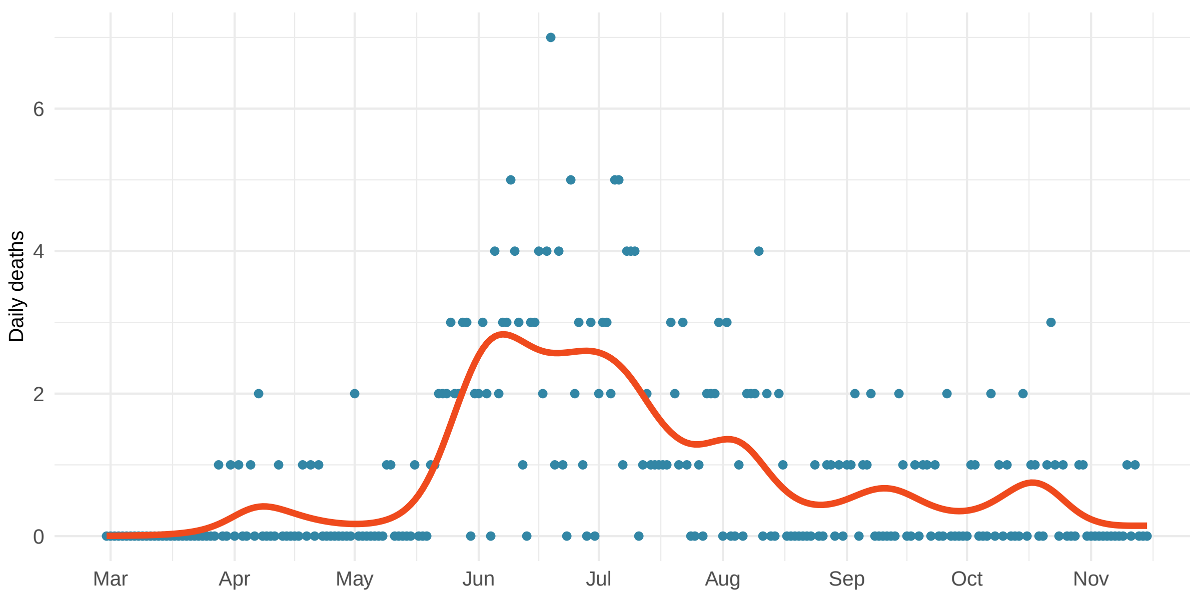


Figure 2b. Estimated cumulative deaths by age group

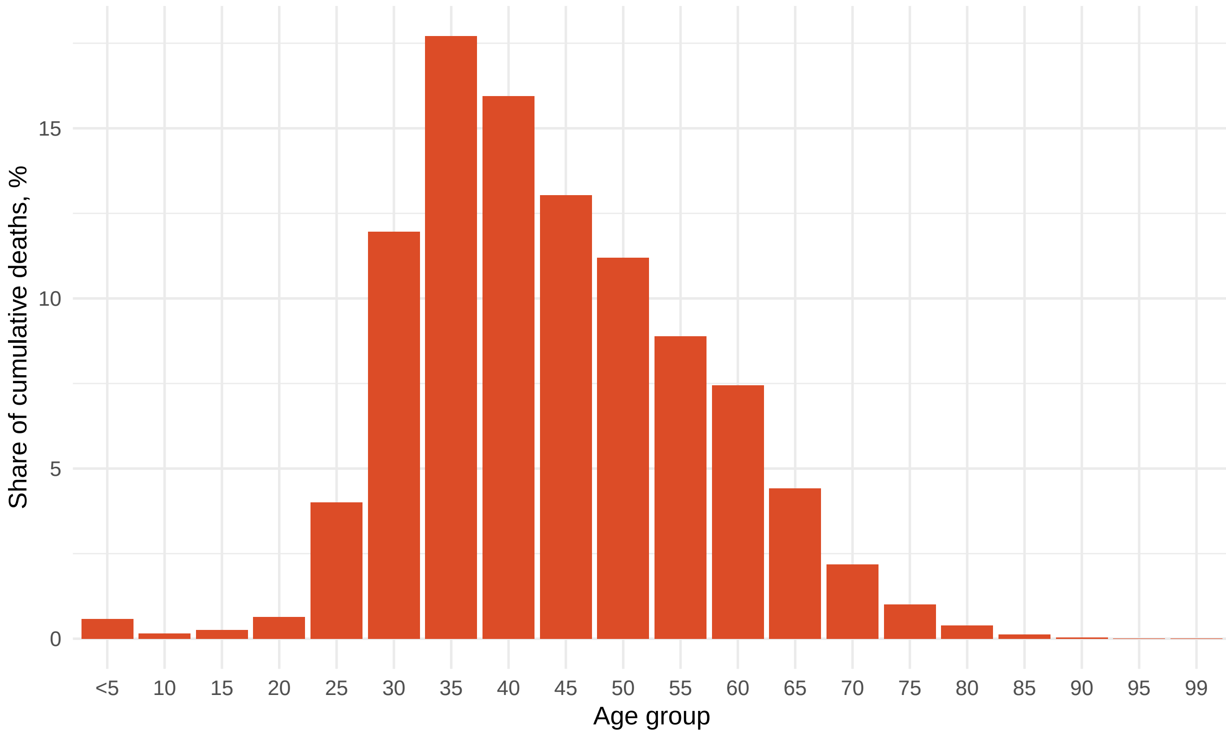


Figure 3. Mean effective R on November 05, 2020. The estimate of effective R is based on the combined analysis of deaths, case reporting and hospitalizations where available. Current reported cases reflect infections 11-13 days prior so estimates of effective R can only be made for the recent past. Effective R less than 1 means that transmission should decline all other things being held the same.

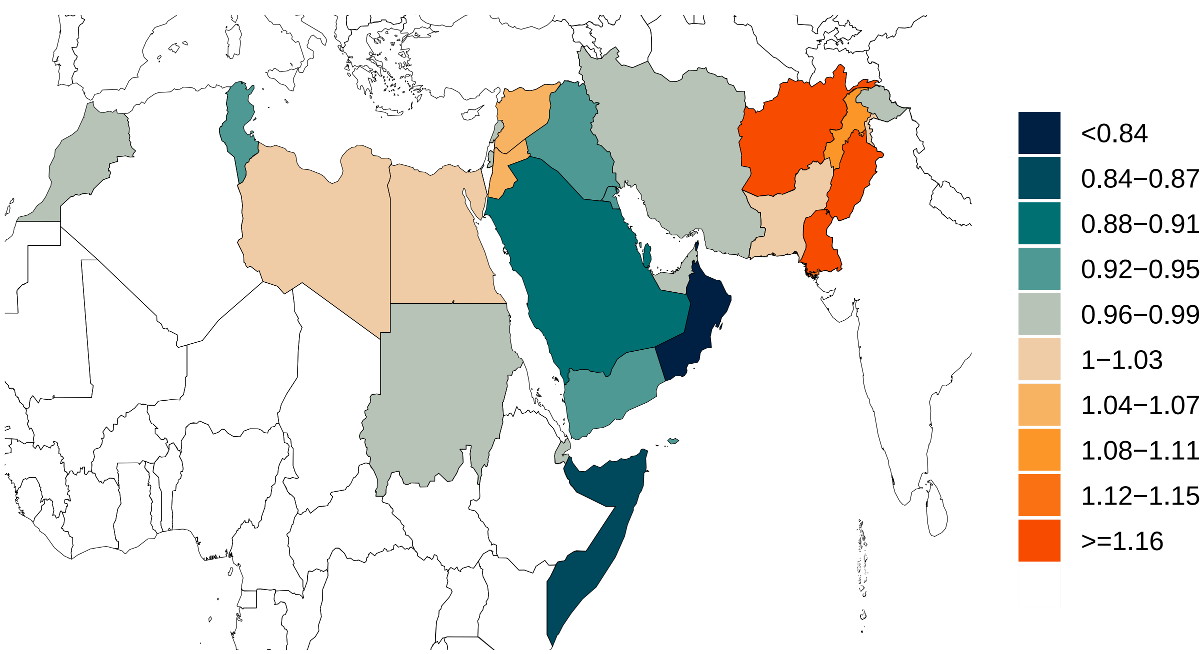


Figure 4. Estimated percent of the population infected with COVID-19 on November 16, 2020

