100-day mission: Model description

1 Simulation rules

- Countries are instantiated with two random variables: the response time, and their importation time
- The response time is the time at which the reporting country reports having seen X hospital cases, where X is a random number between 1 and 20
- The importation time is a random number between 0 and 20 days, where 0 days would be equivalent to the spillover, or origin, country
- The simulation starts at the minimum between the response time and the importation time
- At the response time, the BPSV, if present, is given to people aged 65 and older; testing begins; social distancing begins; economic closures, if in use, are implemented
- At the importation time, five people are moved from compartment S to compartment E
- If closures are being implemented, the rules in Tables 1 and 2 are followed
- The SARS-X–specific vaccine is rolled out starting on day 107 or 372 after the response time, depending on the investment assumption
- All people aged 15 and over are eligible for vaccination, and we assume 80% take it up
- Distribution rate increases linearly to a maximum of 1% of the population per day, at which is stays until 80% coverage is reached
- When vaccine rollout is complete, closures, testing and social distancing end
- When the doubling time is more than 30 days and there are fewer than 1,000 people in hospital, the simulation ends.

Table 1: State transition rules for reactive closure strategies

From/to	No closures	Light closures	Heavy closures
No closures			t = response time OR Hospital occupancy > 95% capacity
Light closures	(Growth rate < 0.025 OR Hospital occupancy < 25% capacity) AND vaccine rollout complete OR $R_t(M(\mathbf{1})) < 1$		Hospital occupancy > 95% capacity
Heavy closures		Hospital occupancy < 25% capacity AND t > 7 + last change time	

Table 2: State transition rules for the elimination strategy

From/to	No closures	Light closures	Heavy closures
No closures			t = response time OR Hospital occupancy > 95% capacity
Light closures	Vaccine rollout complete OR $R_t(M(\mathbf{1})) < 1$		$R_t > 1.2$

From/to	No closures	Light closures	Heavy closures
Heavy closures	Vaccine rollout complete OR $R_t(M(\mathbf{1})) < 1$	$R_t(M_{\text{light closure}}) < 0.95$ AND t > 7 + last change time	

2 Socio-economic costs

We assign monetary values to YLLs and to years of education in order to add health and education costs of mitigation strategies to the costs of economic closures. We define the total socio-economic costs TSC of an epidemic as the sum of the individual costs:

$$\text{TSC} = K_1\text{VLY} + K_2 + K_3\text{VSY}, \tag{1}$$

where K_1 is the number of discounted life years lost and VLY the value of a discounted life year; K_2 is the lost GDP over the period due to reduced economic activity; and K_3 is the number of school years lost and VSY the value of one school year.

2.1 Lost lives

To value lives lost, we make use of the expected remaining life years per age group (Global Burden of Disease Collaborative Network 2021). These are used to estimate the expected number of years of life lost per death, and to estimate the value of a life year. We map the remaining life expectancy $\tilde{l}_a$ for the GBD age groups a to l_g for the model age groups g as a population-weighted average, taking into account the size of each age group, ‘$\tilde{N}_a$‘. For the expected number of life years lost per death, we take into account also the probability to die given infection, $P(D|I,a)$:

`l_g^{\text{(death)}} = \frac{\sum_{a\in g}N_a\tilde{l}_aP(D|I,a)}{\sum_{a\in g}N_aP(D|I,a)};`

`l_g^{\text{(life)}} = \frac{\sum_{a\in g}N_a\tilde{l}_a}{\sum_{a\in g}\tilde{N}_a};`

Expected life years remaining with discounting taken into account can be written

`\hat{l}_g=\sum_{y=1}^{l_g}\frac{1}{(1+r)^{y}}`

for discount rate $r > 0$. The discounted number of years lost given D_g deaths due to COVID-19 for each age group is

`K_1=\sum_gD_g\hat{l}_g^{\text{(death)}}.`

The VLY used by policy makers should reflect the value that members of the society place on reductions of their own mortality. We rely on the intrinsic rather than instrumental interpretation of the valuation of life (Cutler and Summers 2020), and we use existing estimates of the value of a statistical life (VSL) to estimate VLY. We interpret the VSL as a population-weighted average (Ananthapavan et al. 2021; Robinson, Sullivan, and Shogren 2021), where each age group has a VSL defined by the number of expected life years remaining, and where each discounted year has the same value:

$$\text{VSL} = \frac{\sum_g N_g \hat{l}_g^{(\text{life})}}{\sum_g N_g}\text{VLY}. \tag{2}$$

2.2 Lost economic activity

We measure the cost of economic closures in terms of lost gross value added (GVA): the GDP generated by an economic configuration is the maximum GVA (denoted y_j for each sector j) multiplied by the respective sector openings, summed over the period (τ days). The maximum possible GDP (which is with no closures) is

$$Y_0 = \frac{\tau}{365}\sum_{j=1}^{m_S} y_j$$

for m_S sectors, and we use pre-pandemic GVA to define the maximum possible values.

All economic sectors contribute GVA according to the level they are open for production, except for the education sector which contributes its maximum possible GVA, y_{ed}. $x_j(t)$ is the proportion of the workforce contributing to economic production in sector j out of the total workforce N_j on day t. The workforce can be additionally depleted due to self isolation, sickness, hospitalisation and death, leaving a smaller fraction (‘$\hat{x}_j(t)$‘) to contribute to production.

```
\hat{x}_{j}(t)=x_{j}(t) - \left((1-x_{j}(t))p_j^{23}(t)  + (1-x_{j}(t)(1-q_j))p_j^{22}(t)\right)/N_j
```

where q_j is the fraction of the sector working from home. $p_j^{23}(t)$ represents worker sickness and death:

$$p_j^{23}(t) = \sum_{v=0}^{m_V} \left(\left(1 - p_{j,v}^H\right) p^1 p^{19} I_{j,v}^s + p_{j,v}^H p^1 I_{j,v}^s + H_{j,v} + D_{j,v}\right),$$

with $m_V = 2$ vaccines and $p_j^{22}(t)$ represents output from asymptomatic self-isolating workers:

$$p_j^{22}(t) = p^2(t) p^{18} I_j^a.$$

p^{18} is the number of days spent in self isolation per day of infectiousness (e.g. suppose the average infectious period is four days and mandatory self-isolation time is ten days, then $p^{19} = 2.5$ and $p^{18} = p^{19} T^{I^s} / T^{I^a:R}$, where T^{I^s} and $T^{I^a:R}$ are expected infectious periods for symptomatic and asymptomatic, respectively). p^1 is compliance with the requirement to self isolate and $p^2(t)$ is the fraction of cases identified. Other notations are vaccine status v, infectious and asymptomatic $I_{j,v}^a$, infectious and symptomatic $I_{j,v}^s$, hospitalised H, deceased D, and probability to be hospitalised p^H.

Then the total GDP is

```
Y =  \frac{1 }{365} \sum_{j\neq\text{ed}}^{m_S}y_j\int_{t=0}^{\tau}\hat{x}_{j}(t)dt + \frac{\tau }{365}
```

and the GDP loss compared to the maximum is

$$K_2 = Y_0 - Y.$$

2.3 Lost education

The loss due to school closure is

$$K_3 = \frac{1}{365}\int_{t=0}^{\tau} \left(p^{14}(t) N_{j_{\text{school}}} + (1 - p^{14}(t)) p^{25}(t) + (1 - 2p^{14}(t)) p^{24}(t)\right) dt,$$

where $p^{14}(t)$ is the effective amount of education lost per student at time t due to school closure:

$$p^{14}(t) = (1 - p^{16})(1 - x_{\text{ed}}(t)),$$

$N_{j_{\text{school}}}$ is the total number of students, p^{16} is relative effectiveness of remote education and $x_{\text{ed}}(t)$ is the openness of schools, $p^{25}(t)$ represents education lost due to student sickness with COVID-19:

$$p^{25}(t) = \sum_{v=0}^{m_V} \left((1 - p_{j_{\text{school}},v}^H) p^1 p^{19} I_{j_{\text{school}},v}^s + p_{j_{\text{school}},v}^H p^1 I_{j_{\text{school}},v}^s + H_{j_{\text{school}},v}\right),$$

p^{18} is the number of days spent in self isolation per day of infectiousness (e.g. suppose the average infectious period is four days and mandatory self-isolation time is ten days, then $p^{19} = 2.5$ and $p^{18} = p^{19}T^{I^s}/T^{I^a:R}$, where T^{I^s} and $T^{I^a:R}$ are expected infectious periods for symptomatic and asymptomatic, respectively), and $p^{24}(t)$ represents education lost due to asymptomatic self isolation (which comes at a cost only when schools are open):

$$p^{24}(t) = p^2(t)p^{18}I^a_{j_{\text{school}}}.$$

For the value of a year of education, we use the method of (Psacharopoulos, Collis, and Patrinos 2021).

$$\text{VSY} = p^{12} \cdot p^{13} \cdot p^{15}.$$

p^{12} is the present value of lost earnings:

$$p^{12} = \frac{1}{N_{j_{\text{school}}}} \sum_{a \in j_{\text{school}}} \tilde{N}_a \left(\frac{1-(1+r)^{-(m_Y+20-a)}}{r} - \frac{1-(1+r)^{-(20-a)}}{r} \right)$$

for discount rate $r = 0.03$, number $\tilde{N}_a$ students currently age a, and expected number of years of work $m_Y = 45$. p^{13} is mean annual earnings, $p^{15} = 0.08$ is the rate of return for one year.

The value p^{16} represents the effectiveness of remote teaching, which we sample as a standard uniform random variable. We note that no strong predictors of effectiveness of remote teaching have been identified (Patrinos 2023). We assume that losses are linear in duration of school closure, although there is not consensus even on this (Betthäuser, Bach-Mortensen, and Engzell 2023). Important factors to include in future work might be those relating to parental circumstances including education level, engagement and socio-economic status (Moscoviz and Evans 2022). However, these factors might be more pertinent to intra- rather than international modelling.

3 Epi model

3.1 Ordinary differential equations

$$\frac{dS_{j,v}}{dt} = \sum_{u=0}^{v-1} k^9 S^{c_v}_{j,u} - \left(k^1_{j,v}(t) + \sum_{u=v+1}^{m_V} k^{10,c_u}_{j,v}(t) \right) S_{j,v} \tag{3}$$

$$\frac{dS^{c_v}_{j,u}}{dt} = k^{10,c_v}_{j,u}(t)S_{j,u} - \left(k^1_{j,u}(t) + k^9\right) S^{c_v}_{j,u} \tag{4}$$

$$\frac{dE_{j,v}}{dt} = k^1_{j,v}(t) \left(S_{j,v} + \sum_{u=v+1}^{2} S^{c_u}_{j,v} \right) - (k^2 + k^4)E_{j,v} \tag{5}$$

$$\frac{dI^a_{j,v}}{dt} = k^2 E_{j,v} - k^3 I^a_{j,v} \tag{6}$$

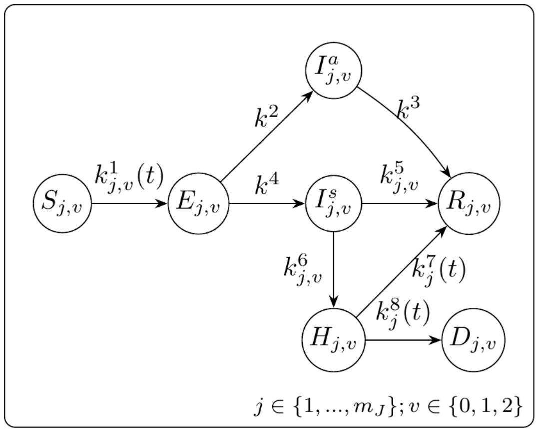
$$\frac{dI^s_{j,v}}{dt} = k^4 E_{j,v} - (k^5_{j,v} + k^6_{j,v})I^s_{j,v} \tag{7}$$

$$\frac{dR_{j,v}}{dt} = k^3 I^a_{j,v} + k^5_{j,v} I^s_{j,v} + k^7_j(t)H_{j,v} - \sum_{u=v+1}^{m_V} k^{10,c_u}_{j,v}(t)R_{j,v} + \sum_{u=0}^{v-1} k^{10,c_v}_{u,j}(t)R_{j,v-1} \tag{8}$$

$$\frac{dH_{j,v}}{dt} = k^6_{j,v} I^s_{j,v} - (k^7_j(t) + k^8_j(t))H_{j,v} \tag{9}$$

$$\frac{dD_{j,v}}{dt} = k^8_j(t)H_{j,v} \tag{10}$$

3.2 Disease state transitions



Disease state transitions. S: susceptible. E: exposed. I^a: asymptomatic infectious. I^s: symptomatic infectious. H: hospitalised. R: recovered. D: died. j: stratum. v: vaccination status.

