Supplement for:

A modelling study investigating short and medium-term challenges for COVID-19 vaccination: from prioritisation to the relaxation of measures

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Content

Supplementary materials

Data sources

Hospitalisation data

We use hospitalisation data stemming from the SI-VIC database, a national surveillance system maintained by the ANS (Agence du Numérique en Santé) and providing real-time information about COVID-19 patients hospitalized in French public and private hospitals. Data, including age, region, date and type of hospitalisation, are sent daily to Santé Publique France, the French national public health agency. Each COVID-19 case is either biologically confirmed or present with a tomographic image which is highly suggestive of SARS-CoV-2 infection. We consider events (e.g. hospitalisations or admission in ICU) by date of occurrence (and not date of reporting) and we correct data for reporting delays (Salje et al. 2020). In our analyses, we consider patients admitted in general wards (*Hospitalisation conventionnelle*) and intensive care units (*Hospitalisation réanimatoire: réanimation, soins intensifs et unité de surveillance continue*). We discard patients hospitalized in psychiatric care units (*Hospitalisation psychiatrique*), in emergency care units (*Soins d'urgence*) and in long-term and rehabilitation units (*Soins de suite et réadaptation*).

Estimation of the prevalence of comorbidities of interest in the French population using the Esteban survey (2014-2016)

We derive estimates of the prevalence of comorbidities accounted for in the model using the Esteban survey, a cross-sectional national health study, carried out in France between 2014 and 2016, on a representative sample of the French adult population (Balicco et al. 2017). This survey describes a sample of 2,105 individuals aged between 18 and 74 y.o. A three-stage geographic sampling based on the selection of urban units, households, and individuals within each household was carried out. In this study, data collection was achieved using face-to-face questionnaires, a self questionnaire and a medical examination. Individual data were then matched with the Système National des Données de Santé (SNDS: National System of Health Data, the French national healthcare system database). Estimated prevalences were weighted to take into account survey design and non-response. The study was registered in the French National Agency for Medicines and Health Products Safety (No. 2012-A00456-34) and was approved by the Advisory Committee for Protection of Persons in Biomedical Research.

The comorbidities of interest are those identified by the Haute Autorité de Santé as being associated with an increased risk of severe outcome after a detailed literature review: complicated hypertension, heart failure, active cancers, chronic obstructive pulmonary disease or respiratory failure, diabetes, chronic kidney disease and obesity. We defined complicated hypertension as high blood pressure during the medical examination and/or antihypertensive treatment delivery associated with at least one of the following complications: diabetes, chronic kidney disease (CKD) as defined below, or declared cardiovascular pathology. Obesity was defined when measured body mass index was ≥30 kg/m^2. Diabetes was defined if people self-reported diabetes, if they were currently using anti-diabetic treatment (oral agents or injections), or if fasting blood glucose was ≥7 mmol/L during medical examination. Chronic kidney disease (CKD) stage 3-5 is defined as a glomerular filtration rate

estimated with MDRD equation < 60 mL/min/1.73m^2 (MDRD: Modification of Diet in Renal Disease). The prevalence of chronic obstructive pulmonary disease (COPD) is estimated using declared data from individuals included in the survey. Active cancers were identified by a hospitalisation on year n or a long-term disease status with a cancer diagnosis (for cancer starting on year n, n-1 or n-2). Because of missing hospitalisation data for year n-1 and n-2, we likely underestimate the prevalence of active cancers. Heart failures were identified by self declaration of patients, hospitalisations with a diagnosis of heart failure on year n or a long-term disease status with heart failure diagnosis in the year prior to the medical examination). The estimated prevalences are detailed in Table S4.

We compared these estimates with those from Europe of Clark et al. (Clark et al. 2020), who estimated the prevalence of comorbidities associated with an increased risk of developing a severe form of COVID-19 to compute global estimates of the number of individuals at risk of severe outcome when infected by SARS-CoV-2 (Figure S15). We find consistent estimates for individuals younger than 50 y.o. and for the prevalence of at least 2 underlying medical conditions in individuals younger than 70 y.o. Other differences might potentially be explained by different definitions of comorbidities associated with an increased risk of COVID-19 and by different data sources used to inform these estimates. For instance, our estimates are based on a survey based on a representative sample of the French population. The prevalence of some of the comorbidities (e.g. COPD) is estimated from patients' self-declaration. These estimates are likely to be lower than those obtained from the Global Burden of Diseases(GBD 2017 Disease and Injury Incidence and Prevalence Collaborators 2018) used in Clark et al. (Clark et al. 2020). They might however better reflect the proportion likely to be identified and targeted by COVID-19 vaccination programs prioritising individuals with such underlying comorbidities. Estimates from Clark et al. are also weighted across all Europe and differences between countries might further explain these discrepancies.

Model details

Model parametrization

The model is informed by data describing the age pyramid of the French population as well as the way individuals from different age groups interact with each other (Béraud et al. 2015). The age groups being considered are: [0-10), [10-18), [18-30), [30-40), [40-45), [45-50), [50-55), [55-60), [60-65), [65-70), [70-75), [75-80), ≥ 80. Furthermore, we make the assumption that children aged 0 to 9 y.o. and those aged 10 to 17 y.o. are respectively 50% and 25% less susceptible to infection than adults (Viner et al. 2020; Davies et al. 2020). The model accounts for age-specific mixing patterns described by contact matrices. These contact matrices have been modified to capture changes associated with control measures (lockdown, telework). We assume that in 2021, contacts outside the household will be reduced by 30% compared to a non-epidemic period (Béraud et al. 2015). These reductions are set to account both for the overall reduction in non-household contacts (e.g. partial attendance in schools, partial telework, closure of restaurants...) as well as the adoption of protective behaviours (e.g. use of face masks, physical distancing…). The model diagram is depicted in Figure S16.

Upon infection, susceptible individuals (S compartment) enter a latent state that lasts on average 4 days (E_1 compartment). They subsequently move to a second exposed

compartment (E_2), in which the average length of stay is 1.0 day and in which they become infectious. They then move to another compartment (compartment I^{mild}/I^{hosp}), upon entry of which a fraction of them will develop symptoms. A fraction of infected individuals will develop a severe form of COVID-19 (trajectory starting from I^{hosp}), requiring an admission into hospital and/or into ICU. We consider that patients are admitted to hospital on average 6 days after symptoms onset if they will require an admission in ICU and 7 days otherwise. Patients are admitted into ICU on average 1.5 days after being hospitalized (Salje et al. 2020). Age-specific probabilities of hospitalisation given infection are estimated from the joint analyses of serological and hospitalisation data collected during the first pandemic wave in Île-de-France and Grand Est, the two regions most affected by COVID-19 during that wave (Lapidus et al. 2021). This approach allows to properly account for the risk of infection that was observed during the first wave in the different age groups and the risk of hospitalisation given infection per age group across this time period. We assume that these probabilities remain constant throughout the epidemic. The age specific probabilities of death given hospitalisation are estimated using the proportion of deaths among patients admitted in hospitals between November 1st, 2020 and January 1st, 2021. We assume that previously infected individuals are protected against reinfection until the end of the study period.

The epidemic is seeded on January 22nd, 2020 with I_0 individuals (a parameter to be estimated) in compartment E_1, distributed across age and comorbidity groups proportionally to the size of the different groups. We estimate values of the reproduction number across different time periods since the beginning of the French epidemic (Table S6). Parameters used in the model are detailed in Table S7.

Accounting for changes in the probability of ICU admission through time

The proportion of patients admitted in ICU upon hospitalisation evolved throughout the epidemic (Lefrancq et al. 2021). We use the same approach as in Salje et al. (Salje et al. 2020) to account for these changes. We fit a linear spline to the probability of being admitted in ICU after hospitalisation. We assume that it decreased from ${p_{ICU}}^{baseline}$ to $\alpha_1 \cdot {p_{ICU}}^{baseline}$ between March 20th, 2020 and April 7th, 2020. We assume that this probability remained constant until July 7th, 2020, where it changed from $\alpha_1 \cdot {p_{ICU}}^{baseline}$ to $\alpha_2 \cdot {p_{ICU}}^{baseline}$ on October 1st, 2020 following a linear trend. We then assume a further change in this probability between October 1st, 2020 and December 1st, 2020 to reach $\alpha_3 \cdot {p_{ICU}}^{baseline}$. The parameters α_1,α_2 and $\alpha_3$are estimated. ${p_{ICU}}^{baseline}$ is derived to ensure the mean probability of ICU admission given hospitalisation used in the model matches the one observed during the first wave (Salje et al. 2020). The average age-specific probabilities of ICU admission between March 20th, 2020 and April 7th, 2020 are estimated using the proportion of patients admitted to ICU during this time period in the different age groups.

Statistical framework

The model is calibrated on the daily number of ICU and hospital admissions between 15 March 2020 and 4 January 2021 reported in the SI-VIC database. Model parameters are estimated using a bayesian Markov Chain Monte Carlo framework. We implement a Metropolis-Hastings algorithm with lognormal proposals and uniform priors. Chains are run for 10,000 iterations ; we remove 2,000 iterations of burn-in. We run 4 chains with different starting points and visually assess their convergence by looking at trace plots.

Let $H^{pred}(t)$ and $H^{obs}(t)$ denote respectively the predicted and observed number of hospital admissions on day t. Let $ICU^{pred}(t)$ and $ICU^{obs}(t)$ denote respectively the predicted and observed number of ICU admissions on day t. We define the likelihood function as:

$$L = \prod_{t=15\,March\,2020}^{4\,January\,2021} g(H^{pred}(t) \mid H^{obs}(t)) \cdot g(ICU^{pred}(t) \mid ICU^{obs}(t))$$

where $g(\cdot|X)$ is a negative binomial distribution of mean X and overdispersion parameter X^{δ}, with δ a parameter to be estimated. Parameters estimates are reported along 95% credible intervals in Table S6.

To simulate hospital and ICU admissions, 100 set of parameters are sampled from the posterior distribution. For each set of parameters $X_i, i \in \{1,\dots,100\}$, we simulate the daily hospital and ICU admissions from the deterministic compartmental model $\{H^{pred}{}_i(t), ICU^{pred}{}_i(t)\}_t$ and then draw at each time step t 100 values for the hospital and ICU admissions on this day from a negative binomial distribution of mean $\{H^{pred}{}_i(t), ICU^{pred}{}_i(t)\}$ and overdispersion parameter $\{[H^{pred}{}_i(t)]^{\delta_i}, [ICU^{pred}{}_i(t)]^{\delta_i}\}$ where δ_i is the overdispersion parameter in the set of parameter X_i.

Comparison between observed and predicted hospital and ICU admissions by age groups are reported in Figure S17.

Stratification by age and comorbidity

In our model, we explicitly account for the fact that the probability to develop severe clinical signs depends on the number of comorbidities (0, 1 or at least 2) and that the effect may vary with age. We consider comorbidities identified by the Haute Autorité de Santé as being associated with an increased risk of severe outcome. The age-specific prevalence of individuals with 0, 1 or at least 2 comorbidities has been estimated from the Esteban survey (Balicco et al. 2017) (Table S4). The probabilities of hospital admission following infection are adjusted by age and by number of comorbidities, using the relative risk of hospital admission following infection by age and comorbidity estimated in the US study COVID-NET (Ko et al. 2020; Centers for Disease Control and Prevention 2020). We considered that having a given number of comorbidities was associated with an increased risk of hospitalisation given infection when there was a statistically significant different risk compared to individuals without any underlying medical conditions. The estimated probabilities stratified by both age and comorbidity are detailed in Table S5.

Parametrization for the vaccine that has a moderate effect on transmission

We detail how we built the scenario for the vaccine *Transmission*. In this scenario, we assume that the vaccine reduces the risk of developing symptoms upon infection, which results in a reduction of the average infectivity of vaccinated individuals. Let $VE_{severity}$ denote the efficacy of the vaccine on the severity of the infection. We assume that the vaccination reduces by $VE_{severity}$ the probability of developing symptoms upon infection or a severe form of COVID-19 requiring hospital care.

$$P[Hosp \mid Infection, Vaccination] = (1 - VE_{severity}) \cdot P[Hosp \mid Inf, No\ vaccination] P[Symptoms \mid Infection, Vaccination] = (1 - VE_{severity}) \cdot P[Symptoms \mid Inf, No\ vaccination]$$

Several analyses have suggested that individuals developing symptoms be more infectious than infected individuals who remain asymptomatic (Li et al. 2020). Let p^{sympto}denote the proportion of infected individuals who will develop symptoms. Let β denote the average transmission rate in the population, β^{sympto} denote the average transmission rate of individuals infected by SARS-CoV-2 developing symptoms and $\beta^{asympto}$ the average transmission of infected individuals remaining asymptomatic. Let $\theta^{asympto}$denote the relative reduction of the transmission rate in asymptomatic compared to symptomatic individuals:$\beta^{asympto} = \theta^{asympto} \cdot \beta^{sympto}$

The average transmission rate can be derived as:

$$\beta = \beta^{sympto} \cdot [p^{sympto} \cdot (1 - \theta^{asympto}) + \theta^{asympto}]$$

Amongst vaccinated individuals, the mean transmission rate $\beta_V$verifies:

$$\beta_V = \beta^{sympto} \cdot [(1 - VE_{severity}) \cdot (1 - \theta^{asympto}) \cdot p^{sympto} + \theta^{asympto}]$$

We define the efficacy of the vaccine on transmission $VE_{transmission}$ by:

$$VE_{transmission} = 1 - \beta_V / \beta = VE_{severity} \cdot \frac{p^{sympto} \cdot (1 - \theta^{asympto})}{p^{sympto} \cdot (1 - \theta^{asympto}) + 1}$$

We assume that the transmission rate of asymptomatic individuals is 55% that of symptomatic individuals (Li et al. 2020) and that 60% of SARS-CoV-2 infected individuals will develop symptoms (Lavezzo et al. 2020). This allows us to derive hypotheses regarding the efficacy for a vaccine that has a moderate impact on transmission.