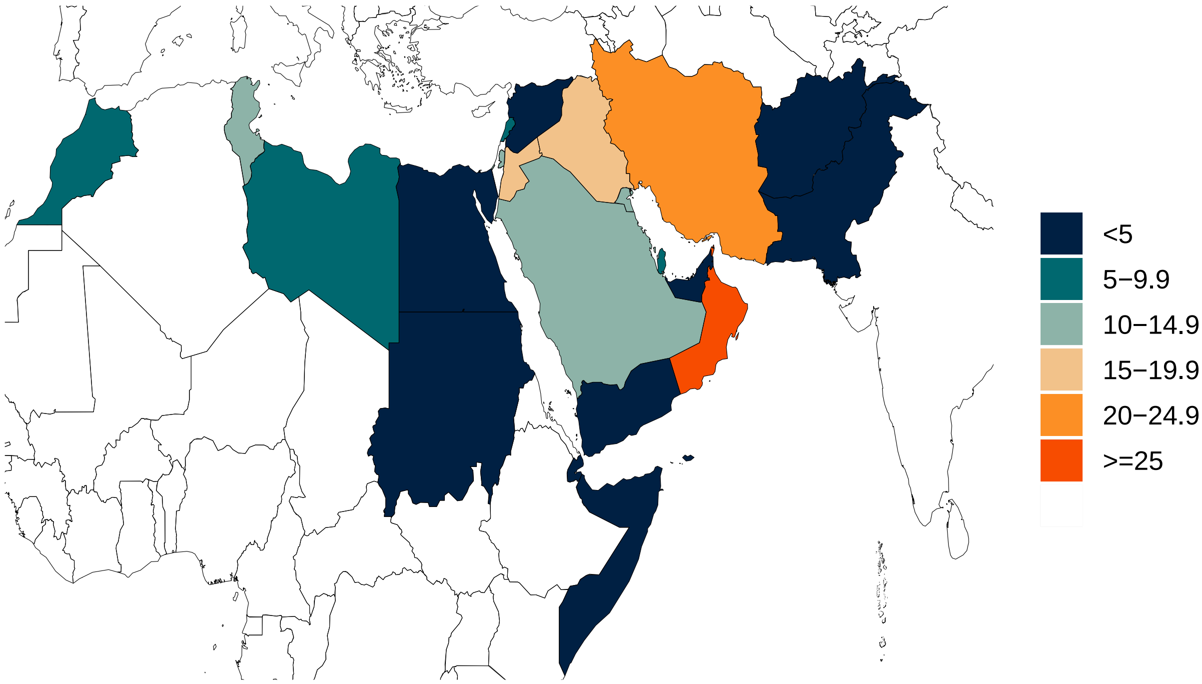


Figure 5. Percent of COVID-19 infections detected. This is estimated as the ratio of reported daily COVID-19 cases to estimated daily COVID-19 infections based on the SEIR disease transmission model.

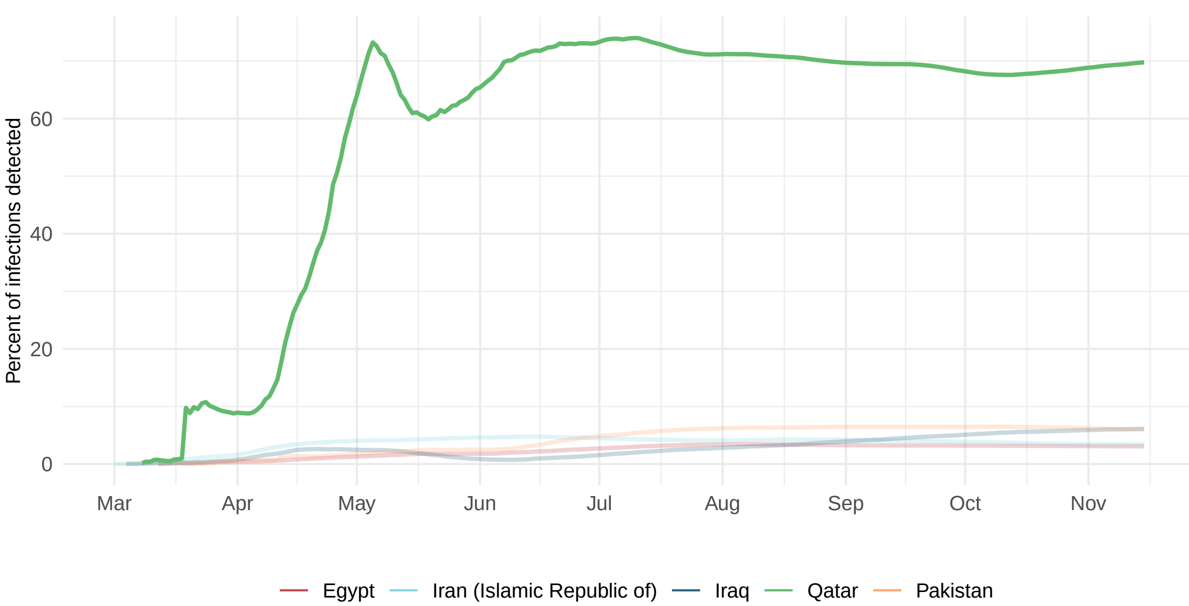
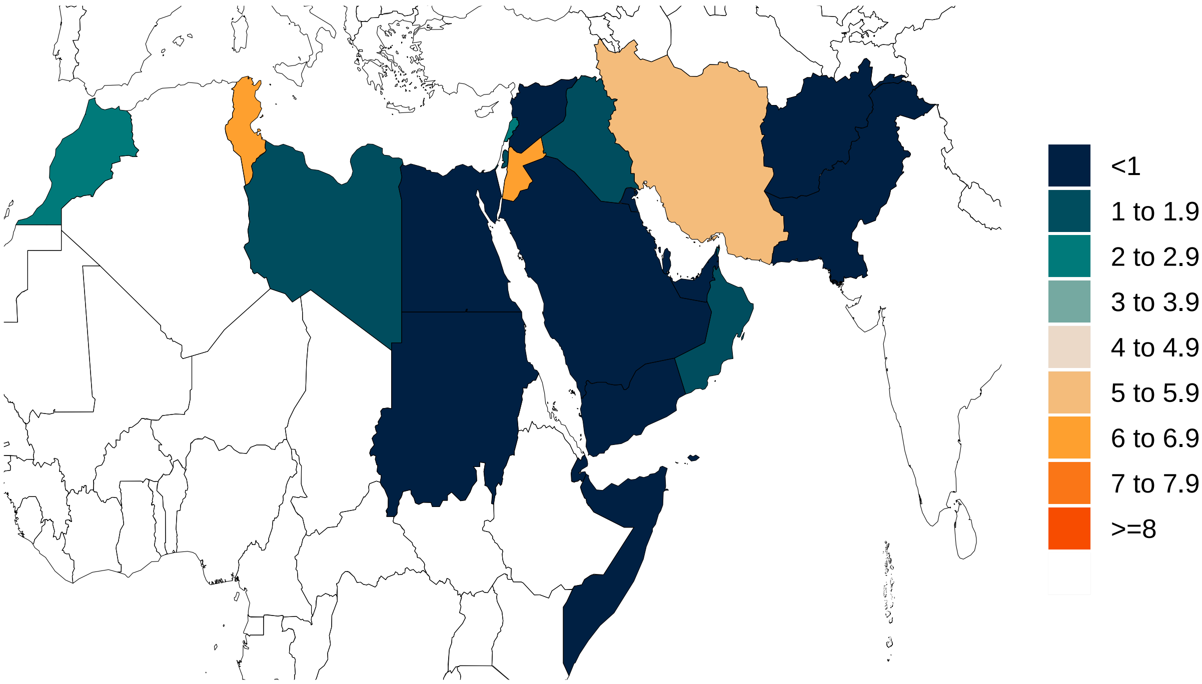