Possible transitions between disease states are shown in Figure figno:1. Transition rates are functions of time t, vaccination status v, and group identity j (where the groups are the 45 sectors and the four age groups).

The rate of infection of susceptible individuals, '$k^1_{j,v}(t)$', is defined as

$$k^1_{j,v}(t) = \eta^E_v \rho(t) \beta \sum_{h=1}^{m_J} M_{j,h}(x) I_h(t) \tag{11}$$

with $m_J = 49$ strata and

```
I_h(t)=\sum_{v=0}^{m_V}\left(\epsilon (1-p^3(t))I_{h,v}^{a}(t)+(1-p^4(t))I_{h,v}^{s}(t)\right).
```

Here, 'η^E_v' is the relative probability to be infected given vaccine status v; $\rho(t)$ is the time-dependent modifier of the rate of infection, β, which captures the impact of social distancing; $M(x)$ is the contact matrix between groups and depends on the economic configuration x; ϵ is the reduction in infectiousness from asymptomatic relative to symptomatic individuals; p^3 and p^4 are the proportions of asymptomatic and symptomatic infectiousness averted, respectively, due to self isolating; and $I^{\cdot}_{h,\cdot}$ is the number of infectious asymptomatic ($I^a_{h,\cdot}$) and symptomatic ($I^s_{h,\cdot}$) people who are unvaccinated ($I^{\cdot}_{h,v=0}$), vaccinated with the BPSV ($I^{\cdot}_{h,v=1}$), or vaccinated with the specific vaccine ($I^{\cdot}_{h,v=2}$) in stratum h.

```
k^2 = \big(1-p^{I^S}\big)/T^{E:I}
```

is the rate to asymptomatic infectiousness, where p^{I^S} is the probability to become symptomatic given infection, and $T^{E:I}$ is the expected duration of the latent period before the onset of infectiousness;

```
k^3 = 1/T^{I^a:R}
```

is the rate of recovery from asymptomatic infection;

```
k^4 = p^{I^S}/ T^{E:I};
```

is the rate of symptom onset;

```
k^{5}_{j,v} =  \big(1-p^H_{j,v}\big) / T_{j,v}^{I^s}
```

is the rate of recovery from symptomatic infection, where $p^H_{j,v}$ is the probability to be hospitalised given symptomatic infection, and $T^{I^s}_{j,v} = p^H_{j,v} T^{I^s:H} + (1 - p^H_{j,v}) T^{I^s:R}$ is the expected time to be in compartment I^s: $T^{I^s:H}$ is the expected duration before hospitalisation and $T^{I^s:R}$ is the expected duration before recovery.

```
p^H_{j,v}=\eta^{H}_{v}\tilde{p}^{H}_{j}
```

is the baseline probability to be hospitalised (‘$\tilde{p}_j^H$‘) adjusted by the vaccine effect protecting against hospitalisation (‘η_v^H‘). Then

```
k^{6}_{j,v} = p^H_{j,v}/T_{j,v}^{I^s}
```

is the rate of hospitalisation following symptomatic infection.

```
k^{7}_{j}(t) = (1-p^{D}_{j}(t)) / T_j^{H}(t)
```

is the rate of recovery of hospitalised patients, where ‘$p_j^D(t) = \tilde{p}_j^D f_H(t)$‘ is the baseline probability to die given hospitalisation, adjusted by a factor encoding the increase in fatality rate as hospital occupancy increases:

```
f_H(t)=\max\{1,1+1.87(H_{\text{tot}}(t)-H_{\text{max}})/H_{\text{max}}\},
```

```
H_{\text{tot}}(t) = \sum_{v=0}^{m_V}\sum_{j=1}^{m_J} H_{j,v}(t).
```

$$T_j^H(t) = p_j^D(t)T^{H:D} + (1 - p_j^D(t))T^{H:R}$$

is the expected time to be in compartment H: $T^{H:D}$ is the expected duration before death and $T^{H:R}$ is the expected duration before recovery. Finally,

```
k^{8}_{j}(t) = p^{D}_{j}(t)/T_j^{H}(t)
```

is the rate of death following hospitalisation.

3.3 Vaccination state transitions

In our model, $v = 0$ refers to unvaccinated people, $v = 1$ to people who have received a full schedule of BPSV, and $v = 2$ to people who have received a full schedule of the specific vaccine. How we model transitions between vaccination states is shown in Figure figno:2.

‘$k_{j,v=0}^{10,c_1}(t)$‘ represents the rates of BPSV vaccination of unvaccinated susceptible and recovered people, and ‘$k_{j,v=1}^{10,c_2}(t)$‘ represents the rates of vaccinating BPSV-vaccinated susceptible and recovered people. ‘$k_{j,v=0}^{10,c_2}(t)$‘ represents the rates of vaccinating people directly with the specific vaccine. Put more succintly, ‘$k_{j,v}^{10,c_u}(t)$‘ is the rate to go from vaccine state v to u. $k^9 = 1/T^c$ is the rate of seroconversion to vaccine-induced immunity, and ‘$k_j^{12}(t) = k_{j,v=0}^1(t)$‘ and ‘$k_j^{19}(t) = k_{j,v=1}^1(t)$‘ are the rates of infection of just-vaccinated people, which returns them to the epidemiological pathway of the lower vaccination level.

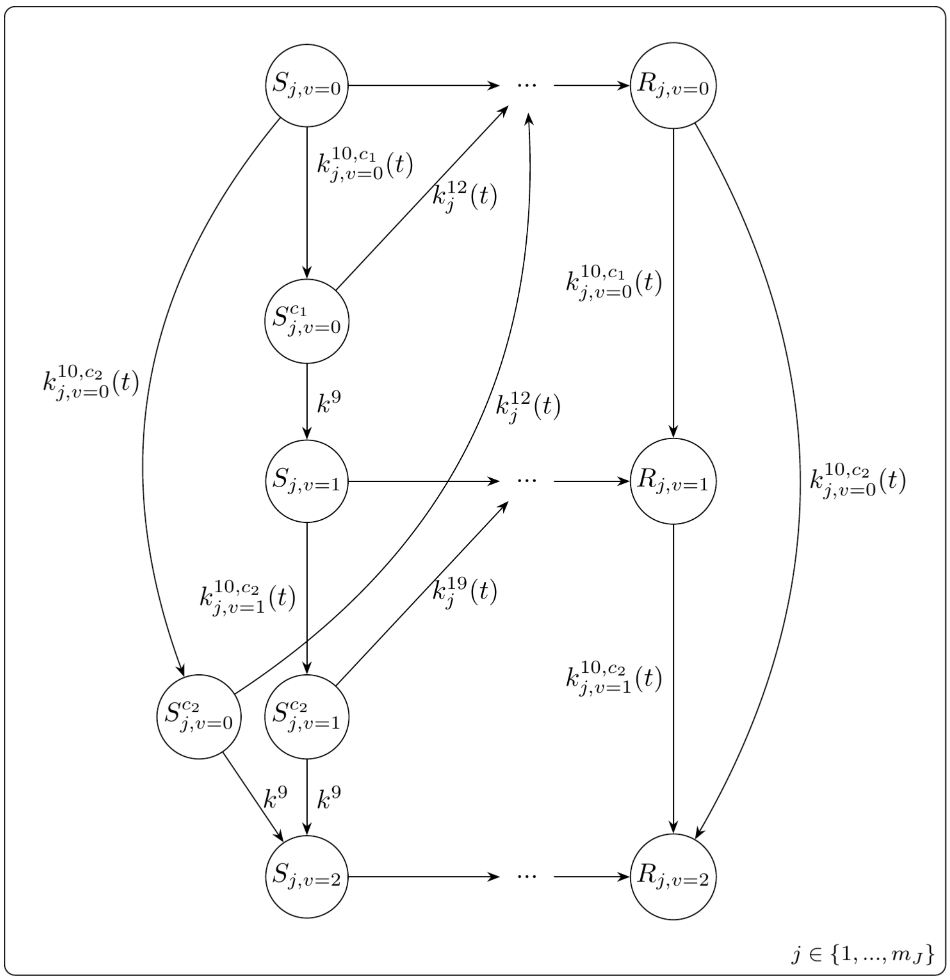
3.4 Contact rates

The configuration x and the proportion of workers working from home q determine the scaling of exposure to infection between different groups for different reasons:

- Worker absence due to sector closure
- Worker absence due to working from home
- Student absence due to school closure
- Customer absence due to sector closure: impact on workers
- Customer absence due to sector closure: impact on customers

We approach this differently from (Haw et al. 2022). Instead of contact matrices from (Prem et al. 2021), we use those from (Walker et al. 2020). Instead of work contacts from (Béraud et al. 2015), we use those from (Jarvis et al. 2023). (Haw et al. 2022) modelled closures using a combination of moving workers between sector compartments and a non-working compartment, and scaling of contacts. Here, we only use contacts to model closures, and do not move workers out of their compartments. An advantage of this is that workers within sectors retain their infection histories.

We construct contact matrix $M(x)$ as the sum of three matrices: $M^{\text{com}}(x)$ (community contacts), $M^{\text{CW}}(x)$ (community-to-worker contacts), and $M^{\text{WC}}(x)$ (worker-to-community contacts). We construct peacetime matrices ($x = \mathbf{1}$) beginning with a “target matrix,” which the three matrices should add up to, which is taken



Vaccine state transitions. S: susceptible. $S^{c_u}, u \in \{1, 2\}$: recently vaccinated but has not yet seroconverted (i.e. is not protected by most recent vaccination). R: recovered. j: stratum. v: initial vaccination status. u: final vaccination status.

from (Walker et al. 2020). By sampling relevant values, we decompose the whole matrix into its component parts. To incorporate closures, each matrix is transformed independently, before they are all added together again.

Matrix $M(\mathbf{1})$ is estimated using as a basis a contact matrix from (Walker et al. 2020). These are 16-by-16 matrices, $\tilde{M}$, for five-year age bands a up to age group 75+. We map the matrix to a four-by-four matrix $\hat{M}$ corresponding to the four age groups g used in the DAEDALUS model, using population sizes $\tilde{N}_a$:

```
\hat{M}_{gg'} = \frac{\sum_{a\in g}\tilde{N}_{a}\sum_{a'\in g'}\tilde{M}_{a,a'}}{\sum_{a\in g}\tilde{N}
```

and $\hat{N}_g$ to represent the population sizes of the DAEDALUS age groups,

```
\hat{N}_g=\sum_{a\in g}\tilde{N}_a.
```

We get to the matrix $M(\mathbf{1})$ by broadcasting the four-by-four matrix to the 49-by-49 one. Contacts from all groups j to working groups h depend on the age group of the group ('$g(j)$'), and the fraction of the age-population represented in group h, where N_h is the number of people in group h:

```
M_{j,h}(\textbf{1}) = \hat{M}_{g(j),g(h)}\frac{N_{h}}{\hat{N}_{g(h)}}
```

for j and h including all groups (working and non-working). Each group j contains people that belong to only one age group g. We refer to the age group of the people in group j as $g(j)$. Then $\hat{N}_{g(h)}$ is the number of people in the age group of group h, so '$\hat{N}_{g(h)} = N_h$' for age groups 0 to 4, 5 to 19 and 65+, and '$\hat{N}_{g(h)} = \sum_{h\in\{1,\ldots,m_S,m_S+3\}} N_h$' for age group 20 to 64.

In setting up a country, we sample values for $\tilde{M}$ (from which we get '$M(\mathbf{1})$'). At the same time, we sample the proportion of contacts that come from workplaces, and workplace-related contacts. From these, we get $M^{\text{CW}}(\mathbf{1})$, constructing the matrices and normalising.

Consumer-to-worker contacts (matrix M^{CW}) describe contacts experienced by workers from consumers per sector. Note that '$M^{\text{CW}}_{j,h}(\mathbf{1}) = 0$' for $j > m_S$. Matrix $M^{\text{WC}}(\mathbf{1})$ is the complement of matrix $M^{\text{CW}}(\mathbf{1})$, computed by multiplying through by population, transposing, and dividing again by population.

With $M(\mathbf{1})$, $M^{\text{CW}}(\mathbf{1})$ and $M^{\text{WC}}(\mathbf{1})$, we learn $M^{\text{com}}(\mathbf{1})$.