$VE_{severity}$	$VE_{transmission}$
90%	29.6%
70%	23.0%

Parametrization for the vaccine that reduces the susceptibility to the infection

We explore scenarios where vaccines reduce the susceptibility to the infection of vaccinated individuals ($VE_{susceptibility}$) as well as the severity of the infection of vaccinated individuals that will eventually be infected ($VE_{severity}$). The overall vaccine efficacy VE_{tot} on the risk of developing a severe form of the disease is a combination of these two effects and can be derived as:

$$1 - VE_{tot} = (1 - VE_{susceptibility}) \cdot (1 - VE_{severity})$$

Setting $VE_{severity}$ to 50%, we obtain the following parametrization for VE_{tot} of 90% or 70%:

	VE_{tot}	Corresponding efficacy on the risk of hospitalisation given infection $VE_{severity}$	Corresponding efficacy on the risk of infection given vaccination $VE_{susceptibility}$
Baseline scenario with an overall efficacy on the risk of hospitalisation given vaccination VE_{tot} of 90%	90%	50%	80%
Scenario explored in a sensitivity analysis with an overall efficacy on the risk of hospitalisation given vaccination VE_{tot} of 70%	70%	50%	40%

As a sensitivity analysis, we also consider a vaccine *Susceptibility* with an additional efficacy of 50% on the infectivity of vaccinated individuals (Figure S12).

Modelling relaxation of control measures

We are interested in exploring the extent to which control measures might be relaxed. To do so, we run a range of scenarios, varying transmission intensity when measures are relaxed. This allows us to compute the corresponding effective reproduction number upon measures relaxation on September 1st, 2021. For each combination of vaccine coverage reached in individuals ≥65 y.o. and individuals aged 18-64 y.o., this allows us to determine the highest effective reproduction number ensuring the peak in daily hospital admissions stays below a specific threshold. Simulations are run until April 1st, 2022. Upon the relaxation of measures, we assume that the contact matrix remains similar to the one used throughout 2021. Potentiel changes in contact patterns upon measures' relaxation should only have a limited impact on our results as we work with normalized matrices (i.e. matrices whose maximum eigenvalues are equal to 1). Let for instance C denote our normalized matrix. This allows us to define a transmission parameter β as R_0/D (where D is the average infectious period) and to define transmission rates as βC. This normalization ensures that transmission intensity is controlled by the value of R_0 and less by the choice of the contact matrix. From this value, we derive the reductions in transmission rates in the general population that remain necessary, exploring different values of the basic reproduction number that characterizes a situation with complete relaxation of measures and no immunity as well as different values for the proportion of the population that might have already been infected upon relaxation of measures. We present the results for different values for the basic reproduction number R_0 to explore the impact of the emergence of more transmissible strains: (i) R_0 of 2.5 and 3 (as estimated in several locations prior the implementation of control measures) (ii) R_0 of 4. This latest value is consistent with a circulating strain 50% more transmissible than the one circulating at the

beginning of 2020 (an increase of R_0 from 2.5-3.0 to 3.75-4.5). As uncertainties remain regarding the increased transmissibility of B.1.1.7 for instance, we conduct a sensitivity analysis looking at R_0 of 3.5 and 4.5 (Figure S14).

To estimate the impact that would have a change in the proportion infected on the transmission rate, we use the next-generation matrix approach(Diekmann, Heesterbeek, and Metz 1990) and assume that the increase or decrease in new infections compared to the baseline scenario is distributed proportionally to the number of susceptible individuals across age groups. Examples of epidemiological trajectories upon measures relaxation in the absence of vaccination are presented in Figure S18.

Model equations

Model equations are detailed below. The indices a and a' are used to denote the different age groups (n_a age groups). The indices c and c' are used to denote the different comorbidity levels (n_c comorbidity levels). The superscript V corresponds to vaccinated compartments. Let $c_{a,a'}$ denote the average daily number of contacts that an individual in age group a has with individuals within the age group a'. Let $1/g_1 = 4\ days$ denote the average length of the latent state E_1. $D = 1/g_2 + 1/g_3\ (= 1 + 3\ days)$ is the mean infectious period. The transmission rate β can be derived from the basic reproduction number R_0 using the next-generation matrix approach:(Diekmann, Heesterbeek, and Metz 1990)

$\beta = R_0\ /\ (\ D \cdot \rho[(c_{a,a'})]\ )$ where $\rho[(c_{a,a'})]$ is the maximum eigenvalue of the matrix $(c_{a,a'})_{a,a'}$.

Let ${p_{a,c}}^{hosp}$ and ${p_{a,c}}^{ICU}$ denote respectively the probability of hospitalisation given infection and the probability of ICU admission given hospitalisation for individuals of age group a and comorbidity levels c. Let $V_{a,c}(t)$ denote the number of individuals belonging to age group a with comorbidity level c that are vaccinated at time t following the vaccination schedule. ${N^{NV}}_{a,c}$ corresponds to the number of individuals belonging to age group a with comorbidity level c that are not vaccinated. Let N_a denote the number of individuals belonging to age group a regardless of their comorbidity level. $1/g_3 + 1/g^{to\ hosp}\ (= 3 + 4\ days)$corresponds to the average delay between disease onset and hospitalisation for individuals that will not require an ICU admission, $1/g_3 + 1/g^{to\ hosp\ ICU}\ (= 3 + 3\ days)$ to the average delay between disease onset and hospitalisation for individuals that will require an hospitalisation in ICU, $1/g^{to\ ICU} = 1.5\ days$ to the average length of stay in general wards prior ICU admission, $2/g^{out\ hosp}$to the average length of stay in general wards for patients that are not admitted to ICU and $2/g^{out\ ICU}$to the average length of stay in ICU. $VE_{severity}$is the efficacy of the vaccine on the reduction of the probability of hospitalisation upon infection, $VE_{infectivity}$is the efficacy of the vaccine on the reduction of the infectiousness of vaccinated individuals and $VE_{susceptibility}$ the efficacy of the vaccine on the reduction of the probability of becoming infected upon contact with an infectious individual for vaccinated individuals.

$$\frac{dS_{a,c}}{dt} = -\beta S_{a,c} \sum_{a'=1}^{n_a} \sum_{c'=1}^{n_c} \left(c_{a,a'} \cdot \frac{I^{mild}_{a',c'} + I^{hosp}_{a',c'} + E_{2a',c'} + (1 - VE_{infectivity}) \cdot (I^{V\,mild}_{a',c'} + I^{V\,hosp}_{a',c'} + E^{V}_{2a',c'})}{N_{a'}} \right) - V_{a,c}(t) \cdot \frac{S_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dE_{1a,c}}{dt} = \beta S_{a,c} \sum_{a'=1}^{n_a} \sum_{c'=1}^{n_c} \left(c_{a,a'} \cdot \frac{I^{mild}_{a',c'} + I^{hosp}_{a',c'} + E_{2a',c'} + (1 - VE_{infectivity}) \cdot (I^{V\,mild}_{a',c'} + I^{V\,hosp}_{a',c'} + E^{V}_{2a',c'})}{N_{a'}} \right) - g_1 E_{1a,c} + V_{a,c}(t) \cdot \frac{E_{1a,c}}{N^{NV}_{a,c}}$$

$$\frac{dE_{2a,c}}{dt} = g_1 E_{1a,c} - g_2 E_{2a,c} - V_{a,c}(t) \cdot \frac{E_{2a,c}}{N^{NV}_{a,c}}$$

$$\frac{dI^{mild}_{a,c}}{dt} = g_2(1 - p^{hosp}_{a,c}) E_{2a,c} - g_3 I^{mild}_{a,c} - V_{a,c}(t) \cdot \frac{I^{mild}_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dI^{hosp}_{a,c}}{dt} = g_2 p^{hosp}_{a,c} E_{2a,c} - g_3 I^{hosp}_{a,c} - V_{a,c}(t) \cdot \frac{I^{hosp}_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dI^{\bar{ICU}}_{a,c}}{dt} = g_3 p^{ICU}_{a,c} I^{hosp}_{a,c} - g^{to\,hosp} I^{\bar{ICU}}_{a,c} - V_{a,c}(t) \cdot \frac{I^{\bar{ICU}}_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dI^{non\bar{}ICU}_{a,c}}{dt} = g_3(1 - p^{ICU}_{a,c}) I^{hosp}_{a,c} - g^{to\,hosp\,non\,ICU} I^{non\bar{}ICU}_{a,c} - V_{a,c}(t) \cdot \frac{I^{non\bar{}ICU}_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dH_{1a,c}}{dt} = g^{to\,hosp\,non\,ICU} I^{non\bar{}ICU}_{a,c} - g^{out\,hosp} H_{1a,c} - V_{a,c}(t) \cdot \frac{H_{1a,c}}{N^{NV}_{a,c}}$$

$$\frac{dH_{2a,c}}{dt} = g^{out\,hosp} H_{1a,c} - g^{out\,hosp} H_{2a,c} - V_{a,c}(t) \cdot \frac{H_{2a,c}}{N^{NV}_{a,c}}$$

$$\frac{dH_{ICU\,a,c}}{dt} = g^{to\,hosp} I^{\bar{ICU}}_{a,c} - g^{ICU} H_{ICU\,a,c} - V_{a,c}(t) \cdot \frac{H_{ICU\,a,c}}{N^{NV}_{a,c}}$$

$$\frac{dICU_{1a,c}}{dt} = g^{ICU} H_{ICU\,a,c} - g^{out\,ICU} ICU_{1a,c} - V_{a,c}(t) \cdot \frac{ICU_{1a,c}}{N^{NV}_{a,c}}$$

$$\frac{dICU_{2a,c}}{dt} = g^{out} ICU_{1a,c} - g^{out\,ICU} ICU_{2a,c} - V_{a,c}(t) \cdot \frac{ICU_{2a,c}}{N^{NV}_{a,c}}$$

$$\frac{dRD_{a,c}}{dt} = g_3 I^{non\,hosp}_{a,c} + g^{out\,hosp} H_{2a,c} + g^{out\,ICU} ICU_{2a,c} - V_{a,c}(t) \cdot \frac{RD_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dS^{V}_{a,c}}{dt} = -\beta \cdot (1 - VE_{susceptibility}) \cdot S^{V}_{a,c} \cdot \sum_{a'=1}^{n_a} \sum_{c'=1}^{n_c} \left(c_{a,a'} \cdot \frac{I^{mild}_{a',c'} + I^{hosp}_{a',c'} + E_{2a',c'} + (1 - VE_{infectivity}) \cdot (I^{V\,mild}_{a',c'} + I^{V\,hosp}_{a',c'} + E^{V}_{2a',c'})}{N_{a'}} \right)$$
$$+ V_{a,c}(t) \cdot \frac{S_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dE^{V}_{1a,c}}{dt} = \beta \cdot (1 - VE_{susceptibility}) \cdot S^{V}_{a,c} \cdot \sum_{a'=1}^{n_a} \sum_{c'=1}^{n_c} \left(c_{a,a'} \cdot \frac{I^{mild}_{a',c'} + I^{hosp}_{a',c'} + E_{2a',c'} + (1 - VE_{infectivity}) \cdot (I^{V\,mild}_{a',c'} + I^{V\,hosp}_{a',c'} + E^{V}_{2a',c'})}{N_{a'}} \right)$$
$$- g_1 E^{V}_{1a,c} + V_{a,c}(t) \cdot \frac{E_{1a,c}}{N^{NV}_{a,c}}$$

$$\frac{dE^{V}_{2a,c}}{dt} = g_1 E^{V}_{1a,c} - g_2 E^{V}_{2a,c} + V_{a,c}(t) \cdot \frac{E_{2a,c}}{N^{NV}_{a,c}}$$