Figure 6. Daily COVID-19 death rate per 1 million on November 16, 2020



Critical drivers

Table 2. Current mandate implementation

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

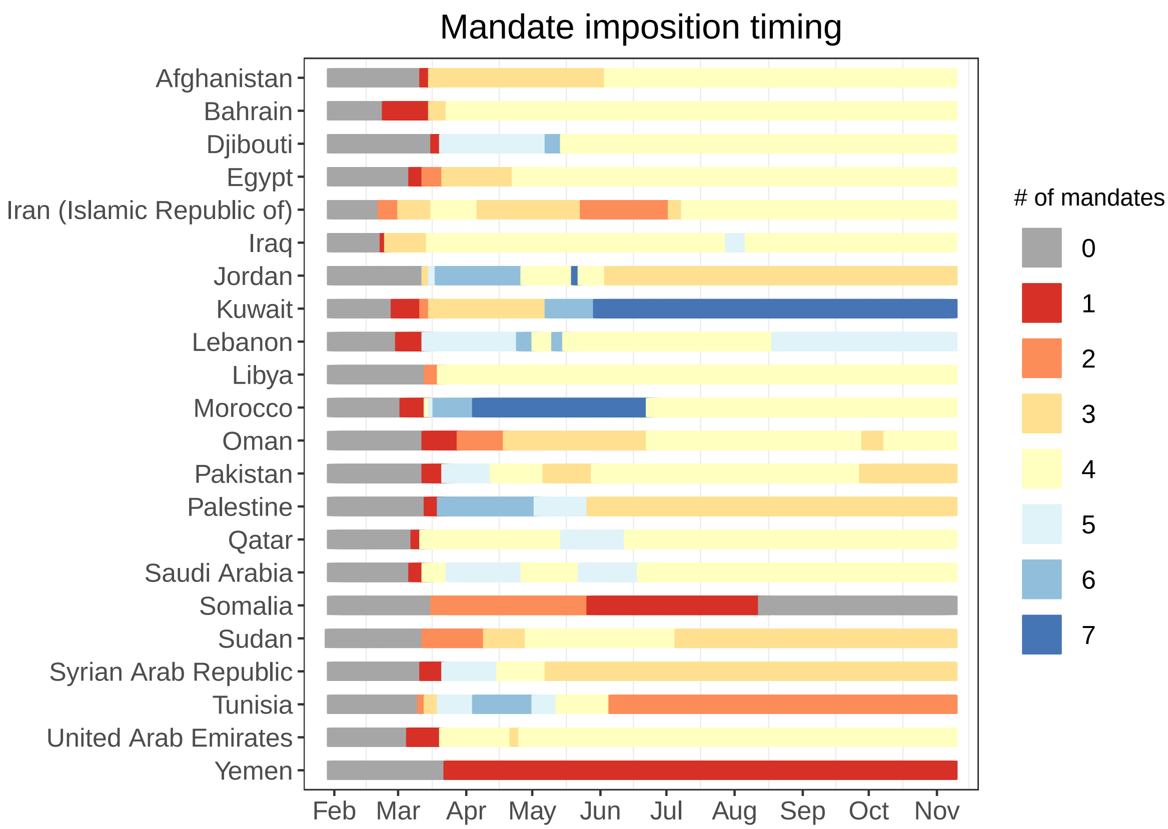


Figure 8a. Trend in mobility as measured through smartphone app use compared to January 2020 baseline

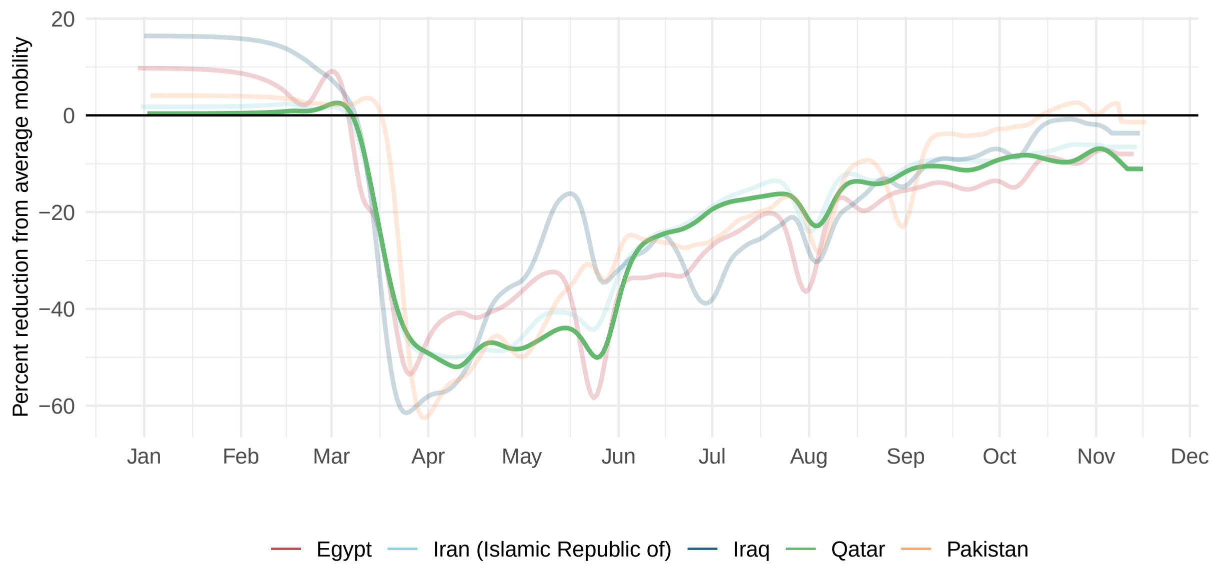


Figure 8b. Mobility level as measured through smartphone app use compared to January 2020 baseline (percent) on November 16, 2020

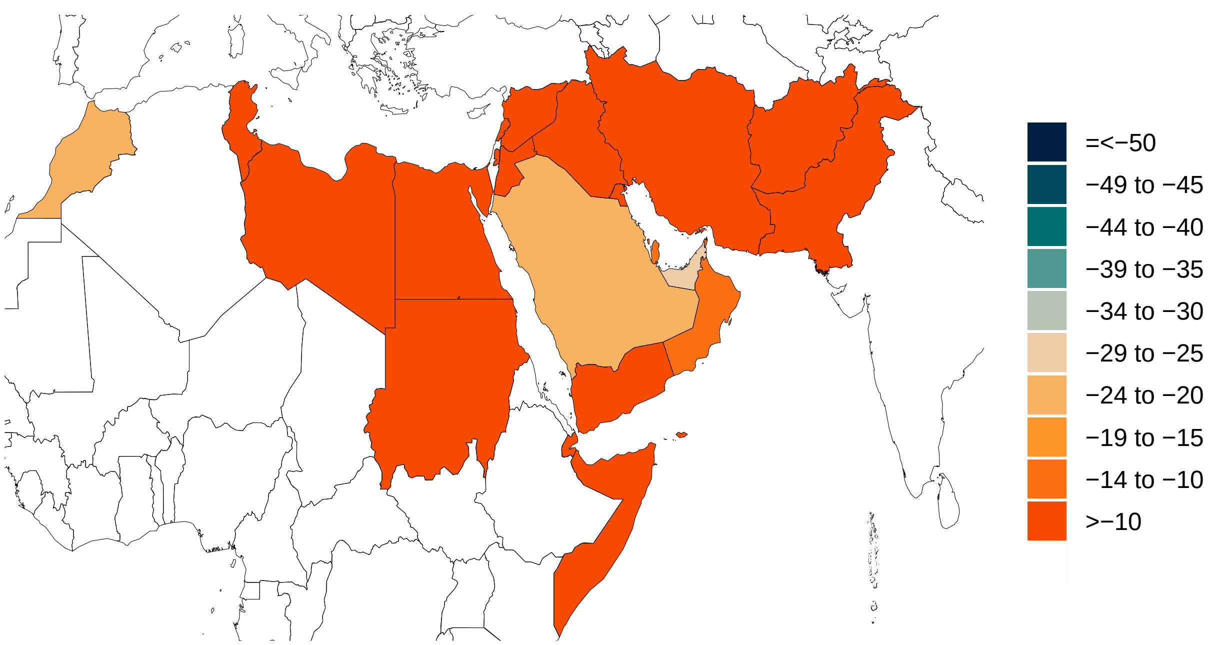


Figure 9a. Trend in the proportion of the population reporting always wearing a mask when leaving home

