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Covid-19 vaccine benefit during the Omicron wave in France

Michel Lubrano
Pierre Michel

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Michel Lubrano† Pierre Michel‡

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Abstract

During the Covid-19 pandemic, the Omicron wave was notable for its highly transmissible and contagious variant of concern, coinciding with the availability of a vaccine that has been rolled out well earlier. In this paper, we address two key questions. First, we seek to design a simple epidemiological model that can best capture the dynamics of Omicron infections. We demonstrate that combining the SIRD and SISD models provides an adequate solution. The second question examines the benefits of vaccination, in terms of both economic activity and lives saved, once the model is implemented. Our results show that without vaccination, the human cost would have been five times higher, and production losses would have doubled, due to stricter confinement measures and a higher death toll. We also quantify the cost of vaccine hesitancy at more than 8,000 extra deaths.

Keywords: Compartment models, Covid-19, Omicron wave, vaccination benefit, vaccine hesitation.
JEL codes: C32, I18.

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†Aix-Marseille Univ, CNRS, AMSE, 5 Bd Maurice Bourdet, 13001 Marseille, France, e-mail: michel.lubrano@univ-amu.fr.

‡Aix-Marseille Univ, CNRS, AMSE, 5 Bd Maurice Bourdet, 13001 Marseille, France, e-mail: pierre.michel@univ-amu.fr.

1 Introduction

The efficacy of the Covid vaccine remains a controversial topic. As a new vaccine, it triggered fears and concerns regarding potential side effects (see e.g. Verger et al. 2021), leading to significant vaccination hesitancy. Several studies have shown that vaccine hesitancy is influenced by various factors, including misinformation, fear of adverse effects, and distrust in government or health authorities. For instance in France, Schwarzinger et al. (2021) found that vaccine hesitancy in the working-age population was notably influenced by the characteristics of new vaccines and the national vaccination strategy. Cambon et al. (2022) highlight that France's vaccine hesitancy, among the highest globally, worsened during the Covid-19 pandemic due to ineffective communication strategies, underscoring the need for a vaccination strategy based on herd immunity messaging, healthcare worker prioritization, citizen engagement, and accessible, free vaccines. Karafillakis et al. (2022) highlighted that vaccine hesitancy was especially prevalent in certain demographic groups across Europe, where healthcare professionals play an essential role in improving the vaccine acceptance process, particularly in France. In the same vein, studies like those by Paris et al. (2021) and Janssen et al. (2021) also have underscored the prevalence of vaccine hesitancy among healthcare professionals in France. Tavolacci et al. (2021) conducted a study among French university students to explore vaccine acceptance, hesitancy, and resistance, finding nearly half of students were opposed or uncertain. Sallam (2021) conducted a global review assessing Covid-19 vaccine acceptance rates, highlighting that while vaccine efficacy and safety are critical, the success of vaccination campaigns is significantly influenced by public and healthcare workers' acceptance, with notably low acceptance rates in France.

Given the multiple factors influencing vaccine acceptance, as illustrated by the studies on vaccine hesitancy in various populations, it becomes clear that understanding the interplay between vaccination and other public health measures is essential. While many studies have been written on Covid-19 transmission, fewer have compared the efficacy of non-pharmaceutical interventions (NPI) and vaccination in France.[1] For instance, Paireau et al. (2023) assess the impact of various NPI, weather conditions, Variants of Concern (VoC) and vaccination coverage on the spread of Covid-19, using the reproduction number, $\mathcal{R}_0$, as a metric. VoC significantly impacted transmission rates and vaccine efficacy (Tamandjou-Tchuem et al. 2023). However, fewer studies have focused on the Omicron wave in France. Tamandjou-Tchuem

[1]Vaccination in France began in Spring 2021, approximately one year after the start of the pandemic. NPI started to be relaxed by Summer 2021 for those who were already vaccinated.

et al. (2023) end their analysis well before the official end of the pandemic. Ganser et al. (2024), using a SEIRD model to assess the effectiveness of both NPIs and vaccination in France, decided to end their empirical analysis intentionally before the official start of Omicron wave, on the argument that "*the Omicron VoC disrupted the epidemiological dynamics*".

We found that the Omicron period was particularly interesting to study as it clearly combines NPI and vaccination strategies and that it also reflect fully the impact of vaccination hesitancy. The Green Pass was introduced on June 9, 2021 (according to our data), creating a clear distinction between vaccinated and unvaccinated individuals, with stronger social restrictions remaining for the unvaccinated (the same type of pass was introduced in Italy). We can find two aims at this strategy: relaxing the stringency of some NPI in order to favour the economic recovery at the risk of a higher rate of transmission while incentivizing vaccination as another way of obtaining herd immunity. So, the Omicron wave displayed quite different features, compared to the previous waves. First, as testing became more available and widespread, reported data are much closer to reality. Second, a plot of daily cases could illustrate the modelling difficulties underlined in Ganser et al. (2024) due, on one side to the very high $\mathcal{R}_0$ at the start of the wave, and on the other side to the very long dampening of this wave, incompatible with a classical SIR model. Clearly, an adapted model has to be designed. Third vaccination became fully available as it already covered more than 50% of the population at the beginning of the Omicron wave. To summarize, the period is fully adapted for measuring the impact of both NPI and vaccination efficacy.

The first goal of our paper is to identify which simple compartment model could fit the Omicron wave, a period characterized by the combination of vaccination and various NPI. Using this model, our second aim is to construct counterfactual scenarios to assess the benefits of vaccination and of the Green Pass, in terms of both the number of avoided deaths and in the reduction of economic losses. Among those scenarios, we shall investigate what would have happened in the absence of vaccine hesitancy.

The paper is organized as follows. Section 2 presents the data used for inference, including sources for cases, deaths, NPI indices, and vaccination coverage in France. In Section 3, we discuss the inadequacy of the original SIRD model for the Omicron wave and explain the necessary modifications. Section 4 introduces the vaccination mechanism and its integration into the model. Section 5 outlines the inference principles used to fit the model to the data and in particular how vaccination hesitancy can be modelled. In Section 6, we evaluate the economic benefits of vaccination through counterfactual scenarios. Section 7 concludes the paper.

2 Data

There are numerous data sources for Covid-19. The most well-known international database is the *Covid-19 Data Repository* by the *Center for Systems Science and Engineering* (CSSE) at *Johns Hopkins University* (JHU CSSE Covid-19 Data). However, the *Blavatnik School of Government* of the University of Oxford provides data that not only includes policy information but also, more recently, vaccination data (see Hale et al. 2021). In particular, their severity index differentiates between vaccinated and unvaccinated individuals. The data were collected starting from January 1, 2020, which is considered the start of the pandemic (though it actually began on January 20, 2020). Data collection ended in December 2022, while the WHO declared the end of the pandemic in May 2023.

It is important to note the availability of other data sources for France, published by *Santé Publique France*, as detailed in Ganser et al. (2024). These are also aggregated data, but provided with detailed information at the department level. We will use the Oxford data, as we aim to estimate the simplest possible model rather than a geographical model. Finally, we notice Worldometers.info (2024) as another source of information, covering the entire world.

2.1 Data files and content

We focus on the Omicron wave and on the onset of vaccination in France. For this analysis, the relevant period begins in January 2021 and ends with the last month of collected data, December 2022, covering thus a period of two full years. A total of $158,385$ deaths have been attributed to Covid in France over the full three years of the pandemic. The total number of cases is much higher, at $38,266,999$, indicating that Covid affected nearly half of the French population.