$M^{\text{com}}(\mathbf{1})$ is decomposed into its constituent parts, representing intra- and inter-household interactions (home), school interactions (sch) and hospitality interactions (CC):

```
M^{\text{com}}(\textbf{1})=M^{\text{home}} + M^{\text{sch}}(\textbf{1}) + M^{\text{CC}}(\textbf{1})
```

Values for $M^{\text{sch}}(\mathbf{1})$ come from sampled values representing the fractions of contacts that come from school. School contacts are estimated separately in two age groups (pre-school age: 0-–4 (Figure 1); school age: 5-–19 (Figure 2)): $M^{\text{sch}}(\mathbf{1})$ has entries of zero for groups not in school, and values for 0 to 4 year olds and 5 to 19 year olds.

Finally, $M^{\text{CC}}(\mathbf{1})$ is sampled as a fraction of $M^{\text{com}}(\mathbf{1}) - M^{\text{sch}}(\mathbf{1})$ (Figure 3), which leaves M^{home}.

3.4.1 Matrix M^{com}: community contacts

We construct $M^{\text{com}}(x)$ from its constituent parts, representing intra- and inter-household interactions (home), school interactions (sch) and hospitality interactions (CC):

```
M^{\text{com}}(x)=M^{\text{home}} + M^{\text{sch}}(x) + M^{\text{CC}}(x).
```

School contacts under x are the peacetime values scaled by the extent of closure. x_{ed} is the extent to which schools are open, so that the number of contacts per person scales superlinearly with school closure.

$$M^{\text{sch}}_{j,j}(x) = x_{\text{ed}}^2 M^{\text{sch}}_{j,j}(\mathbf{1}). \tag{12}$$

Matrix $M^{\text{CC}}(x)$ gives the contacts made in the hospitality sector:

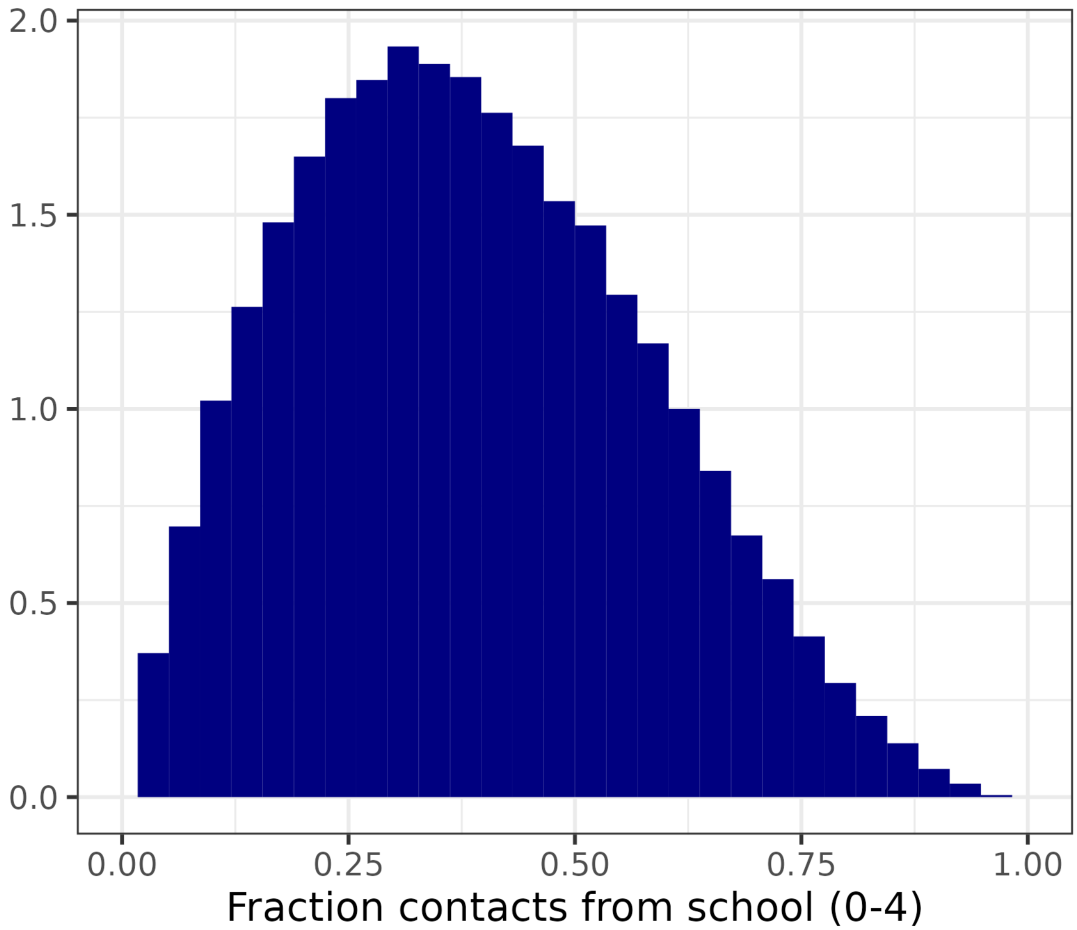


Figure 1: Fraction of contacts made at school for ages 0 to 4.

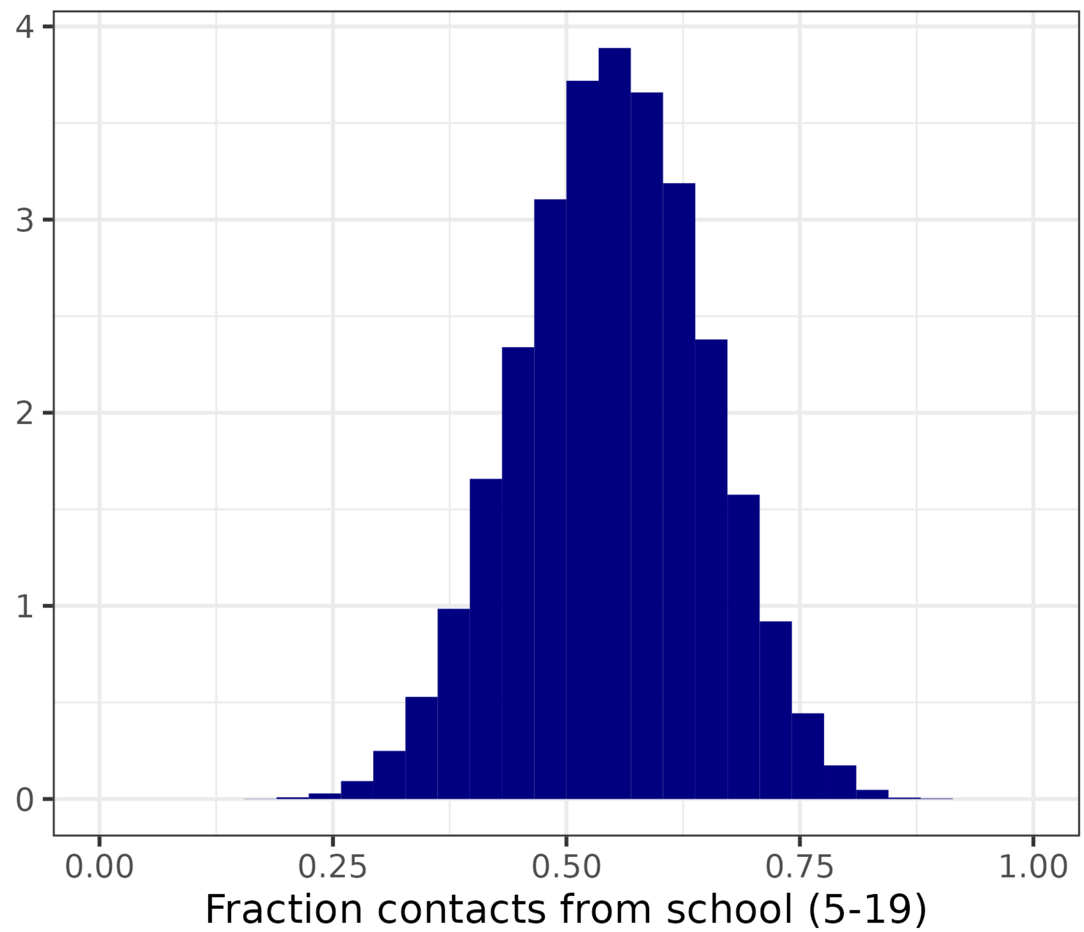


Figure 2: Fraction of contacts made at school for ages 0 to 4.

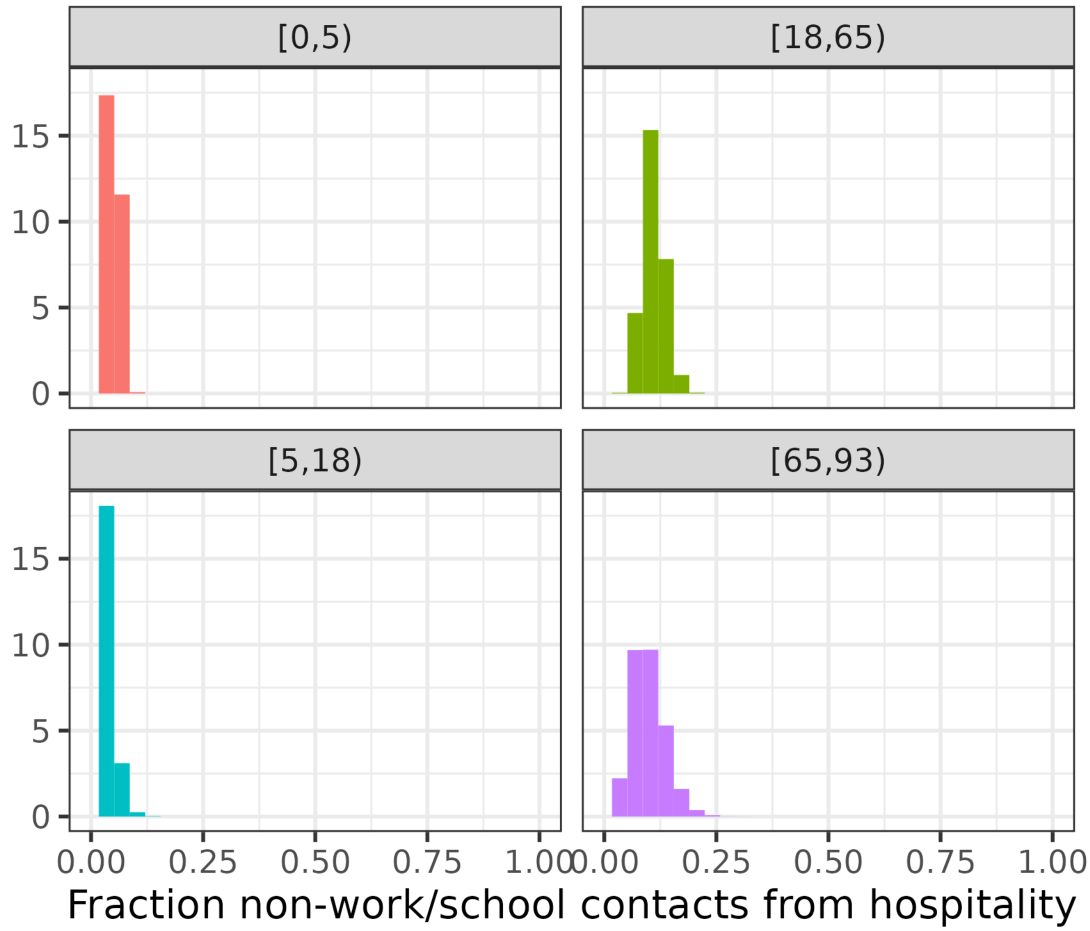


Figure 3: Fraction of non-school and non-work contacts made in hospitality settings, by age group.

$$M^{\mathrm{CC}}(x) = (p^{27})^2 M^{\mathrm{CC}}(\mathbf{1}) \tag{13}$$

The value p^{27} is the workforce-weighted average extent to which the hospitality sectors are open, so that the number of contacts per person scales superlinearly according to closure:

p^{27} = \frac{\sum_jx_{j}N_j}{\sum_jN_j}

where we sum over only the hospitality sectors.

3.4.2 Matrix $M^{\mathbf{CW}}$: Consumer-to-worker contacts

$$M^{\mathrm{CW}}_{j,h}(x) = (x_j(1-q_j))^2 M^{\mathrm{CW}}_{j,h}(\mathbf{1}), \tag{14}$$

for $h \in \{1, ..., m_J\}$.