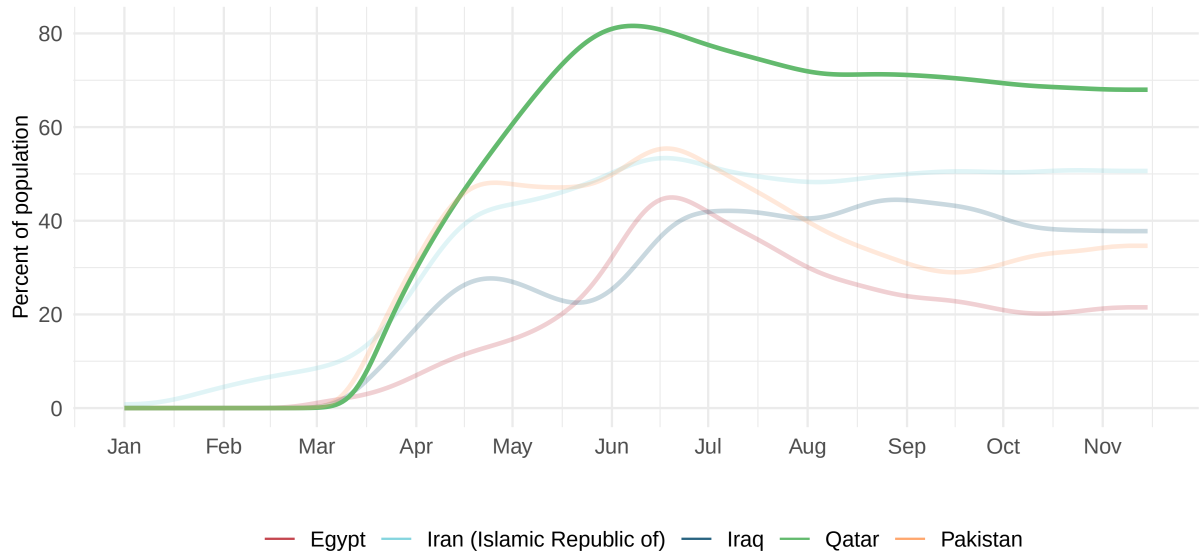


Figure 9b. Proportion of the population reporting always wearing a mask when leaving home on November 16, 2020