Remark 1 *Although these data were corrected for statistical anomalies, they do not appear to have been corrected for variations in testing intensity. The number of detected cases depends heavily on the volume of tests performed. We can nevertheless assume that the Omicron wave is correctly reported, as testing was widely available during this period. This is of course not the case for the previous waves.*

2.2 Some landmarks

The official start date of the Omicron wave is 21 November 2021, when the Omicron variant became dominant over the Delta variant. However, the wave

itself began slightly earlier, as shown in Figure 1. Thus, the starting date

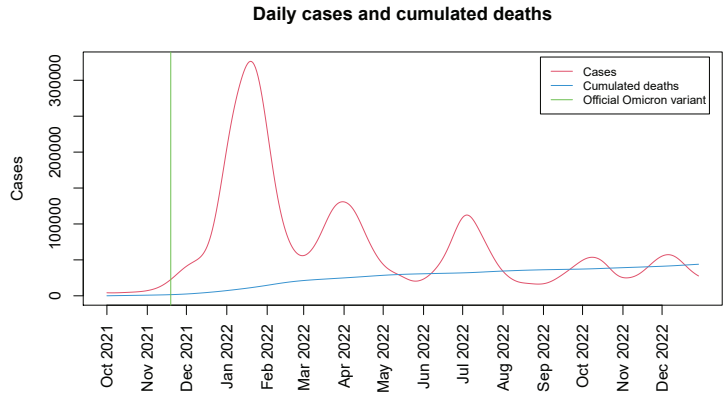


Figure 1: The Omicron wave and its official starting date

of our sample for modelling cases and deaths will be 8 October 2021, which corresponds to the lowest number of cases before the peak on 21 January 2022, implying a total of 450 observations for estimating the parameters of our compartment model, that is to say more than one year.

Figure 1 illustrates the empirical challenge we are facing. The observations around the peak can be effectively modelled by a standard compartment model with a very high reproducing rate, as documented in the literature (between 6 and 10, see e.g. Davido et al. 2022 and Liu and Rocklöv 2022). The issue is that the number of cases experiences at least four rebounds, leading to a prolonged dampening period, corresponding presumably to the conjunction of several possible factors such as reinfection, the presence of residual variants, or the varying efficiency of NPIs. This is not compatible with a standard SIRD compartment model which implies a quick dampening when herd immunity is reached. In the next section, we will explore which type of model can accurately reproduce both a very high $\mathcal{R}_0$ and an extended dampening phase.

2.3 Policy and vaccination data

The Oxford data set provides information on vaccination and social restriction policies. Vaccination data began to be collected at the end of January 2021.[2] The French government began differentiating between vaccinated and

[2]From that date till the peak of the Omicron wave, the fatality rate was around 2% (as measured from our data). From the peak of the Omicron wave till the end of December 2022, its average falls down to less than 0.2%.

unvaccinated individuals in terms of the stringency index on 9 June 2021.[3] The peak of the Omicron wave occurred on 21 January 2022, and the end of the sample period is 31 December 2022. Therefore, the period from 1 January 2021, to 31 December 2022 is particularly interesting as it capture the combined effects of both vaccination and lockdowns. Policy measures are illustrated in Figure 2. This period is therefore entirely concerned by the combination of a voluntary vaccination policy and evolving social restrictions.

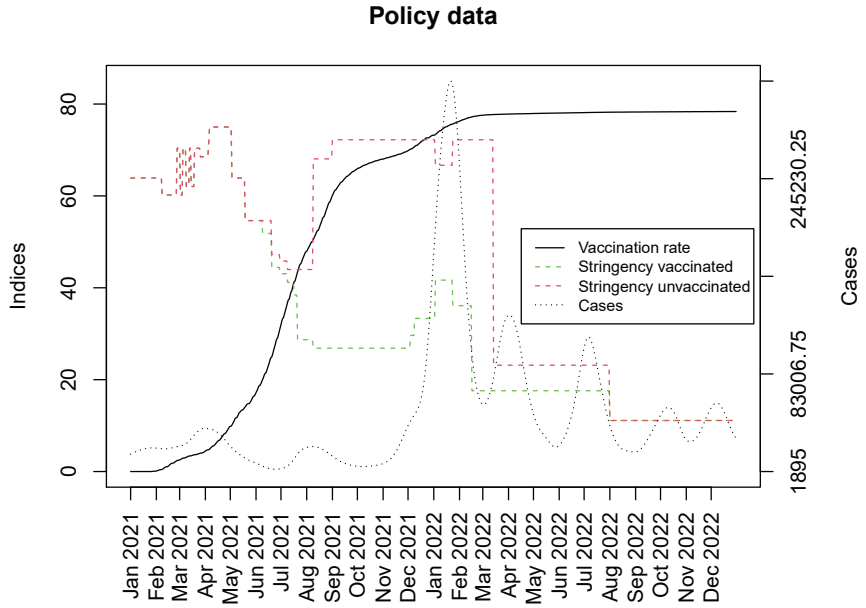


Figure 2: Vaccination and NPI facing the Omicron wave

3 The inadequacy of the original SIRD model for the Omicron wave

The SIRD model by Kermack and McKendrick (1927) and its variants are commonly used in simulation approaches to explore counterfactual scenarios in an epidemiological context (see e.g. Gollier 2020, Gollier 2021, Eichenbaum et al. 2021, Davido et al. 2022, Ganser et al. 2024). Therefore, it is essential to understand the dynamic properties of the SIRD model in the absence of any interventions. Note that this is a macro model, designed to explain the behaviour of groups and not of individuals.

[3]The Green Pass was introduced on 9 June 2021, and ended on 31 July 2022.

3.1 The basic SIRD model

In the original SIRD compartment model, the population of size N is divided into four mutually exclusive compartments. The Susceptible (S) compartment includes all individuals who are at risk of becoming infected (I), typically the entire population at the start of the pandemic (here 67×10^6). However, the sample we consider is starting well after the first wave, so a part of the population has already been infected and has recovered. Consequently, S can now be much smaller than the total population size, making it a first challenge to accurately determine the true value of S.

A person in the infected group I can infect multiple individuals in the susceptible group S, recover and transit to the recovered group R, or die, joining the deceased group D. A conservation identity states that $N = S + I + R + D$, since there is no birth or immigration in the model, implying that $dN_t/dt = 0$ (the population size remains constant when accounting for deaths).

Transitions between the four groups is described by a system of differential equations in continuous time:

$$\begin{cases} \dfrac{dS_t}{dt} = -\beta \dfrac{S_t}{N} I_t, \\ \dfrac{dI_t}{dt} = \beta \dfrac{S_t}{N} I_t - \gamma I_t, \\ \dfrac{dR_t}{dt} = (1-\pi)\gamma I_t, \\ \dfrac{dD_t}{dt} = \pi \gamma I_t. \end{cases} \tag{1}$$

In this model, two essential parameters, β and γ, govern the entire dynamics:

1. β is the contact rate, which measures the speed of transmission of the infection. It is a social parameter, as it depends on the frequency of social contacts between individuals. β is the inverse of the typical time T_C between two contacts. This parameter can vary significantly between waves and is the object of inference when the model is confronted to data. NPIs aim at reducing the contact rate, making this parameter time varying.

2. γ is the recovery rate, defined as the inverse of the time T_R required to recover from the infection. This is a biological parameter, with T_R typically ranging between 7 and 14 days for Covid. It is assumed to be constant for a given variant of the virus and is usually fixed when estimating a SIRD model.

The ratio $\mathcal{R}_0 = \beta/\gamma = T_R/T_C$ is fundamental for understanding the dynamics of the epidemic. If $\mathcal{R}_0 > 1$, the epidemic spreads exponentially until there are not enough susceptible individuals left to be contaminated. If $\mathcal{R}_0 < 1$, the epidemic vanishes quickly. Parameter π represents the fatality rate, or the probability of dying upon infection. While it does not play a fundamental role in the dynamics of the model, it determines the number of deaths, which is an important factor when designing a sanitary policy.