Here, there is superlinear scaling of $M^{\mathrm{CW}}_{j,h}(\mathbf{1})$ with respect to working from home and with respect to sector closure, as both workers and members of the community are absent from the workplace as the sector moves online and becomes more closed.

3.5 Social distancing

We parametrise the effects of 'social distancing' in the model using Google's mobility data (Figure 4). These changes in mobility were consequences of both government mandates and individual's choices. As we cannot separate the two, we consider a range of possibilities, based on the range of mobility changes observed for a given level of stringency (Figure 5). In our model, the mandated economic configuration leads to a change in contacts. We associate the reduction in contacts, which translates as a relative reduction in transmission, with the reduction in mobility.

- We want to write mobility as a function of mandate and some epi outcome, e.g. deaths: $\rho(t) = (1-p^8)f(d(t), e(t)) + p^8$ where $\rho(t)$ is mobility, d is deaths per million, e is government mandate, and '$0 < p^8 < 1$' is the baseline.
- We want mobility to drop monotonically with both the mandate and the epi outcome: $\frac{df}{dy} < 0$, $\frac{df}{dg} < 0$.
- We want a maximum mobility of 1 when both the mandate and the epi outcome are 0: $f(0, 0) = 1$.
- We want mobility to approach p^8 when the mandate and the epi outcome become large: $\lim_{x\to 10^6, e\to 1} f(d, e) = 0$.
- We want to allow for the possibility of redundancy between the two variables: $f(0, 0)/f(0, e) > f(x, 0)/f(d, e)$ and $f(0, 0)/f(d, 0) > f(0, e)/f(d, e)$ for $d, e > 0$.

A simple model to achieve these criteria is:

$$f(d, e) = \frac{1}{1 + p^9 y + p^{10} e}$$

with $p^9, p^{10} > 0$.

However, we might also want a model that can be parametrised with a distribution whose uncertainty covers the whole range of possible eventualities. The equivalent model with compounded effects would be

$$f_1(d, e) = \frac{1}{1 + p^9 d}\frac{1}{1 + p^{10} e}.$$

The equivalent model with completely overlapping effects would be

$$f_2(d, e) = \frac{1}{1 + \max(p^9 d, p^{10} e)}.$$

Then we could include 'model uncertainty' via some parameter $\beta \sim \mathcal{U}(0, 1)$, defining

$$f(d, e) = (f_1(d, e))^{p^{11}} (f_2(d, e))^{(1-p^{11})}.$$

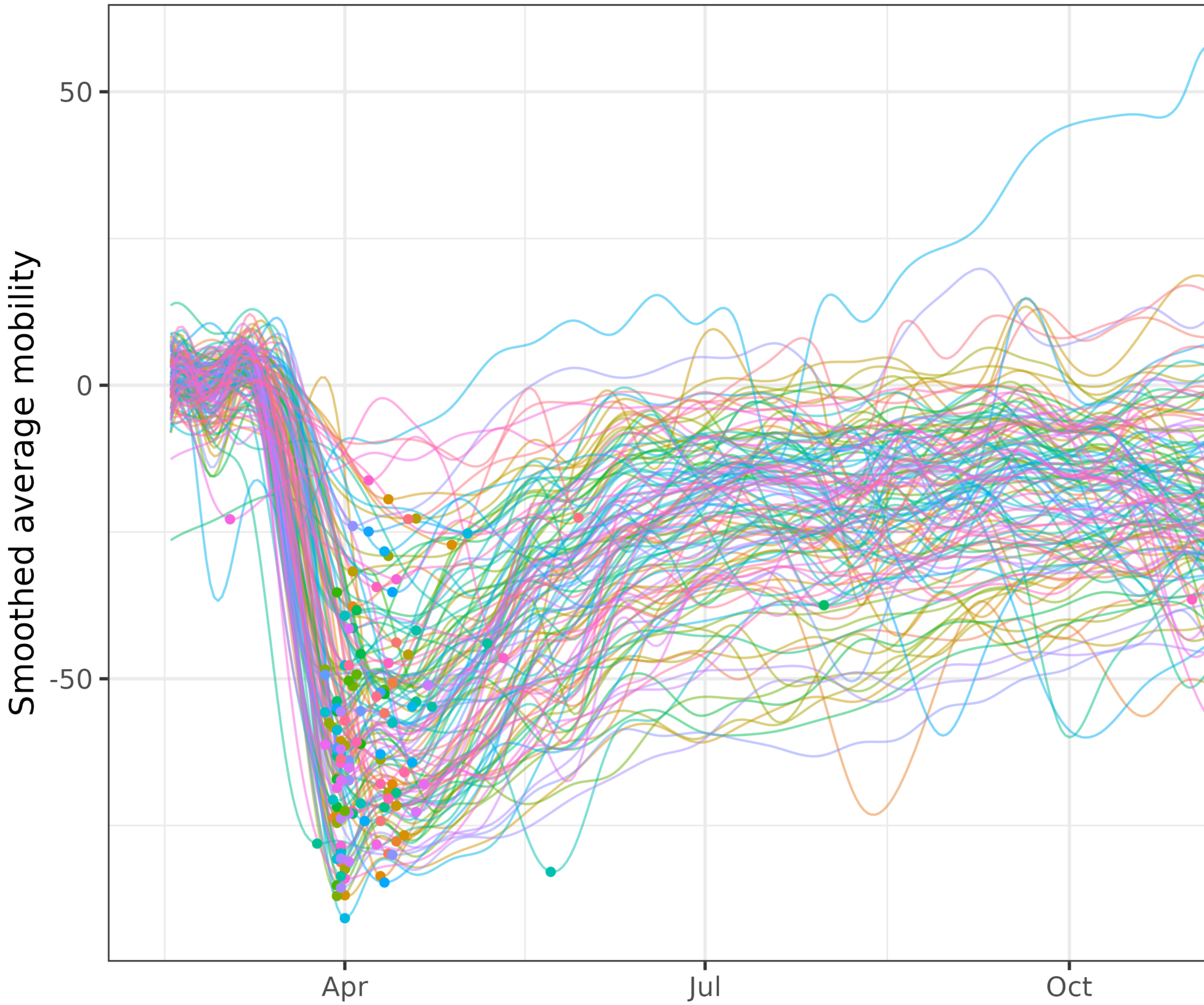


Figure 4: Mobility trajectories in 2020 for all countries, with points showing the point at which the largest drop was observed. Trajectories are averaged over "Retail and recreation", "Transit stations" and "Workplaces" and smoothed with a spline of 80 knots.

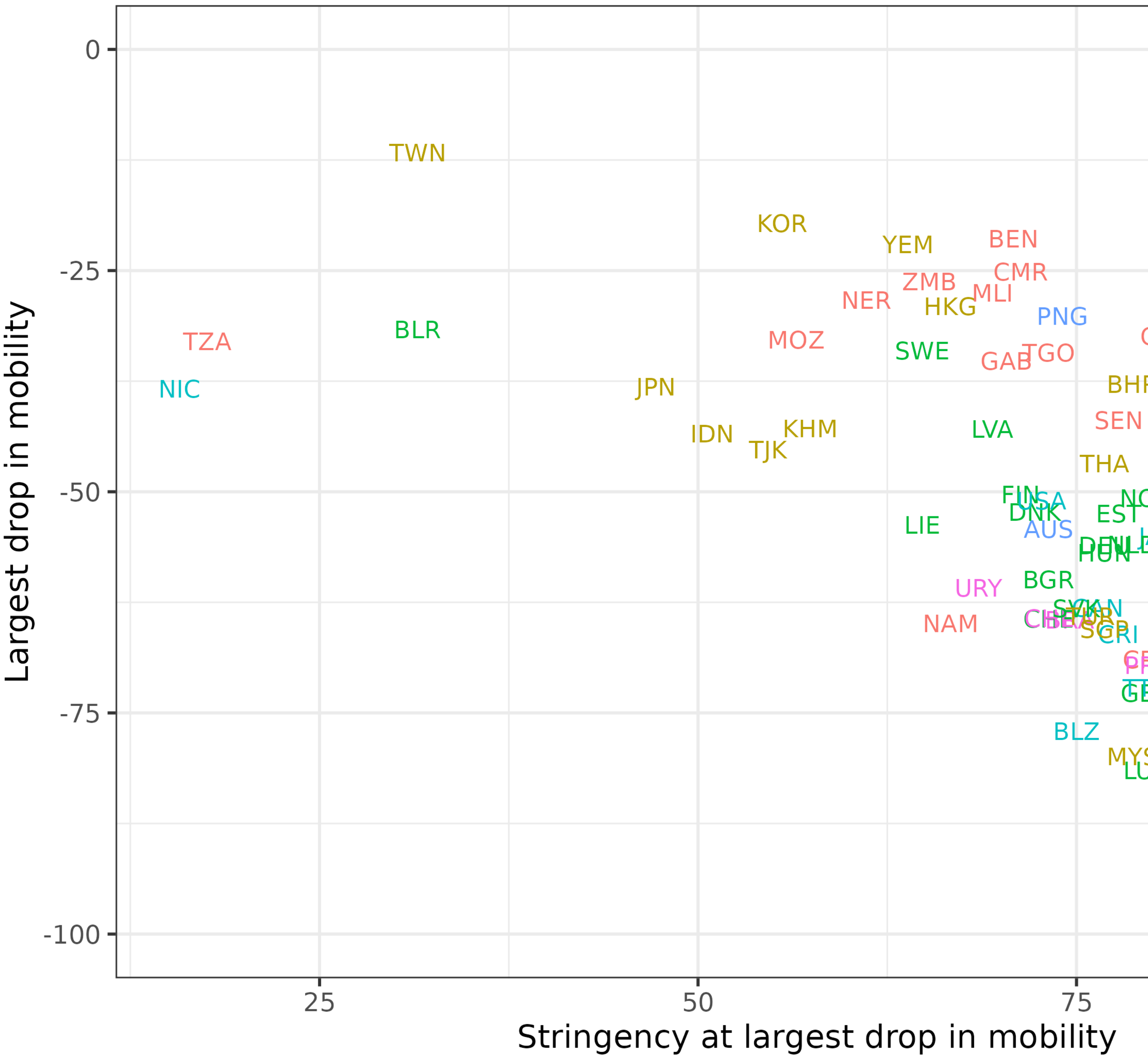


Figure 5: The largest drop in mobility plotted against the stringency on that date.

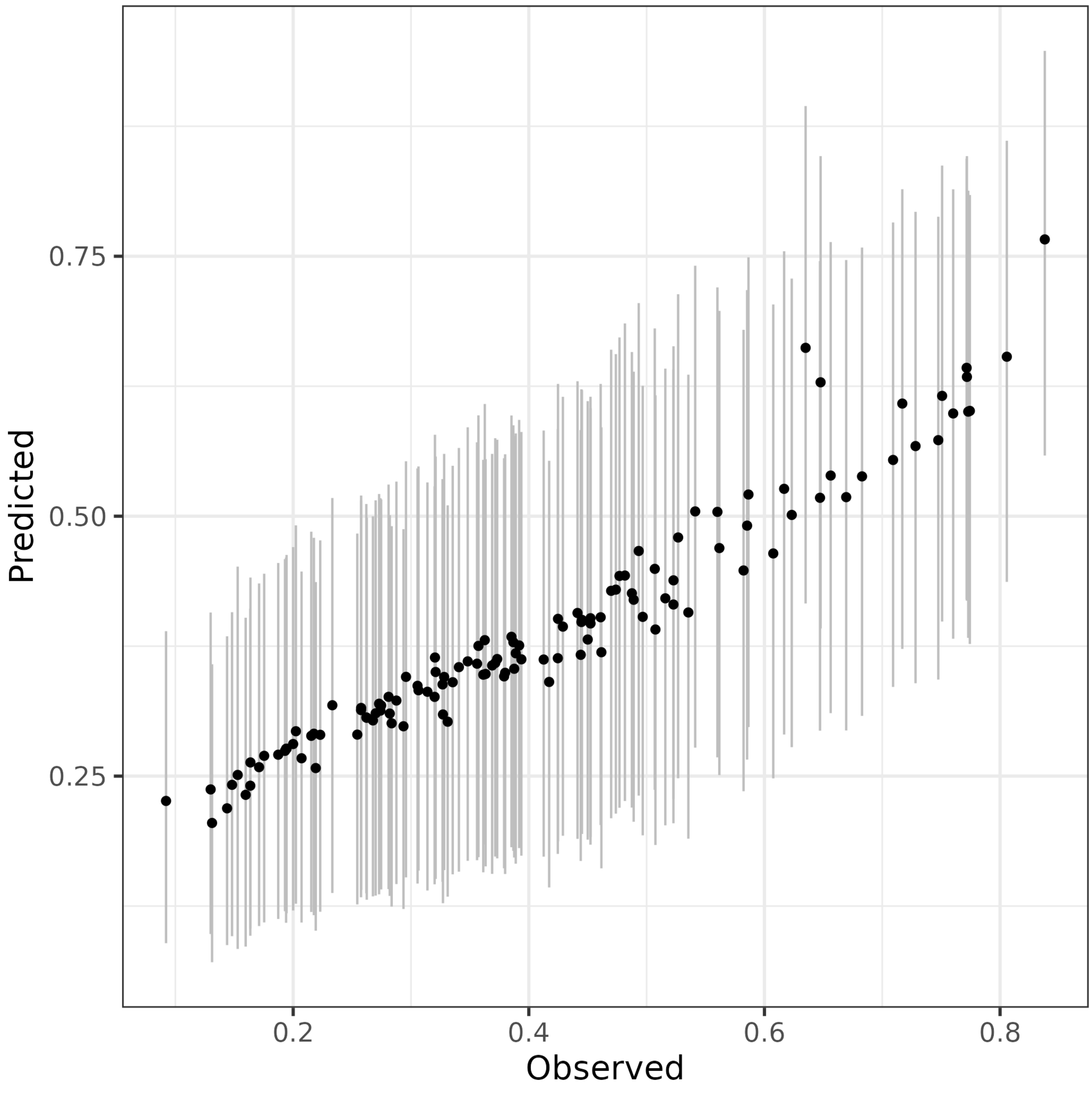


Figure 6: Fit of model to data.