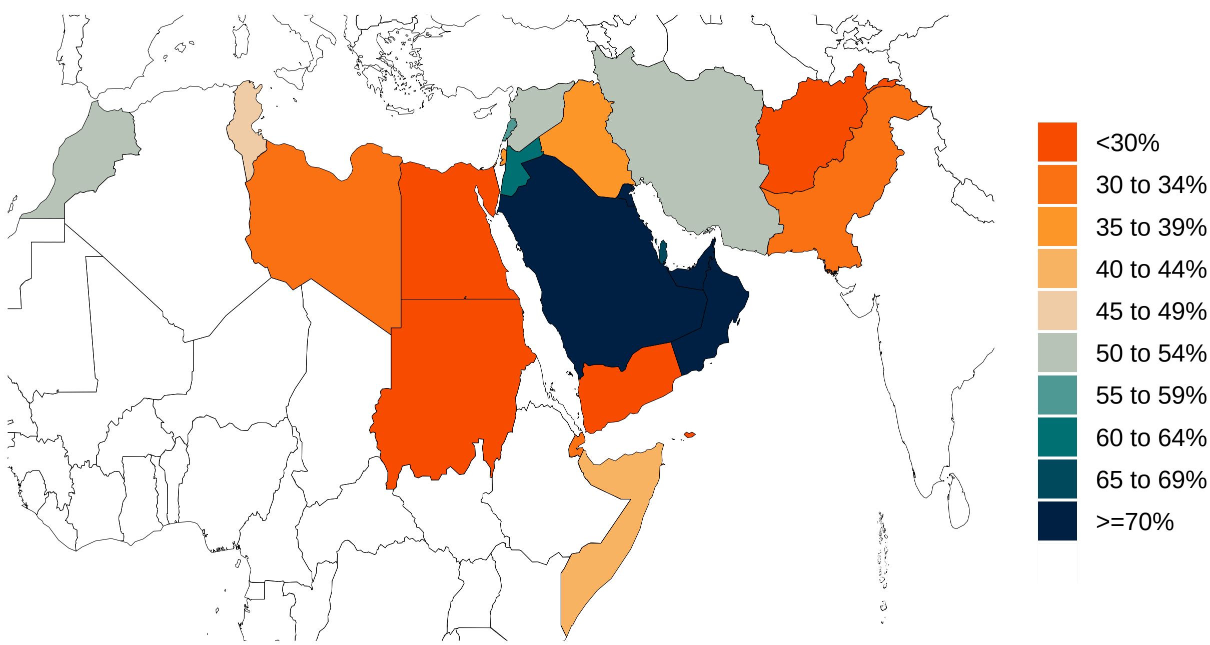


Figure 10a. Trend in COVID-19 diagnostic tests per 100,000 people

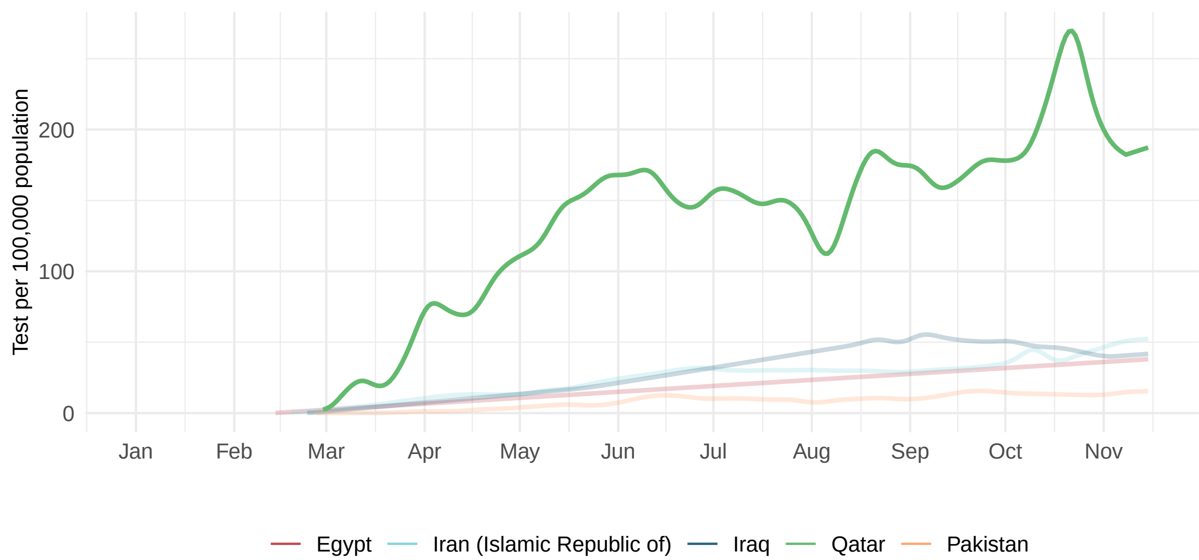


Figure 10b. COVID-19 diagnostic tests per 100,000 people on November 12, 2020

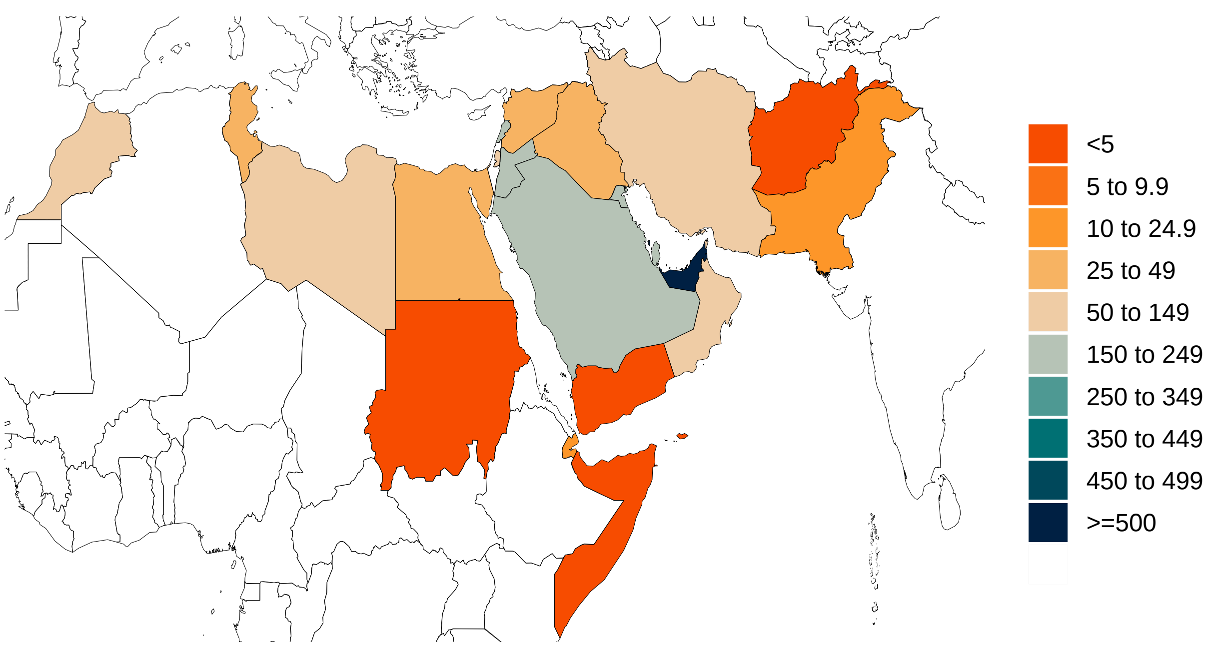
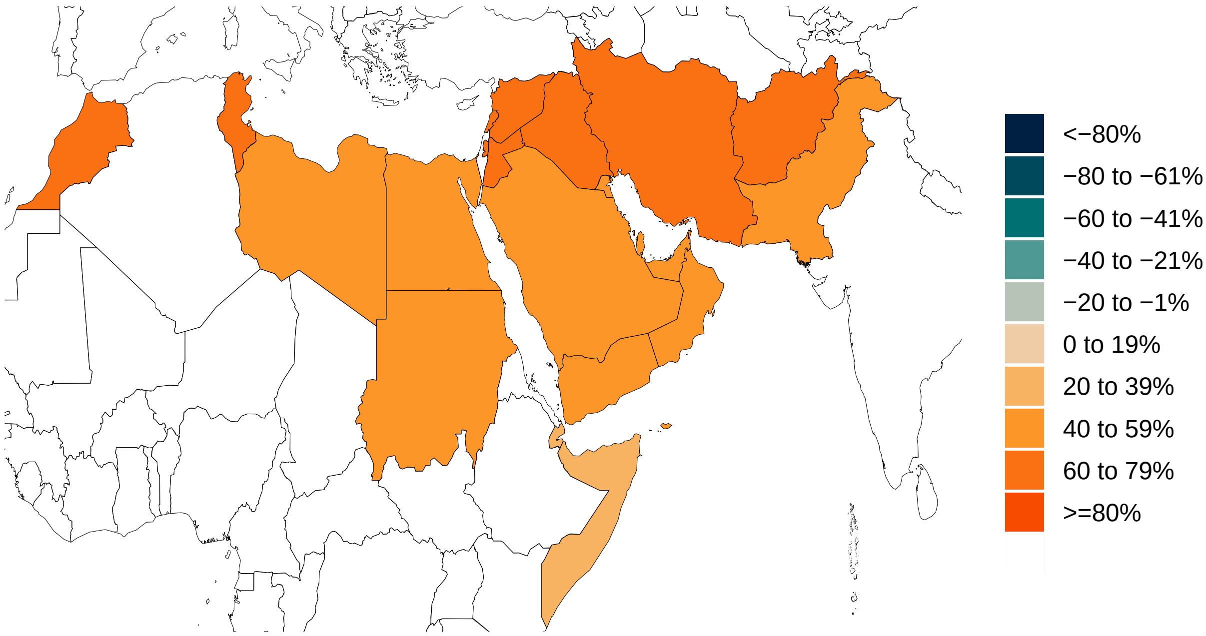


Figure 11. Increase in the risk of death due to pneumonia on February 1 compared to August 1



Projections and scenarios

We produce three 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.

Figure 12. Cumulative COVID-19 deaths until March 01, 2021 for three scenarios.

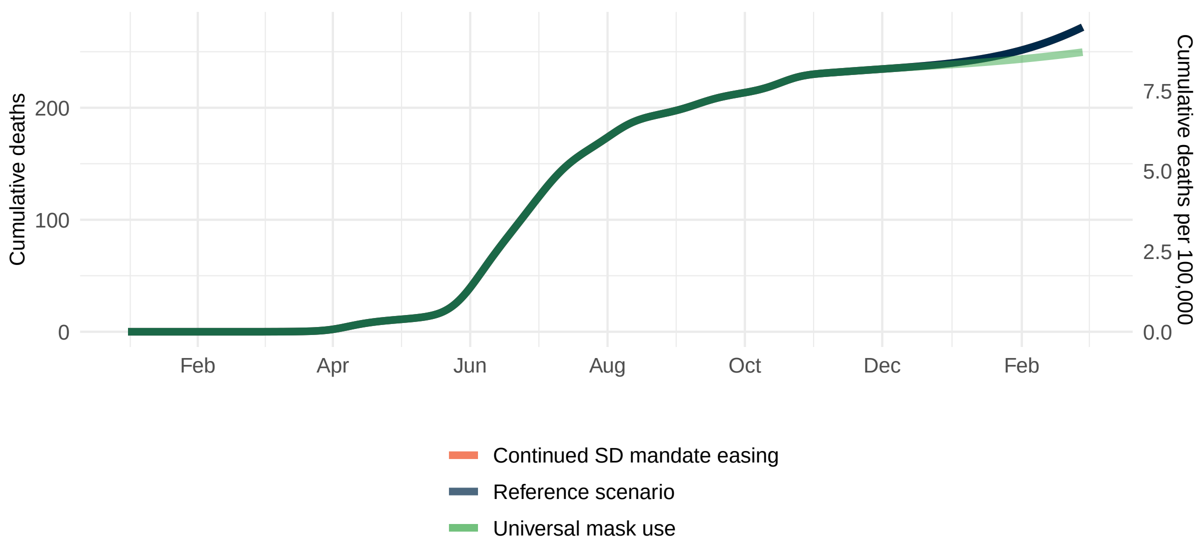


Fig 13. Daily COVID-19 deaths until March 01, 2021 for three scenarios.

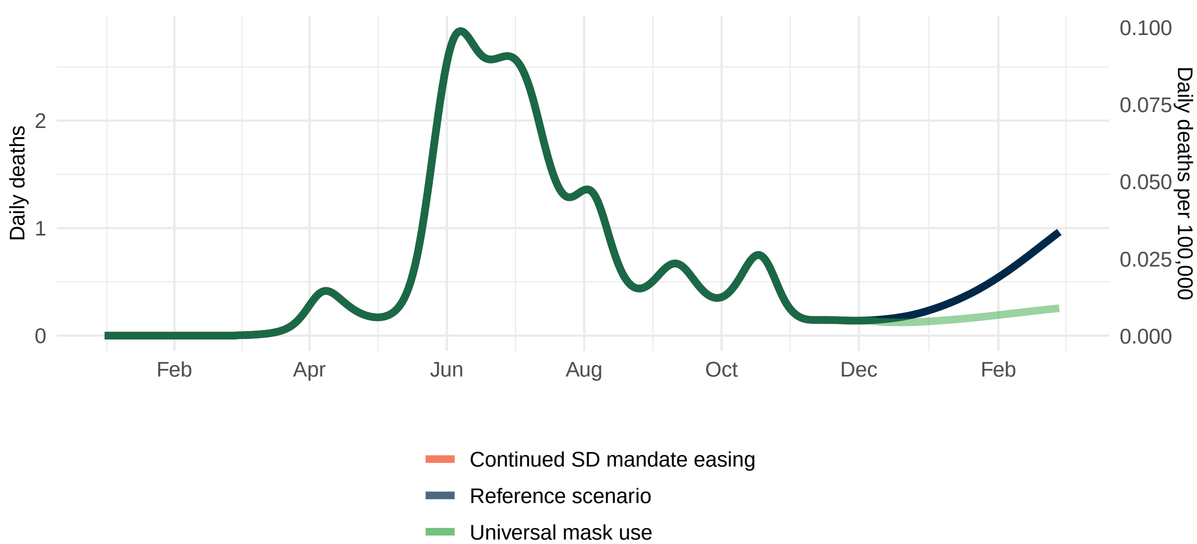


Fig 14. Daily COVID-19 infections until March 01, 2021 for three scenarios.