A key feature of the simple SIRD model is that an infected person can either recover or die, but cannot be reinfected, as once recovered, an individual becomes immune to the virus. With the important consequence that the epidemic eventually ends due to herd immunity. However, this assumption must be adjusted for Covid, as individuals who have recovered can be reinfected, or may remain immune for an unknown length period. This motivates our concern to expand the SIRD model into a SIRDS model, which we will now explain.

3.2 From a SIRD to a SIRDS model

In order to allow for the possibility of reinfection, we introduce a new parameter δ representing a fraction of the recovered individuals ($R_t = \gamma I_t$) that can return back into the susceptible group. This modification is determinant to allow the model to better capture the slow dampening of the Omicron wave:

$$\begin{cases} \dfrac{dS_t}{dt} = -\beta \dfrac{S_t}{N} I_t + \delta\gamma I_t, \\ \dfrac{dI_t}{dt} = \beta \dfrac{S_t}{N} I_t - \gamma I_t, \\ \dfrac{dR_t}{dt} = (1 - \pi - \delta)\gamma I_t, \\ \dfrac{dD_t}{dt} = \pi\gamma I_t, \end{cases} \tag{2}$$

Thus, we modify only two of the four equations of the original model. To illustrate how this new parameter affects the dynamics of the initial model, we now present simulations in Example 1.

Example 1 *We simulated both the SIRD and SIRDS models using parameter values consistent with the Omicron wave. We set* $\mathcal{R}_0 = 6.0$ *and* $T_R = 14$ *days for recovery, and* $\pi = 0.04$*. The initial infected population* I_0 *was set to* $N \times 10^{-6}$ *to position the peak of infection at a visually appropriate point. Then,* $S_0 = N - I_0 - R_0 - D_0$ *with* $D_0 = 0$ *and* $R_0 = 0$*. The population size* N *was chosen so that the simulated peak matched the observed Omicron*

peak, Imax. Assuming $N = \eta \times Imax$ *and given the other parameters and* $\delta = 0$*, an optimisation program leads to* $\eta = 1.861688$ *and* $N = 607,547$*, implying that 10% of the population was exposed to the Omicron variant.*

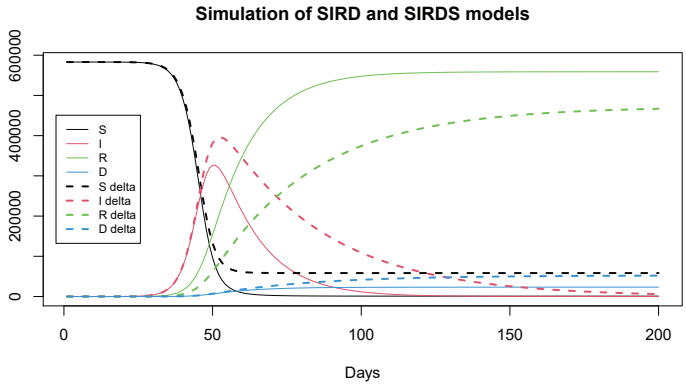


Figure 3: The dynamic impact of reinfection

The introduction of $\delta = 0.6$ *allows individuals to become susceptible again after recovering from the infection. As a result, the wave persists longer than in the original SIRD model, as displayed in Figure 3. This modification is crucial for accounting for the wavelets that occur after the main peak, as illustrated in Figure 1. The initial* $\mathcal{R}_0$ *remains unchanged, as is typical in any SIS model.*

If we had chosen to disregard the end of the Omicron sample, as in Tamandjou-Tchuem et al. (2023), or simply ended our data collection by October 31st, 2021, as Ganser et al. (2024) did, the value of δ *could have been much smaller. In fact, although Ganser et al. (2024) explicitly consider the possibility of reinfection, they assume that reinfection only occurs after one year.*

Let us now introduce the possibility of a lockdown, which makes the transmission parameter β variable over time.

3.3 Lockdowns

β is a social parameter that depends on social behaviours and restrictions, governing the rate at which the virus spreads. The purpose of a NPI is to reduce β by implementing social restrictions. Therefore, this parameter is made time-varying with:

$$\beta_t = \beta(1 - \theta\ell_t), \tag{3}$$

where ℓ_t represents the degree of severity of a lockdown and $\theta \in [0, 1]$ the efficiency of the confinement policy. The value of ℓ_t can be obtained by the Oxford severity index, as discussed in Section 2. This information is particularly valuable because it does not only reflect the efforts of health authorities to control the spread of the epidemic, but also provides insights into the economic cost of these measures, as individuals subject to confinement are unable to work. There is thus a trade-off between containment efforts ℓ_t and the economic cost they induce, that led to intense debates in the public (see e.g. Romijn et al. 2025 for the Netherlands). This kind of debate and hesitation can introduce a variation in the value of θ, a possible explanation for the presence of small rebounds during the end of the Omicron wave.

4 Introducing the vaccination mechanism

We aim to investigate the interaction between confinement measures and vaccination. To achieve this, we need to extend our initial model, allowing for vaccination as another mechanism to impede the diffusion of the pandemic.

4.1 Vaccination and compartments: the SIRDSV model

With Covid-19, the situation is more complex as the one described in usual vaccination models (see e.g. Schlickeiser and Kröger 2021). With Covid-19, vaccination primarily protects against the most severe aspects of the disease rather than preventing infection altogether (for details, see e.g. Tamandjou-Tchuem et al. 2023). Consequently, vaccinated individuals can still be reinfected. Additionally, the application of stringency measures designed to lower β_t often depends on individual vaccination status with the famous Green Pass. To account for these complexities, we first divide each compartment into two groups based on vaccination status. Using the observed vaccination proportion v_t from the data set, we decompose each compartment as follows:

$$\begin{aligned} S_t &= v_t S_t + (1 - v_t) S_t, \\ I_t &= v_t I_t + (1 - v_t) I_t, \\ R_t &= v_t R_t + (1 - v_t) R_t, \\ D_t &= v_t D_t + (1 - v_t) D_t, \end{aligned}$$

assuming that the splitting of the population is uniform across all compartments.

We have now to introduce the dynamics of vaccination through a time varying parameter ρ_t, which represents the daily vaccination rate. Vaccination applies exclusively to individuals who have not yet been vaccinated, so

ρ_t naturally tends to zero as the proportion of vaccinated individuals reaches saturation. The specific values of ρ_t over time will be determined using a separate model, as detailed in Section 5.1 below. Incorporating this dynamics to the initial model with its compartment decomposition, our final vaccination model is expressed as follows:

$$\begin{cases} \dfrac{dS_t}{dt} = -(\beta_{1t}, \beta_{2t}) \begin{pmatrix} v_t \\ 1-v_t \end{pmatrix} \dfrac{S_t I_t}{N} + \delta(\gamma_1, \gamma_2) \begin{pmatrix} v_t \\ 1-v_t \end{pmatrix} I_t - \rho_t(1-v_t)S_t, \\ \dfrac{dI_t}{dt} = (\beta_{1t}, \beta_{2t}) \begin{pmatrix} v_t \\ 1-v_t \end{pmatrix} \dfrac{S_t I_t}{N} - (\gamma_1, \gamma_2) \begin{pmatrix} v_t \\ 1-v_t \end{pmatrix} I_t, \\ \dfrac{dR_t}{dt} = [\gamma_1(1-\pi_1-\delta), \gamma_2(1-\pi_2-\delta)] \begin{pmatrix} v_t \\ 1-v_t \end{pmatrix} I_t + \rho_t(1-v_t)S_t, \\ \dfrac{dD_t}{dt} = (\pi_1\gamma_1, \pi_2\gamma_2) \begin{pmatrix} v_t \\ 1-v_t \end{pmatrix} I_t. \end{cases} \tag{4}$$

A complementary statistical model will be used to estimate the time-varying ρ_t, based on the observed proportion of vaccinated individuals, v_t.

