THE LANCET
Public Health

Supplementary appendix

This appendix formed part of the original submission and has been peer reviewed. We post it as supplied by the authors.

Supplement to: Russell TW, Wu JT, Clifford S, et al. Effect of internationally imported cases on internal spread of COVID-19: a mathematical modelling study. *Lancet Public Health* 2020; published online Dec 7. https://doi.org/10.1016/S2468-2667(20)30263-2.

Supplementary information for:

The effect of internationally imported cases on internal spread of COVID-19: a mathematical modelling study

Table of Contents

A. Detailed methodology for country COVID-19 prevalence and incidence estimates **2**

1. Adjusting for temporally varying under-ascertainment 2

2. Adjusting for under-ascertainment 3

3. Estimating infections 3

4. Incidence and prevalence estimates 3

5. Sources of uncertainty 3

6. Limitations of our methods 4

Estimating under-ascertainment 4

Estimating incidence and prevalence 4

B. Estimating international travellers in the absence of travel restrictions (Scenario A) **7**

C. Expected imported and local cases by country **9**

D. Figures with sensitivity and uncertainty analyses **17**

E. Sensitivity analysis on the impact of mortality under-ascertainment in low- and middle-income countries (LMICs) **20**

F. Sensitivity analysis on the temporal variation in prevalence and incidence estimates **21**

G. Summary of all results for all scenarios and conditions **22**

H. Illustration of the chosen thresholds on incidence **23**

I. Policy recommendations based on recent reproduction number estimates **25**

J. Sensitivity analysis on flight volumes **27**

K. Centre for Mathematical Modelling of Infectious Diseases (CMMID) COVID-19 working group **29**

References **30**

A. Detailed methodology for country COVID-19 prevalence and incidence estimates

1. Adjusting for temporally varying under-ascertainment

We estimate prevalence and incidence for each country (with greater than 10 deaths in total). To do so, we estimate the level of under-ascertainment of symptomatic cases according to the methods in (1) within a fully Bayesian framework. The result of the inference is a time-dependent posterior distribution, representing the level of case ascertainment for each country. We then adjust the confirmed cases for each country using the median of the posterior distribution on each day, and the lower and upper 95% credible intervals. This process results in a 95% credible interval of the true number of symptomatic cases for each country. When considering all infections and not just symptomatic cases, we perform a final step adjusting for potential asymptomatic and presymptomatic infections. We assume that a large range (between 10% and 70%) of infections are asymptomatic (2–5).

To estimate the proportion of symptomatic cases ascertained over time, we fit a Gaussian process to a statistical Bayesian model for daily new deaths. The likelihood of the model, written in its simplest form, is given by

$$\begin{aligned} \mathrm{D}_{c,t} &\sim \mathrm{Poisson}(\lambda_{c,t}), \\ \lambda_{c,t} &= \mathrm{bCFR} \frac{\mathrm{dC}_{c,t}}{a^*_{c,t}}, \end{aligned}$$

where $\mathrm{D}_{c,t}$ is the number of daily deaths for country on day . We assume a Poisson observation process, with a rate given by $\lambda_{c,t}$, the product of the assumed true baseline case fatality ratio bCFR and the total number of cases with a known outcome by day t. The true number of cases is given by "adjusting" the ascertained number of cases $\mathrm{dC}_{c,t}$ with the ascertainment rate $a^*_{c,t}$. Specifically, the ratio of the two gives the true number of symptomatic cases in country c on day t. With the ascertainment rate defined in the likelihood function as a parameter, we are able to use the confirmed death data to fit our model and infer a time-dependent posterior distribution for this parameter.

The time-dependent ascertainment rate is defined as

$$\begin{aligned} \Phi^{-1}(a^*_{c,t}) &= f_c(t) + \epsilon_{c,t}, \\ \epsilon_{c,t} &\sim N(0, \sigma^2_{c,1}), \end{aligned}$$

where $f_c(t)$ is a nonparametric function of time for country c, $\epsilon_{c,t}$ are independent normally distributed random variables to attempt to explain daily variation in ascertainment for country c and finally $\Phi^{-1}(x)$ is the inverse of the probit function mapping the ascertainment rate to the unit interval - the range of supported values of the ascertainment rate. We model $f_c(t)$ as a realisation of a univariate zero-mean Gaussian process:

$$f_c(t) \sim \mathcal{GP}(\mathbf{0}, k(t, t'; \theta_c)).$$

The details of this Gaussian process, for example the specific parameterisation of the covariance matrix and the kernel function and the priors used can be found in the study which originally developed this model (1).

2. Adjusting for under-ascertainment

Firstly, we impute corresponding dates to the ascertainment estimates for each country. We do so by assuming the delay from confirmation to death follows the mean of an estimated distribution from the literature (6) of 13 days. We have, at this stage, effectively produced a time series of daily ascertainment rates, if we consider only the median and the lower/upper 95% credible intervals of the posterior distribution. Finally, we adjust the confirmed cases on each day using the ascertainment estimates.

3. Estimating infections

We estimate the total number of infections from the adjusted symptomatic case curves for each country (adjusted for under-ascertainment) by inflating them using a large assumed range of infections which are asymptomatic/presymptomatic (and therefore unlikely to be included in the confirmed case counts). This range is 10% - 70% of all infections. A wide range is assumed to reflect the still-present uncertainty in the true figure (2–5).

4. Incidence and prevalence estimates

To estimate incidence for each country, we calculated the mean number of infections over the same time period as the time period considered for the expected number of imported cases (which depends on the specific scenario). This time period is typically either a week or a month depending on what exactly is being considered. However, our inference framework provides us with a crude incidence estimate for each country on each day. Therefore, we are able to perform ad-hoc calculations within the same framework over arbitrary time periods, if the traveller data used to estimate expected numbers of imported cases is over a different time period or of a different temporal resolution. To estimate prevalence, we use cumulative incidence, summed over the mean (10 days) of a distribution of the infectious period (7)), as a proxy for prevalence.

5. Sources of uncertainty

Several sources of uncertainty are captured in our final uncertainty range:

- the inferred infectious period, with an uncertainty range reported in Table 1 of the main text.
- the assumed proportion of asymptomatic infections, with an assumed range of [10%, 70%]. We assume such a wide range for the proportion of asymptomatic infections to reflect the uncertainty still present in such estimates. If the true proportion varies between different locations, then our risk rating estimates and therefore the conclusions of our paper, may vary too. However, our results and conclusions are robust against this proportion if such proportions turn out to be similar between different countries and regions.
- the confirmation-to-death distribution, with an uncertainty range with a 95% CI of (8.7, 20.9) that we integrate over in the Gaussian process fitting procedure (6).

6. Limitations of our methods

We summarise the limitations of the original study here briefly and we discuss the limitations of the additional steps - extending the methods in (1) - employed in this study to arrive at prevalence estimates in detail. We do so, as the original study (1) which develops and describes the under-ascertainment model includes a verbose description of the limitations of the methods, up to the point of estimating incidence, in the Discussion section of the main text. Furthermore, the original study (1) goes into more detail about such limitations in its Supplementary Material.

Estimating under-ascertainment

In order to estimate under-ascertainment in a flexible manner, we assume a global baseline severity of COVID-19 of 1.4% (with the credible interval of 1.1% – 1.7%) integrated over in the model in a fully Bayesian framework. It is known that CFR of COVID-19 varies between locations. However, given that our analysis is on the scale of countries, and the uncertainty in the estimate is included in the final 95% credible intervals of our reported results (along with other sources of uncertainty), the effects of the assumption are relatively minor. We do however perform an additional sensitivity analysis in the original study (1), whereby we adjust the baseline CFR value for each country based on the underlying age-distribution of each country, using age-stratified CFR estimates (8). In doing so, we test the sensitivity of the model to the assumed CFR value. We find that our conclusions are broadly unchanged, and our cumulative incidence estimates are in good agreement with available seroprevalence results (1). For other limitations of these estimates, please refer to the main text and supplementary material of the original study (1).

Estimating incidence and prevalence

Extending the methods of (1) - whereby the resulting outputs of the mathematical model are posterior distributions for adjusted incidence over time for all countries (adjusted for under-ascertainment) - to arrive at prevalence estimates adds some limitations to the final estimates. The most pertinent of which is the additional assumptions about timing. Given that the outputs of the original model take the form of incidence measurements, and our estimates are on the scale of countries, whereby estimates are bound to be crude for a multitude of reasons, we use cumulative incidence as a proxy measure for prevalence. To do so, we sum the recent incidence levels over the mean of an estimated distribution for the time-to-infectiousness and infectious periods (which sum to 10 days, (7)) to arrive at prevalence estimates. We include the time-to-infectiousness distribution to allow for some level of presymtomatic transmission (7).

Incorporating these entire distribution into the otherwise fully Bayesian framework would alleviate this as a limitation of our study. However, in doing so, some of the desirable scalability and flexibility of the model as it stands would be lost, as additional assumptions about recovery and death rates would be required, which have been shown to vary significantly globally. In an attempt to keep the analysis scalable and parsimonious, applied in the same way globally, we opt for the simple adjustment to arrive at prevalence. In doing so, we are producing relatively crude estimates. However, we believe that the uncertainty included in the model as to the true proportion of asymptomatic infections – the source of most of the uncertainty in the 95% lower and upper

credible intervals of the results reported – overshadows any additional minor error introduced by using cumulative incidence over the infectious period as a proxy for prevalence.

Parameter	Description	Value (95% CI or CrI if applicable) or prior specification	Literature source (if applicable)
c_t	Number of new cases on day t	N/A	ECDC website (9)
d_t	Number of new deaths on day t	N/A	ECDC website (9)
$\hat{a}_{c,t}$	The proportion of cases ascertained on day t	N/A	N/A
f_t	Discretised probability density of death on day t	Mean: 13 days (8.7 - 20.9) SD: 12.7 days (6.4 - 21.8)	Linton et al. (2020) (6)
bCFR	The assumed baseline CFR	1.4% (1.2% - 1.5%)	Verity et al. (2020) (8)
$\mathrm{dCFR}_{c,t}$	The country specific delay-adjusted CFR	N/A	N/A
$\epsilon_{c,t}$	Error variance term in GP	$\epsilon_{c,t} \sim N(0, \sigma^2_{c,1})$	N/A

Table S1: A summary of the parameters, distributions and output quantities either as inputs or outputs of our under-ascertainment model. A full, more detailed table can be found in Russell et al. (2020) (1)***.***

B. Estimating international travellers in the absence of travel restrictions (Scenario A)

We constructed four scenarios of the number of international travellers in the absence of travel restrictions. Scenario A uses May 2019 data on the number of passengers booked on international flights from the Official Aviation Guide (OAG), Scenario B compares May 2019 and May 2020 flight numbers from the OpenSky database to estimate more recent traveller volumes. Scenarios C and D are similar, but use September 2019 and 2020 figures.

Our 2020 figures may be an underestimate, since many countries had already imposed travel restrictions in May 2020, and hence may have depressed international traveller numbers because of that. To investigate this effect, we examined traveller numbers in countries with different levels of travel restrictions. To do this, we used the Oxford COVID-19 Government Response Tracker (OxCGRT), which collects data on a number of common policy responses, typically NPIs, that governments and policymakers have been enacting as responses to the COVID-19 pandemic (10). This contains 17 indicators: eight directly relate to containment of the virus, such as school closures and travel restrictions; four describe economic policies, such as income support for citizens; and five describe health system policies such as testing regimes or emergency funding for healthcare systems.