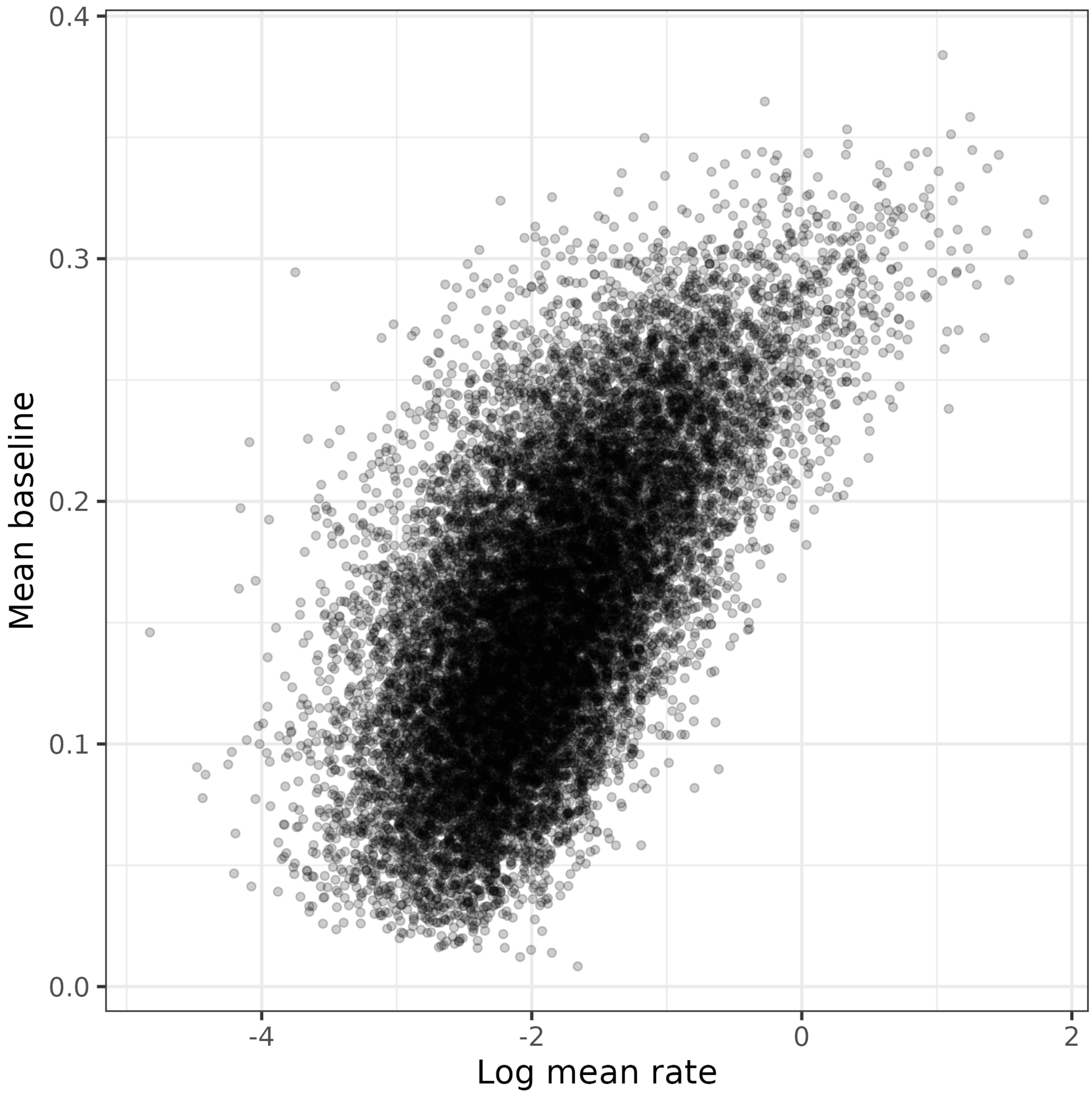


Figure 7: Posterior distribution for parameters p^9 and p^8.

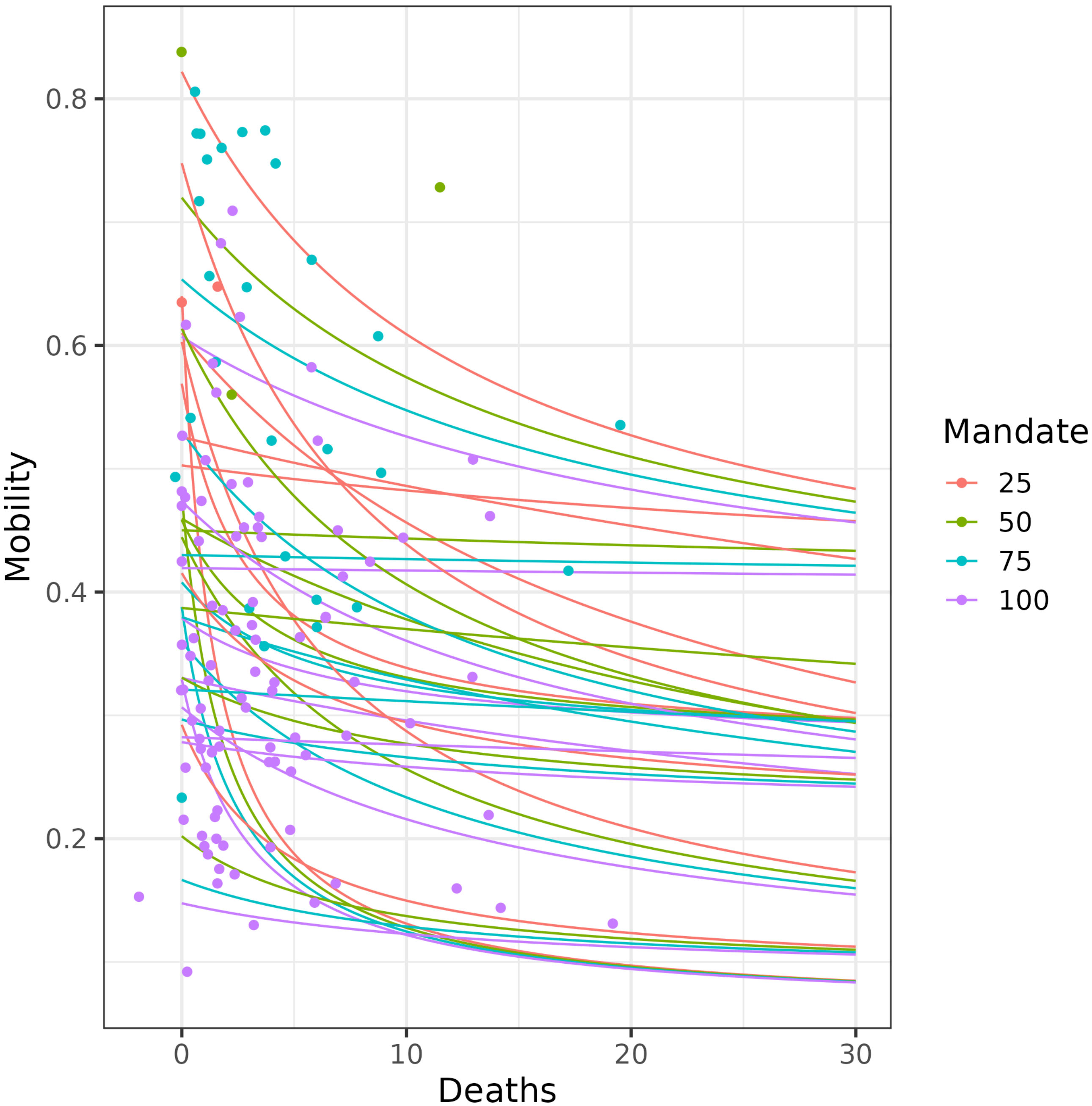


Figure 8: Sampled curves for four levels of mitigation. Data shown as points.

3.6 Self isolating

We assume that infectious people who know their status have a compliance $p^1 \sim (U)(0,1)$ with the instruction to self isolate, starting one day into their infectious period. We assume constant infectiousness over time and that a fraction p^{26} of the symptomatic infectiousness is presymptomatic. Then the amount of infectiousness averted of symptomatic people is $p^4 = p^1(1-p^{26})$, who isolate due to the onset of symptoms. The fraction of asymptomatic cases identified by testing is $p^2(t)$. We assume asymptomatic cases have the same probability to self isolate and that test results are returned after p^{17} days of infectiousness. Then the infectiousness that testing averts is $p^3(t) = p^1p^2(t)\min(0,(T^{I^a:R}-p^{17})/T^{I^a:R})$.

4 Econ model

4.1 Configurations

Table 3: Economic configurations used to implement strategies. Values are the openness of the sector expressed as a percentage. Elimination values are taken from Australia. Lockdown and Economic Closures values are taken from the UK. School Closures values are taken from Indonesia.

Sector	Heavy closures	Light closures	Heavy closures	Light closures	Heavy closures	Light closures
Agriculture, hunting, forestry	86	100	86	88	100	100
Fishing and aquaculture	86	100	86	88	100	100
Mining and quarrying, energy producing products	90	100	90	91	67	79
Mining and quarrying, non-energy producing products	90	100	90	91	100	100
Mining support service activities	90	100	90	91	100	100
Food products, beverages and tobacco	70	100	70	94	100	100
Textiles, textile products, leather and footwear	70	98	70	94	89	92
Wood and products of wood and cork	70	98	70	94	100	95
Paper products and printing	70	98	70	94	100	98
Coke and refined petroleum products	70	88	70	94	87	88
Chemical and chemical products	70	88	70	94	100	100
Pharmaceuticals, medicinal chemical and botanical products	70	88	70	94	100	100
Rubber and plastics products	70	88	70	94	87	100
Other non-metallic mineral products	70	88	70	94	92	89

Sector	Heavy closures	Light closures	Heavy closures	Light closures	Heavy closures	Light closures
Basic metals	70	100	70	94	100	100
Fabricated metal products	70	100	70	94	90	100
Computer, electronic and optical equipment	70	100	70	94	90	100
Electrical equipment	70	100	70	94	90	100
Machinery and equipment, nec	70	100	70	94	89	95
Motor vehicles, trailers and semi-trailers	70	100	70	94	66	82
Other transport equipment	70	100	70	94	66	82
Manufacturing nec; repair and installation of machinery and equipment	70	98	70	94	98	100
Electricity, gas, steam and air conditioning supply	89	97	89	100	94	94
Water supply; sewerage, waste management and remediation activities	92	97	92	98	100	100
Construction	56	94	56	92	95	95
Wholesale and retail trade; repair of motor vehicles	64	100	64	100	92	97
Land transport and transport via pipelines	63	100	63	82	83	100
Water transport	63	100	63	82	81	98
Air transport	63	18	63	82	16	42
Warehousing and support activities for transportation	63	91	63	82	64	91
Postal and courier activities	63	91	63	82	64	91
Accommodation and food service activities	10	92	10	85	77	91
Publishing, audiovisual and broadcasting activities	88	100	88	91	100	100
Telecommunications	88	100	88	91	100	100
IT and other information services	88	100	88	91	100	100
Financial and insurance activities	94	100	94	96	100	100
Real estate activities	98	100	98	98	100	100

Sector	Heavy closures	Light closures	Heavy closures	Light closures	Heavy closures	Light closures
Professional, scientific and technical activities	85	100	85	92	90	95
Administrative and support services	66	90	66	80	90	95
Public administration and defence; compulsory social security	100	100	100	100	96	100
Education	10	100	10	100	10	10
Human health and social work activities	75	100	75	92	100	100
Arts, entertainment and recreation	55	94	55	71	90	96
Other service activities	54	94	54	83	90	96
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	49	94	49	53	90	96

4.2 Impact of tourism

4.2.1 Food and accommodation services sector

As there is no “tourism” sector in the 45-sector classification we are using, to model the impact of changes to tourism, we identify the “Food and accommodation services” sector with tourism. This is imperfect. The correlation of their % contributions to GDP is 0.64 and the order of magnitude is similar (1 to 7% vs 2 to 10% of GDP). The other two sectors considered (Air transport and Arts, entertainment and recreation) have little correlation with tourism in terms of % of GDP. (See Figure 9.)