Our model does not explicitly include a separate compartment for vaccinated individuals. Instead, each compartment is split between vaccinated and unvaccinated. To capture the differences in dynamics between vaccinated and unvaccinated individuals, we have introduced distinct parameters for transmission (β_{1t},β_{2t}), for recovery (γ_1, γ_2) and for mortality (π_1, π_2). This approach captures the differences in susceptibility, recovery and mortality between the two groups, enriching the model's dynamics and softening the uniform splitting assumption.

4.2 Identification

It is difficult to achieve identification of all the parameters of this model, as we observe only global variables (cases, deaths and the proportion of vaccinated) and not individual data where we could know who is vaccinated and who is not vaccinated. We thus have to fix some of the parameters, using external sources of information.

We shall first fix γ_1 and γ_2, the recovery rates. Among common values, it is reasonable to assume that vaccinated individuals recover twice quicker, $\gamma_1 = 1/7$ and $\gamma_2 = 1/14$. We shall estimate the mortality rate π_2 of unvaccinated, but we will fix π_1 to 0.005, corresponding to a mortality rate of 0.5% for vaccinated individuals who became infected (see e.g. Tamandjou-Tchuem et al. 2023). Let us now examine specifically the case of the transmission parameters. After 9 June 2021, the government implemented distinct

restrictive measures based on individuals' vaccination status. While vaccination remained voluntary, strong incentives were introduced to encourage uptake, as will be discussed in section 5.1 below. These differentiated measures were discontinued on 1st August 2022, when the vaccination rate had reached 78%, with no significant increase observed thereafter. Let ℓ_{1t} and ℓ_{2t} represent the severity indices for vaccinated and unvaccinated individuals, respectively. Using these indices, we can define the transmission rates β_1 and β_2 as follows:

$$\begin{cases} \beta_{1t} = \beta(1 - \theta\ell_{1t}), \\ \beta_{2t} = \beta(1 - \theta\ell_{2t}). \end{cases} \tag{5}$$

There is only one parameter β to estimate, the difference in transmission due to vaccination is thus supposed to be fully anticipated by the differentiated severity measures of the government. We assume that θ is common to all individuals, whatever their vaccinated status. We shall fix it to 1 for expository purposes and to 0.9 when estimating the model. The reinfection parameter δ is identified, thanks to the very asymmetric shape of the Omicron peak. The daily vaccination rate ρ_t is obtained as the by-product of an auxiliary statistical model, as explained below, a model designed to depict the vaccination proportion v_t over time.

4.3 Model flow

We summarize the functioning of the model in Figure 4. Only susceptible

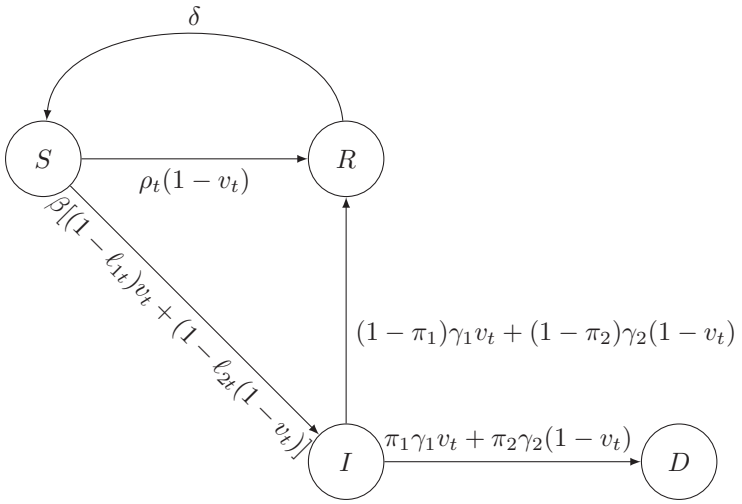


Figure 4: Compartments and vaccination

individuals who have not yet been vaccinated are eligible for vaccination. Once vaccinated, they transit directly to the recovered compartment, as in basic vaccination models. However, a fraction of these individuals may become susceptible again, as represented by the δ loop. This process occurs regardless of their vaccination status, which is a limitation of our model. The transmission rate β is influenced by the differentiated restrictions ℓ_{1t} and ℓ_{2t}. The authorities assume that vaccinated individuals have a lower transmission rate, leading to a significant lower severity of confinement measures (ℓ_{1t}) for them. Infected individuals can either recover or die, with the proportions depending on their vaccination status.

4.4 The economic cost of a pandemic

Eichenbaum et al. (2021) were the first to analyse the interaction between economic agents making decisions and the flow of a pandemic, building what they call a SIR-macro model. In this model, agents adapt their consumption and labour supply for production, considering the risk of contamination. Containment policies are introduced by a Pigouvian tax on consumption, designed to limit virus propagation. An optimal confinement policy maximizes a welfare function formed by a weighted sum of individual inter-temporal utilities.

For evaluating the cost of a pandemic, Gollier (2021) simply adds to the canonical SIR model a production function with an exogenous labour supply, leading to a much simpler model. In normal conditions, the entire population of size N is working and produces a daily output $w \times N$, where w is the daily wage rate assumed to correspond to labour productivity (a fixed coefficient production function). The first effect of the pandemic is to reduce production by removing two compartments from the workforce N_t: the infected and the deceased. Thus, at any given date, the production is limited to $w \times (S_t + R_t)$, where S_t represents the susceptible individuals and R_t the recovered individuals who are still able to work, including vaccinated and non-vaccinated. This means that the production over time during a pandemic is determined by two unobserved variables, S_t and R_t, as only I_t and D_t are observed.

Let us now introduce the possibility of a confinement, with a differentiation between vaccinated and non-vaccinated with ℓ_{1t} and ℓ_{2t}. In this case, a portion of the susceptible individuals are removed from production (excluding remote work) and the production is reduced to:

$$w \times [(1 - \ell_t)S_t + R_t], \tag{6}$$

with $\ell_t = \ell_{1t}v_t + \ell_{2t}(1 - v_t)$. The daily economic loss W_t corresponds to the

difference between total production in normal times ($w \times N$) and the reduced production given in (6):

$$W_t = w \times [N - (1 - \ell_t)S_t - R_t]. \tag{7}$$

The economic loss W_t is maximum at the peak of the wave. The average economic loss can be measured as the average of W_t over the simulation period and this average can be reported when divided by N in order to have a proportion.

We should note that the factor $(1-\ell_t)$ affects only the susceptible population and not the recovered individuals. Initially, when no tests were available, it made sense to assume that the recovered individuals were not able to work. During the Omicron wave, however, tests became widely available, allowing for the possibility that recovered individuals could return to work. Moreover, given that the infection is cyclical and reinfections can occur, some of the recovered individuals will be reclassified as susceptible, making them subject to confinement measures again. Therefore, the economic impact actually accounts for the fact that not only the susceptible population but also a portion of the recovered population may be restricted in their ability to work due to reinfection.

For the while, we have not spoken of the cost of lost lives. This brings us to the delicate question of the statistical value of life. In Gollier (2020), this values is fixed it to 20 years of gross domestic product (GDP) per capita, denoted by χ. This leads to the following formula for the total cost of lost lives:

$$L = \chi D_T, \tag{8}$$

where T is the length of the pandemic (or the length of the simulation period) and D_T the cumulated number of deaths at the end of the simulation period. In this approach, the value of life is assumed to be the same for everybody. The quantity L represents the economic cost of the lives lost during the pandemic and is an important aspect when evaluating the overall impact of the pandemic, both from an epidemiological and welfare standpoint. It combines the human and economic dimensions of the tragedy of lost lives, providing a tangible estimate of the consequences of the disease. However, reporting also the raw number of deaths is important in order to compare our results with those of the epidemiological literature.