$$\frac{dI^{V\,mild}_{a,c}}{dt} = g_2(1 - \cdot(1 - VE_{severity}) \cdot p^{hosp}_{a,c}) E^{V}_{2a,c} - g_3 I^{V\,mild}_{a,c} + V_{a,c}(t) \cdot \frac{I^{mild}_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dI^{V\,hosp}_{a,c}}{dt} = g_2 \cdot (1 - VE_{severity}) \cdot p^{hosp}_{a,c} E^{V}_{2a,c} - g_3 I^{V\,hosp}_{a,c} + V_{a,c}(t) \cdot \frac{I^{hosp}_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dI^{V\,\bar{ICU}}_{a,c}}{dt} = g_3 p^{ICU}_{a,c} I^{V\,hosp}_{a,c} - g^{to\,hosp} I^{V\,\bar{ICU}}_{a,c} + V_{a,c}(t) \cdot \frac{I^{\bar{ICU}}_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dI^{V\,non\bar{}ICU}_{a,c}}{dt} = g_3(1 - p^{ICU}_{a,c}) I^{V\,hosp}_{a,c} - g^{to\,hosp\,non\,ICU} I^{V\,non\bar{}ICU}_{a,c} + V_{a,c}(t) \cdot \frac{I^{\bar{hosp}}_{a,c}}{N^{NV}_{a,c}}$$

$$\frac{dH^{V}_{1a,c}}{dt} = g^{to\,hosp\,non\,ICU} I^{V\,non\bar{}ICU}_{a,c} - g^{out\,hosp} H^{V}_{1a,c} + V_{a,c}(t) \cdot \frac{H_{1a,c}}{N^{NV}_{a,c}}$$

$$\frac{dH^{V}_{2a,c}}{dt} = g^{out\,hosp} H^{V}_{1a,c} - g^{out\,hosp} H^{V}_{2a,c} + V_{a,c}(t) \cdot \frac{H_{2a,c}}{N^{NV}_{a,c}}$$

$$\frac{dH^{V}_{ICU\,a,c}}{dt} = g^{to\,hosp} I^{V\,\bar{ICU}}_{a,c} - g^{ICU} H^{V}_{ICU\,a,c} + V_{a,c}(t) \cdot \frac{H_{ICU\,a,c}}{N^{NV}_{a,c}}$$

$$\frac{dICU^{V}_{1a,c}}{dt} = g^{ICU} H^{V}_{ICU\,a,c} - g^{out\,ICU} ICU^{V}_{1a,c} + V_{a,c}(t) \cdot \frac{ICU_{1a,c}}{N^{NV}_{a,c}}$$

$$\frac{dICU^{V}_{2a,c}}{dt} = g^{out} ICU^{V}_{1a,c} - g^{out\,ICU} ICU^{V}_{2a,c} + V_{a,c}(t) \cdot \frac{ICU_{2a,c}}{N^{NV}_{a,c}}$$

$$\frac{dRD^{V}_{a,c}}{dt} = g_3 I^{V\,non\,hosp}_{a,c} + g^{out\,hosp} H^{V}_{2a,c} + g^{out\,ICU} ICU^{V}_{2a,c} + V_{a,c}(t) \cdot \frac{RD_{a,c}}{N^{NV}_{a,c}}$$

Supplementary figures

Figure S1

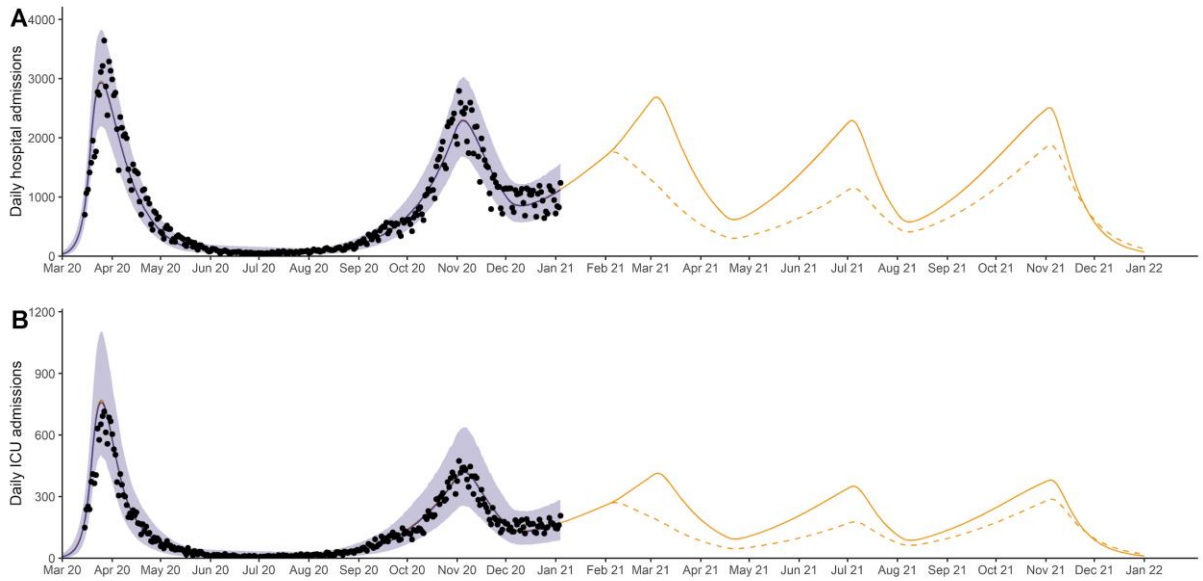

Figure S1: Epidemiological scenarios for 2021. Daily **(A)** hospital and **(B)** ICU admissions in the baseline scenario used for 2021 (solid line) and the scenario with a more controlled epidemic (dashed line) used as a sensitivity analysis. Trajectories are displayed in the absence of vaccination. The shaded areas correspond to 95% credible intervals.

Figure S2

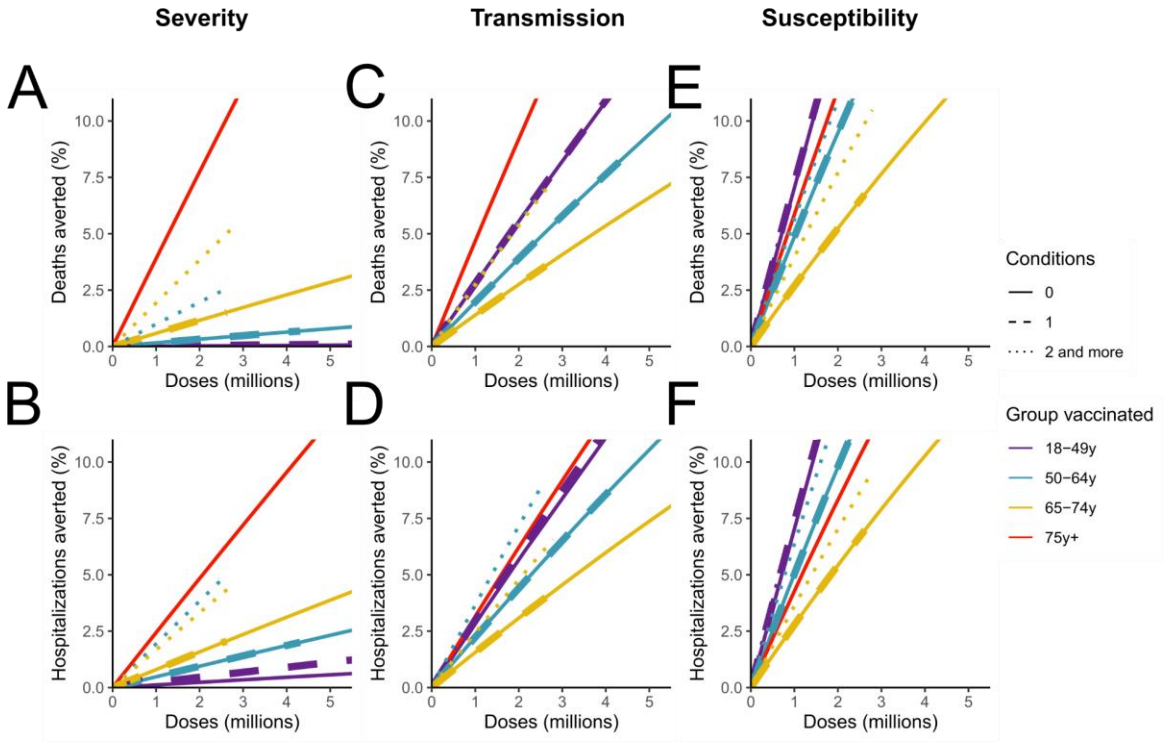

Figure S2: Sensitivity analysis changing the epidemiological scenario. (A) Deaths and **(B)** hospitalisation averted for a vaccine reducing the severity of the infection by 90%. **(C)** Deaths and **(D)** hospitalisation averted for a vaccine reducing the severity of the infection by 90% with a moderate impact on transmission (30%). **(E)** Deaths and **(F)** hospitalisation averted for a vaccine reducing the susceptibility to SARS-CoV-2 infection (80%) and the severity of the infection by 90%. Results are reported in our baseline epidemiological scenario describing a more controlled epidemic. Results are reported in the epidemiological scenario describing a more controlled epidemic. To increase readability, results are reported for less than 5 million doses administered and less than 10% of deaths or hospitalisations averted.

Figure S3

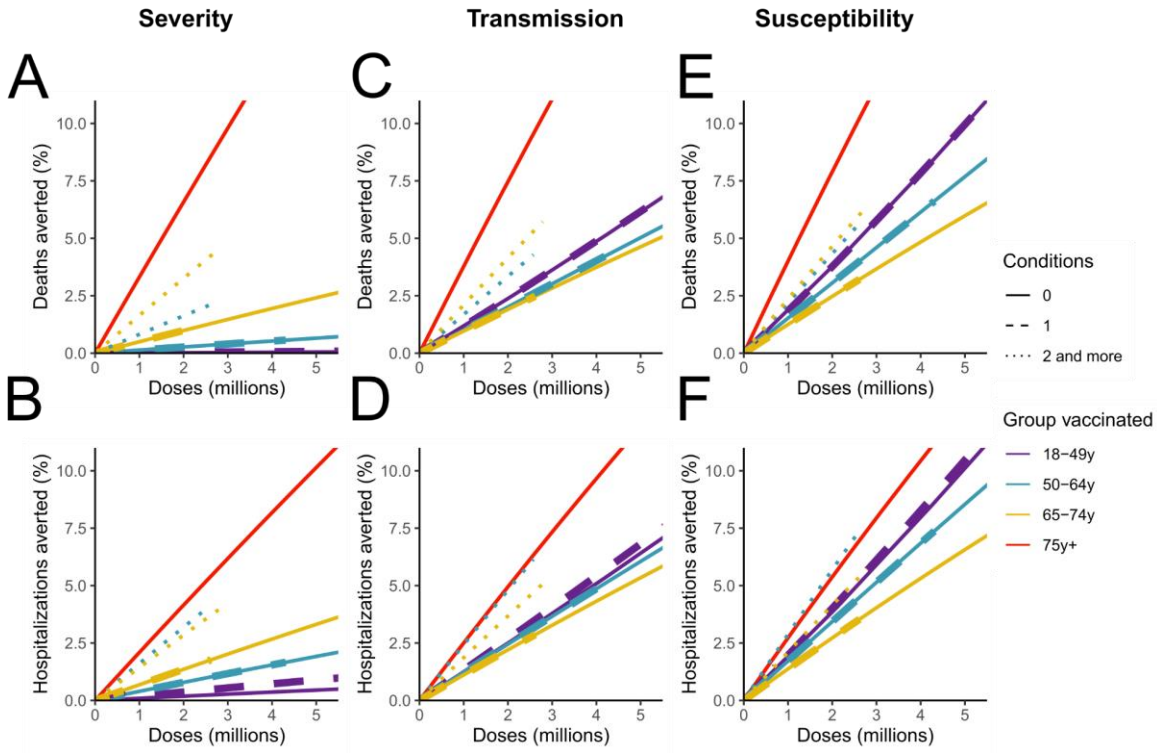

Figure S3: Sensitivity analysis changing the vaccine efficacy. (A) Deaths and **(B)** hospitalisation averted for a vaccine reducing the severity of the infection by 70%. **(C)** Deaths and **(D)** hospitalisation averted for a vaccine reducing the severity of the infection by 70% with a moderate impact on transmission (30%). **(E)** Deaths and **(F)** hospitalisation averted for a vaccine reducing the susceptibility to SARS-CoV-2 infection (40%) and the severity of the infection by 70%. Results are reported in our baseline epidemiological scenario describing a more controlled epidemic. In the absence of vaccination, such a scenario would result in 330,000 COVID-19 hospitalisations and 66,000 hospital deaths. In the absence of vaccination, such a scenario would result in 501,000 COVID-19 hospitalisations and 102,000 hospital deaths. To increase readability, results are reported for less than 5 million doses administered and less than 10% of deaths or hospitalisations averted.