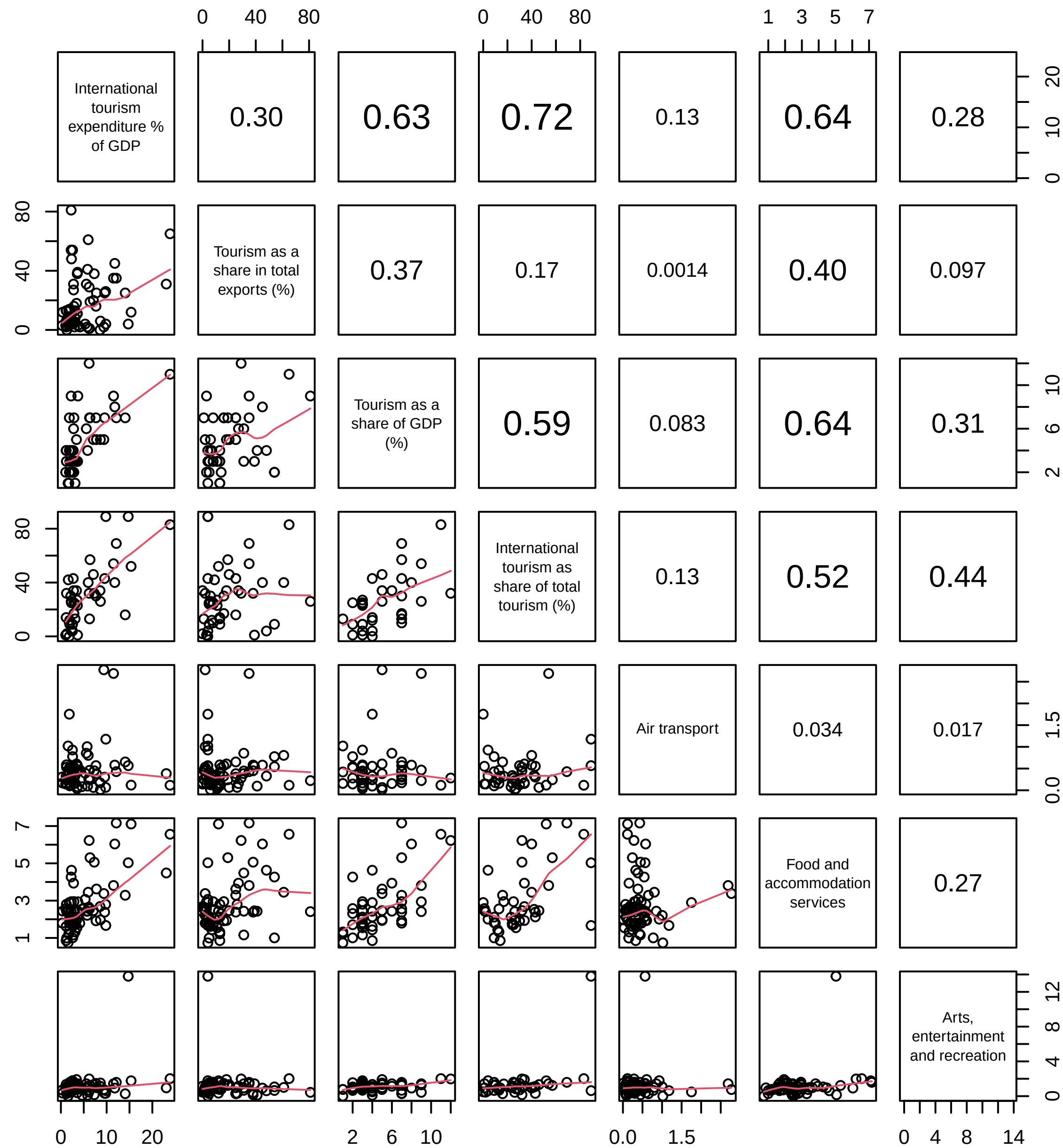


Figure 9: Correlations between tourism-related data. First: https://www.unwto.org/tourism-statistics/key-tourism-statistics. Second to fourth: https://www.unwto.org/tourism-data/international-tourism-and-covid-19. Fifth to seventh: OECD.

4.2.2 Sector shrinkage as a result of the pandemic

For many countries, tourism was reduced in the COVID-19 pandemic not because of domestic mandates but because of reduced international travel. Therefore, the fraction of tourism that comes from abroad is a factor that can determine the impact of a pandemic on a country's GDP potentially independently of what happens within the country. (A useful model extension would be to include some dependence on country factors, e.g. case numbers.)

We model mitigation via business closures, which are mandated by sector. We represent openness with values x which range from 0 to 1, 1 representing maximum openness. To capture the impact of reduced international travel, we set the maximum openness of the food and accommodation services sector to be limited by international tourism as:

```
x = \min\{\hat{x}, 1+ b(c-1)\}
```

where '$\hat{x}$' is the openness of the sector according to the schedule (i.e. the mitigation strategy), b is the proportion of tourism that is international, and c is the fraction international tourism reduces to as a consequence of the pandemic. I.e. the tourism remaining is the domestic $(1-b)$ plus that that comes in from abroad (bc).

Therefore, the contribution of the GVA of the food and accommodation services sector is limited either by the pandemic, or by the mitigation measures - whichever is lower.

4.2.3 Loss of international tourists

We model the distribution of c using data from 2020 (Figure 10, bottom-right plot). We fit to it a log-normal distribution, and find mean value -1.39 and standard deviation 0.39 (Figure 11). We use these values as inputs for all country models.

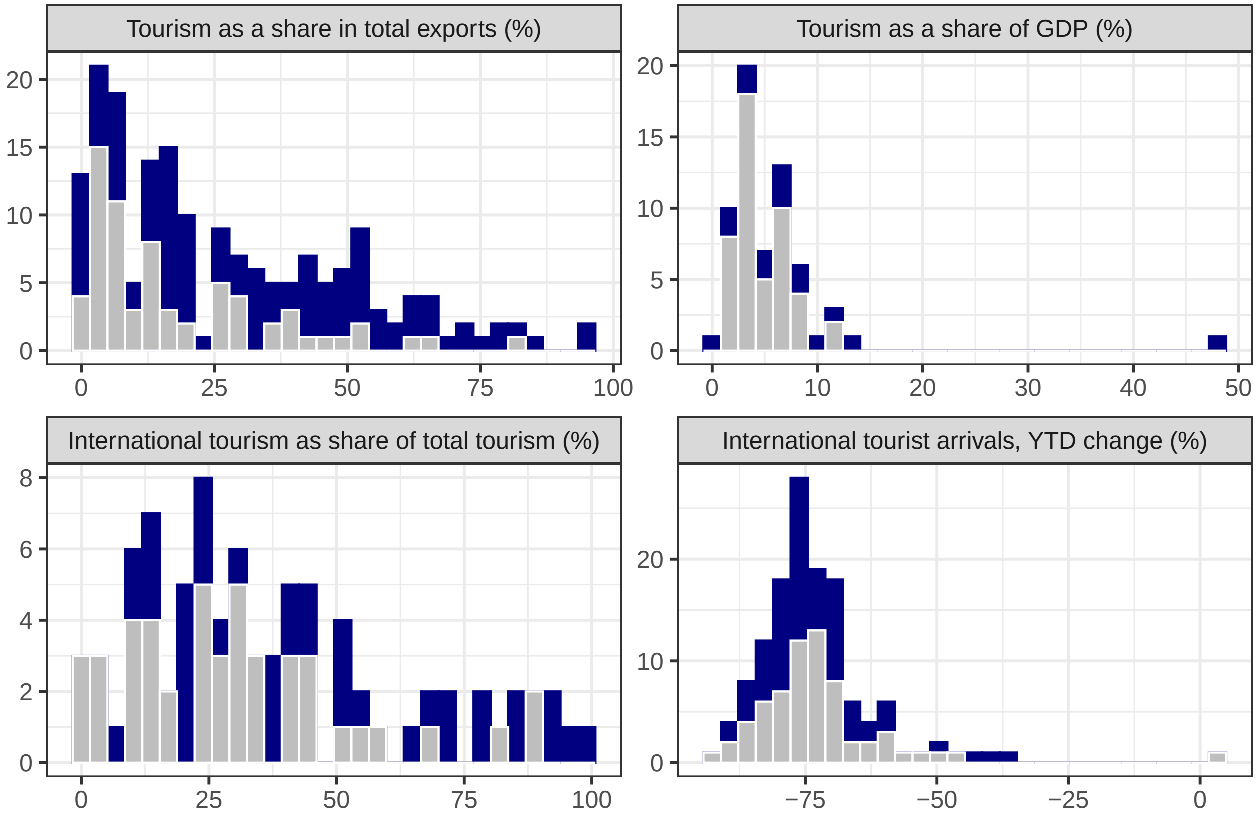


Figure 10: Distributions of tourism-related data from https://www.unwto.org/tourism-data/international-tourism-and-covid-19. In grey are the subset of countries for which we have GVA data by sector.

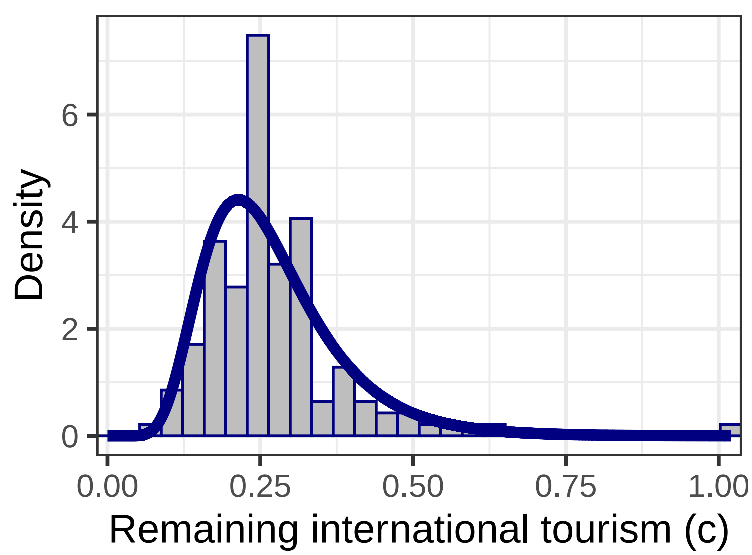


Figure 11: Fit of log-normal distribution to loss-of-tourism data.

4.2.4 Dependence on international tourism

We model b as a function of the share of GDP that comes from the sector. Note that the data we have for this are biased towards high-income countries.