4.5 Differences with other vaccination models

Before the Covid-19 pandemic, many compartment models were developed to include vaccination, as reviewed for instance in Schlickeiser and Kröger

(2021). These models typically assume that once individuals are vaccinated, they move directly from the susceptible compartment to the recovered or vaccinated compartments and are no longer at risk of infection. Assuming the total population N is normalized to 1.0 with $S + I + R + D = 1$ and incorporating a deceased compartment, the basic model reviewed in Schlickeiser and Kröger (2021) can be described as follows, where ρ_t is the daily vaccination rate:

$$\begin{cases} \dfrac{dS_t}{dt} = -\beta S_t I_t - \rho_t S_t, \\ \dfrac{dI_t}{dt} = \beta S_t I_t - \gamma I_t, \\ \dfrac{dR_t}{dt} = (1-\pi)\gamma I_t + \rho_t S_t, \\ \dfrac{dD_t}{dt} = \pi\gamma I_t. \end{cases} \tag{9}$$

The model of Gollier (2021) is an extension of this basic vaccination model, including an age structure. Focussing on the Alpha VoC, it introduces a vaccinated compartment, which accounts for a delay before antibodies become effective. However, once individuals are vaccinated or recovered, they are assumed to have reached full immunity and cannot be reinfected. Gollier (2021) uses this model to explore different vaccination strategies at the beginning of the vaccination campaign.

With the Delta and Omicron VoCs, the situation became more complex, as vaccinated individuals were not fully immune to the virus. They can still transmit the virus, be reinfected, and even die (but at a lower rate). Consequently, many researchers opted for an SIS model, which does not necessarily include a separate compartment for vaccinated individuals. For instance, Gualtieri et al. (2022) consider a simple SIS model that differentiates three susceptible compartments based on the severity of exposure to the virus. In their model, vaccination shifts individuals from the compartment with higher exposure severity to that with lower severity, while recovery from infection similarly returns individuals to the lowest severity compartment. Using calibration and simulations, they analyse how vaccination influences the evolution of disease prevalence over time.

Ganser et al. (2024) aim to estimate a complex SEIRD model on French data, distinguishing between asymptomatic, symptomatic and hospitalized infected individuals. They analyse the effects of vaccination on two critical aspects of the epidemic. First, they assess its impact on transmission dynamics by introducing a parameter that modifies the value of β_t. Second, they evaluate how vaccination influences the risk of hospitalization through a second parameter. Thus, the vaccination process is not explicitly mod-

elled, arguing that the number of administered doses is fully observable. As a result, their model does not include a specific compartment for vaccinated individuals. Moreover, the assumption that only hospitalized individuals can die (and at a uniform rate regardless of the vaccination status) may introduce some limitations. This could lead to differences when simulating counterfactual scenarios.

The SEIR model proposed by Ghostine et al. (2021) is slightly different. The aim of the model is still to analyse the impact of vaccination on the spread of Covid-19, but it takes into account seven compartments. In addition to the standard compartments (susceptible, exposed, infected, recovered and deceased) the model introduces two additional compartments: quarantined and vaccinated. Susceptible individuals who are vaccinated transition into the vaccinated compartment. However, due to vaccine inefficacy, a small proportion of vaccinated individuals revert to the exposed compartment. Their model leads to a more complex expression for the basic reproduction number $\mathcal{R}_0$. To estimate the parameters, they use a variant of the Kalman filter. The goal is to predict the number of deaths, recoveries and confirmed cases while taking into account the effects of vaccination and time-varying parameters. They study the impact of varying the vaccination rate on the spread of the epidemic. It is important to note that the authors fixed the inefficacy parameter to $\sigma = 0.05$, which corresponds to the theoretical value for the Pfizer-BioNTech vaccine against the original virus. We know that the efficacy of vaccine against the Omicron variant is much lower and that its efficacy declines over time.

5 Inference principles

We have decided to estimate our SIRDSV model on data starting on 8 October 2021, just before the official discovery of the Omicron variant as a new VoC, on 21 November 2021, and roughly at the time when tests were no longer free of charge (15 October 2021). The peak of the wave occurred on 21 January 2022. Our sample ends on 31 December 2022, providing a total of 450 observations. Vaccination, however, began much earlier, in January 2021, as illustrated in Figure 2. At the beginning of our sample, the vaccination rate was already 66%, increasing to 78% by its end. Here, "vaccinated" refers to individuals considered fully vaccinated with a complete initial vaccination protocol, excluding booster doses.[4] We first explain how we estimate ρ_t,

[4]Another source for vaccination data is the website *Our World in Data* `https://ourworldindata.org/covid-vaccinations`. We find there daily COVID-19 vaccine doses administered per million people 7-day rolling average. All doses, includ-

the time varying daily vaccination rate in a separate model, before exposing inference principles for the remaining parameters of our SIRDSV model.

5.1 An auxiliary growth model to explain vaccination behaviour

The daily vaccination rate, ρ_t, typically varies for the simple reason that as more of the population gets vaccinated, ρ_t tends to approach zero. Moreover, since the vaccine was quite new, there was a strong vaccination hesitancy, encouraged by the fact that individuals could escape the most stringent social restrictions if they could provide a negative test. With the end of free testing on 15 October 2021, we observe an increase in the daily vaccination rate. We propose to use a growth model, fitted to the observed series v_t, covering the period from January 2021 to December 2022, in order to construct an estimated series of ρ_t (the derivative of the estimated growth model) which will later be injected into our SIRDSV model.

A growth model such as that of Richards (1959) is a good starting point for explaining the proportion of vaccinated individuals as a function of time:

$$v(t) = \frac{K}{[1 + \kappa \exp(-r\kappa(t - \tau))]^{1/\kappa}}, \tag{10}$$

where K is the maximum vaccinated proportion of the vaccinated population, r is the rate of diffusion and τ is the date of the inflection point.[5] An additional parameter κ measures the deviation of Richards' model from the simple logistic model (obtained for $\kappa = 1$). The daily vaccination rate ρ_t corresponds to the first derivative of this model and is given by:

$$\rho_t = \frac{\partial v(t)}{\partial t} = rK \frac{\kappa \exp(-r\kappa(t - \tau))}{[1 + \kappa \exp(-r\kappa(t - \tau))]^{1+1/\kappa}}. \tag{11}$$

At the inflection point ($t = \tau$) the daily vaccination rate is maximum with:

$$\rho_{max} = rK \frac{\kappa}{(1 + \kappa)^{1+1/\kappa}}. \tag{12}$$

However, even though this model is quite general, it does not allow for irregularities in the vaccination profile. We need to use a double sigmoid function

ing boosters, are counted individually.

[5]There is a discussion about the useful parametrization of this model as explained in Wang et al. (2012). We have adopted the parametrization recommended in that paper where r represents directly the growth rate.

with $v(t) = v_1(t) + v_2(t)$ in order to take into account the vaccine hesitancy observed in the data, leading us to consider a double Richards model:

$$v(t) = \frac{K_1}{[1 + \kappa \exp(-r_1 \kappa (t - \tau_1))]^{1/\kappa}} + \frac{K_2 - K_1}{[1 + \kappa \exp(-r_2 \kappa (t - \tau_2))]^{1/\kappa}},$$

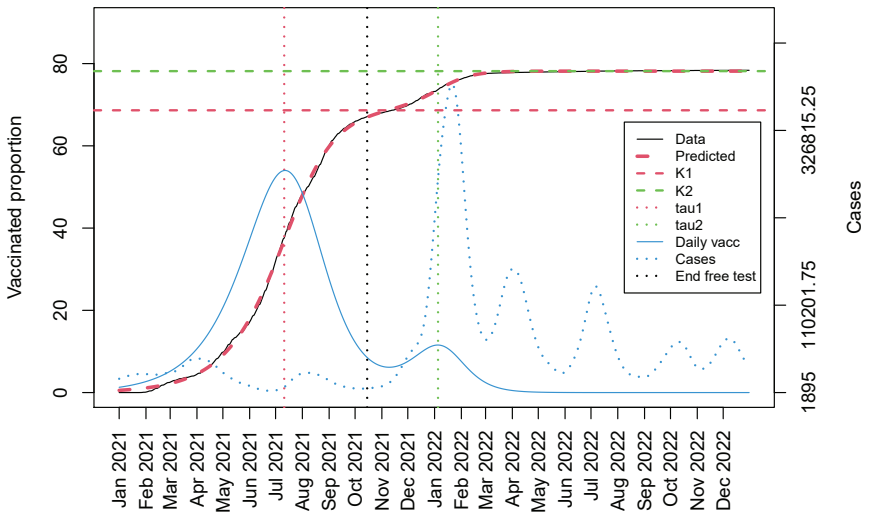
where we have imposed the constraint that κ is the same for the two components.