The full dataset can be found here: https://raw.githubusercontent.com/OxCGRT/covid-policy-tracker/master/data/OxCGRT_latest.csv and the working paper which describes the 17 measured indicators, what type of variable they are (ordinal, binary, etc) and how precisely they are defined, can be found here: https://www.bsg.ox.ac.uk/sites/default/files/2020-09/BSG-WP-2020-032-v7.0.pdf.

We use one of the indicators; the variable: "C8_International travel controls". This records restrictions on international travel that each country imposes, and takes five levels depending on the stringency of the restrictions. Tables S2 and S3 show the definition of each level of the variable, the number of countries in that category and the number of international arrivals in May 2020 (compared to May 2019) and September 2020 (compared to September 2019), respectively, for countries in that category. There is no obvious directionality of the relationship between the level of restrictions and extent of the fall in arrivals.

International travel control rating (10)	**Countries**	**% of arrivals (May 2020/May2019)**
0 - No measures	2	72.2%
1 - Screening	3	57.1%
2 - Quarantine arrivals from high-risk regions	7	67.7%
3 - Ban on arrivals from some regions	35	46.1%
4 - Ban on all regions or total border closure	140	83.2%

Table S2. International arrivals in May 2020, as a percentage of arrivals in May 2019, stratified by international travel control rating of country according to the Oxford COVID-19 Government Response Tracker (10).

International travel control rating (10)	**Countries**	**% of arrivals (September 2020/September 2019)**
0 - No measures	11	92.1%
1 - Screening	22	62.6%
2 - Quarantine arrivals from high-risk regions	42	57.7%
3 - Ban on arrivals from some regions	64	53.9%
4 - Ban on all regions or total border closure	48	85.1%

Table S3. International arrivals in September 2020, as a percentage of arrivals in September 2019, stratified by international travel control rating of country according to the Oxford COVID-19 Government Response Tracker (10).

C. Expected imported and local cases by country

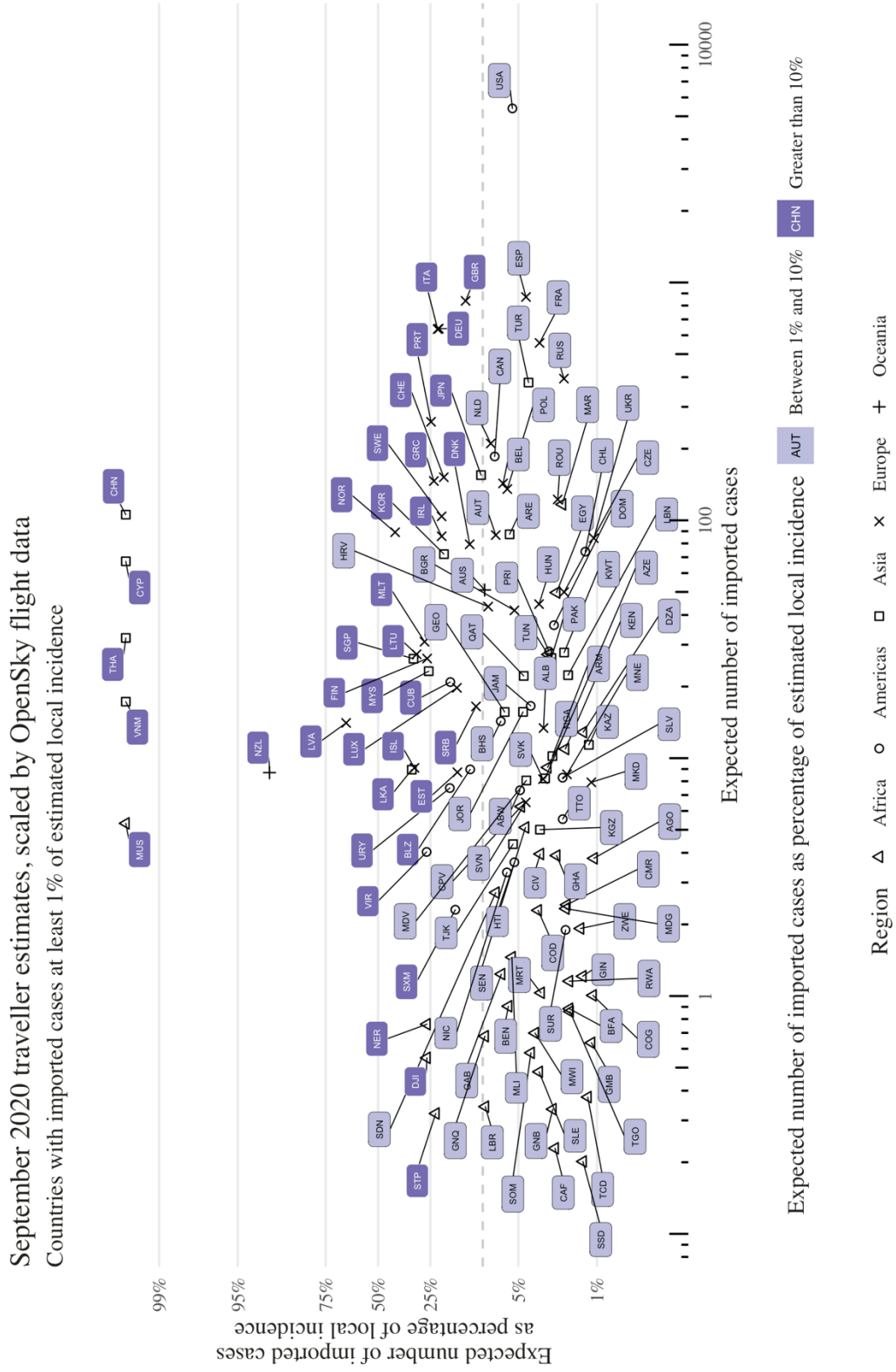

Figure S1. Scatter plot showing the percentage of local daily incidence that daily imported cases represent, where the expected number of imported cases is at least 1% of local incidence. The dashed line represents 10% of local incidence from imported cases. Letters in the boxes are the ISO 3-letter country code (see Table S4 for the list). NB: For New Zealand (NZL) and China (CHN), imported cases represent at least 100% of local incidence.

Table S4: Median and 95% intervals for expected daily number of imported cases, estimated daily number of new local cases, the ratio of these two quantities, recent time-varying reproduction number estimates (cite EpiForecasts) and a qualitative description of the implication of the Rt estimate with the following definitions: Rt < 0.95 equals “Epidemic Decreasing”; 0.95 <= Rt < 1.0 equals “Epidemic Slowly Decreasing”; Rt = 1.0 equals “Epidemic Stable”; 1 < Rt <= 1.05 equals “Epidemic Slowly Increasing” and finally Rt > 1.05 equals “Epidemic Increasing”. Calculations performed assuming Scenario D travel volumes, i.e. estimated September 2020 traveller volumes. Countries are divided by region and sorted by increasing ratio of imported to local cases, for all countries.

Country	Three-letter ISO code	Expected imported cases (95% CrI)	Local cases (95% CrI)	Imported cases per local (95% CrI)	Rt estimate (90% CrI)	Description
Albania	ALB	13.4 (7.2, 24.1)	445 (198, 950)	0.030 (0.008, 0.121)	1.01 (0.84-1.3)	Epidemic near tipping point
Algeria	DZA	12.9 (6.7, 23.9)	966 (439, 1994)	0.013 (0.003, 0.054)	0.98 (0.89-1.15)	Epidemic near tipping point
Angola	AGO	3.8 (2.0, 6.9)	355 (153, 773)	0.011 (0.003, 0.045)	1.04 (0.68-1.49)	Epidemic near tipping point
Argentina	ARG	167.4 (62.9, 341.6)	61457 (21800, 127502)	0.003 (0.000, 0.016)	0.86 (0.33-1.24)	Epidemic Decreasing
Armenia	ARM	10.2 (5.0, 19.2)	406 (195, 811)	0.025 (0.006, 0.098)	1.22 (0.82-1.71)	Epidemic Increasing
Aruba	ABW	7.3 (3.3, 15.5)	152 (81, 293)	0.048 (0.011, 0.192)	0.95 (0.25-1.51)	Epidemic near tipping point
Australia	AUS	50.9 (25.1, 101.8)	528 (238, 1100)	0.096 (0.023, 0.428)	0.64 (0.19-1.05)	Epidemic Decreasing
Austria	AUT	86.7 (45.5, 161.2)	1111 (613, 1944)	0.078 (0.023, 0.263)	1.14 (0.67-1.56)	Epidemic Increasing
Azerbaijan	AZE	8.2 (4.1, 15.4)	282 (148, 537)	0.029 (0.008, 0.104)	1.06 (0.64-1.57)	Epidemic Increasing
Bahamas	BHS	14.3 (6.3, 31.0)	202 (85, 450)	0.071 (0.014, 0.365)	1.22 (0.36-2.55)	Epidemic Increasing
Bahrain	BHR	8.3 (4.3, 15.6)	1245 (685, 2162)	0.007 (0.002, 0.023)	1.07 (0.73-1.44)	Epidemic Increasing
Bangladesh	BGD	14.2 (7.2, 26.8)	4511 (2261, 8375)	0.003 (0.001, 0.012)	0.92 (0.72-1.09)	Epidemic Decreasing
Belarus	BLR	10.0 (5.0, 18.8)	1161 (513, 2495)	0.009 (0.002, 0.037)	0.99 (0.74-1.21)	Epidemic near tipping point
Belgium	BEL	143.0 (75.1, 268.8)	2114 (1169, 3597)	0.068 (0.021, 0.230)	1.06 (0.32-1.88)	Epidemic Increasing
Belize	BLZ	9.0 (4.1, 20.7)	71 (33, 171)	0.126 (0.024, 0.635)	1.06 (0.35-1.81)	Epidemic Increasing
Benin	BEN	0.9 (0.5, 1.6)	15 (7, 34)	0.061 (0.014, 0.229)	0.66 (0-1.14)	Epidemic Decreasing
Bolivia (Plurinational State of)	BOL	9.3 (3.5, 42.1)	1437 (748, 9475)	0.006 (0.000, 0.056)	0.88 (0.4-1.47)	Epidemic Decreasing