We write

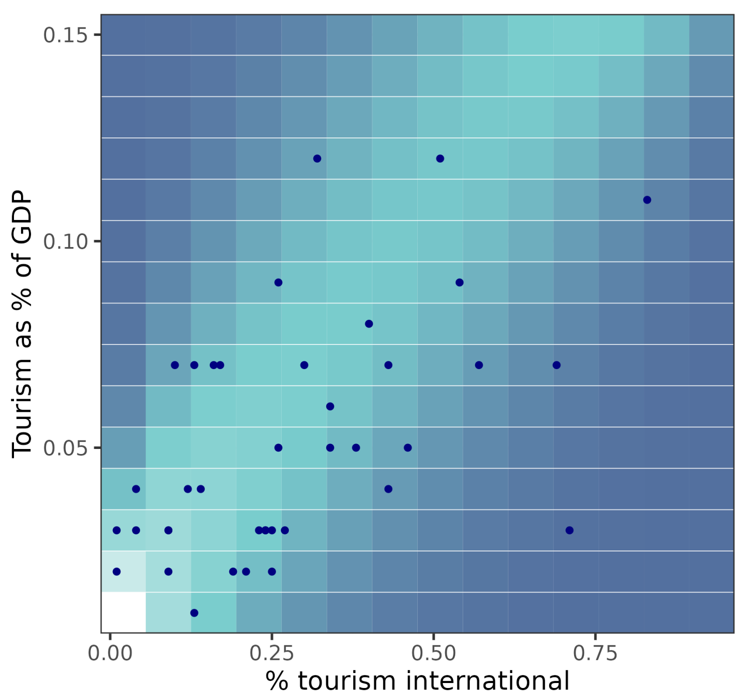
$$b \sim \text{Beta}(\alpha(z), \beta(z))$$

where z is the fraction of GDP coming from the Food and accommodation sector. We learn three parameters p^5, p^6 and p^7 to best fit the relationship between z and b in countries we have observations for:

$$p^5 = \alpha(z) + \beta(z)$$

$$p^6 z + p^7 = \frac{\alpha(z)}{\alpha(z) + \beta(z)}$$

Here, p^5 controls the variance of the distribution and p^6 and p^7 the linear relationship between z and b. Using an optimisation routine in R we find $p^5 = 5.93$, $p^6 = 3.66$ and $p^7 = 0.099$. Results are shown in Figure figno:3. We use these values as inputs for all country models.



Predicting the percentage of tourism that comes from abroad as a function of the size of the sector. Each row represents a beta distribution whose mean is determined by the size of the sector (z). Blue points show the data we have available (grey bars in Figure 10).

4.3 Remote working

For each sector in each country, we have the 90% interval for the proportion of people who can work from home from (Gottlieb et al. 2021). We assume that the value we sample within the range is related to internet infrastructure, so that a low value in one sector implies low values in all sectors. We:

- take the subset of countries in the income group (LLMIC / UMIC / HIC);
- take the minimum of the lower bounds by sector (5%);
- take the maximum of the upper bounds by sector (95%);
- sample from a uniform distribution between these bounds, taking the same quantile for each sector.

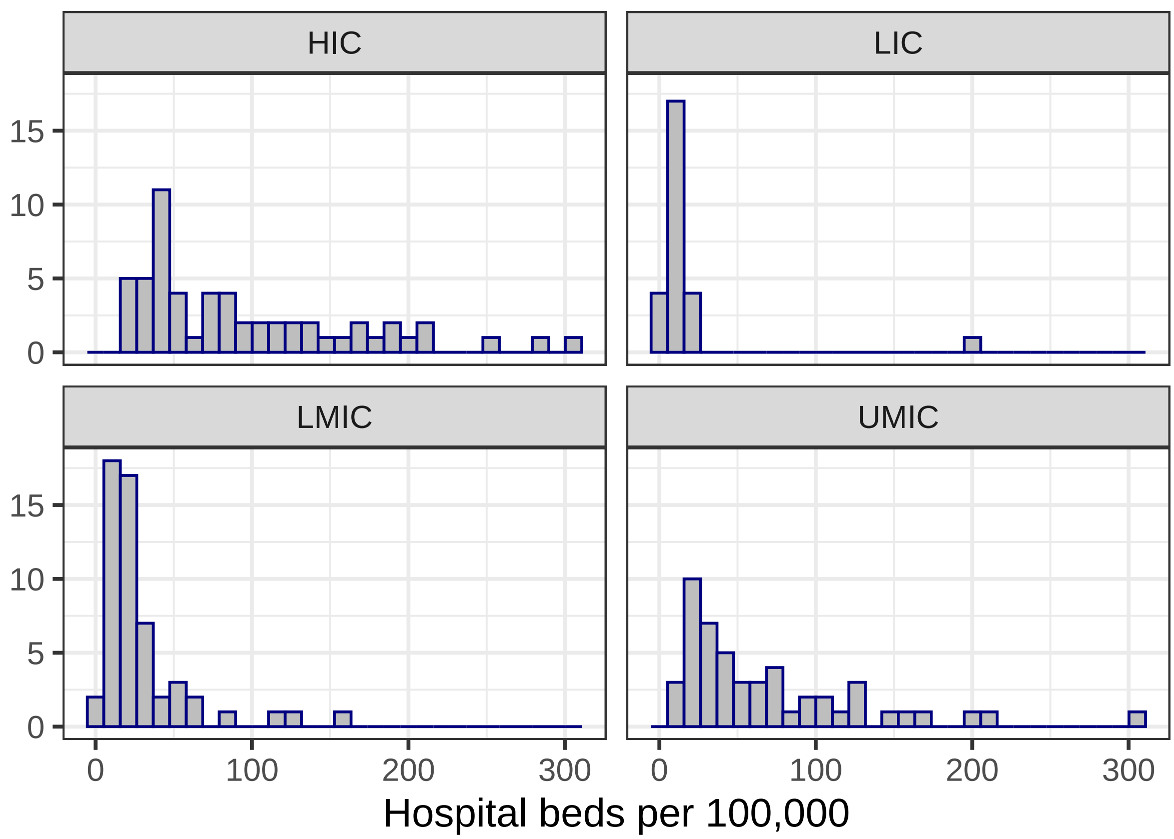
5 Parametric distributions

Table 4: Parameter distributions.

Parameter	Income group	Distribution	Parameter 1	Parameter 2
internet coverage	LLMIC	Beta	1.78	3.11
internet coverage	UMIC	Beta	14.32	6.44
internet coverage	HIC	Beta	9.57	1.39
remaining international tourism	all	Log normal	-1.39	0.39
Labour share of GVA	LLMIC	Beta	5.09	4.51
Labour share of GVA	UMIC	Beta	7.06	8.18
Labour share of GVA	HIC	Beta	7.97	6.87
Hospital capacity	LLMIC	Gamma	1.3	20.2
Hospital capacity	UMIC	Gamma	1.73	40.73
Hospital capacity	HIC	Gamma	2.05	46.57
Public transport fraction	LLMIC	Beta	4.88	3.65
Public transport fraction	UMIC	Beta	2.06	2.59
Public transport fraction	HIC	Beta	3.23	11.65
tourism P1+P2	all	NA	6.73	NA
Tourism to international	all	NA	4.14	0.05
pupil teacher ratio	LLMIC	Gamma	9.15	0.32
pupil teacher ratio	UMIC	Gamma	13.29	0.82
pupil teacher ratio	HIC	Gamma	14.53	1.17
school1 fraction	all	Beta	2.14	3.38
school2 fraction	all	Beta	13.23	10.85
work fraction	all	Beta	11.11	13.82
hospitality1 fraction	all	Beta	21.08	381.2
hospitality2 fraction	all	Beta	3.71	88.67
hospitality3 fraction	all	Beta	19.44	149.4
hospitality4 fraction	all	Beta	7.69	62.33
hospitality age1	all	NA	0.63	0.09
hospitality age2	all	NA	0.57	0.06
hospitality age3	all	NA	0.85	0.08
hospitality age4	all	NA	0.56	0.41

5.1 Hospital capacity

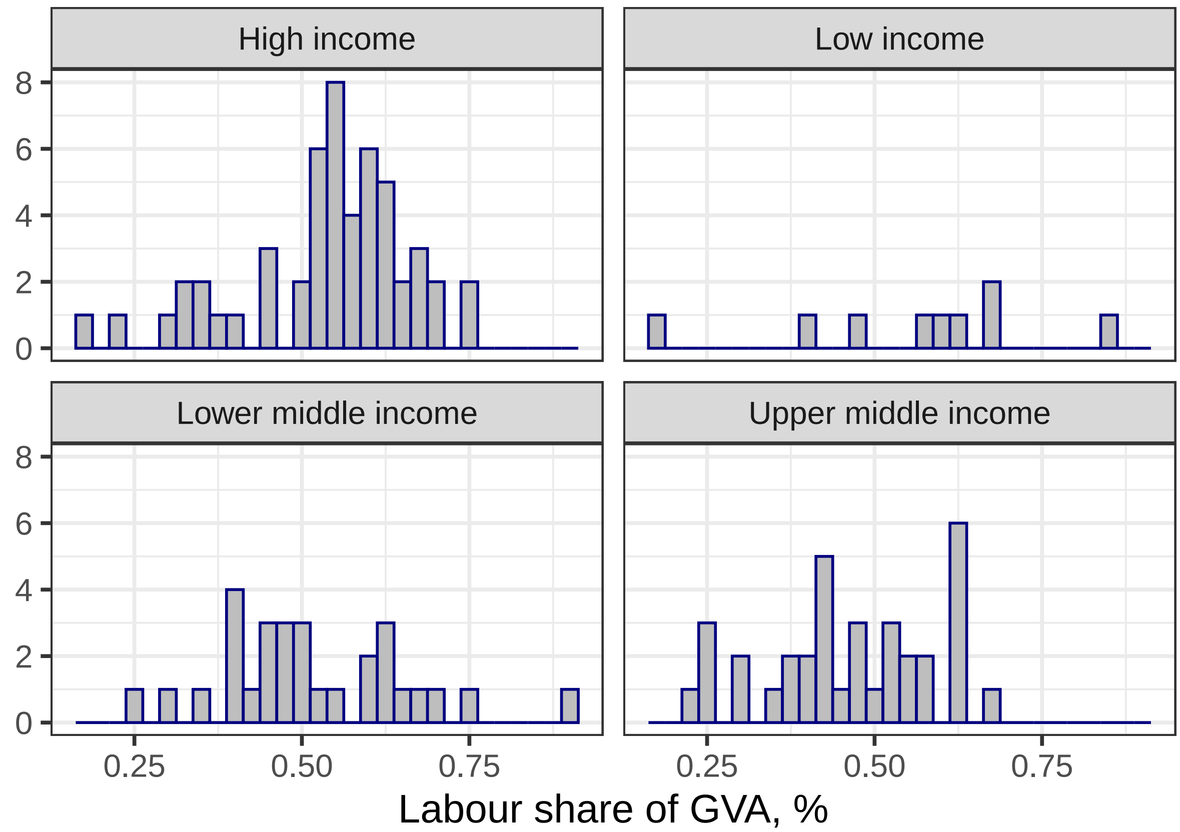
We model these values with gamma distributions. For LLMICs, we have parameters 1.3 and 0.05. For UMICs, we have parameters 1.73 and 0.02. For HICs, we have parameters 2.05 and 0.02. (Data sources: World Bank (beds); OECD, WHO euro (bed occupancy rates).)



Hospital capacity: available beds minus usual occupancy.