Figure S4

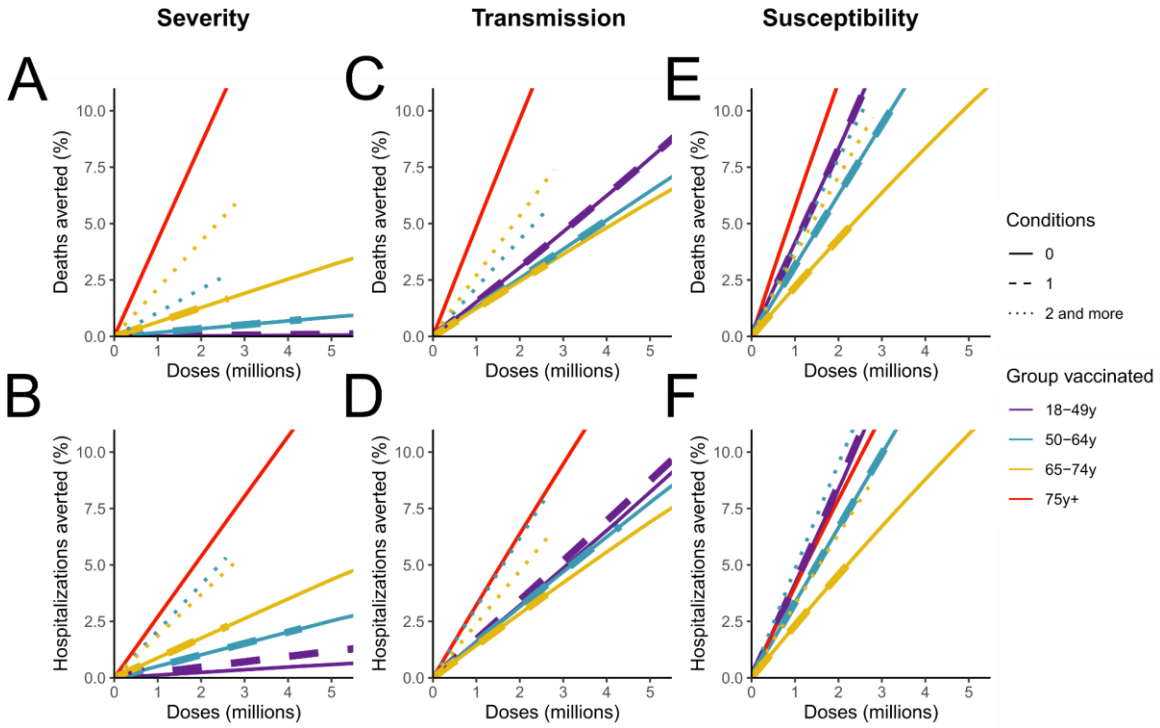

Figure S4: Sensitivity analysis changing the vaccine roll-out pace. (A) Deaths and **(B)** hospitalisation averted for a vaccine reducing the severity of the infection by 90%. **(C)** Deaths and **(D)** hospitalisation averted for a vaccine reducing the severity of the infection by 90% with a moderate impact on transmission (30%). **(E)** Deaths and **(F)** hospitalisation averted for a vaccine reducing the susceptibility to SARS-CoV-2 infection (80%) and the severity of the infection by 90%. Results are reported in our baseline epidemiological scenario describing a more controlled epidemic. In the absence of vaccination, such a scenario would result in 330,000 COVID-19 hospitalisations and 66,000 hospital deaths. In the absence of vaccination, such a scenario would result in 501,000 COVID-19 hospitalisations and 102,000 hospital deaths. Results are reported for a roll-out pace of 450,000 doses per day. To increase readability, results are reported for less than 5 million doses administered and less than 10% of deaths or hospitalisations averted.

Figure S5

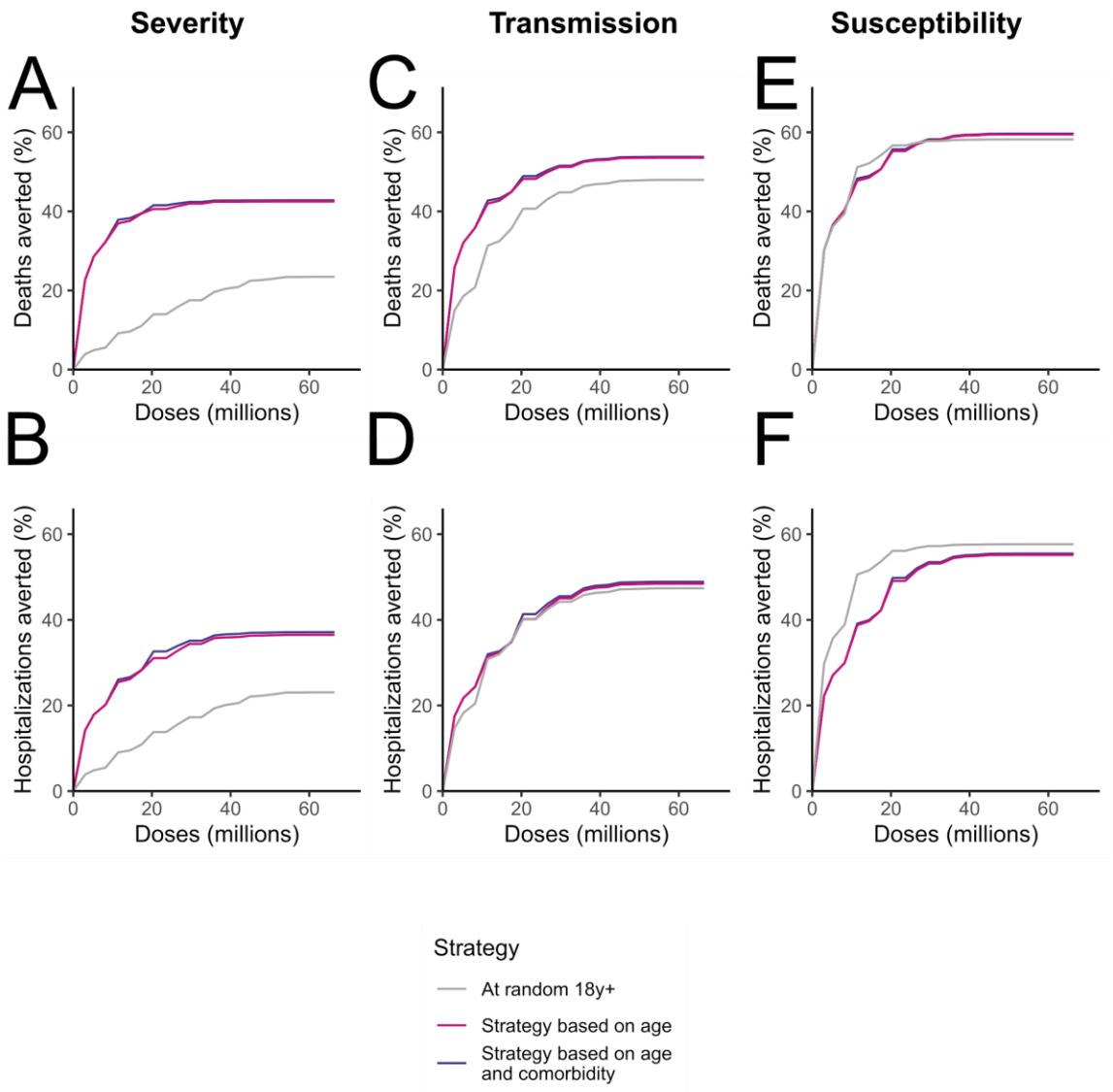

Figure S5: Sensitivity analysis changing the epidemiological scenario. (A) Deaths and **(B)** hospitalisations averted **(A)** for a vaccine reducing the severity of the infection (90%). **(C)** deaths and **(D)** hospitalisations averted for a vaccine reducing the severity of the infection (90%) with a moderate impact on transmission (30%). **(E)** Deaths and **(F)** hospitalisations averted for a vaccine reducing the susceptibility to SARS-CoV-2 infection (80%) and reducing the severity by 90%. In the absence of vaccination, such a scenario would result in 330,000 COVID-19 hospitalisations and 66,000 hospital deaths.

Figure S6

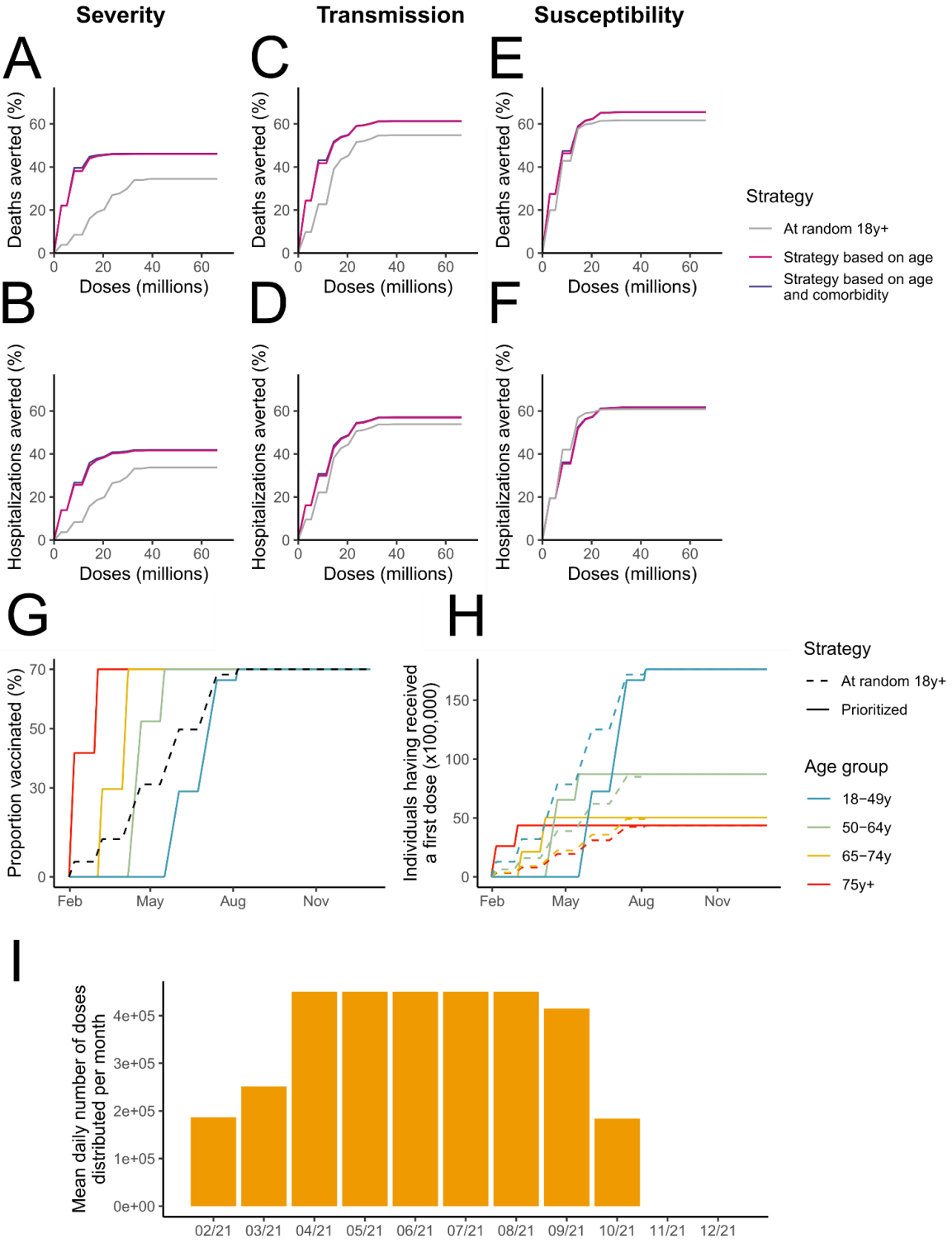

Figure S6: Sensitivity analysis changing the vaccine roll-out pace (450,000 doses per day). (A) Deaths and **(B)** hospitalisations averted **(A)** for the vaccine *Severity*. **(C)** Deaths and **(D)** hospitalisations averted for the vaccine *Transmission*. **(E)** Deaths and **(F)** hospitalisations averted for the vaccine *Susceptibility.* **(G)** Proportion of the population and **(H)** number of individuals having received a first dose throughout 2021 in the different age groups by prioritisation strategy. (I) Mean daily number of doses distributed per month under this roll-out pace scenario.