Country	Three-letter ISO code	Expected imported cases (95% CrI)	Local cases (95% CrI)	Imported cases per local (95% CrI)	Rt estimate (90% CrI)	Description
Bosnia and Herzegovina	BIH	5.6 (3.0, 10.2)	1202 (556, 2445)	0.005 (0.001, 0.018)	0.98 (0.74-1.21)	Epidemic near tipping point
Botswana	BWA	0.9 (0.4, 1.6)	86 (45, 175)	0.010 (0.003, 0.037)	NA	NA
Brazil	BRA	472.5 (236.0, 897.1)	101227 (50819, 190795)	0.005 (0.001, 0.018)	0.96 (0.85-1.02)	Epidemic near tipping point
Bulgaria	BGR	41.8 (22.2, 77.8)	773 (351, 1588)	0.054 (0.014, 0.221)	1.31 (0.86-2.04)	Epidemic Increasing
Burkina Faso	BFA	0.9 (0.5, 1.6)	50 (26, 110)	0.018 (0.004, 0.062)	NA	NA
Cabo Verde	CPV	6.3 (3.4, 11.8)	132 (69, 274)	0.047 (0.012, 0.171)	1.08 (0.49-1.59)	Epidemic Increasing
Cameroon	CMR	2.4 (1.3, 4.4)	129 (70, 240)	0.019 (0.005, 0.063)	0.86 (0.27-1.43)	Epidemic Decreasing
Canada	CAN	185.6 (94.2, 354.7)	2331 (1142, 4505)	0.080 (0.021, 0.311)	0.95 (0.3-1.63)	Epidemic near tipping point
Central African Republic (the)	CAF	0.2 (0.1, 0.4)	10 (5, 27)	0.024 (0.004, 0.084)	0.76 (0.14-1.2)	Epidemic Decreasing
Chad	TCD	0.4 (0.2, 0.7)	31 (7, 129)	0.012 (0.002, 0.096)	0.88 (0.09-1.55)	Epidemic Decreasing
Chile	CHL	73.8 (28.9, 156.7)	5788 (2008, 12562)	0.013 (0.002, 0.078)	0.99 (0.9-1.11)	Epidemic near tipping point
China	CHN	105.7 (52.0, 209.1)	46 (24, 245)	1.000 (0.212, 1.000)	0.54 (0-0.98)	Epidemic Decreasing
Colombia	COL	221.6 (109.2, 428.9)	25809 (12811, 48609)	0.009 (0.002, 0.033)	0.99 (0.81-1.18)	Epidemic near tipping point
Congo (the)	COG	1.0 (0.5, 1.8)	92 (49, 191)	0.011 (0.003, 0.037)	0.96 (0.19-1.85)	Epidemic near tipping point
Costa Rica	CRI	16.9 (8.0, 34.7)	2546 (1304, 4974)	0.007 (0.002, 0.027)	0.99 (0.68-1.15)	Epidemic near tipping point
Côte d'Ivoire	CIV	4.0 (2.1, 7.2)	123 (67, 217)	0.032 (0.010, 0.107)	0.85 (0.05-1.93)	Epidemic Decreasing
Croatia	HRV	43.4 (22.9, 80.7)	481 (242, 1021)	0.090 (0.022, 0.333)	1.09 (0.79-1.37)	Epidemic Increasing
Cuba	CUB	20.9 (10.0, 42.8)	116 (60, 259)	0.180 (0.038, 0.710)	0.74 (0.01-1.96)	Epidemic Decreasing
Cyprus	CYP	67.3 (34.8, 129.5)	12 (6, 26)	1.000 (1.000, 1.000)	0.24 (0-0.86)	Epidemic Decreasing
Czechia	CZE	49.9 (26.4, 93.8)	2528 (1391, 4454)	0.020 (0.006, 0.067)	1.3 (0.96-1.7)	Epidemic Increasing
Denmark	DNK	79.3 (42.1, 147.3)	621 (343, 1070)	0.128 (0.039, 0.430)	1.03 (0.42-1.64)	Epidemic near tipping point
Djibouti	DJI	0.6 (0.3, 1.0)	2 (1, 5)	0.264 (0.057, 0.966)	0.79 (0.22-1.32)	Epidemic Decreasing
Dominican Republic	DOM	36.2 (16.8, 75.4)	1490 (767, 2757)	0.024 (0.006, 0.098)	0.86 (0.51-1.24)	Epidemic Decreasing

Country	Three-letter ISO code	Expected imported cases (95% CrI)	Local cases (95% CrI)	Imported cases per local (95% CrI)	Rt estimate (90% CrI)	Description
DRC	COD	2.3 (1.2, 4.2)	68 (25, 180)	0.034 (0.007, 0.171)	1.48 (0.51-3.53)	Epidemic Increasing
Ecuador	ECU	18.8 (6.9, 111.4)	2282 (1124, 24340)	0.008 (0.000, 0.099)	0.79 (0-1.35)	Epidemic Decreasing
Egypt	EGY	49.7 (25.9, 92.0)	2150 (1024, 4220)	0.023 (0.006, 0.090)	0.95 (0.7-1.12)	Epidemic near tipping point
El Salvador	SLV	8.3 (3.8, 17.3)	406 (179, 878)	0.020 (0.004, 0.097)	0.97 (0.65-1.35)	Epidemic near tipping point
Equatorial Guinea	GNQ	0.7 (0.4, 1.3)	7 (4, 16)	0.096 (0.023, 0.351)	0.22 (0-1.03)	Epidemic Decreasing
Estonia	EST	8.7 (4.5, 16.8)	55 (29, 112)	0.159 (0.041, 0.576)	NA	NA
Eswatini	SWZ	0.1 (0.0, 0.1)	89 (37, 200)	0.001 (0.000, 0.003)	0.91 (0.54-1.25)	Epidemic Decreasing
Ethiopia	ETH	5.5 (2.8, 10.4)	1699 (932, 3013)	0.003 (0.001, 0.011)	1 (0.71-1.35)	Epidemic near tipping point
Finland	FIN	26.2 (13.9, 48.6)	100 (54, 193)	0.263 (0.072, 0.900)	1.08 (0.49-1.78)	Epidemic Increasing
France	FRA	557.0 (297.2, 1025.3)	17068 (9185, 31233)	0.033 (0.010, 0.112)	1.18 (0.94-1.54)	Epidemic Increasing
Gabon	GAB	1.2 (0.7, 2.3)	18 (10, 33)	0.070 (0.020, 0.234)	0.79 (0.11-1.24)	Epidemic Decreasing
Gambia (the)	GMB	0.6 (0.3, 1.2)	57 (28, 164)	0.011 (0.002, 0.043)	0.71 (0-1.23)	Epidemic Decreasing
Georgia	GEO	15.6 (8.0, 29.2)	239 (128, 444)	0.066 (0.018, 0.228)	1.4 (0.72-1.84)	Epidemic Increasing
Germany	DEU	639.8 (336.0, 1204.6)	2930 (1621, 5026)	0.218 (0.067, 0.743)	1.24 (0.83-1.73)	Epidemic Increasing
Ghana	GHA	3.9 (2.0, 7.6)	169 (92, 307)	0.023 (0.006, 0.083)	0.88 (0.44-1.38)	Epidemic Decreasing
Greece	GRC	146.3 (77.3, 277.0)	619 (281, 1308)	0.237 (0.059, 0.986)	1.14 (0.74-1.64)	Epidemic Increasing
Guam	GUM	1.0 (0.5, 2.2)	152 (59, 388)	0.007 (0.001, 0.037)	0.96 (0.27-1.64)	Epidemic near tipping point
Guatemala	GTM	13.8 (6.4, 29.0)	1849 (887, 3608)	0.007 (0.002, 0.033)	1.05 (0.83-1.51)	Epidemic near tipping point
Guinea	GIN	1.2 (0.6, 2.2)	90 (49, 162)	0.013 (0.004, 0.046)	0.94 (0.46-1.33)	Epidemic Decreasing
Guinea-Bissau	GNB	0.3 (0.2, 0.6)	13 (5, 38)	0.025 (0.005, 0.119)	1.13 (0.46-2.43)	Epidemic Increasing
Guyana	GUY	1.7 (0.8, 3.7)	236 (100, 520)	0.007 (0.002, 0.037)	0.84 (0.33-1.33)	Epidemic Decreasing
Haiti	HTI	3.6 (1.7, 7.7)	67 (24, 191)	0.054 (0.009, 0.319)	0.82 (0.18-1.13)	Epidemic Decreasing
Honduras	HND	6.7 (3.1, 14.1)	2123 (972, 4339)	0.003 (0.001, 0.014)	0.91 (0.35-1.21)	Epidemic Decreasing

Country	Three-letter ISO code	Expected imported cases (95% CrI)	Local cases (95% CrI)	Imported cases per local (95% CrI)	Rt estimate (90% CrI)	Description
Hungary	HUN	44.4 (23.6, 83.5)	1347 (700, 2659)	0.033 (0.009, 0.119)	1.24 (0.66-1.95)	Epidemic Increasing
Iceland	ISL	9.1 (4.8, 17.4)	29 (15, 57)	0.318 (0.084, 1.000)	NA	NA
India	IND	264.6 (135.7, 494.3)	208052 (108532, 376374)	0.001 (0.000, 0.005)	0.93 (0.78-1.07)	Epidemic Decreasing
Indonesia	IDN	114.2 (57.2, 214.5)	15831 (7876, 29819)	0.007 (0.002, 0.027)	0.96 (0.78-1.11)	Epidemic near tipping point
Iran (Islamic Republic of)	IRN	96.7 (48.7, 180.5)	22960 (11467, 43002)	0.004 (0.001, 0.016)	1.07 (0.78-1.32)	Epidemic Increasing
Iraq	IRQ	17.6 (9.1, 33.0)	9904 (5040, 18370)	0.002 (0.000, 0.007)	0.98 (0.87-1.08)	Epidemic near tipping point
Ireland	IRL	85.7 (45.0, 165.0)	412 (226, 724)	0.208 (0.062, 0.729)	1.19 (0.47-1.84)	Epidemic Increasing
Israel	ISR	47.0 (23.3, 92.9)	6902 (3834, 11521)	0.007 (0.002, 0.024)	0.92 (0.44-1.33)	Epidemic Decreasing
Italy	ITA	636.5 (338.4, 1172.8)	2859 (1579, 4763)	0.223 (0.071, 0.743)	1.25 (0.77-1.94)	Epidemic Increasing
Jamaica	JAM	16.6 (7.6, 35.2)	425 (183, 952)	0.039 (0.008, 0.192)	1.01 (0.45-1.68)	Epidemic near tipping point
Japan	JPN	154.9 (71.1, 323.6)	1499 (635, 3132)	0.103 (0.023, 0.509)	1.12 (0.61-1.8)	Epidemic Increasing
Jersey	JEY	0.0 (0.0, 0.0)	5 (2, 27)	0.000 (0.000, 0.000)	0.38 (0-1.17)	Epidemic Decreasing
Jordan	JOR	15.7 (8.1, 29.8)	344 (179, 675)	0.046 (0.012, 0.166)	1.36 (0.69-1.74)	Epidemic Increasing
Kazakhstan	KAZ	11.4 (5.4, 22.5)	960 (401, 2079)	0.012 (0.003, 0.056)	0.9 (0.47-1.46)	Epidemic Decreasing
Kenya	KEN	10.9 (5.4, 21.6)	568 (245, 1244)	0.019 (0.004, 0.088)	1.14 (0.73-1.7)	Epidemic Increasing
Kuwait	KWT	27.8 (14.6, 52.4)	1409 (775, 2499)	0.020 (0.006, 0.068)	1.12 (0.84-1.47)	Epidemic Increasing
Kyrgyzstan	KGZ	5.0 (2.4, 10.2)	155 (84, 564)	0.032 (0.004, 0.121)	0.96 (0-2.08)	Epidemic near tipping point
Latvia	LVA	14.1 (7.4, 26.7)	21 (8, 58)	0.662 (0.127, 1.000)	0.49 (0-1.15)	Epidemic Decreasing
Lebanon	LBN	22.3 (11.5, 42.4)	1227 (675, 2153)	0.018 (0.005, 0.063)	1.01 (0.75-1.21)	Epidemic near tipping point
Lesotho	LSO	0.1 (0.0, 0.1)	41 (17, 114)	0.002 (0.000, 0.007)	0.87 (0.08-1.38)	Epidemic Decreasing
Liberia	LBR	0.3 (0.2, 0.7)	4 (2, 17)	0.095 (0.010, 0.436)	0.42 (0-1.19)	Epidemic Decreasing
Libya	LBY	2.3 (1.1, 4.6)	1698 (828, 3287)	0.001 (0.000, 0.006)	1.04 (0.79-1.37)	Epidemic near tipping point
Lithuania	LTU	27.3 (14.5, 52.1)	89 (48, 172)	0.308 (0.085, 1.000)	1.14 (0.41-1.88)	Epidemic Increasing