5.2 Labour share of GVA

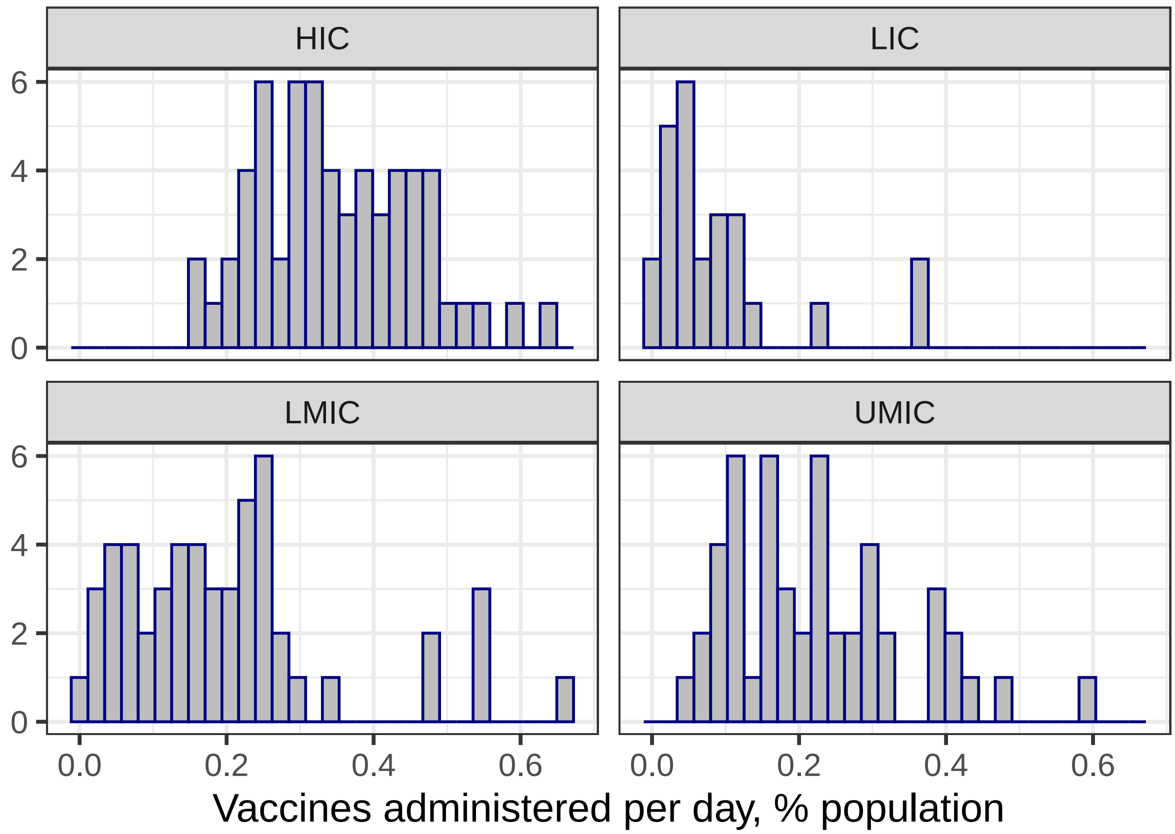
We estimate the average annual income per working-age adult as the total GVA multiplied by the fraction of GVA that goes to labour divided by the number of working-age adults. For the fraction of GVA that goes to labour we use PWT estimates from 2011 (Figure figno:5).



Fraction of GVA that goes to labour (PWT, 2011).

We model these values with Beta distributions. For LLMICs, we have parameters 5.09 and 4.51. For UMICs, we have parameters 7.06 and 8.18. For HICs, we have parameters 7.97 and 6.87.

5.3 Vaccine administration



Vaccines administered per day, on average, in each country as a percent of population. Data source: fully vaccinated people from OWID (2022).

6 Notation

In general in this notation, subscripts are indices, and superscripts are never indices but instead define new labels. In particular, note that numerical superscripts are attached to letters k for rates and p for parameters. Where a power is applied to one of these letters, the letter will be enclosed in parentheses for clarity.

Table 5: Capital letters

Letter	Script	Subscript	Superscript
A			
B			
C	consumption		community (contacts)
D	COMPARTMENT: Died		related to death state
E	COMPARTMENT: Exposed		related to exposed state
F			
G			
GDP	GDP		
H	COMPARTMENT: Hospitalised		related to hospitalised state
$H_{\max}$	hospital capacity		
I	Infectious		
I^a	COMPARTMENT: Infectious asymptomatic		related to asymptomatic state
I^s	COMPARTMENT: Infectious symptomatic		related to symptomatic state
J		MAX: strata	
K	Loss (cost calculation)		
L	number of people by sector (workforce in place)		
M^{com}	CONTACTS: community		
M^{home}	CONTACTS: community, home		
M^{CC}	CONTACTS: community, customers		
M^{trav}	CONTACTS: community, public transport		
M^{sch}	CONTACTS: community, school		
M^{WW}	CONTACTS: work, workers		
M^{WC}	CONTACTS: work, worker to customer		
M^{CW}	CONTACTS: work, customer to worker		
M	CONTACTS: total		
$\tilde{M}$	Total contacts by five-year age bands		
$\hat{M}$	Total contacts by DAEDALUS age groups		
N	number of people by stratum		
$\tilde{N}$	Number of people by five-year age bands		
$\hat{N}$	Number of people in DAEDALUS age groups		
O	–		
P	(probability)		
Q			
R	COMPARTMENT: Recovered		related to recovered state

Letter	Script	Subscript	Superscript
R_0	Basic reproduction number		
R_t	Effective reproduction number		
S	COMPARTMENT: Susceptible	MAX: sectors	
S^c	COMPARTMENT: Susceptible seroconverting		
T^c	duration from vaccination to protection		
T^H	duration in hospital		
$T^{H:D}$	duration in hospital given death		
$T^{H:R}$	duration in hospital given recovery		
T^{I^a}	duration asymptomatic		
T^{I^s}	duration symptomatic		
$T^{I^s:H}$	duration symptomatic given hospitalised		
$T^{I^s:R}$	duration symptomatic given recovery		
$T^{E:I}$	latent period		
U			
V		MAX: vaccines	
W			worker (contacts)
X			
Y	GDP	MAX: years	
Y_0	max GDP		
Z			

Table 6: Lower-case letters

Letter	Script	Subscript	Superscript
a		INDEX: age index, five-year age bands	asymptomatic
b	proportion of tourism that is international		
c	fraction international tourism reduces to as a consequence of the pandemic		seroconverting
d	deaths per million		
e	government mandate		
ed		education sector (j index)	
f	functions: sd, hospitalisation		
g		INDEX: age index, DAEDALUS age groups	
h		INDEX: dummy index	
i			self isolating
j		INDEX: stratum index	
k	state transition rates		
l	life expectancy		
m_J	number of strata		
m_S	number of sectors		
m_V	number of vaccines		
m_Y	number of years in work		

Letter	Script	Subscript	Superscript
n			
o	–		
p	parameters		
q	proportions working from home		
r	discount rate		
s			symptomatic
school		student strata (j index)	
t	time (day)		
u	dummy variable	INDEX: dummy index	
v		INDEX: vaccination status	
w			
x	sector openness		
y	GVA	INDEX: year	
z	fraction of GDP coming from the Food and accommodation sector		

Table 7: Greek letters

Letter	Definition
α	
β	transmission rate
γ	
δ	
ϵ	ratio transmission from asymptomatic
ζ	
η	vaccine effects
θ	
ι	
κ	
λ	
μ	
ν	growth rate
o	–
π	
ρ	transmission modifier
σ	
τ	max time
υ	–
ϕ	
χ	
ψ	
ω	

Table 8: Rates

Letter	Definition
k^1	rate of infection
k^2	rate of onset of asymptomatic infection
k^3	rate of recovery from asymptomatic infection

Letter	Definition
k^4	rate of onset of symptomatic infection
k^5	rate of recovery from symptomatic infection
k^6	rate of hospitalisation
k^7	rate of recovery from hospitalisation
k^8	rate of death from hospitalisation
k^9	rate of vaccine seroconversion
k^{10}	vaccination rate
k^{11}	
k^{12}	rate of infection
k^{13}	
k^{14}	
k^{15}	
k^{16}	
k^{17}	
k^{18}	
k^{19}	rate of infection

Table 9: Parameters

Letter	Definition
p^{I^S}	probability to be symptomatic
$\tilde{p}^H$	Basic probability to be hospitalised
p^H	Adjusted probability to be hospitalised
$\tilde{p}^D$	Basic probability to die
p^D	Adjusted probability to die
p^1	Compliance with the instruction to self isolate
p^2	fraction of cases identified by testing
p^3	proportion of asymptomatic infectiousness averted due to self isolating
p^4	proportion of symptomatic infectiousness averted due to self isolating
p^5	tourism parameter
p^6	tourism parameter
p^7	tourism parameter
p^8	minimum mobility
p^9	deaths coefficient for mobility
p^{10}	mandate coefficient for mobility
p^{11}	mobility mixing parameter
p^{12}	present value of lost earnings
p^{13}	mean annual earnings
p^{14}	effective amount of education lost per student
p^{15}	rate of return for one year of education
p^{16}	relative effectiveness of remote education
p^{17}	number of days from onset of infectiousness to self isolation
p^{18}	number of asymptomatic days spent in self isolation per day of infectiousness
p^{19}	number of symptomatic days spent in self isolation per day of infectiousness
p^{20}	number of days from onset of symptoms to self isolation

Letter	Definition
p^{21}	public transport mode share
p^{22}	work absence, asymptomatic (cost calculation)
p^{23}	work absence, symptomatic (cost calculation)
p^{24}	school absence, asymptomatic (cost calculation)
p^{25}	school absence, symptomatic (cost calculation)
p^{26}	fraction of symptomatic infectiousness that is presymptomatic
p^{27}	hospitality openness

Ananthapavan, Jaithri, Marj Moodie, Andrew J. Milat, and Rob Carter. 2021. "Systematic review to update 'value of a statistical life' estimates for Australia." *International Journal of Environmental Research and Public Health* 18 (11). https://doi.org/10.3390/ijerph18116168.

Betthäuser, Bastian A, Anders M Bach-Mortensen, and Per Engzell. 2023. "A systematic review and meta-analysis of the evidence on learning during the COVID-19 pandemic." *Nature Human Behaviour* 7 (March). https://doi.org/10.1038/s41562-022-01506-4.

Béraud, Guillaume, Sabine Kazmercziak, Philippe Beutels, Daniel Levy-Bruhl, Xavier Lenne, Nathalie Mielcarek, Yazdan Yazdanpanah, Pierre Yves Boëlle, Niel Hens, and Benoit Dervaux. 2015. "The French connection: The first large population-based contact survey in France relevant for the spread of infectious diseases." *PLoS ONE* 10 (7): 1–22. https://doi.org/10.1371/journal.pone.0133203.

Cutler, David M., and Lawrence H. Summers. 2020. "The COVID-19 pandemic and the $16 trillion virus." *JAMA* 324 (15). https://doi.org/10.1257/pol.20170046.

Global Burden of Disease Collaborative Network. 2021. "Global Burden of Disease Study 2019 (GBD 2019) Reference Life Table." Seattle, United States of America: Institute for Health Metrics; Evaluation (IHME).

Gottlieb, Charles, Jan Grobovšek, Markus Poschke, and Fernando Saltiel. 2021. "Working from home in developing countries." *European Economic Review* 133: 103679. https://doi.org/10.1016/j.euroecorev.2021.103679.

Haw, David, Giovanni Forchini, Patrick Doohan, Paula Christen, Matteo Pianella, Rob Johnson, Sumali Bajaj, et al. 2022. "Optimizing social and economic activity while containing SARS-CoV-2 transmission using DAEDALUS." *Nature Computational Science* 2: 223–33. https://doi.org/10.25561/83928.

Jarvis, Christopher I, Pietro Coletti, Jantien A Backer, James D Munday, Christel Faes, Philippe Beutels, Christian L. Althaus, et al. 2023. "Social contact patterns following the COVID-19 pandemic: a snapshot of post-pandemic behaviour from the CoMix study." *MedRxiv*.

Moscoviz, Laura, and David K Evans. 2022. "Learning loss and student dropouts during the COVID-19 pandemic: A review of the evidence two years after schools shut down." Washington, DC: Center for Global Development.

Patrinos, Harry Anthony. 2023. "The longer students were out of school, the less they learned." *Journal of School Choice* 17 (2): 161–75. https://doi.org/10.1080/15582159.2023.2210941.

Prem, Kiesha, Kevin van Zandvoort, Petra Klepac, Rosalind M. Eggo, Nicholas G. Davies, Alex R. Cook, and Mark Jit. 2021. "Projecting contact matrices in 177 geographical regions: An update and comparison with empirical data for the COVID-19 era." *PLoS Computational Biology* 17 (7). https://doi.org/10.1371/journal.pcbi.1009098.

Psacharopoulos, George, Victoria; Collis, and Patrinos. 2021. "The COVID-19 Cost of School Closures in Earnings and Income across the World." *Comparative Education Review* 65 (2).

Robinson, Lisa A., Ryan Sullivan, and Jason F. Shogren. 2021. "Do the benefits of COVID-19 policies exceed the costs? Exploring uncertainties in the age–VSL relationship." *Risk Analysis* 41 (5): 761–70. https://doi.org/10.1111/risa.13561.

Walker, Patrick G. T., Charles Whittaker, Oliver J. Watson, Marc Baguelin, Peter Winskill, Arran Hamlet, Bimandra A. Djafaara, et al. 2020. "The impact of COVID-19 and strategies for mitigation and suppression in low- and middle-income countries." *Science* 369 (6502): 413–22. https://doi.org/10.1126/science.abc0035.