Figure S7

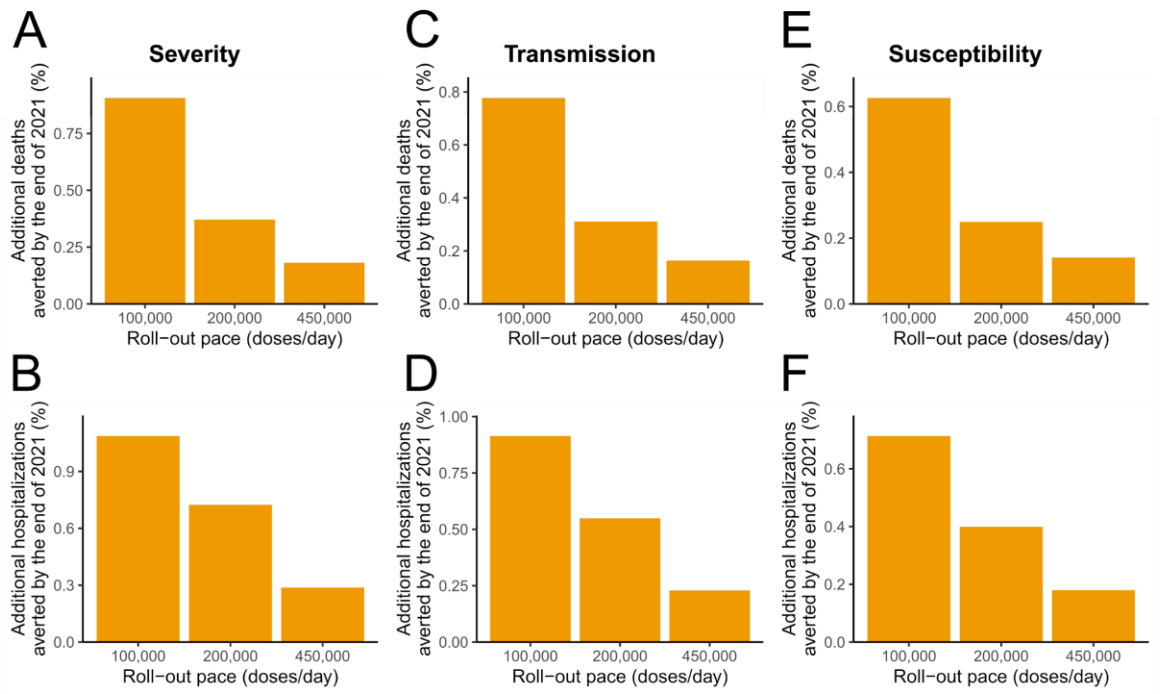

Figure S7: Comparison of the prioritization strategy based on age and comorbidities and the prioritization strategy based on age solely. Difference between the **(A)** proportion of deaths and the **(B)** proportion of hospitalisations averted in the prioritization strategy based on age and comorbidities and the prioritization strategy based on age for the vaccine *Severity*. Difference between the **(C)** proportion of deaths and the **(D)** proportion of hospitalisations averted in the prioritization strategy based on age and comorbidities and the prioritization strategy based on age for the vaccine *Transmission*. Difference between the **(E)** proportion of deaths and the **(F)** proportion of hospitalisations averted in the prioritization strategy based on age and comorbidities and the prioritization strategy based on age for the vaccine *Susceptibility*. Different roll-out paces are explored.

Figure S8

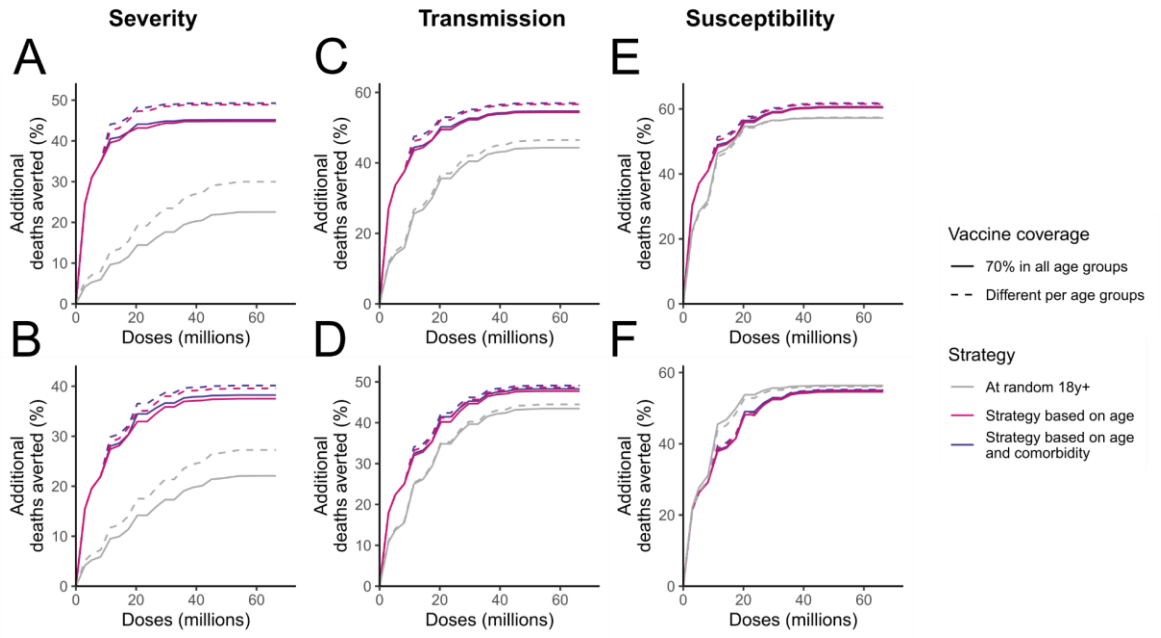

Figure S8: Sensitivity analysis changing the target vaccine coverage in the different age groups. (A) Deaths and **(B)** hospitalisations averted for the vaccine Severity. **(C)** Deaths and **(D)** hospitalisations averted for the vaccine Transmission. **(E)** Deaths and **(F)** hospitalisations averted for the vaccine Susceptibility. The plain lines correspond to our baseline scenario with a target vaccine coverage of 70% in the different age groups. The dashed lines correspond to a scenario with target vaccine coverages based on vaccine coverage measured in March 2021 by the CoviPrev survey, a behavioural survey performed by Santé Publique France, the French public health agency. This corresponds to a vaccination intent of 36% for 18-24 y.o., 29% for 25-34 y.o., 55% for 35-49 y.o., 58% for 50-64 y.o. and 79% for those older than 65 y.o.(Santé Publique France 2021)

Figure S9

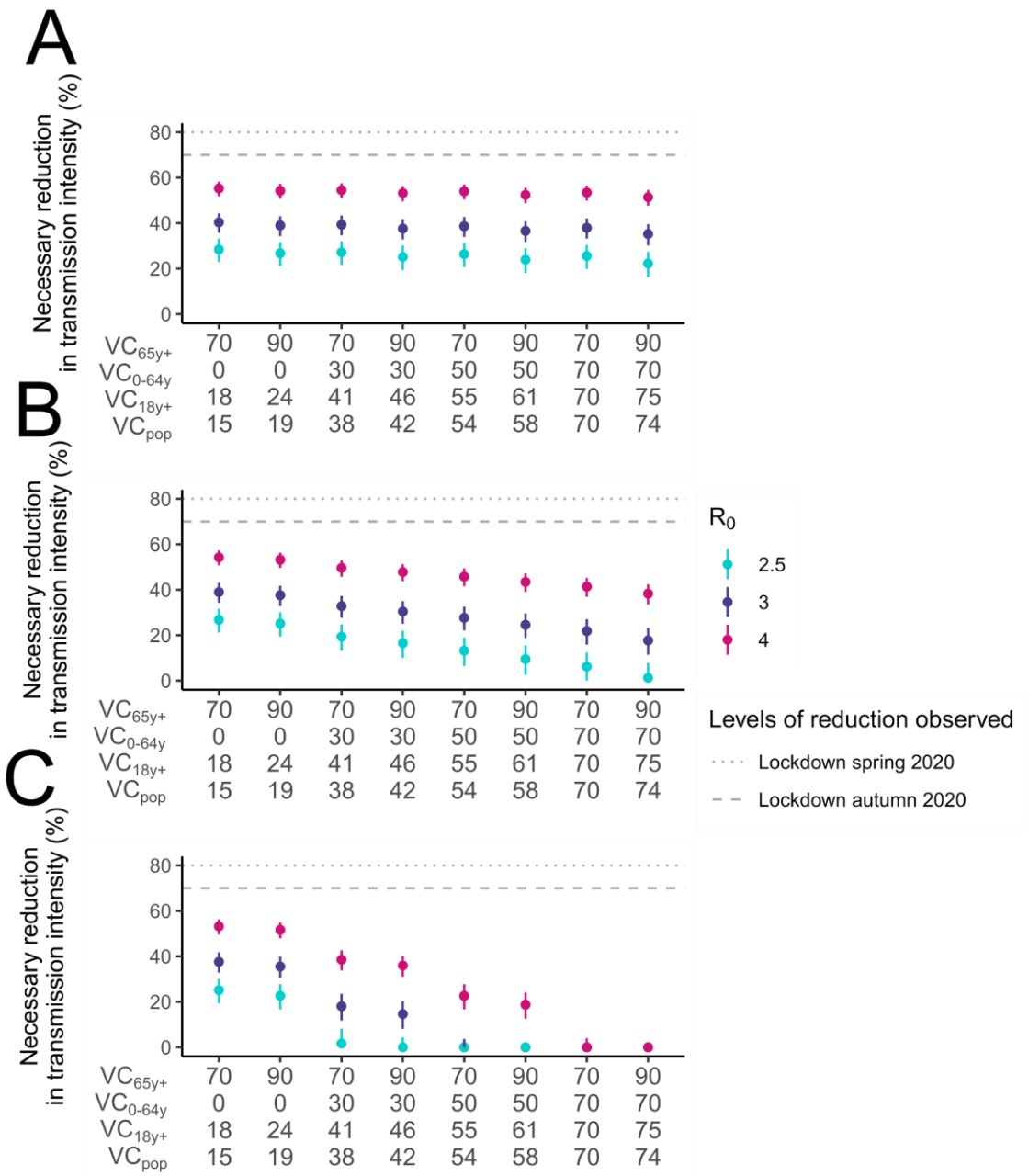

Figure S9: Sensitivity analysis with vaccination of 0-17 y.o. - Manageable relaxation of measures by levels of vaccine coverage ensuring the peak in daily hospital admissions remains below 1,000. Reductions in transmission that remain necessary in September **(A)** for the vaccine *Severity*, **(B)** for the vaccine *Transmission*, **(C)** for the vaccine *Susceptibility*. Different levels of vaccine coverage in 0-64 y.o. ($VC_{0\text{-}64y}$) and in ≥65 y.o. (VC_{65y+}) (in %) and values of the basic reproduction number R_0 assuming complete relaxation are explored. The reductions are computed assuming a proportion ever infected in France upon relaxation of 30% (range 25%-35% corresponding to the vertical bars). For each combination of vaccine coverage in 18-64 y.o. and ≥65 y.o., we report the corresponding vaccine coverage in those older than 18 y.o. (VC_{18y+}) and in the general population (VC_{pop}).

Figure S10

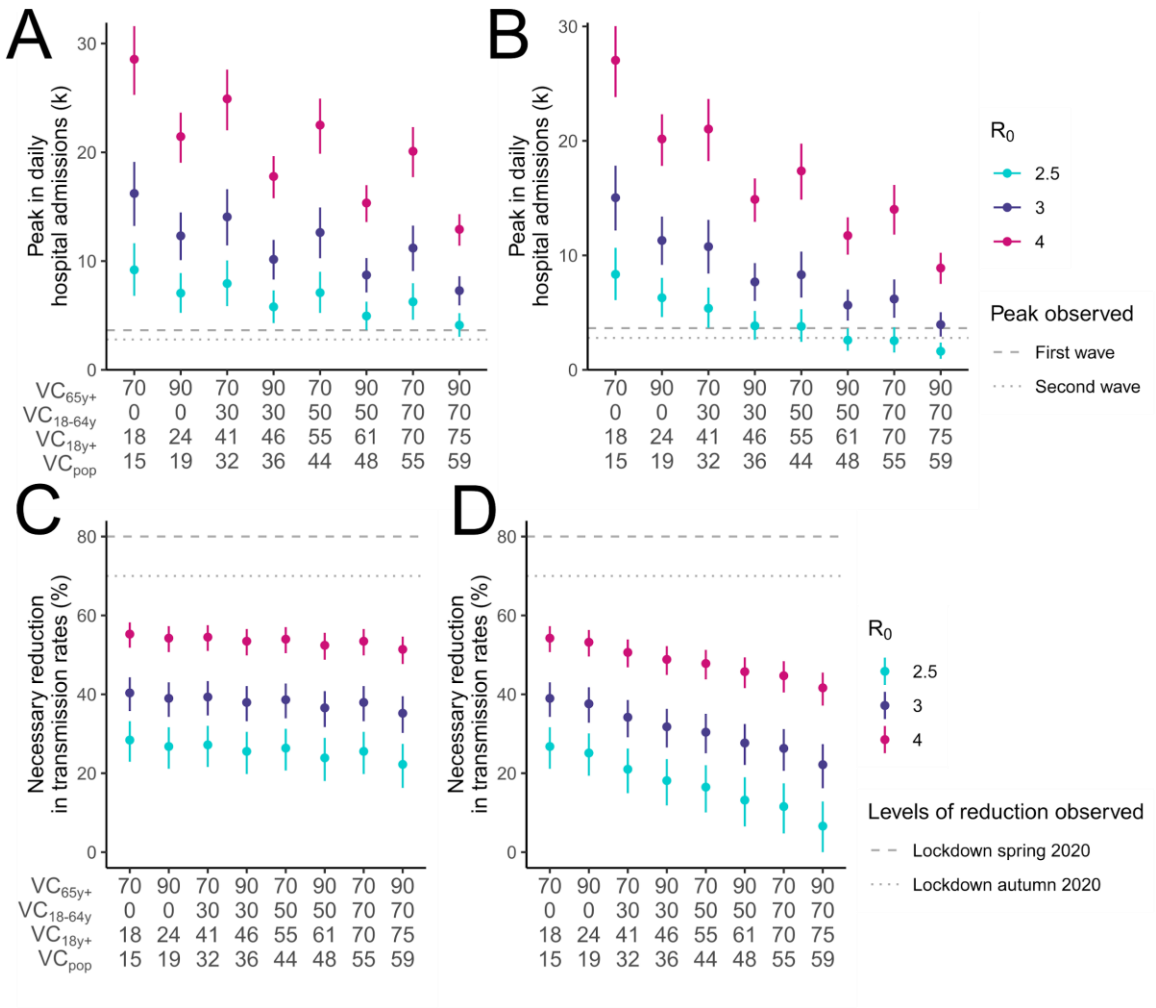

Figure S10: Sensitivity analysis for different vaccine characteristics - Manageable relaxation of measures by levels of vaccine coverage. Peak in daily hospital admissions for different combinations of vaccine coverages in 18-64 y.o. ($VC_{18\text{-}64y}$) and ≥65 y.o. (VC_{65y+}). **(A)** for the vaccine *Severity* and **(B)** for the vaccine *Transmission*. Reduction in transmission rates that remain necessary to avoid reaching 1,000 daily hospital admissions **(C)** for the vaccine *Severity* and **(D)** for the vaccine *Transmission*. For each combination of vaccine coverage in 18-64 y.o. and ≥65 y.o., we report the corresponding vaccine coverage in those older than 18 y.o. (VC_{18y+}) and in the general population (VC_{pop}). The metrics are computed assuming a proportion ever infected in France upon relaxation of 30% (range 25%-35% corresponding to the vertical bars).