Country	Three-letter ISO code	Expected imported cases (95% CrI)	Local cases (95% CrI)	Imported cases per local (95% CrI)	Rt estimate (90% CrI)	Description
Luxembourg	LUX	19.8 (10.5, 36.7)	123 (67, 226)	0.161 (0.047, 0.546)	0.76 (0-1.91)	Epidemic Decreasing
Madagascar	MDG	2.3 (1.3, 4.2)	122 (62, 253)	0.019 (0.005, 0.067)	0.83 (0.34-1.17)	Epidemic Decreasing
Malawi	MWI	0.7 (0.4, 1.4)	20 (10, 49)	0.036 (0.007, 0.139)	0.77 (0.24-1.38)	Epidemic Decreasing
Malaysia	MYS	23.2 (12.3, 43.5)	90 (49, 169)	0.257 (0.073, 0.879)	1.38 (0.9-1.97)	Epidemic Increasing
Maldives	MDV	8.1 (4.3, 14.5)	189 (104, 331)	0.043 (0.013, 0.140)	1.04 (0.4-2.48)	Epidemic near tipping point
Mali	MLI	1.5 (0.8, 2.7)	26 (12, 71)	0.057 (0.011, 0.216)	1.05 (0.51-1.72)	Epidemic near tipping point
Malta	MLT	30.9 (16.5, 57.5)	113 (47, 329)	0.274 (0.050, 1.000)	0.65 (0-1.27)	Epidemic Decreasing
Mauritania	MRT	1.0 (0.5, 2.0)	33 (17, 70)	0.032 (0.008, 0.112)	0.75 (0-1.33)	Epidemic Decreasing
Mauritius	MUS	5.3 (2.9, 9.9)	1 (0, 5)	1.000 (0.536, 1.000)	NA	NA
Mexico	MEX	493.0 (236.5, 990.2)	55291 (27620, 105572)	0.009 (0.002, 0.036)	0.97 (0.78-1.13)	Epidemic near tipping point
Moldova (the Republic of)	MDA	8.2 (4.2, 15.3)	1381 (664, 2698)	0.006 (0.002, 0.023)	1.05 (0.92-1.22)	Epidemic near tipping point
Montenegro	MNE	8.6 (4.4, 15.9)	460 (214, 952)	0.019 (0.005, 0.074)	1.1 (0.78-1.48)	Epidemic Increasing
Morocco	MAR	116.7 (63.0, 213.9)	5690 (2772, 10987)	0.021 (0.006, 0.077)	1.06 (0.79-1.4)	Epidemic Increasing
Mozambique	MOZ	1.6 (0.8, 2.8)	293 (159, 533)	0.005 (0.002, 0.018)	0.75 (0.11-1.36)	Epidemic Decreasing
Myanmar	MMR	6.9 (3.3, 13.7)	1882 (898, 3690)	0.004 (0.001, 0.015)	1.05 (0.44-1.65)	Epidemic near tipping point
Nepal	NPL	11.8 (5.9, 23.2)	2596 (1360, 4955)	0.005 (0.001, 0.017)	1.08 (0.72-1.47)	Epidemic Increasing
Netherlands	NLD	210.5 (110.9, 399.4)	2451 (1356, 4203)	0.086 (0.026, 0.295)	1.13 (0.25-2.07)	Epidemic Increasing
New Zealand	NZL	8.7 (4.2, 17.8)	10 (4, 29)	0.907 (0.147, 1.000)	NA	NA
Nicaragua	NIC	3.3 (1.6, 6.9)	53 (28, 129)	0.063 (0.012, 0.248)	0.89 (0.01-1.74)	Epidemic Decreasing
Niger	NER	0.8 (0.4, 1.4)	3 (1, 17)	0.264 (0.022, 1.000)	0.71 (0-1.21)	Epidemic Decreasing
Nigeria	NGA	9.1 (4.6, 18.2)	330 (181, 585)	0.028 (0.008, 0.101)	2.01 (0.35-6.08)	Epidemic Increasing
North Macedonia	MKD	7.9 (4.3, 14.3)	703 (314, 1497)	0.011 (0.003, 0.046)	1.03 (0.81-1.3)	Epidemic near tipping point
Norway	NOR	89.1 (46.8, 166.3)	217 (119, 390)	0.411 (0.120, 1.000)	0.88 (0-1.64)	Epidemic Decreasing

Country	Three-letter ISO code	Expected imported cases (95% CrI)	Local cases (95% CrI)	Imported cases per local (95% CrI)	Rt estimate (90% CrI)	Description
Oman	OMN	15.3 (7.8, 29.2)	2260 (1034, 4622)	0.007 (0.002, 0.028)	0.98 (0.66-1.34)	Epidemic near tipping point
Pakistan	PAK	26.4 (13.7, 49.7)	1029 (559, 1889)	0.026 (0.007, 0.089)	1.15 (0.79-1.6)	Epidemic Increasing
Panama	PAN	14.1 (6.7, 30.1)	1561 (747, 3099)	0.009 (0.002, 0.040)	0.97 (0.79-1.14)	Epidemic near tipping point
Paraguay	PRY	4.8 (2.1, 10.0)	2858 (1367, 5639)	0.002 (0.000, 0.007)	0.87 (0.52-1.22)	Epidemic Decreasing
Peru	PER	69.6 (35.4, 136.4)	11254 (6250, 18793)	0.006 (0.002, 0.022)	0.9 (0.22-1.67)	Epidemic Decreasing
Philippines (the)	PHL	47.0 (22.2, 102.6)	8290 (3726, 21027)	0.006 (0.001, 0.028)	0.94 (0.62-1.26)	Epidemic Decreasing
Poland	POL	135.4 (71.9, 257.1)	2173 (1044, 4225)	0.062 (0.017, 0.246)	1.28 (0.94-1.64)	Epidemic Increasing
Portugal	PRT	259.6 (140.7, 478.2)	1049 (575, 1923)	0.248 (0.073, 0.832)	1.15 (0.89-1.42)	Epidemic Increasing
Puerto Rico	PRI	28.1 (12.6, 60.2)	1045 (522, 2007)	0.027 (0.006, 0.115)	0.98 (0.71-1.15)	Epidemic near tipping point
Qatar	QAT	22.2 (11.4, 41.8)	494 (258, 1099)	0.045 (0.010, 0.162)	0.99 (0.53-1.53)	Epidemic near tipping point
Romania	ROU	122.4 (65.4, 228.5)	5434 (2670, 10391)	0.023 (0.006, 0.086)	1.09 (0.87-1.35)	Epidemic Increasing
Russian Federation (the)	RUS	394.3 (185.4, 752.0)	19888 (9087, 37818)	0.020 (0.005, 0.083)	1.12 (0.94-1.32)	Epidemic Increasing
Rwanda	RWA	1.2 (0.6, 2.2)	65 (35, 125)	0.018 (0.005, 0.063)	0.95 (0.46-1.42)	Epidemic near tipping point
Sao Tome and Principe	STP	0.3 (0.2, 0.6)	1 (1, 4)	0.230 (0.044, 0.836)	0.85 (0-2.56)	Epidemic Decreasing
Saudi Arabia	SAU	53.2 (25.5, 101.0)	5965 (2545, 11643)	0.009 (0.002, 0.040)	0.96 (0.81-1.07)	Epidemic near tipping point
Senegal	SEN	5.1 (2.7, 9.4)	118 (58, 252)	0.043 (0.011, 0.161)	0.87 (0.56-1.13)	Epidemic Decreasing
Serbia	SRB	16.5 (8.4, 31.5)	145 (79, 281)	0.114 (0.030, 0.400)	1.12 (0.68-1.7)	Epidemic Increasing
Sierra Leone	SLE	0.5 (0.2, 0.9)	15 (7, 40)	0.033 (0.006, 0.127)	0.91 (0.42-1.35)	Epidemic Decreasing
Singapore	SGP	26.2 (13.6, 50.2)	81 (41, 213)	0.322 (0.064, 1.000)	0.76 (0-1.76)	Epidemic Decreasing
Sint Maarten	SXM	2.3 (1.1, 4.8)	14 (6, 44)	0.165 (0.024, 0.755)	NA	NA
Slovakia	SVK	8.2 (4.3, 16.1)	268 (148, 469)	0.030 (0.009, 0.109)	1.28 (0.77-1.98)	Epidemic Increasing
Slovenia	SVN	6.5 (3.4, 12.3)	151 (82, 281)	0.043 (0.012, 0.151)	1.54 (0.64-2.95)	Epidemic Increasing
Somalia	SOM	0.6 (0.3, 1.1)	15 (7, 42)	0.039 (0.007, 0.147)	0.62 (0-1.01)	Epidemic Decreasing

Country	Three-letter ISO code	Expected imported cases (95% CrI)	Local cases (95% CrI)	Imported cases per local (95% CrI)	Rt estimate (90% CrI)	Description
South Africa	ZAF	43.8 (22.3, 82.0)	9004 (4456, 17044)	0.005 (0.001, 0.018)	1.04 (0.69-1.44)	Epidemic near tipping point
South Korea	KOR	72.1 (33.4, 151.3)	359 (158, 853)	0.201 (0.039, 0.958)	0.79 (0.21-1.32)	Epidemic Decreasing
South Sudan	SSD	0.2 (0.1, 0.4)	15 (7, 38)	0.013 (0.003, 0.056)	0.69 (0-1)	Epidemic Decreasing
Spain	ESP	869.3 (471.5, 1658.9)	20252 (11081, 45721)	0.043 (0.010, 0.150)	1.04 (0.71-1.35)	Epidemic near tipping point
Sri Lanka	LKA	8.9 (4.7, 16.6)	27 (15, 53)	0.330 (0.090, 1.000)	NA	NA
Sudan	SDN	2.7 (1.4, 5.1)	35 (19, 71)	0.078 (0.019, 0.272)	0.39 (0-1)	Epidemic Decreasing
Suriname	SUR	1.9 (1.0, 3.5)	99 (42, 225)	0.019 (0.004, 0.083)	0.79 (0.17-1.37)	Epidemic Decreasing
Sweden	SWE	103.9 (55.6, 189.0)	498 (276, 857)	0.209 (0.065, 0.686)	0.97 (0.57-1.24)	Epidemic near tipping point
Switzerland	CHE	151.8 (80.6, 280.7)	755 (417, 1297)	0.201 (0.062, 0.672)	1.08 (0.63-1.81)	Epidemic Increasing
Syrian Arab Republic (the)	SYR	1.4 (0.7, 2.6)	348 (151, 752)	0.004 (0.001, 0.018)	1.11 (0.59-1.76)	Epidemic Increasing
Tajikistan	TJK	4.4 (2.0, 8.2)	78 (43, 159)	0.056 (0.013, 0.193)	0.97 (0.4-1.31)	Epidemic near tipping point
Thailand	THA	32.0 (16.1, 62.0)	10 (5, 26)	1.000 (0.615, 1.000)	NA	NA
Togo	TGO	0.9 (0.5, 1.6)	49 (17, 149)	0.018 (0.003, 0.092)	0.87 (0.09-1.3)	Epidemic Decreasing
Trinidad and Tobago	TTO	5.5 (2.5, 11.9)	272 (118, 595)	0.020 (0.004, 0.100)	0.84 (0.19-1.37)	Epidemic Decreasing
Tunisia	TUN	27.3 (14.5, 49.5)	994 (465, 1991)	0.027 (0.007, 0.106)	1.21 (0.67-1.52)	Epidemic Increasing
Turkey	TUR	379.6 (197.2, 706.2)	9304 (4657, 17532)	0.041 (0.011, 0.152)	1.07 (0.74-1.48)	Epidemic Increasing
UAE	ARE	87.3 (45.0, 164.7)	1467 (810, 2572)	0.060 (0.017, 0.203)	1.08 (0.79-1.49)	Epidemic Increasing
Uganda	UGA	2.3 (1.2, 4.5)	339 (183, 637)	0.007 (0.002, 0.025)	0.88 (0.45-1.29)	Epidemic Decreasing