Let us estimate this model on the 730 observations of the full vaccination period (January 2021 to December 2022) and report the estimation results in Table 1 together with the implied vaccination rate ρ_t in Figure 5.

Table 1: A Double-Richards model for vaccination

	K	τ	r	κ
First component	68.64	193	0.024	1.54
	(159.43)	(291.88)	(45.69)	(19.22)
Second component	78.17	371	0.036	
	(1322)	(178)	(9.22)	

t-statistics are given below between parentheses. Optimization was done in `R` with `nls.lm` of package `minpack.lm`. K has to be divided by 100 in order to find the proportion of vaccinated individuals.



The left axis is for vaccination v_t. Daily vaccination rates were multiplied by 100 for display. The right axis is for daily cases.

Figure 5: Fitting a growth model for vaccination diffusion

There was a first vaccination wave before the Omicron VoC when 69% of the population was covered, and then the daily vaccination rate dropped dramatically. With the appearance of the Omicron wave and the end of free testing on 15 October 2021, the vaccination campaign resumed, reaching a peak just before the peak of the Omicron wave and leading to a final vaccination coverage of 78%. We noticed that the speed of diffusion increased between the two waves of vaccination, from $r_1 = 0.024$ to $r_2 = 0.036$. The distance between the two peaks of vaccination was six months. Finally, note that restricted models such as double Gompertz ($\kappa = 0$) and double logistic ($\kappa = 1$) are both rejected by the data.

5.2 Loss functions for inference

A SIRDSV model simulates the trajectory of daily cases I_t and the cumulative number of deaths D_t. Since we have observations for these two quantities, we can define a quadratic loss function for parameter inference by minimizing the discrepancy between the simulated and observed values:

$$L(\vartheta) = \frac{1}{n}\sum_t (I_t(\vartheta) - I_t^{Obs})^2 + \frac{1}{n}\sum_t (D_t(\vartheta) - D_t^{Obs})^2. \tag{13}$$

In this equation, I_t^{Obs} is the smoothed number of daily observed cases, D_t^{Obs} is the cumulative number of observed deaths since the start of the estimation period, while $I_t(\vartheta)$ and $D_t(\vartheta)$ are the simulated daily cases and cumulative deaths respectively, from the model given parameters ϑ. This follows a methodology partly adopted by Ganser et al. (2024). An additional term can be included in the loss function to capture the quadratic distance between the simulated and observed peaks of daily cases:

$$\begin{aligned} L(\vartheta) = &\frac{1}{n}\sum_t (I_t(\vartheta) - I_t^{Obs})^2 + \frac{1}{n}\sum_t (D_t(\vartheta) - D_t^{Obs})^2 \\ &+ (\max_t(I_t(\vartheta)) - \max_t(I_t^{Obs}))^2. \end{aligned} \tag{14}$$

Adding this information enhances both the calibration and interpretability of the simulated model. The date of the peak depends on the initial condition I_0, making it wise to estimate I_0 alongside the other parameters.[6]

[6]For a given set of parameter values ϑ, the model is simulated using an Euler discretisation with a time step of $dt = 1/10$. This approach necessitates interpolating the intra-day missing values for the two differentiated severity indices, ℓ_{1t} and ℓ_{2t}. For the proportion of vaccinated v_t, we use decimal values of t for simulating the double Richards model, conditionally on the estimated parameters.

5.3 Fixing the size of the exposed compartment

In most papers, the size of N is either normalized to 1.0, or fixed to the total population size, 67×10^6 for France. This approach works well when the pandemic is at its starting point. At the start of the Omicron wave, we have already an unknown proportion of the population that has got either herd immunity or vaccine immunity. So an intermediate value for N has to be found, much lower than 67×10^6. We know that at the start of vaccination, already 2,636,045 individuals had been infected and at the start of our sample, this figure had gone up to 6,874,967. At the end of our sample, the pandemic will have affected $38,266,999$ people, equivalent to 57% of the French population. In order to provide a realistic guess for N, we can go back to Example 1. We have simulated a SIRDS model, calibrated on plausible β and γ values for the Omicron wave in France. Conditionally on those values, we estimated a value for N, so as to match the simulated value of the peak of infections with its observed counterpart for Omicron. We found $N = 607,547$, a value that we propose to use in our SIRDSV model.

6 The economic benefit of vaccination

We first estimate our model (4), along the principles discussed above, so as to construct what we term the benchmark model. We then develop four distinct scenarios, varying vaccination rates and confinement severity, in order to measure the benefits of vaccination.

6.1 Estimation results for the benchmark

Our model estimation focuses on the Omicron period, spanning from early October 2021 to the end of December 2022. For the benchmark scenario, we assume recovery rates of $\gamma_1 = 1/7$ for vaccinated individuals and $\gamma_2 = 1/14$ for unvaccinated, reflecting a faster recovery observed among the vaccinated. The confinement efficiency parameter is set at $\theta = 0.9$ and mortality rate for vaccinated $\pi_1 = 0.005$. For v_t and ρ_t, we took the simulated values of the estimated double Richards model. Table 2 provides the estimation results for this benchmark.

Table 2: Model estimates with vaccination for the Omicron period

	β	π_1	π_2	δ	γ_1	γ_2	θ	RSS
Estimate	0.685	0.005	0.057	0.838	1/7	1/14	0.9	0.00506
S.E.	(0.136)	(-)	(0.045)	(0.118)	(-)	(-)	(-)	
Student-t	5.037	(-)	1.256	7.072	(-)	(-)	(-)	

We used the Huber sandwich estimator for standard errors. RSS is the root mean squared error.

The estimated value of β yields an approximate basic reproduction number $\mathcal{R}_0$ of 4.80 for vaccinated individuals and 9.60 for unvaccinated individuals, reflecting the corresponding effects of γ_1 and γ_2.[7] The high value of δ captures the important difference between ℓ_1 and ℓ_2 and aligns with the observed reduction in vaccine efficacy against the Omicron variant (see e.g. Davido et al. 2022). Furthermore, the estimated fatality rate for unvaccinated is ten times that of the vaccinated, which corresponds well with documented data (see e.g. Blanpain 2023).