Figure S11

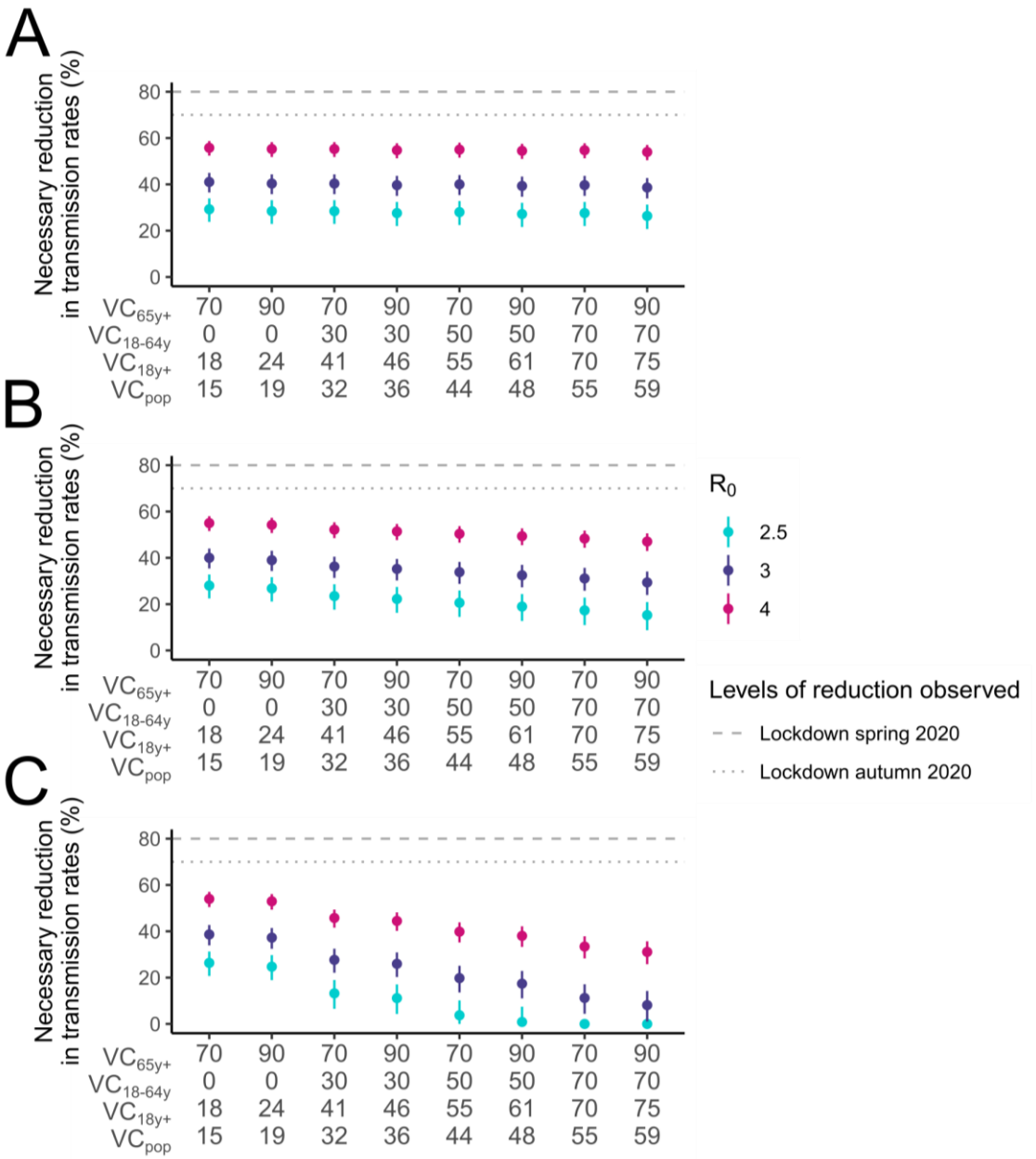

Figure S11: Sensitivity analysis with less efficient vaccines - Manageable relaxation of measures by levels of vaccine coverage ensuring the peak in daily hospital admissions remains below 1,000. Reductions in transmission that remain necessary in September **(A)** for a vaccine reducing the severity of the infection by 70%, (**B)** for a vaccine reducing the severity to the infection by 70% with a moderate impact on transmission (23%), **(C)** for a vaccine reducing the susceptibility (40%) to SARS-CoV-2 infection and the severity of the infection (70%). Different levels of vaccine coverage in 18-64 y.o. ($VC_{18\text{-}64y}$) and in ≥65 y.o. (VC_{65y+}) (in %) and values of the basic reproduction number R_0 assuming complete relaxation are explored. The reductions are computed assuming a proportion ever infected in France upon relaxation of 30% (range 25%-35% corresponding to the vertical bars). For each combination of vaccine coverage in 18-64 y.o. and ≥65 y.o., we report the corresponding vaccine coverage in those older than 18 y.o. (VC_{18y+}) and in the general population (VC_{pop}).

Figure **S12**

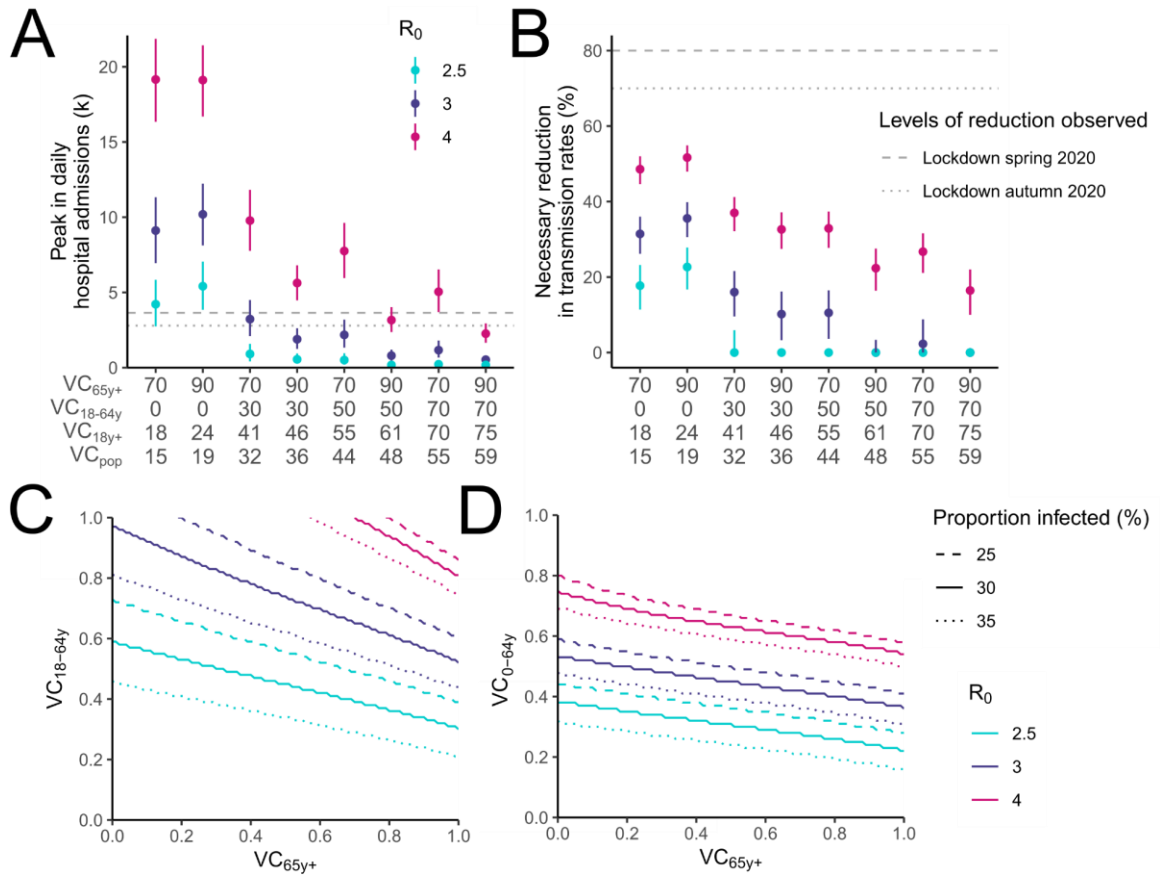

Figure S12: Sensitivity analysis considering a vaccine with an effectiveness of 80% on susceptibility, of 90% on severity and of 50% on infectivity. **(A)** Peak in daily hospital admissions for different combinations of vaccine coverages in 18-64 y.o. ($VC_{18\text{-}64y}$) and ≥65 y.o. (VC_{65y+}). **(B)** Reduction in transmission rates necessary to avoid reaching 1,000 daily hospital admissions. **(C)** Combinations of vaccine coverages in 18-64 y.o. and ≥65 y.o. and in **(D)** 0-64 y.o. and ≥65 y.o. necessary to avoid reaching 1,000 daily hospital admissions. Different values of the basic reproduction number R_0 assuming complete relaxation are explored. The reductions computed in (A-B) assume a proportion ever infected in France of 30% (range 25%-35% corresponding to the vertical bars) upon relaxation on September 1st 2021. For each combination of vaccine coverage in 18-64 y.o. and ≥65 y.o., we report the corresponding vaccine coverage in those older than 18 y.o. (VC_{18y+}) and in the general population (VC_{pop}). In (C-D), different values for the proportion of people ever infected in France at the date of relaxation of measures are explored.