D. Figures with sensitivity and uncertainty analyses

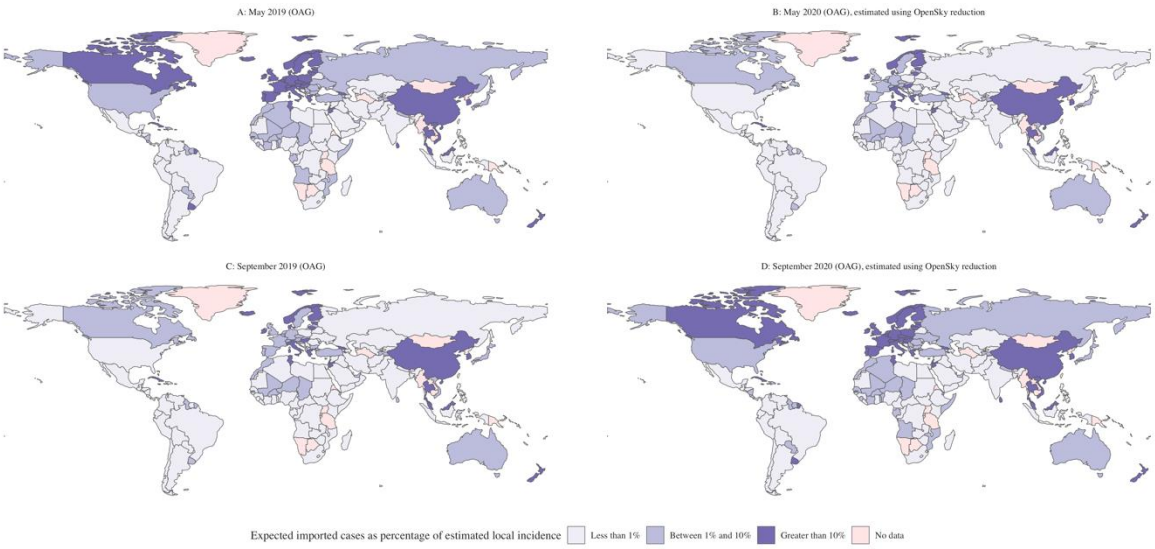

Figure S2: Lower 95% credible interval of our risk rating by country, in the absence of international travel restrictions, in each of the four scenarios about international travellers in May 2020. (A) Travel assumed to be at the same levels as May 2019. (B) Traveller numbers scaled downwards based on the ratio of flights between May 2019 and May 2020. (C) Travel assumed to be at the same levels as September 2019. (D) Traveller numbers scaled downwards based on the ratio of flights between September 2019 and September 2020 reported by OpenSky.

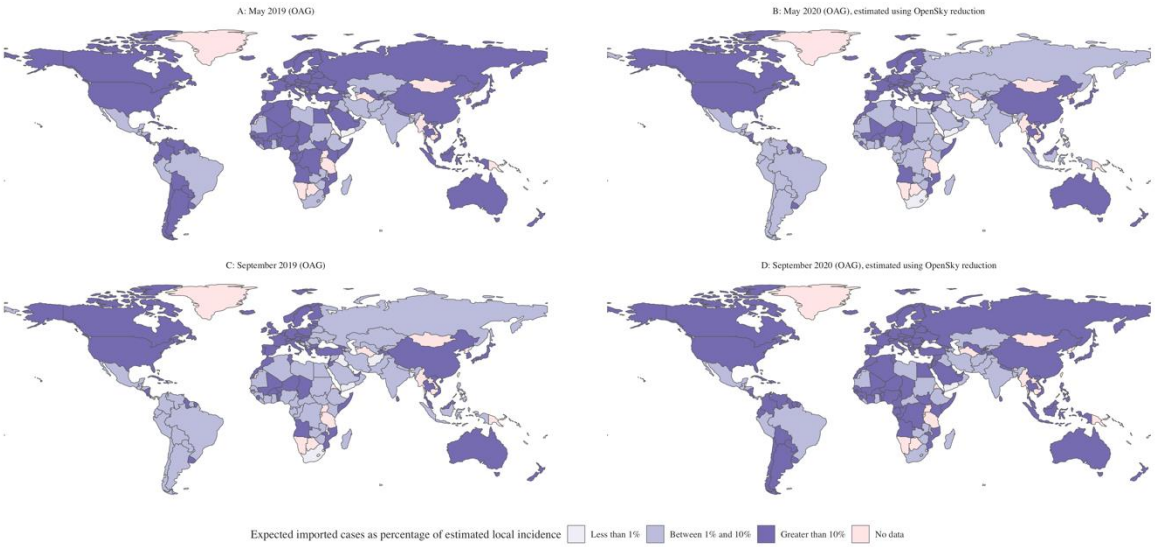

Figure S3: Upper 95% credible interval of our risk rating by country, in the absence of international travel restrictions, in each of the four scenarios about international travellers in May 2020. (A) Travel assumed to be at the same levels as May 2019. (B) Traveller numbers scaled downwards based on the ratio of flights between May 2019 and May 2020. (C) Travel assumed to be at the same levels as September 2019. (D) Traveller numbers scaled downwards based on the ratio of flights between September 2019 and September 2020 reported by OpenSky.

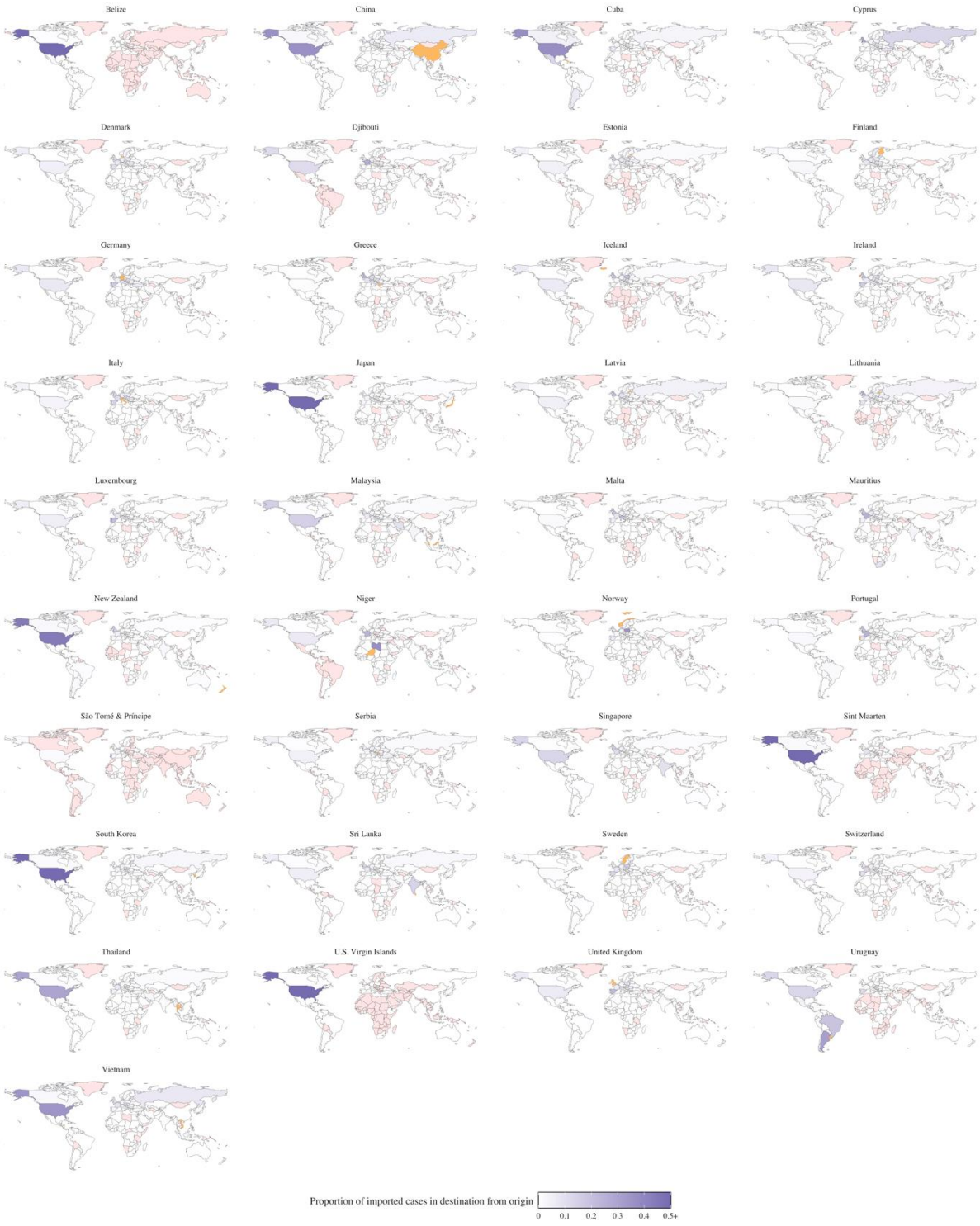

Figure S4: Proportion of estimated imported cases in destination (orange) imported from each origin (purples). Countries with no data (pink) either have missing prevalence estimates and/or there is no data on international flights between this origin-destination pair.

E. Sensitivity analysis on the impact of mortality under-ascertainment in low- and middle-income countries (LMICs)

We estimated the level of under-ascertainment in COVID-19 case reporting in different countries by examining their case-fatality risk (CFR), assuming that COVID-19 deaths are correctly ascertained. In high-income countries, COVID-19 deaths do not appear to be underreported by orders of magnitude, when compared to excess all-cause mortality over the same period; see for example (11) for a comparison in England.

In low- and middle-income settings, the completeness of COVID-19 death reporting has been questioned. To address this, we conducted an additional sensitivity analysis to test the effect of relaxing a key assumption in our prevalence estimates - i.e. that death data are reasonably complete even if case data are not. In this analysis, the number of infections in all LMICs are scaled up according to the death under-ascertainment estimates from one of the few studies which have estimated the death ascertainment rate in LMICs (12). The study in question estimates that in South Africa around 80% of COVID caused deaths have been missed. A recent report estimated much higher mortality under-ascertainment in Damascus, Syria (13), but we did not use these figures from a fragile state where the recent crisis has had a major effect on health service functionality, as they may not be representative of other LMICs.

Hence we conducted two additional scenarios: (i) 50% under-ascertainment of deaths, and (ii) 80% under-ascertainment

Hence the under-ascertainment estimates are adjusted accordingly for all LMICs. New resulting risk ratings are shown on a map in Figure S4.