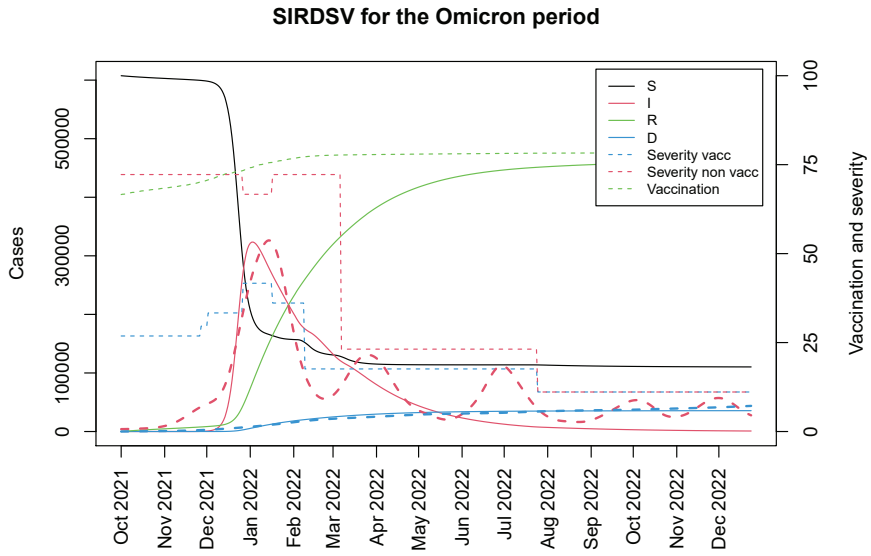


Figure 6: Simulation fitted to the data

Figure 6 shows a good fit for the cumulative deaths. While the fading wavelets following the Omicron peak are not accurately reproduced, the general tendency aligns well with observed data, except toward the end of the

[7]The approximate $\mathcal{R}_0$ is computed as β/γ, although the true formula is $\beta/(\gamma+\rho)$. In this case, the daily vaccination rate is very small with $\rho_t = 0.00066$ at the official start of the Omicron wave, while $\gamma_2 = 1/14 = 0.071$.

sample period, where the model tends to approach zero too quickly after September 2022. Nevertheless, this model provides a rich framework for simulations, enabling us to disentangle the effects of NPI and of vaccination and the impact of vaccination hesitancy.

We have thus provided a reasonable representation of the Omicron wave and its fading decay with a model that accounts for two mechanisms during this period, as illustrated in Figure 6. At the start of our estimation sample, the number of cases was relatively low, together with 66% of the population already vaccinated, although the daily vaccination rate, ρ_t, had begun to slow down (see Figure 5). As cases started to rise and just before the surge caused by the Omicron VoC, the daily vaccination rate increased again, together with the stringency index for the unvaccinated. This period is thus characterized by a blend of vaccination efforts and of NPIs, and our model effectively integrates these dual mechanisms. So we can ask immediately two questions: what was the impact of vaccination hesitancy and what was the efficiency of the Green Pass against the diffusion of this VoC? Our last question refers to the impact of an absence of vaccination.

6.2 A counterfactual model for vaccination hesitancy

What would have been the vaccination profile without vaccination hesitancy? This is an important question, as we want to measure its cost on the spread of the epidemics. In order to answer this question, we have first to image what would have been the vaccination rate of the population in this case. Once we have found this new profile, we have to plug it into our benchmark model and see what the number of cases and the number of deaths would have been. For this we have to make a certain number of assumptions concerning the statistical model that we used in section 5.1.

1. Without hesitancy the vaccination profile would have followed a simple Richards model.

2. The peak of vaccination would have been reached two weeks earlier, implying $\tau = 179$ instead of the estimated value $\tau_1 = 193$

3. 86% of the population would have received two doses instead of the observed 78.17%. The figure of 86% corresponds to the Spanish vaccination coverage which is the maximum coverage observed in large European countries at that time.

4. The speed of vaccination corresponds to what was estimated for the second wave, $r_2 = 0.036$, after the end of free testing.

5. Conditionally on the other parameters, the value of κ determines the value of the maximum daily vaccination rate, as can be seen from (12). This is a capacity limitation of the health system. We obtain the same peak value rate as that estimated by our double Richards model for $\kappa = 0.614$.

Altogether, we obtain the new vaccination profile depicted in Figure 7. With this new vaccination profile, coverage continues to increase after 15 October 2021. The daily vaccination rate decreases at a lower pace than what is actually observed, so that no rebound in the vaccination campaign is necessary in order to reach the final coverage of 86%. And the vaccination campaign ends at a similar date in April 2022.

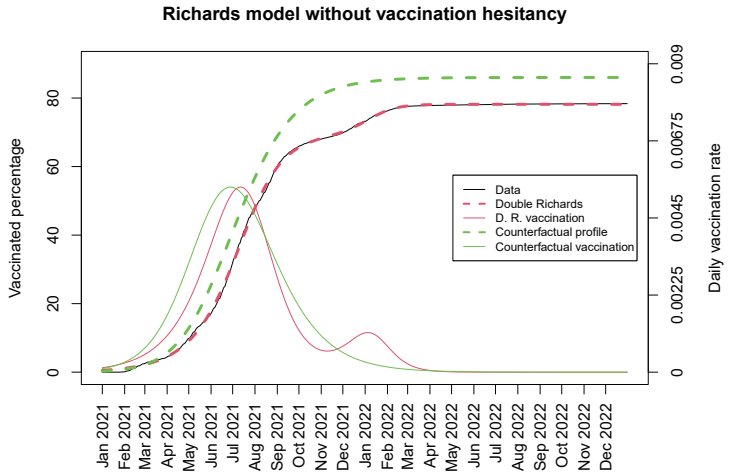


Figure 7: A counterfactual vaccination profile

6.3 Simulation results

Through simulation, we now aim to disentangle the two mechanisms of vaccination and of NPIs by considering counterfactual scenarios. We shall compare each counterfactual scenario to the benchmark model, which represents the observed situation. The initial condition I_0 is chosen so that the simulated peak aligns exactly with the observed peak date of the Omicron wave, conditionally on the other estimated parameters. This initial condition will remain fixed across all simulations to ensure consistency with the stringency index used, in the model. Our four counterfactual scenarios are as follows:

1. The first counterfactual scenario aims at evaluating the impact of the Green Pass policy. Specifically, we examine what would have happened

if the government had relied solely on vaccination, without implementing stricter confinement measures for the unvaccinated. The vaccination rate remains the same, but the stringency index is set to its lower observed values, regardless of vaccination status.

2. The second counterfactual scenario builds on the previous one, but assumes that the severity index is set to its highest observed values, irrespective of vaccination status. This scenario reflects the consequences of the reduced vaccine efficacy against the Omicron variant compared to the Delta variant, for which vaccination had provided stronger protection.

3. The third counterfactual scenario aims at measuring the cost of vaccine hesitancy in France. For this, we assume for that that the vaccination profile corresponds to the description made in section 6.2. The severity index is left as it is in the benchmark model, including thus a differentiation between vaccinated and non-vaccinated, but of course the vaccinated proportion vary.

4. The fourth counterfactual scenario explores what would have occurred in the absence of any vaccine, relying solely on NPI. The severity index is set to its maximum observed values. This corresponds to an attempt of mastering the spread of the epidemics, as was done in many European countries, before the availability of a vaccine.

We report the simulation results for these four scenarios in Table 3, where we show both the simulated production loss (computed according to equation 7), the simulated cost of lives lost (8) and the simulated number of deaths. The final column provides the ratio of these values compared to the benchmark model. The economic cost of the pandemic is measured by the difference between the full potential production and the actual production resulting from a reduced active population. We report the simulated number of deaths, which will allow for future comparisons with the epidemiological literature.