Figure S13

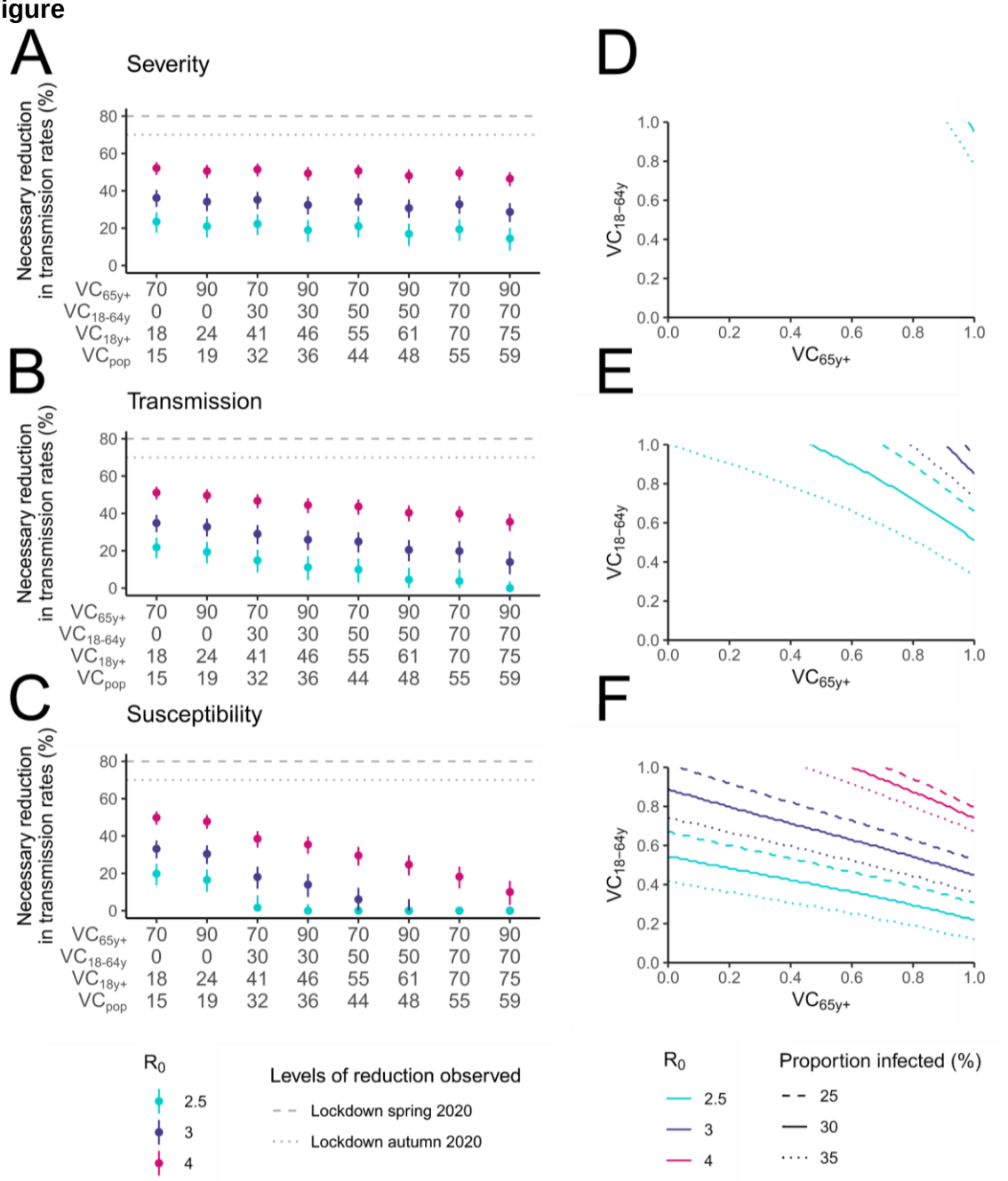

Figure S13: Sensitivity analysis - Manageable relaxation of measures by levels of vaccine coverage ensuring the peak in daily hospital admissions remains below 2,000. Reductions in transmission that remain necessary in September **(A)** for the vaccine *Severity*, **(B)** for the vaccine *Transmission*, **(C)** for the vaccine *Susceptibility*. Different levels of vaccine coverage in 18-64 y.o. ($VC_{18\text{-}64y}$) and in ≥65 y.o. (VC_{65y+}) (in %) and values of the basic reproduction number R_0 assuming complete relaxation are explored. The reductions are computed assuming a proportion ever infected in France upon relaxation of 30% (range 25%-35% corresponding to the vertical bars). Combinations of vaccine coverages in 18-64 y.o. and ≥65 y.o. that are necessary to avoid reaching 2,000 daily hospital admissions **(D)** for the vaccine *Severity*, **(E)** for the vaccine *Transmission*, **(F)** for the vaccine *Susceptibility*. For each combination of vaccine coverage in 18-64 y.o. and ≥65 y.o., we report the corresponding vaccine coverage in those older than 18 y.o. (VC_{18y+}) and in the general population (VC_{pop}).

Figure S14

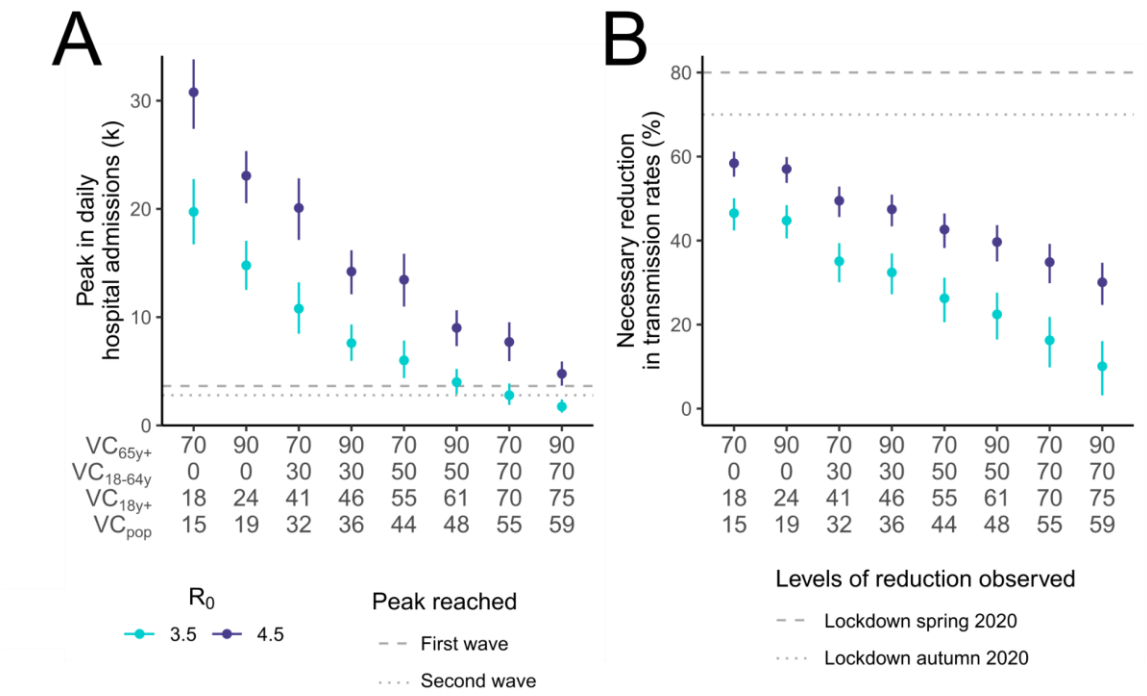

Figure S14: Sensitivity analysis for different values of R_0 upon measures' relaxation - Manageable relaxation of measures by levels of vaccine coverage. (A) Peak in daily hospital admissions for different combinations of vaccine coverages in 18-64 y.o. (VC18-64y) and ≥65 y.o. (VC65y+). (B) Reduction in transmission rates that remain necessary to avoid reaching 1,000 daily hospital admissions. Results are reported for the Vaccine Susceptibility. For each combination of vaccine coverage in 18-64 y.o. and ≥65 y.o., we report the corresponding vaccine coverage in those older than 18 y.o. (VC18y+) and in the general population (VCpop). The metrics are computed assuming a proportion ever infected in France upon relaxation of 30% (range 25%-35% corresponding to the vertical bars).

Figure S15

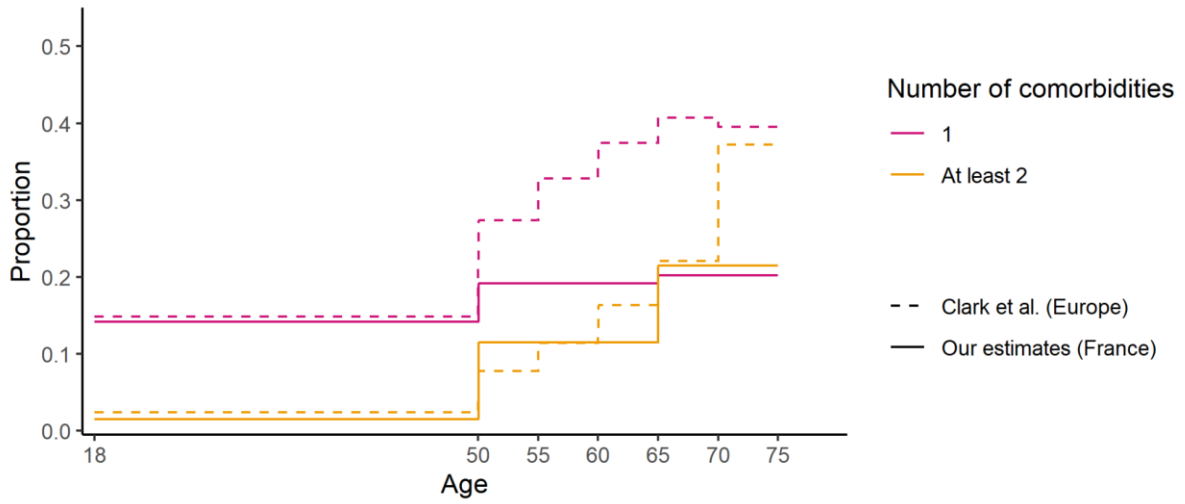

Figure S15: Comparison of the prevalence of comorbidities estimated from the Esteban survey in France and those of Clark et al. for Europe.

Figure S16

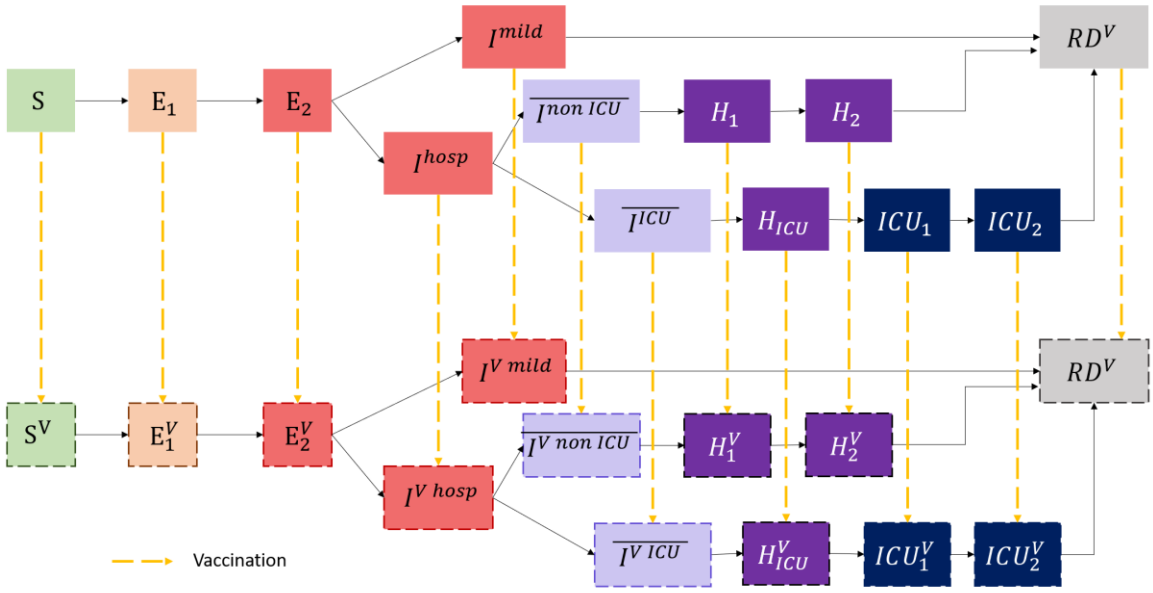

Figure S16: Model diagram

Figure S17

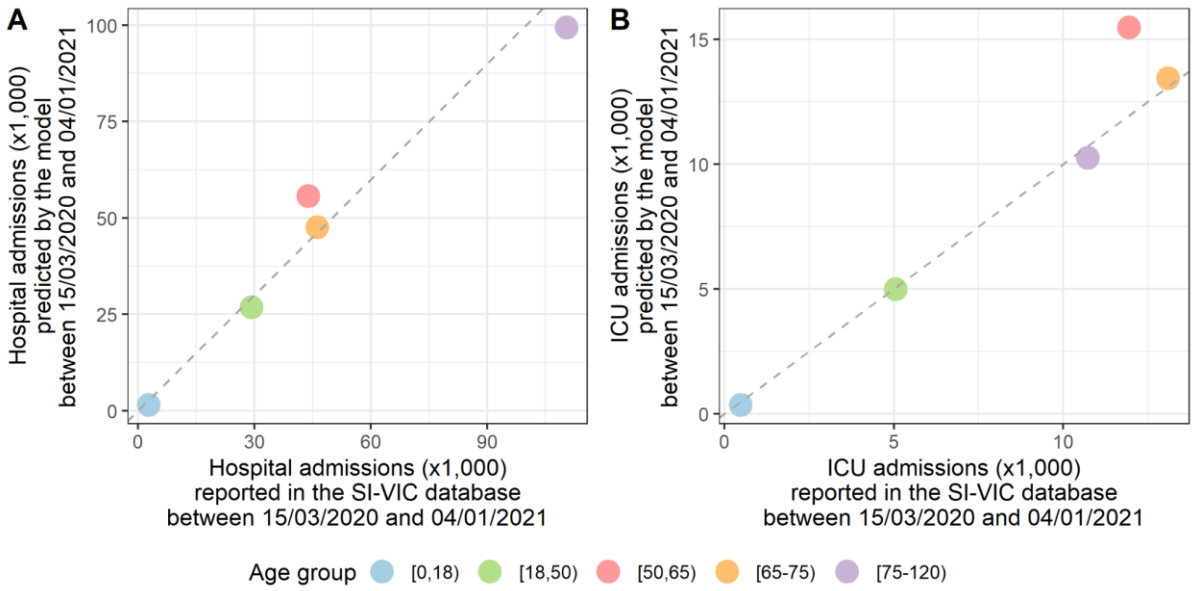

Figure S17: Comparison between observed and predicted admissions in healthcare settings by age group. (A) Comparison between hospital admissions predicted by the model and reported in the SI-VIC database between March 15th, 2020 and January 4th, 2021 in different age categories. (B) Comparison between ICU admissions predicted by the model and reported in the SI-VIC database between March 15th, 2020 and January 4th, 2021 in different age categories. The grey dashed line corresponds to the bisector of the first quadrant angle.