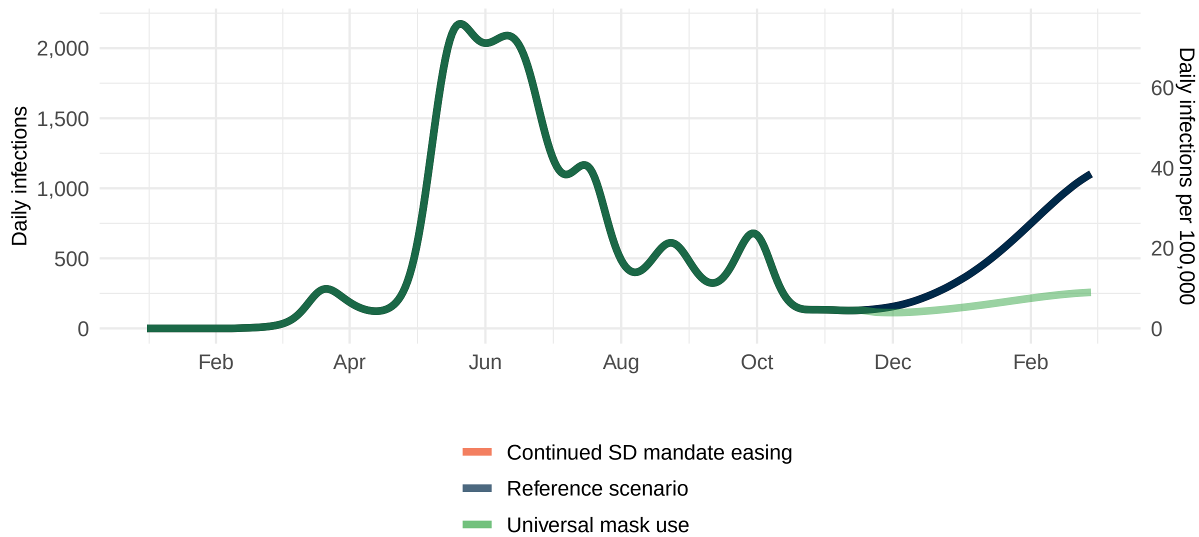


Fig 15. Month of assumed mandate re-implementation. (Month when daily death rate passes 8 per million, when reference scenario model assumes mandates will be re-imposed.)

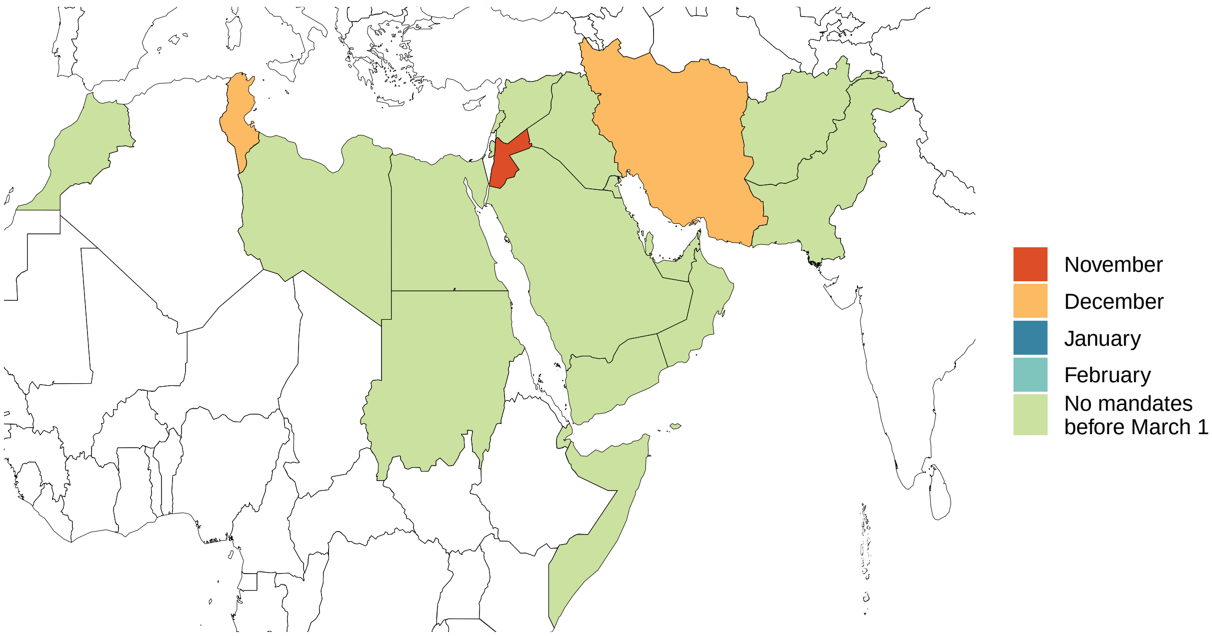


Figure 16. Forecasted percent infected with COVID-19 on March 01, 2021

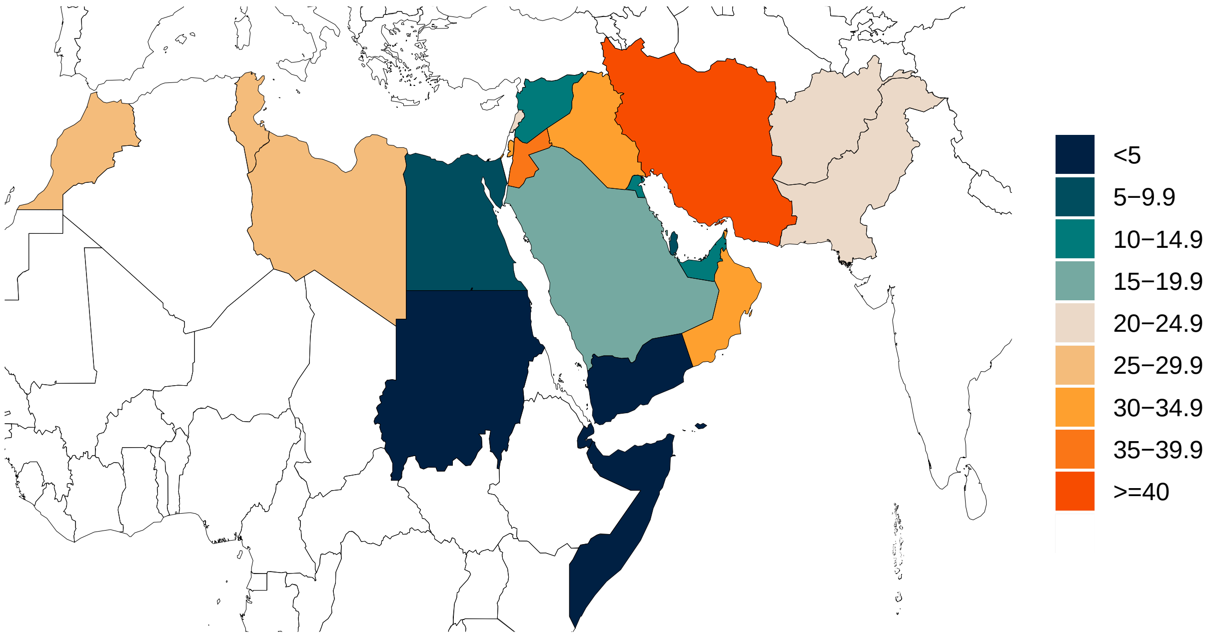


Figure 17. Daily COVID-19 deaths per million forecasted on March 01, 2021 in the reference scenario