(A) We assume that 50% of deaths are ascertained in LMICs. (B) We assume 20% of deaths are ascertained in LMICs. Currently, scenario (B) is the closest to the small amount of available evidence. However, as can be seen (at least from the median of our estimates, middle column), our conclusions are relatively robust to such changes, as LMICs typically have fewer flight passengers overall.

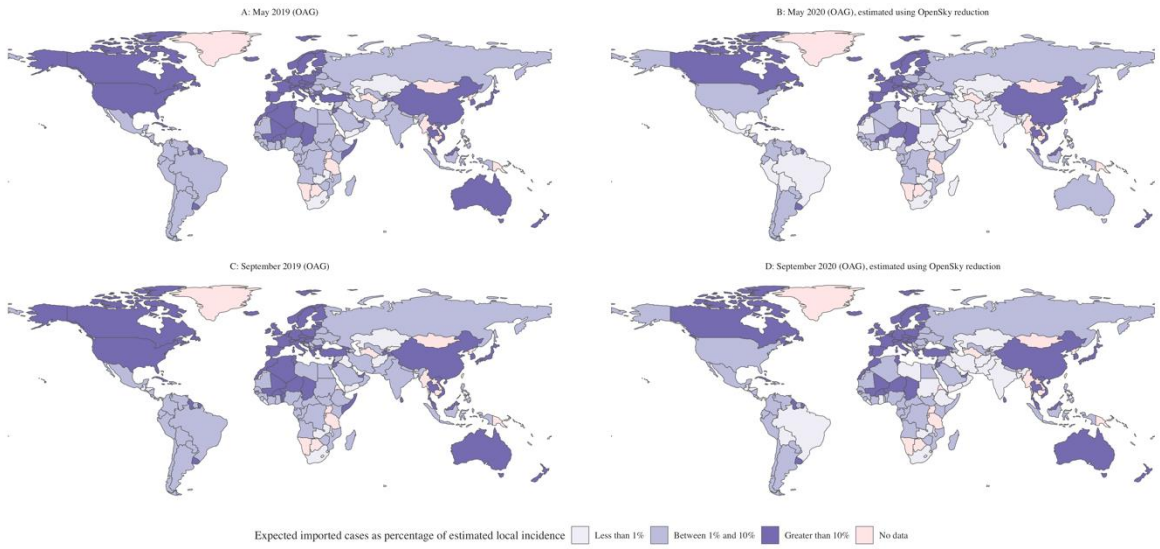

Figure S5 Sensitivity of risk-ratings to under-ascertainment of deaths in LMICs.

F. Sensitivity analysis on the temporal variation in prevalence and incidence estimates

The risk-rating results presented in the main text (Figure 1) assume the mean prevalence and incidence estimates, after adjusting for under-ascertainment in May and September 2020. To test whether our conclusions were broadly unchanged at different time-points of the pandemic, we performed the same analysis using prevalence and incidence estimates from July 2020 (Figure S6). In doing so, we are able to see that our conclusions are broadly unchanged. In fact, slightly fewer countries have high risk-ratings in July than May or September 2020. The four scenarios use precisely the same traveller assumptions as the four scenarios in Figure 1 in the main text.

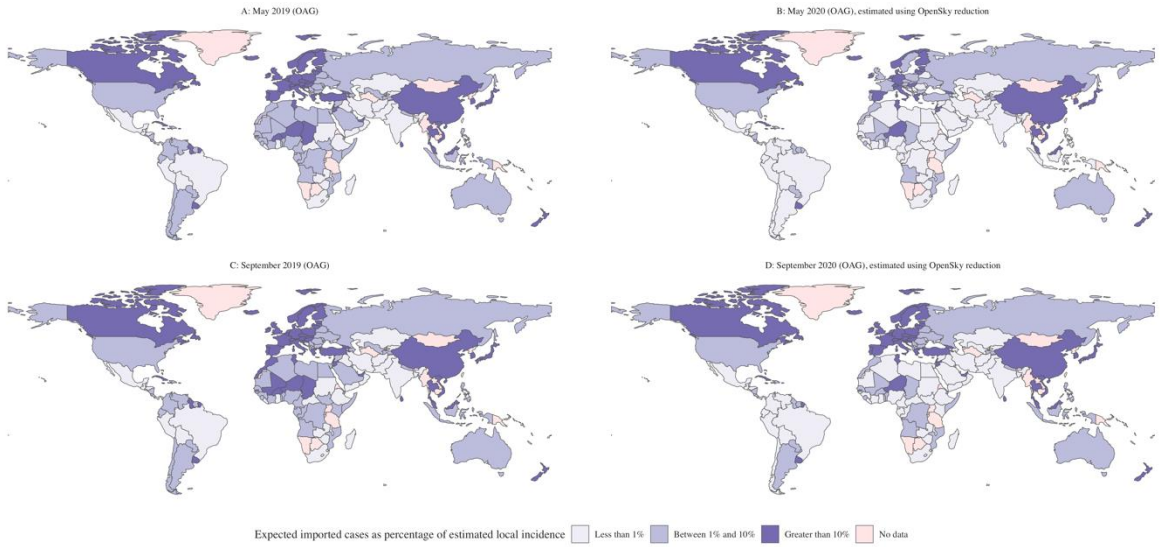

Figure S6: Sensitivity of risk-ratings to prevalence and incidence estimates from July 2020 rather than May or September 2020 (for Scenarios A & B or C & D respectively), under the same four traveller scenarios as in the main text.

G. Summary of all results for all scenarios and conditions

Table S5: Number of countries stratified by traveller scenario and by conditions based on risk rating and reproduction number (R_t) estimates. The total number of countries included for May traveller scenarios is 136. The total number of countries for September traveller scenarios is 162.

Traveller scenario	Risk rating <1% (95% CrI)	Risk rating between 1% and 10% (95% CrI)	Risk rating ≤10% (95% CrI)	Risk rating >10% (95% CrI)	R_t estimate between 0.95 and 1.05 or risk rating ≥1% (95% CrI)	R_t estimate <0.95 or >1.05 and risk rating <1% (95% CrI)
A	4 (4 - 16)	30 (3 - 57)	34 (7 - 73)	102 (63 - 129)	132 (123 - 132)	2 (2 - 11)
B	8 (4 - 39)	54 (18 - 64)	62 (22 - 103)	74 (33 - 114)	129 (108 - 132)	5 (2 - 26)
C	21 (4 - 71)	85 (46 -85)	106 (50 - 140)	56 (22 - 112)	149 (120 - 158)	13 (4 - 40)
D	44 (8 - 97)	81 (57 - 81)	125 (65 – 162)	37 (8 - 85)	139 (99 - 156)	22 (6 - 61)

H. Illustration of the chosen thresholds on incidence

The focus of our study is the relative impact travel restrictions have in countries at various stages and severities of COVID-19 epidemics. In doing so, we chose 0.1%, 1% and 10% as values of interest of the contribution imported cases make to the overall transmission within each country. We are aware that such values are arbitrarily chosen, and as such, require justification. To do so, we aim to show that the contribution of 0.1% and 1% to a simulated standard COVID-19 epidemic, would be all but undetectable, if transmission locally was ongoing. We use a deterministic SEIR model, parameterised using epidemiological estimates for COVID-19. It is clear that such contributions of 0.1% and 1% to overall incidence within a country, during an ongoing COVID-19 epidemic, would be undetectable (Figure S7).

The equations used to simulate the epidemic are the standard continuous-time system of ordinary differential equations for an S (Susceptible), E (Exposed), I (Infected) and R (Removed) model, which has been used throughout the COVID-19 pandemic, as it allows for an incubation period where individuals are exposed, but not yet infectious. We state the equations explicitly

$$\frac{dS}{dt} = -\beta S(t)I(t),$$
$$\frac{dE}{dt} = \beta S(t)I(t) - \delta E(t),$$
$$\frac{dI}{dt} = \delta E(t) - \gamma I(t),$$
$$\frac{dR}{dt} = \gamma I(t).$$

Given that γ represents the reciprocal of the infectiousness period and δ the reciprocal of the incubation period, they were chosen for our simulation to be 5 and 7 respectively (6,7). Furthermore, given estimates for the reproduction number for an unmitigated COVID-19 epidemic are in the range between 2 to 3 (14), we chose $R_0 = 3$. We acknowledge that the justification is purely illustrative. However, it is clear that such differences in incidence would be unnoticed where ongoing COVID epidemics are occurring (Figure S7). We therefore believe that such chosen values are reasonable, even though the exact values are arbitrary.

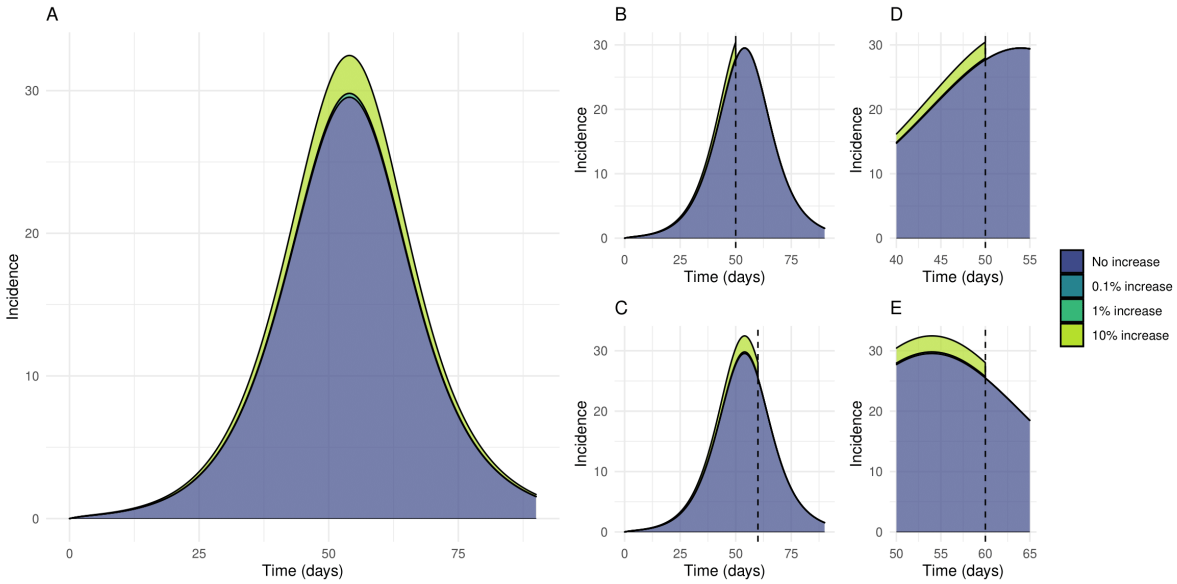

Figure S7: Increasing the incidence of a standard SEIR-model simulated epidemic to justify the risk-rating thresholds. We show the effect of increasing the incidence of an epidemic simulated from a standard SIR model, with $R_0 = 3$ (14), $\gamma = 1/5$ (6) and $\delta = \frac{1}{7}$ (7) by the arbitrary threshold levels discussed in the paper: 0.1%, 1% and 10%. These represent the difference that would be made relaxing travel restrictions in a country where imported cases account for 0.1%, 1% and 10% of locally transmitted cases respectively. The difference in the resulting epidemic is very minimal, indicating that the thresholds in our analysis are sensible even though their exact values are arbitrary. Panel A: increasing the incidence throughout all of a simulated epidemic. Panel B: Introducing an intervention near the peak of a simulated epidemic which reduces the increased versions of the incidence back to the baseline values. Panel C: The same idea as Panel B, but the hypothetical intervention is introduced after the peak. Panel D: a zoomed in version of Panel B. Panel E: a zoomed in version of Panel C.

