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Age-dependent effects in the transmission and control of COVID-19 epidemics

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Supplementary Information

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Parameter	Description	Applies in fits	Value	Reference
d_E	Incubation period (E to I_P and E to I_S; days)	All	$\sim gamma(\mu = 3.0, k = 4)$	Derived from refs. 1,2
d_P	Duration of preclinical infectiousness (days)	All	$\sim gamma(\mu = 2.1, k = 4)$	Derived from ref. 2
d_C	Duration of clinical infectiousness (I_C to R; days)	All	$\sim gamma(\mu = 2.9, k = 4)$	Ref. 3
d_S	Duration of subclinical infectiousness (days)	All	$\sim gamma(\mu = 5, k = 4)$	Assumed
u_i	Susceptibility for age group *i*	Varies by age in Wuhan hypothesis 2, otherwise all ages equal	Estimated	
y_i	Probability of clinical infection for age group *i*	Varies by age in Wuhan hypothesis 3, otherwise all ages equal	Either fixed (50%) or estimated	Ref. 4
f	Relative infectiousness of subclinical cases	All	50% (0% and 100% in sensitivity analysis)	Assumed
c_{ij}	Number of age-*j* individuals contacted by an age-*i* individual per day	All	Country-specific contact matrix.	China[5]; UK[6]; Zimbabwe[7]
N_i	Number of age-*i* individuals	All	Demographic data	Ref. 8
Δt	Time step for discrete-time simulation	All	0.25 days	
A_{min}, A_{max}	Age range of seed cases	Wuhan	Estimated	
t_{seed}	Day upon which seeding of infections starts	All	Estimated	
q_H	Relative change in non-school contacts during lunar new year holidays	Wuhan	Estimated	
q_L	Relative change in non-school contacts following large-scale restrictions	Wuhan, South Korea, Shanghai, Beijing, Italy	Estimated	
t_L	Day upon which large-scale restrictions start	Wuhan, South Korea, Shanghai, Beijing, Italy	Fixed to January 23 for Wuhan; estimated for other settings	

Supplementary Table 1. Model parameters.

Parameter	Description	Prior
u_i	Susceptibility to infection upon contact with an infectious person	Non-age-varying: $u_i \sim normal(\mu = 0.1, \sigma = 0.025, min = 0)$ Age-varying: young, middle, and old age fit as $a_y \sim normal(\mu = 15, \sigma = 15, min = 0, max = 30)$ $a_m \sim normal(\mu = 45, \sigma = 15, min = 30, max = 60)$ $a_o \sim normal(\mu = 75, \sigma = 15, min = 60, max = 90)$ Susceptibility for young, middle, and old age fit as $u_y \sim normal(\mu = 0.1, \sigma = 0.025, min = 0)$ $u_m \sim normal(\mu = 0.1, \sigma = 0.025, min = 0)$ $u_o \sim normal(\mu = 0.1, \sigma = 0.025, min = 0)$ Then $u_i = coss(i \vert a_y, b_y, a_m, b_m, a_o, b_o)$ (see final row)
y_i	Clinical fraction on infection	Non-age-varying: $y_i = 0.5$ Age-varying: young, middle, and old age fit as $a_y \sim normal(\mu = 15, \sigma = 15, min = 0, max = 30)$ $a_m \sim normal(\mu = 45, \sigma = 15, min = 30, max = 60)$ $a_o \sim normal(\mu = 75, \sigma = 15, min = 60, max = 90)$ Susceptibility for young, middle, and old age fit as $y_y \sim normal(\mu = 0.5, \sigma = 0.1, min = 0, max = 0.5)$ $y_m = 0.5$ $y_o \sim normal(\mu = 0.5, \sigma = 0.1, min = 0.5, max = 1)$ Then $y_i = coss(i \vert a_y, y_y, a_m, y_m, a_o, y_o)$ (see below)
t_{seed}	Timing of introduction of cases	$t_{seed} \sim normal(\mu = 15, \sigma = 30, min = 0, max = 30)$
q_H	Multiplicative factor for transmission during holiday period	$q_H \sim beta(\alpha = 2, \beta = 2)\ scaled\ to\ 0 - 2$
q_L	Multiplicative factor for transmission during large-scale restrictions	$q_L \sim beta(\alpha = 2, \beta = 2)$
A_{min}, A_{max}	Age bounds for introduced cases	$A \sim normal(\mu = 60, \sigma = 20, min = 40, max = 80)$ $A_{range} \sim beta(\alpha = 2, \beta = 2)\ scaled\ to\ 0 - 10$ $A_{min} = A - A_{range}$ $A_{max} = A + A_{range}$
$coss(a \vert x_1, y_1, x_2, y_2, x_3, y_3)$	Cosine-smoothing function	For a given age *a* (the midpoint age of age group *i*) the function evaluates to $y_1$for $a \le x_1$, to y_2 for $a = x_2$, and to y_3 for $a \ge x_3$. Values of a between $x_1$and $x_2$are interpolated between y_1 and y_2, and values of a between x_2 and x_3 are interpolated between y_2 and y_3, where the interpolation takes the shape of a cosine curve between $-\pi$ and π.