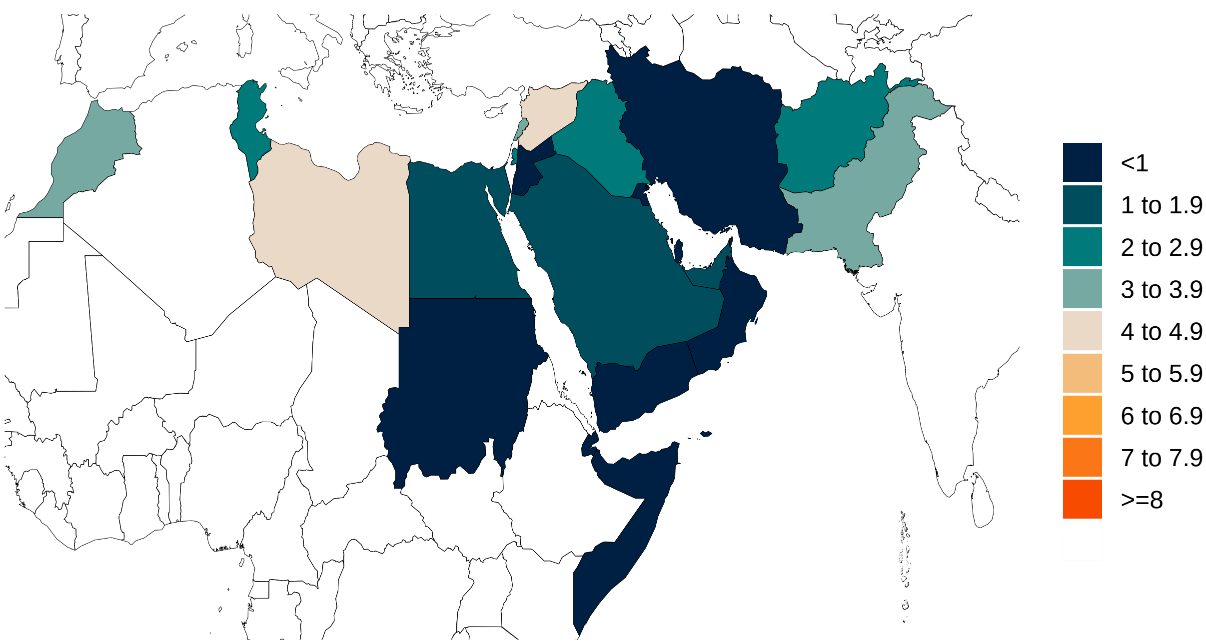


Figure 18. Comparison of reference model projections with other COVID modeling groups. For this comparison, we are including projections of daily COVID-19 deaths from other modeling groups when available: Delphi from the Massachussets Institute of Technology (Delphi; https://www.covidanalytics.io/home), 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 availble locations in that region.

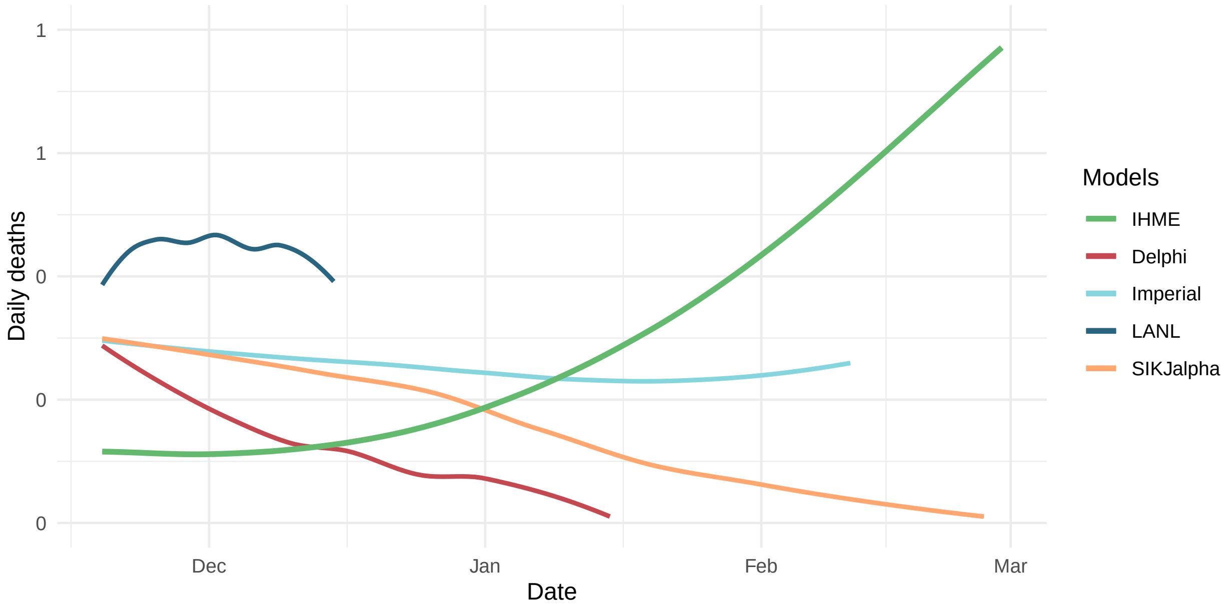


Figure 19. The estimated inpatient hospital usage is shown over time. The percent of hospital beds occupied by COVID-19 patients is color coded based on observed quantiles of the maximum proportion of beds occupied by COVID-19 patients. Less than 5% is considered *low stress*, 5-9% is considered *moderate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