I. Policy recommendations based on recent reproduction number estimates

We present the results of Figures 2 and 3 in the main text, with an extra condition - on top of the greater than 1% overall risk rating – to be included in the results. The new condition is that the internal epidemic within each arrival country is near its "tipping point". I.e. where recent time-dependent reproduction number estimates (R_t) are close to one. Specifically, we require that $0.95 \leq R_t \leq 1.05$ for countries to be included in these results.

The aim of the new condition is to provide countries with a more nuanced and detailed policy recommendation. The

We use R_t estimates from the regularly updated online dashboard named EpiForecasts (15), rather than using our crude prevalence estimates. We do so as the backcalculation procedure - to infer the most likely infection time, given the date of confirmation of a case - within the EpiForecasts model fitting framework is more statistically robust than our own (15). Specifically, they use a deconvolution method within a Gaussian process framework, allowing for a fully Bayesian inference of the likely infection times. Whereas, our estimates rely on mean-shifting the dates by the mean of the distribution between confirmation-to-death (6). Plus, the estimates are publicly available and ready in a user-friendly form to download making them more convenient than performing extra calculations on our prevalence estimates.

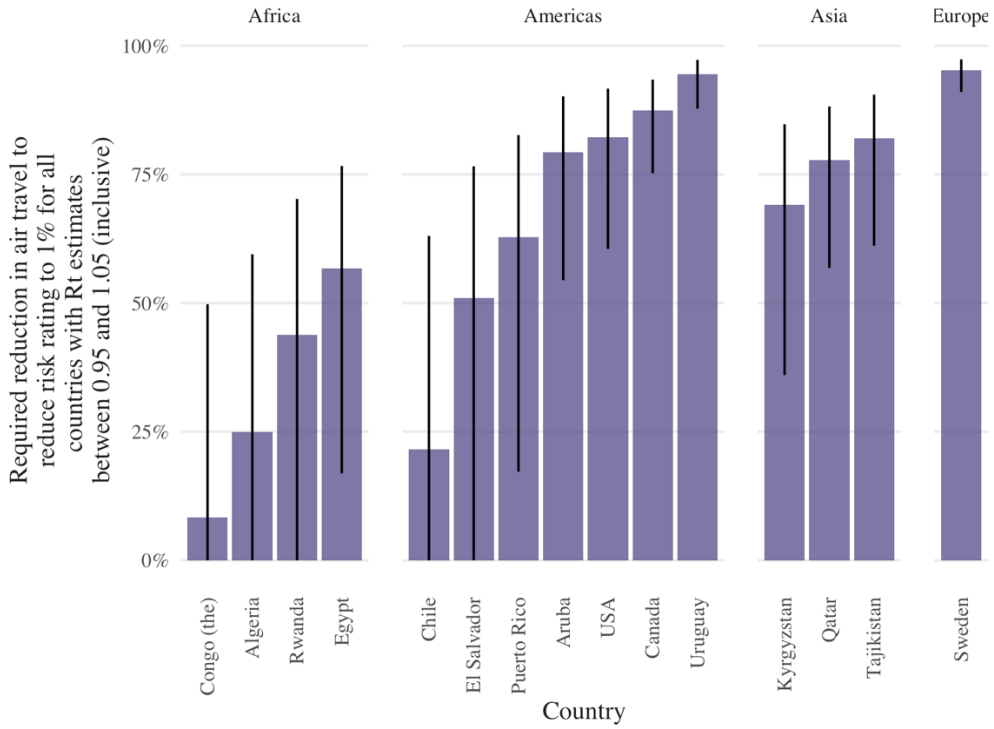

Figure S8: The required reduction in air travellers for countries to achieve a 1% risk-rating overall, for countries with a greater than an estimated 1% risk rating and a recent reproduction number estimate, close to its *tipping point*: between 0.95 and 1.05.

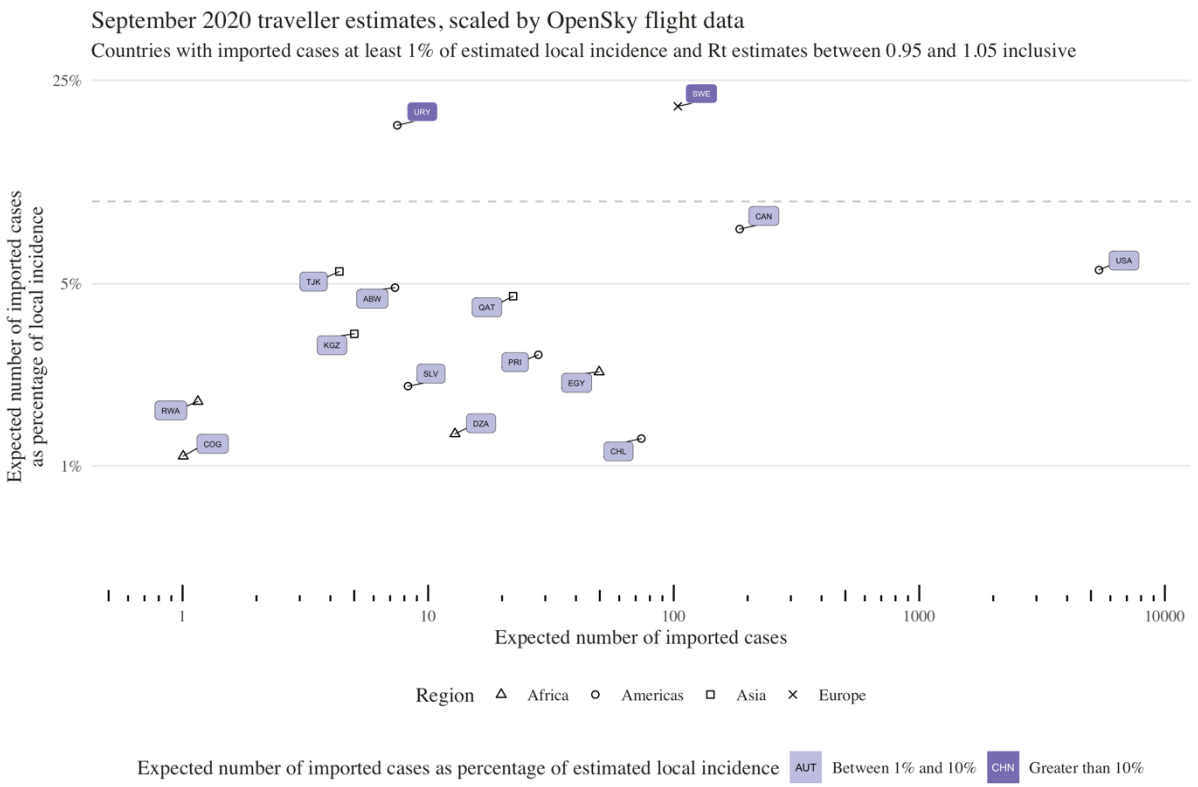

Figure S9: Scatter plot showing the percentage of local daily incidence that daily imported cases represent, where the expected number of imported cases is at least 1% of local incidence and recent Rt estimates from (15) **are close to their *tipping point*: between 0.95 and 1.05. The dashed line represents 10% of local incidence from imported cases.**

J. Sensitivity analysis on flight volumes

It has been estimated by the International Air Transport Association (IATA) that aircraft occupancy has decreased by 50.6% in 2020 compared with 2019. Therefore, we tested our conclusions against assumptions relating to aircraft occupancy. We perform this sensitivity under the most plausible travel assumptions in the main text, scenarios B and D (Figure S10 and S11 respectively).

We assume that flights are 80% full and 50% full and present the results as separate panels in each figure. We also present the 95% credible intervals of our results as separate columns in the same figure.

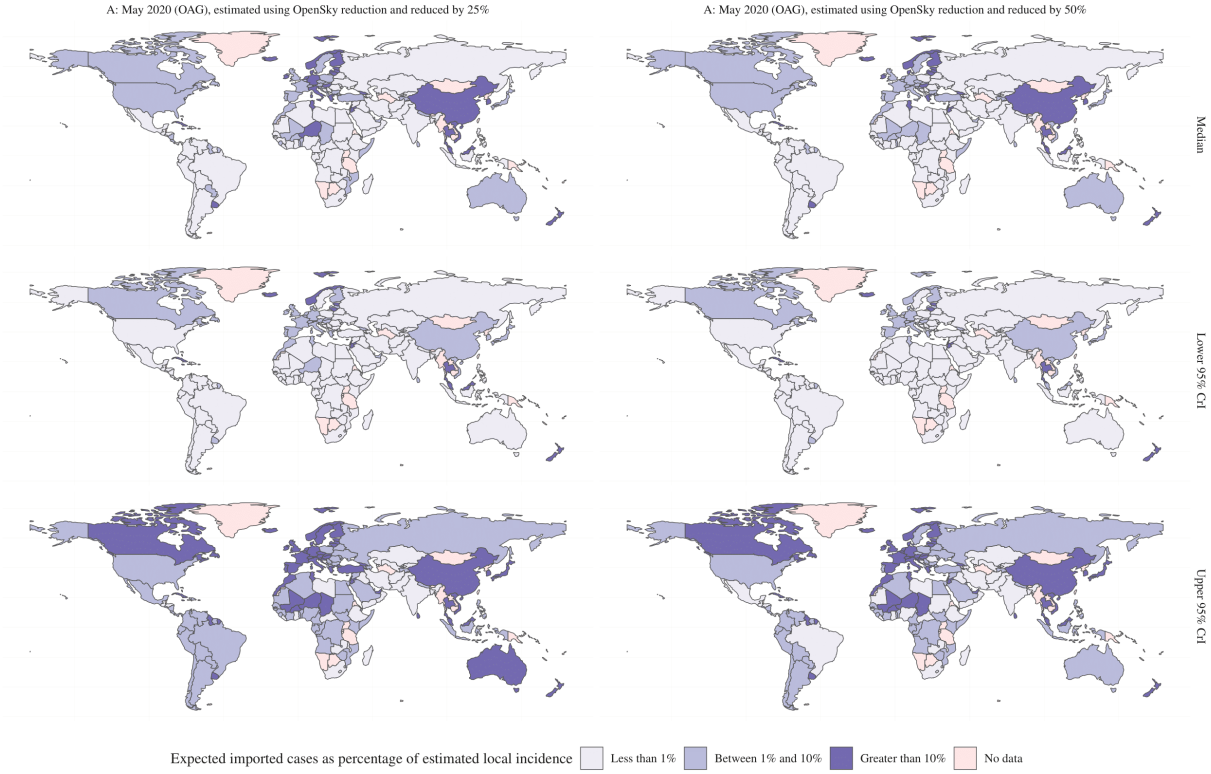

Figure S10: Sensitivity analysis assuming different levels of aircraft occupancy in 2020. Under the same assumptions of scenario B in the main text (May 2020 travel volumes, estimated using 2020 OAG data downscaled by OpenSky reduction factors). We assume flights are 80% full in 2020 compared to 2019 and present.