Table 3: Estimated benefit of vaccination over the whole Omicron period

Scenario	Cases	Prod. loss in %	Deaths	Death in %	Prod. loss	Life loss
Benchmark model	23,457,641	23.29	34,984	5.76	1.00	1.00
Vaccine, low severity	23,787,261	22.26	36,567	6.02	0.96	1.05
Vaccine, high severity	23,194,330	26.23	33,601	5.53	1.13	0.96
No vaccine hesitancy	22,490,615	20.63	27,132	4.47	0.89	0.78
No vaccine, high severity	45,593,846	54.60	185,496	30.53	2.34	5.30

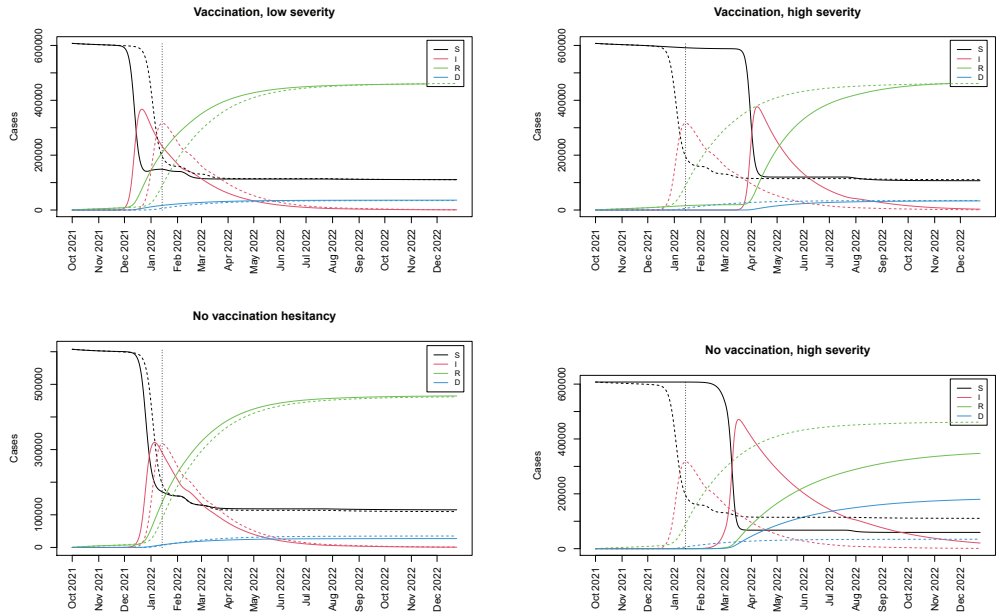
Deaths is the simulated total number of deaths due to COVID for the Omicron wave. Production losses are measured by the ratio between the production loss for a scenario and the same figure for the benchmark. A ratio lower than 1.0 means a lower production loss. Life loss is the ratio between the simulated number of deaths and that of the benchmark.

1. The Green Pass was designed to impose less stringent restrictions on those who chose to get vaccinated, while individuals who remain unvaccinated faced stronger restrictions, both to limit transmission and to incentivize vaccination. If the government opted to apply a uniform low level of restrictions to everyone, the Omicron wave would have started earlier and reached a higher peak, as shown in the top panel of Figure 8. This scenario would have resulted in a 4% increase of production, but also a 4% rise in the number of deaths. Thus, the Green Pass proved beneficial in saving lives, albeit at a mild production cost.

2. Conversely, if severe restrictions had been maintained for all, the wave would have been delayed, leading to a modest 4% reduction in deaths, but a 13% increase in production loss. Therefore, the Green Pass can be viewed as a reasonable trade-off between lives and livelihood.

3. Vaccine hesitancy implied a delay in reaching the peak of vaccination and a lower vaccinial coverage. If France had managed to reach the Spanish vaccinial coverage, this would have resulted in a 11% decrease in the production loss and in a 22% decrease in the number of deaths. So the cost of the vaccinial hesitancy is quite important. It implied an increase of 967,026 cases and of 7,852 deaths.

4. Finally, in the absence of any vaccine, the production loss would have been twice higher and the number of death more than 5 times higher.



Simulation of the concerned variant is in plain lines, benchmark is in dotted lines.

Figure 8: Comparing strategies in front of the Omicron wave

These simulations show the importance of vaccination for fighting the pandemic. NPI and the green pass did have an influence, but mainly in moving the date of the peak for the infected. NPIs imply a trade-off between lives and livelihood, or in other terms a trade-off between production and the number of deaths. With vaccination, that trade-off vanishes as there is both a gain in term of production and in term of lives saved.

6.4 Comparison with results from the French literature

The calibrated age-structure model of Gollier (2021) is quite simple. It aims at finding the best vaccine allocation facing the Alpha VoC, so well before the Omicron wave and just at the beginning of the vaccination wave. It relies on some extreme assumptions such as the 100% vaccine efficiency, a common fatality rate and the full efficiency of herd immunity. In the absence of a vaccine, the stop-and-go policy designed to flatten-the-curve has no other outcome than reaching herd immunity, while an efficient allocation of vaccines manages to kill the epidemic at a much quicker pace. A one week delay in vaccination implies 2,500 additional deaths, while his antivax assumption implies an additional death toll of 60,000. Without vaccination,

Gollier (2021) evaluates the death toll to 450,000 and this number is divided by 10 for full speed vaccination.

Pageaud et al. (2021) calibrated a SEIR model before the emergence of the Delta VoC, which includes hospitalization and vaccination. Vaccinated individuals can develop only an asymptomatic form of Covid. Without vaccination and the Alpha VoC (December 2020), they reach a number of deceased varying between 210,000 and 620,000, depending on the chosen severity for NPI. With one year vaccination campaign, this number is reduced to 60,000.

Ganser et al. (2024) estimated a quite more complex model, using a much richer data set including hospitalization, details about VoCs and meteorological data, and statistical inference for many parameters. However, their period runs from 1 March 2020 to 31 October 2021. So they start their estimation period from the very beginning of the pandemic, but stop just before the Omicron wave, which officially started on 21 November 2021. They cover the start of vaccination, i.e. 25 January 2021 which is the date of the first reported doses. They stop when the rate of vaccination is 68%. Because they observe the number of administered doses per day, they decided not to model the vaccination process with a specific compartment, but simply as two parameters reducing transmission and hospitalization. In particular, they have a single death rate as they assume that only hospitalized can die, irrespective of their vaccination status. Let us now report these different results in Table 4.

Table 4: Estimated effect of vaccination in the French literature

	VoC	Deaths	Cases	Hospitalisation
		Gollier (2021)		
No vaccination	Alpha	450,000		
Vaccination		45,000		
Antivax cost		60,000		
		Pageaud et al. (2021)		
No vax, strong NPI	Alpha	210,000		
No vax, weak NPI		620,000		
Vaccination		60,000		
		Ganser et al. (2024)		
Benchmark	Alpha, Delta	92,000	10,306,000	470,000
No vaccination		249,000	20,269,000	1,930,000
		Our simulations		
Benchmark	Omicron	34,526	23,688,080	
No vaccination		185,496	45,593,846	
Antivax cost		7,852	967,026	

Vaccination has reduced the number of deaths in all cases. But its simulated impact ranges from a factor of 2.7 (Ganser et al. 2024), to 10 (Gollier

2021). With our simulation, we have the intermediate factor of 5.3. The antivax movement led to an increase in the number of deaths, but this number is subject to great variations, from 8,000 with our model to 60,000 in Gollier (2021). Some models rely totally on calibration (Gollier 2021, Pageaud et al. 2021), the other use data to estimate parameters, with however some calibrated parameters. In fact, not all the parameters are identified in a compartment model, making partial calibration a necessity. This might explain the variance of the results reported in Table 4.

7 Conclusion

The Omicron wave represents a quite original period for which adjusting an epidemiologic model was quite difficult. It covers a policy mix between vaccination and NPI. With a somehow slightly more complex compartment model than the simple SIRD model, we have managed to combine the two types of policies with the goal to measure the benefit of vaccination when facing a much more contagious wave. By comparing the results of our simulated scenarios which used the same characteristics and parameters, we have reached the conclusion that without vaccination, the number of deaths would have exploded, even if confinement had remained the same. The cost of vaccinial hesitation was finally quite significant with 8,000 extra deaths. Gollier (2021), assumed that 30% of the population refused vaccination, assuming implicitly that 100% could be covered when the maximum observed rate for Covid in Europe was 86% in Spain. He found thus a much higher number of extra deaths. Another explanation for his result relies certainly in the assumptions he made about vaccine efficiency.

Those results were obtained with a finally not so complex model when compared to those used in the medical or economic literature. Our model just takes into account the possibility of reinfection with an extra parameter. It has the great advantage of being estimated on a sample covering the full Omicron wave, that the other models do not. However, we should not forget that we have a macro model, based on macro data. We have gross numbers with just proportions of vaccinated. We cannot follow individual cases.

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