Supplementary Table 2. Details of model fitting.

Location	Mixing matrix details
Wuhan City, China	We used mixing matrices measured in Shanghai in 2017/2018[5], adapted to the demographics of Wuhan prefecture. This implicitly assumes that Shanghai mixing patterns are representative of large cities in China.
Regions of China: Anhui, Guangdong, Guangxi, Hubei, Hunan, Jiangsu, Jiangxi, Jilin Shaanxi, Shandong, Sichuan, Tianjin, Zheijiang provinces; Beijing, Shanghai.	We used mixing matrices measured in Shanghai in 2017/2018[5], adapted to the demographics of each province / city.
Regions of Italy: Lombardia, Piemonte, Trento Veneto, Friulli Venezia Giulia, Liguria, Emilia-Romagna, Toscana, Marche, Lazio, Campania, Puglia regions; Milan.	We used mixing matrices measured in Italy in 2005/2006[6], adapted to the demographics of each region / city. This assumes that these contact patterns will still be representative of contact patterns in 2020.
Ontario, Canada	We used synthetic contact matrices, generated based on demographic information about the country[9].
Japan	We used synthetic contact matrices, generated based on demographic information about the country[9].
Singapore	We used synthetic contact matrices based on demographic information about the country[9].
South Korea	We used synthetic contact matrices based on demographic information about the country[9].
Birmingham, UK	We used mixing matrices measured in the UK in 2005/2006[6], adapted to the demographics of Birmingham. This assumes that these contact patterns will still be representative of contact patterns in 2020.
Bulawayo, Zimbabwe	We used mixing matrices measured in Manicaland, Zimbabwe in 2013[7], adapted to the demographics of Bulawayo. This implicitly assumes that Manicaland mixing patterns are representative of Bulawayo.
146 capital cities	We used synthetic contact matrices, generated based on demographic information about each country[9].

Supplementary Table 3. Details on mixing matrices used in the study.

Wuhan: Model 1		
age_y	6	(4.2-7.2)
age_m	55	(46-60)
age_o	64	(60-68)
susc_y	0.003	(0.00014-0.0076)
susc_m	0.044	(0.032-0.054)
susc_o	0.084	(0.079-0.09)
seed_start	19	(16-22)
seed_age	61	(42-79)
seed_age_range	4.9	(1.5-8.9)
qH	1.4	(1.3-1.5)
qL	0.41	(0.3-0.56)
Wuhan: Model 2		
age_y	19	(14-29)
age_m	50	(40-60)
age_o	68	(60-79)
susc	0.055	(0.052-0.059)
symp_y	0.037	(0.0051-0.062)
symp_m	0.3	(0.19-0.42)
symp_o	0.65	(0.52-0.77)
seed_start	16	(14-20)
seed_age	46	(30-67)
seed_age_range	1.3	(0.5-1.9)
qH	1.3	(1.2-1.4)
qL	0.43	(0.31-0.56)
Wuhan: Model 3		
susc	0.046	(0.045-0.048)
seed_start	20	(17-21)
seed_age	64	(37-80)
seed_age_range	4.2	(0.93-8.7)
qH	1.4	(1.3-1.5)
qL	0.33	(0.21-0.42)
Beijing, Shanghai		
susc	0.074	(0.055-0.1)
B_seed_t0	20	(15-25)
S_seed_t0	21	(16-26)
seed_d	3.8	(1.4-6.2)
lockdown_t	54	(53-56)
qH	1.2	(0.71-1.7)
qL	0.16	(0.11-0.22)
	0.074	(0.055-0.1)
South Korea		
susc	0.099	(0.089-0.11)
seed_t0	8.3	(5-12)
seed_d	3.3	(0.79-6.2)
lockdown_t	53	(52-54)
qL	0.047	(0.0041-0.095)
Lombardy		
susc	0.084	(0.075-0.096)
conf_mean	7.6	(2.7-13)
conf_shape	11	(3.7-20)
onset_known	0.36	(0.061-0.62)
seed_t0	15	(11-20)
seed_d	3.6	(0.83-6.3)
lockdown_t	50	(47-54)
qL	0.48	(0.28-0.72)

Supplementary Table 4. Posterior means and 95% HDIs from fitting the dynamic transmission model (Figs. 1 and 2, main text).

Supplementary references

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