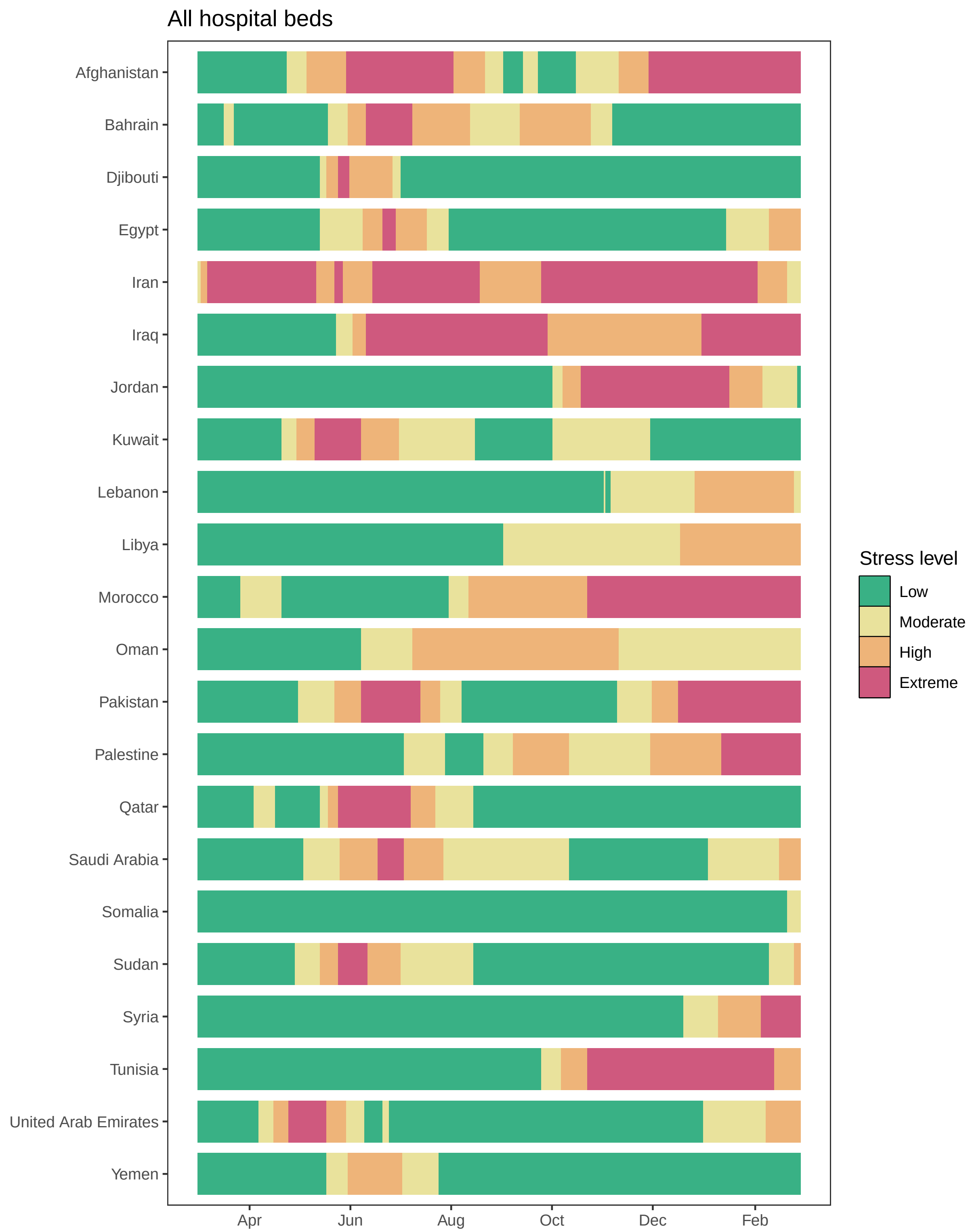


Figure 20. The estimated intensive care unit (ICU) usage is shown over time. The percent of ICU beds occupied by COVID-19 patients is color coded based on observed quantiles of the maximum proportion of ICU beds occupied by COVID-19 patients. Less than 10% is considered *low stress*, 10-29% is considered *moderate stress*, 30-59% is considered *high stress* and greater than 60% is considered *extreme stress*.

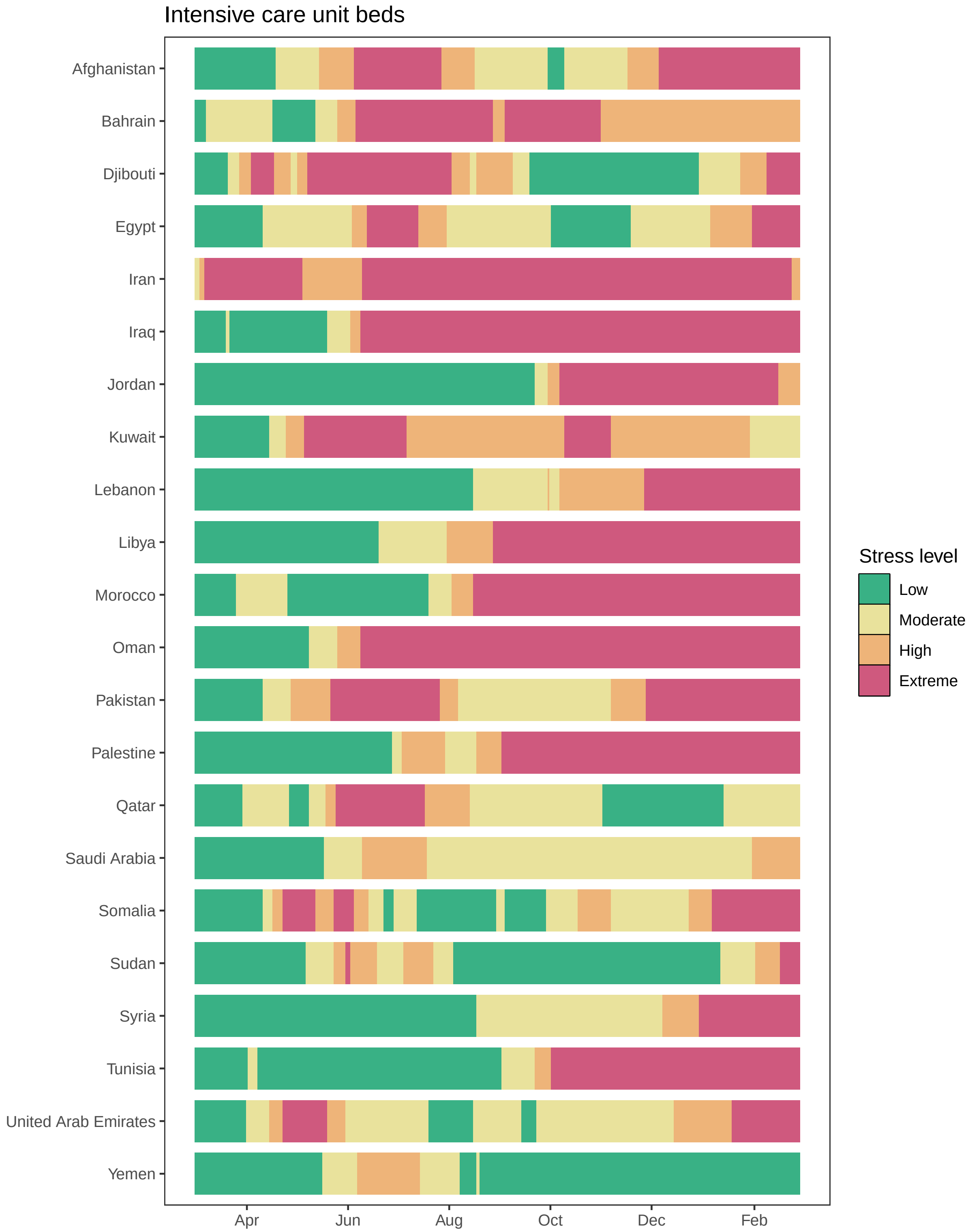


Table 3. Ranking of COVID-19 among the leading causes of mortality in the full year 2020. Deaths from COVID-19 are projections of cumulative deaths on Jan 1, 2021 from the reference scenario. Deaths from other causes are from the Global Burden of Disease study 2019 (rounded to the nearest 100).

Cause name	Annual deaths	Ranking
Ischemic heart disease	800	1
Road injuries	700	2
Diabetes mellitus	300	3
COVID-19	240	4
Stroke	200	5
Cirrhosis and other chronic liver diseases	200	6
Chronic kidney disease	100	7
Self-harm	100	8
Tracheal, bronchus, and lung cancer	100	9
Falls	100	10

Table 4. Table of the number of deaths at varying levels of the cumulative percent of the population that is infected with COVID-19. The infection fatality rate can be used to figure out how many people may eventually die from COVID-19 before a community arrives at herd immunity. Since we do not know the level at which herd immunity may be reached for COVID-19, the table below shows the total number of deaths that would be expected in Qatar for various levels of herd immunity. These estimates assume that there does not exist an effective vaccine and that no significant improvements in treatment will be made. We estimated that the all age infection fatality ratio of of November 18, 2020 in Qatar was 0.1%.

Cumulative incidence	Deaths
30%	1,000
35%	1,000
40%	1,000
45%	1,000
50%	2,000
55%	2,000
60%	2,000
65%	2,000
70%	2,000
75%	2,000
80%	3,000
85%	3,000
90%	3,000
95%	3,000

Recognition and thanks

Mask data sources:

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.

A note of thanks:

We would like to extend a special thanks to the Pan American Health Organization (PAHO) for key data sources; our partners and collaborators in Argentina, Brazil, Bolivia, Chile, Colombia, Cuba, the Dominican Republic, Ecuador, Egypt, Honduras, Israel, Japan, Malaysia, Mexico, Moldova, Panama, Peru, the Philippines, Russia, Serbia, South Korea, Turkey, and Ukraine for their support and expert advice; and to the tireless data collection and collation efforts of individuals and institutions throughout the world.

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Further, IHME is grateful to the Microsoft AI for Health program for their support in hosting our COVID-19 data visualizations on the Azure Cloud. We would like to also extend a warm thank you to the many others who have made our COVID-19 estimation efforts possible.