Figure S18

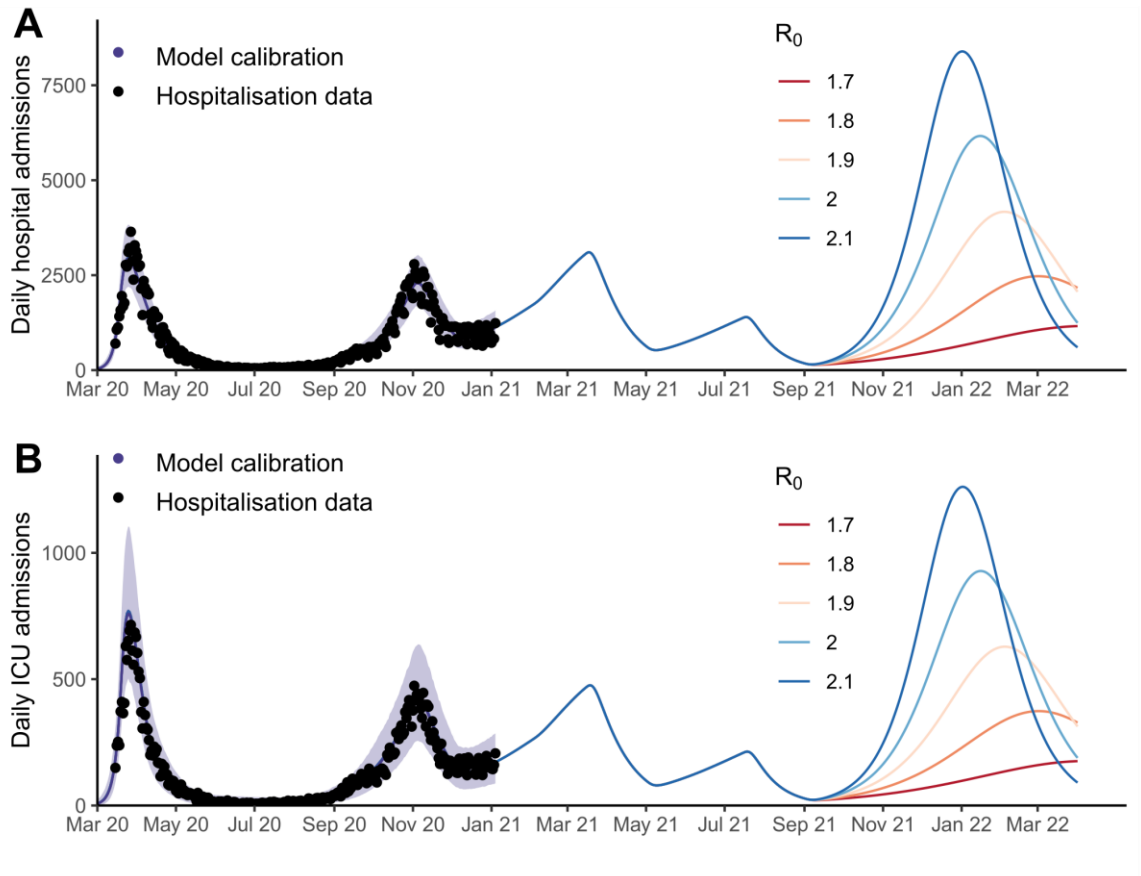

Figure S18: Examples of rebound scenarios used to study the relaxation of control measures. (A) Daily hospital admissions and **(B)** daily ICU admissions through time. The results are presented for different values of the basic reproduction number R_0 upon measures relaxation on September 1st, 2021 and in the absence of vaccination. In the plotted scenario, 28% of the population has been infected by SARS-CoV-2 on September 1st, 2021.

Supplementary tables

Table S1: Delivery calendar used for doses allocation (million doses). As monthly information was not available for the second semester of 2021, we assume that doses will be delivered homogeneously throughout this period (one sixth every month of the doses of the second semester). These numbers are computed based on a delivery calendar communicated by the French Ministry of Health on February 11th, 2021 assuming a 5% loss rate.

Date	Doses (million)
February 2021	5.23
March 2021	7.79
April 2021	17.77
May 2021	20.62
June 2021	20.43
July-December 2021	163.21

Table S2: Size of age and comorbidity groups considered in the different vaccination strategies (in millions). These numbers are computed from INSEE (National Institute of Statistics and Economic) population estimates data using estimates of the prevalence of comorbidities detailed in Table S4.

Number of conditions	0	1	At least 2	Total
Age group				
18-49 y.o.	21.22	3.58	0.38	25.18
50-64 y.o.	8.65	2.39	1.43	12.47
65-74 y.o.	4.2	1.46	1.55	7.21
Over 75 y.o.	-			6.25

Table S3: Severity parameters stratified by age and number of conditions used in the simulations for the year 2021. See section Stratification by age and comorbidity in Supplementary Text.

Age group	Number of conditions	Probability of hospitalisation given infection	Probability of ICU admission given hospitalisation	Probability of death given hospitalisation
0-9 y.o.	0	0.002	0.176	0.001
	1	0.005	0.176	0.001
	2	0.011	0.176	0.001
	≥ 3	0.011	0.229	0.002
10-17 y.o.	0	0.001	0.176	0.001
	1	0.002	0.176	0.001
	2	0.004	0.176	0.001
	≥ 3	0.005	0.229	0.002
18-29 y.o.	0	0.003	0.101	0.006
	1	0.008	0.101	0.006
	2	0.018	0.101	0.006
	≥ 3	0.019	0.132	0.011
30-39 y.o.	0	0.004	0.129	0.012
	1	0.012	0.129	0.012
	2	0.026	0.129	0.012
	≥ 3	0.028	0.167	0.021
40-44	0	0.006	0.169	0.03

y.o.	1	0.016	0.169	0.03
	2	0.035	0.169	0.03
	≥ 3	0.037	0.219	0.053
45-49 y.o.	0	0.012	0.183	0.03
	1	0.012	0.183	0.03
	2	0.034	0.183	0.03
	≥ 3	0.063	0.238	0.054
50-54 y.o.	0	0.021	0.202	0.041
	1	0.021	0.202	0.041
	2	0.06	0.202	0.041
	≥ 3	0.112	0.263	0.073
55-59 y.o.	0	0.029	0.208	0.058
	1	0.029	0.208	0.058
	2	0.084	0.208	0.058
	≥ 3	0.157	0.27	0.106
60-64 y.o.	0	0.04	0.221	0.101
	1	0.04	0.221	0.101
	2	0.116	0.221	0.101
	≥ 3	0.216	0.288	0.183
65-69	0	0.052	0.226	0.126

y.o.	1	0.052	0.226	0.126
	2	0.052	0.226	0.126
	≥ 3	0.2	0.294	0.228
70-74 y.o.	0	0.096	0.204	0.163
	1	0.096	0.204	0.163
	2	0.096	0.204	0.163
	≥ 3	0.37	0.266	0.294

Table S4: Prevalence of comorbidities estimated from the Esteban survey. Results are reported in %.

	Age-group				
Number of conditions	18-49 y.o.	50-64 y.o.	65-74 y.o.	≥ 75 y.o.	Total
0	84.2 (81.0-87.4)	69.4 (64.8-73.9)	58.3 (51.7-65.0)		75.6 (73.2-78.1)
1	14.2 (11.1-17.3)	19.2 (15.4-23.0)	20.2 (15.0-25.4)		16.7 (14.5-18.9)
2	1.3 (0.4-2.3)	6.2 (3.8-8.5)	13.2 (7.9-18.5)		4.6 (3.4-5.8)
At least 3	0.2 (0.0-0.5)	5.3 (3.0-7.7)	8.3 (4.5-12.1)		3.1 (2.1-4.0)

Table S5: Relative risk by comorbidity levels used to derive comorbidity specific probabilities of severe outcomes. * indicates when relative risks where considered significant.

	Source	Age	0	1	2	3 and more
Relative risk of hospitalisation given infection	(Ko et al. 2020)	< 45 y.o.	1.0 (Ref.)	2.6 (2.0-3.5) *	5.8 (4.0-8.3) *	6.2 (3.1-12.7) *
		45-64 y.o.	1.9 (1.4-2.6)	2.2 (1.4-3.6)	5.5 (3.5-8.7) *	10.3 (4.3-24.7) *
		≥ 65 y.o.	3.3 (2.3-4.6)	2.7 (2.0-3.6)	5.3 (2.1-12.9)	12.7 (4.4-37.1) *
Relative risk of ICU admission given hospitalisation	(Kim et al. 2021)	-	1.0 (Ref.)	0.95 (0.75-1.2)	1.1 (0.9-1.34)	1.30 (1.09-1.54) *
Relative risk of death given hospitalisation	(Kim et al. 2021)	-	1.0 (Ref.)	0.81 (0.56-1.18)	0.93 (0.67-1.28)	1.81 (1.44-2.28) *

Table S6: Parameter estimates with 95% credible interval

Parameter	Estimate [95% credible interval]	Corresponding reduction in transmission rates compared to the period prior 17 March 2020 (for reproduction numbers) [95% credible interval]
Reproduction number before 17 March 2020	3.36 [3.02 - 3.73]	-
Reproduction number 17 March 2020 - 11 May 2020	0.62 [0.61 - 0.63]	0.82 [0.79 - 0.84]
Reproduction number 11 May 2020 - 1 August 2020	1.02 [1.01 - 1.03]	0.7 [0.66 - 0.73]
Reproduction number 1 August 2020 - 30 October 2020	1.42 [1.41 - 1.43]	0.58 [0.53 - 0.62]
Reproduction number 30 October 2020 - 30 November 2020	0.82 [0.79 - 0.84]	0.76 [0.73 - 0.78]
Reproduction number after 30 November 2020	1.34 [1.29 - 1.38]	0.6 [0.56 - 0.64]
Parameter associated to the change in the probability of ICU admission between 30 March 2020 and 7 April 2020 α_1	0.59 [0.5 - 0.68]	
Parameter associated to the change in the probability of ICU admission between 1 July 2020 and 1 October 2020 α_2	0.79 [0.71 - 0.9]	
Parameter associated to the change in the probability of ICU admission between 1 October 2020 and 12 December 2020 α_3	0.57 [0.51 - 0.65]	
Initial number of infected individuals	6.89 [1.68 - 27.82]	
Overdispersion parameter δ	0.5 [0.47 - 0.52]	

Table S7: Summary of model parameters

Parameter	Description	Source
$1/g_1 = 4\ days$	Mean time spent in the E_1 compartment (Length of the latent phase)	(Salje et al. 2020)
$1/g_2 = 1\ day$	Mean time spent in the E_2 compartment (Length of the pre-symptomatic infectious phase)	(Salje et al. 2020)
$1/g_3 = 3\ days$	Mean time spent in the I^{mild}/I^{hosp} compartment (Length of the symptomatic infectious phase for those who will develop symptoms)	(Salje et al. 2020)
$1/g_{to\ hosp} = 4\ days$	Mean time spent in the $\underline{I^{non\ ICU}}$ compartment	(Salje et al. 2020)
$1/g_{to\ hosp\ ICU} = 3\ days$	Mean time spent in the $\underline{I^{ICU}}$ compartment	(Salje et al. 2020)
$1/g_{to\ ICU} = 1.5\ days$	Mean time spent in the H_{ICU} compartment (Mean time spent in general ward beds prior ICU admission)	(Salje et al. 2020)
$2/g_{out\ hosp}$	Mean time spent in $H_1 \cup H_2$ (general ward beds for patients not admitted to ICU)	Arbitrary
$2/g_{out\ ICU}$	Mean time spent in ICU	Arbitrary
R	Reproduction number across different time windows	Estimated - Table S6
${p_{a,c}}^{hosp}$	Probability of hospitalization given infection among individuals of age group a with comorbidity level c	Adjusted - Table S3
${p_{a,c}}^{ICU}$	Probability of hospitalization given infection among individuals of age group a with comorbidity level c	Adjusted - Table S3
${p_{a,c}}^{death}$	Probability of death given infection among individuals of age group a with comorbidity level c	Adjusted - Table S3
$\alpha_1, \alpha_2, \alpha_3$	Parameters used to fit a linear spline to the probability of ICU admission since the beginning of the epidemic	Estimated - Table S6
I_0	Initial number of infected individuals (in compartment E_1). (Distributed across age and comorbidity groups proportionally to the size of the different groups)	Estimated - Table S6
$VE_{severity}$	Reduction in the probability of hospitalisation upon infection among vaccinated individuals compared to unvaccinated individuals	See Methods
$VE_{infectivity}$	Reduction of the infectivity of vaccinated individuals compared to unvaccinated individuals	See Methods
$VE_{susceptibility}$	Reduction of the susceptibility to SARS-CoV-2 infection of vaccinated individuals compared to unvaccinated individuals	See Methods

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