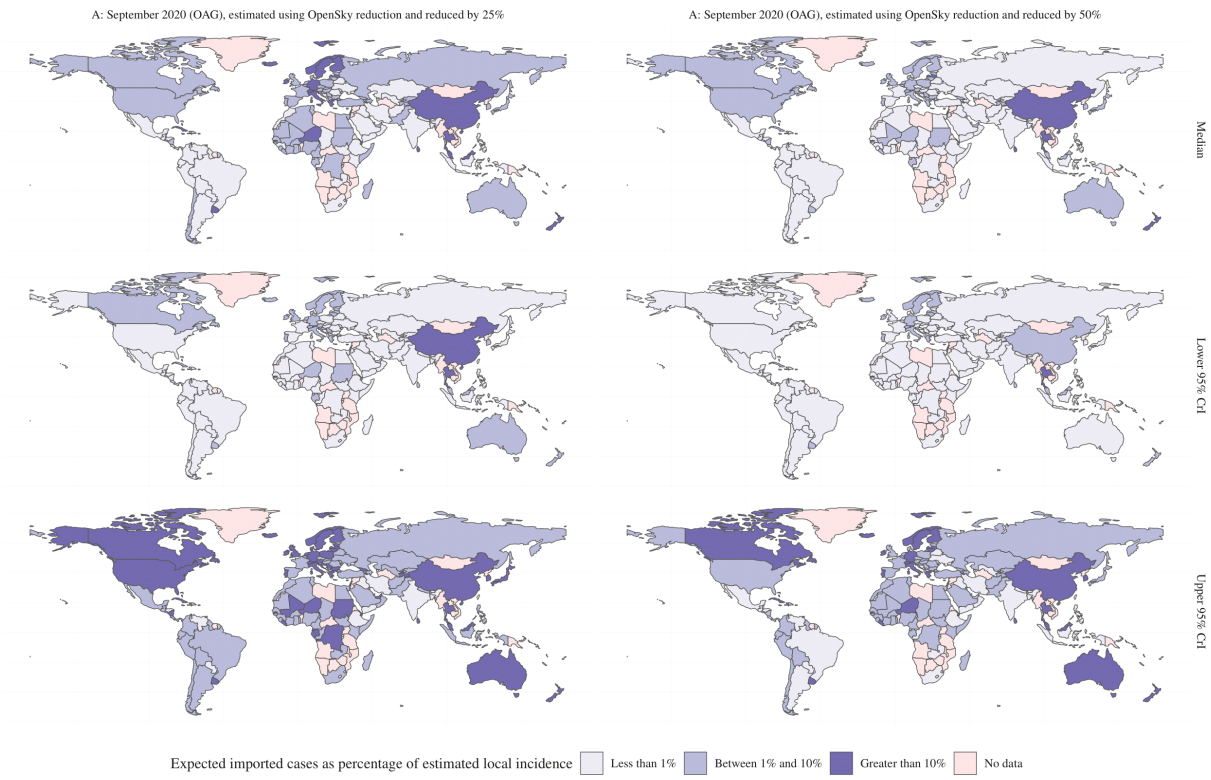

Figure S11: Sensitivity analysis assuming different levels of aircraft occupancy in 2020. Under the same assumptions of scenario B in the main text (May 2020 travel volumes, estimated using 2020 OAG data downscaled by OpenSky reduction factors). We assume flights are 50% full in 2020 compared to 2019 and present.

K. Centre for Mathematical Modelling of Infectious Diseases (CMMID) COVID-19 working group

The following authors were part of the Centre for Mathematical Modelling of Infectious Disease (CMMID) COVID-19 Working Group. Each contributed in processing, cleaning and interpretation of data, interpreted findings, contributed to the manuscript, and approved the work for publication (members are listed in a randomised order): Matthew Quaife, Gwenan M Knight, Kathleen O'Reilly, Oliver Brady, Fiona Yueqian Sun, Joel Hellewell, Arminder K Deol, Megan Auzenbergs, James W Rudge, Christopher I Jarvis, Georgia R Gore-Langton, Thibaut Jombart, Charlie Diamond, James D Munday, Rachel Lowe, Sebastian Funk, Akira Endo, Damien C Tully, Jon C Emery, Petra Klepac, Stefan Flasche, Samuel Clifford, Stephane Hue, Katherine E. Atkins, Nicholas G. Davies, Anna M Foss, Quentin J Leclerc, Graham Medley, Amy Gimma, Rosalind M Eggo, Rein M G J Houben, Emily S Nightingale, Carl A B Pearson, Simon R Procter, Sam Abbott, Yang Liu, Nikos I Bosse, Hamish P Gibbs, David Simons, Billy J Quilty, Alicia Rosello, Sophie R Meakin, Kiesha Prem, Timothy W Russell, Kevin van Zandvoort, C Julian Villabona-Arenas.

Each contributed in processing, cleaning and interpretation of data, interpreted findings, contributed to the manuscript, and approved the work for publication.

The following funding sources are acknowledged as providing funding for the working group authors. Alan Turing Institute (AE). BBSRC LIDP (BB/M009513/1: DS). This research was partly funded by the Bill & Melinda Gates Foundation (INV-001754: MQ; INV-003174: KP, YL; NTD Modelling Consortium OPP1184344: CABP, GM; OPP1180644: SRP; OPP1183986: ESN; OPP1191821: KO'R, MA). DFID/Wellcome Trust (Epidemic Preparedness Coronavirus research programme 221303/Z/20/Z: CABP, KvZ). DTRA (HDTRA1-18-1-0051: JWR). Elrha R2HC/UK DFID/Wellcome Trust/This research was partly funded by the National Institute for Health Research (NIHR) using UK aid from the UK Government to support global health research. The views expressed in this publication are those of the author(s) and not necessarily those of the NIHR or the UK Department of Health and Social Care (KvZ). ERC Starting Grant (#757688: CJVA, KEA; #757699: JCE, RMGJH; 757699: MQ). This project has received funding from the European Union's Horizon 2020 research and innovation programme - project EpiPose (101003688: KP, PK, YL). This research was partly funded by the Global Challenges Research Fund (GCRF) project 'RECAP' managed through RCUK and ESRC (ES/P010873/1: AG, CIJ, TJ). HDR UK (MR/S003975/1: RME). Nakajima Foundation (AE). NIHR (16/137/109: CD, FYS, YL; 16/137/109 & 16/136/46: BJQ; Health Protection Research Unit for Immunisation NIHR200929: NGD; Health Protection Research Unit for Modelling Methodology HPRU-2012-10096: TJ; PR-OD-1017-20002: AR). Royal Society (Dorothy Hodgkin Fellowship: RL; RP\EA\180004: PK). UK DHSC/UK Aid/NIHR (ITCRZ 03010: HPG). UK MRC (LID DTP MR/N013638/1: GRGL, QJL; MC_PC 19065: RME;

MR/P014658/1: GMK). Authors of this research receive funding from UK Public Health Rapid Support Team funded by the United Kingdom Department of Health and Social Care (TJ). Wellcome Trust (206250/Z/17/Z: TWR; 206471/Z/17/Z: OJB; 208812/Z/17/Z: SFlasche; 210758/Z/18/Z: JDM, JH, NIB, SA, SFunk, SRM). No funding (AKD, AMF, DCT, SH).

References

1. Using a delay-adjusted case fatality ratio to estimate under-reporting [Internet]. CMMID Repository. 2020 [cited 2020 Sep 21]. Available from: https://cmmid.github.io/topics/covid19/global_cfr_estimates.html

2. Seroprevalence of anti-SARS-CoV-2 IgG antibodies in Geneva, Switzerland (SEROCoV-POP): a population-based study - The Lancet [Internet]. [cited 2020 Sep 21]. Available from: https://www.thelancet.com/journals/lancet/article/PIIS0140-67362031304-0/fulltext

3. Mizumoto K, Kagaya K, Zarebski A, Chowell G. Estimating the asymptomatic proportion of coronavirus disease 2019 (COVID-19) cases on board the Diamond Princess cruise ship, Yokohama, Japan, 2020. Eurosurveillance. 2020 Mar 12;25(10):2000180.

4. The contribution of asymptomatic SARS-CoV-2 infections to transmission on the Diamond Princess cruise ship | eLife [Internet]. [cited 2020 Sep 21]. Available from: https://elifesciences.org/articles/58699

5. Asymptomatic SARS-CoV-2 infections: a living systematic review and meta-analysis | medRxiv [Internet]. [cited 2020 Sep 21]. Available from: https://www.medrxiv.org/content/10.1101/2020.04.25.20079103v3

6. Linton NM, Kobayashi T, Yang Y, Hayashi K, Akhmetzhanov AR, Jung S, et al. Incubation Period and Other Epidemiological Characteristics of 2019 Novel Coronavirus Infections with Right Truncation: A Statistical Analysis of Publicly Available Case Data. Journal of Clinical Medicine. 2020 Feb;9(2):538.

7. Temporal dynamics in viral shedding and transmissibility of COVID-19 - Google Search [Internet]. [cited 2020 Sep 21]. Available from: https://www.google.com/search?client=firefox-b-e&q=Temporal+dynamics+in+viral+shedding+and+transmissibility+of+COVID-19

8. Verity R, Okell LC, Dorigatti I, Winskill P, Whittaker C, Imai N, et al. Estimates of the severity of coronavirus disease 2019: a model-based analysis. The Lancet Infectious Diseases. 2020 Jun 1;20(6):669–77.

9. Download the daily number of new reported cases of COVID-19 by country worldwide [Internet]. [cited 2020 Sep 21]. Available from: https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide

10. Hale T, Angrist N, Cameron-Blake E, Hallas L, Kira B, Majumdar S, et al. Oxford COVID-19 Government Response Tracker [Internet]. Coronavirus Government Response Tracker. [cited 2020 Nov 9]. Available from: https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker

11. Public Health England. Excess mortality in England, week ending 04 September 2020 [Internet]. Public Health England; [cited 2020 Sep 21]. Available from: https://fingertips.phe.org.uk/static-reports/mortality-surveillance/excess-mortality-in-england-latest.html

12. Moultrie T, Dorrington R, Laubscher R, Groenewald P, Bradshaw D. Excess deaths: additional measures and approaches to understanding COVID-19 related mortality in South Africa. [Internet]. Burden of Disease Research Unit, South African Medical Research Council.; [cited 2020 Sep 21]. Available from: https://www.samrc.ac.za/sites/default/files/files/2020-08-12/Excess%20deaths_4%20Aug%202020.pdf.

13. Watson OJ, Alhaffar M, Mehchy Z, Whittaker C, Akil Z, Gharibah M, et al. Report 31 - Estimating under-ascertainment of COVID-19 mortality: an analysis of novel data sources to provide insight into COVID-19 dynamics in Damascus, Syria [Internet]. Imperial College London; [cited 2020 Sep 21]. Available from: http://www.imperial.ac.uk/medicine/departments/school-public-health/infectious-disease-epidemiology/mrc-global-infectious-disease-analysis/covid-19/report-31-syria/

14. Davies NG, Kucharski AJ, Eggo RM, Gimma A, Edmunds WJ, Jombart T, et al. Effects of non-pharmaceutical interventions on COVID-19 cases, deaths, and demand for hospital services in the UK: a modelling study. The Lancet Public Health. 2020 Jul 1;5(7):e375–85.

15. Abbott S, Hellewell J, Thompson RN, Sherratt K, Gibbs HP, Bosse NI, et al. Estimating the time-varying reproduction number of SARS-CoV-2 using national and subnational case counts. Wellcome Open Res. 2020 Jun 1;5:112.