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A modelling study on the vaccination against COVID-19 in the state of Rio de Janeiro, Brazil

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\textbf{ABSTRACT}

The long-awaited roll-out of vaccination programmes against COVID-19 from across the globe has fuelled hope for a reduction in the incidence of cases and deaths, as well as the resumption of economic and social activities. Despite being the most effective measure to mitigate the pandemic, especially in regions where non-pharmaceutical interventions had been ineffective, many people suffered from the lack of efforts by government officials to conduct vaccination. In Brazil, vaccination has always been cutting across party political and ideological lines, which have delayed the start of vaccination and brought the whole process into disrepute. Such disputes put the immunisation of the population in the background and create additional hurdles beyond the pandemic, mistrust and scepticism over vaccines. We conduct a mathematical modelling study to analyse the impacts of late vaccination and with slowly increasing coverage, as well as how harmful it would be if part of the population refused to get vaccinated or missed the second dose in the state of Rio de Janeiro, Brazil. The general framework we propose can be extended to analyse the epidemic situation in any region. Our results indicate that if the start of vaccination had been 30 days earlier, combined with efforts to drive vaccination rates up, about 18,000 deaths could have been averted. Furthermore, the slow pace of vaccination and the low demand for the second dose could cause a resurgence of cases as early as 2022.

\textbf{Introduction}

As of February 25, 2020, when the first case of infection with SARS-CoV-2 (severe acute respiratory syndrome coronavirus 2) was reported in Brazil\textsuperscript{1}, the country has accumulated more than 18 million confirmed cases (https://ourworldindata.org/covid-cases) and, on June 19, 2021, Brazil’s death toll surpassed half a million. To date, upwards of ten per cent of all cases in the world were identified in Brazil and, considering a seven-day rolling average, the country has had at least a thousand deaths a day for more than 200 days since the onset of the epidemic. SARS-CoV-2 circulated undetected in Brazil for more than a month\textsuperscript{2} and, even after Brazil declared COVID-19 (coronavirus disease) a national public health emergency on February 3, 2020\textsuperscript{3}, the Brazilian government has managed the epidemic very loosely so far\textsuperscript{4–6}, without a cooperative effort and strategic planning to fight the pandemic. Brazil also faces many economic and socio-cultural challenges that affect mitigation strategies, such as large disparity in the mortality rate in economically disadvantaged regions\textsuperscript{7}, the uneven geographic distribution of intensive care unit (ICU) beds\textsuperscript{8,9}, and lack of investment and vulnerability of the health system\textsuperscript{10}. Each federative unit is self-governing for decisions regarding efforts to curb the spread of the disease\textsuperscript{11}, which leads to inequalities, such as unbalanced social distancing measures and lack of mass testing and viral spread tracking.

Despite the critical situation to contain the ensuing epidemic and the resurgence of cases (especially with the emergence of new variants\textsuperscript{12}), Brazil had delays in starting the vaccination campaign, compared to other countries\textsuperscript{13,14}, which took place on January 17, 2021. Even with a slight increase in the pace of vaccination in recent weeks, vaccination efforts remain far below what is required, with only 32.89\% of the national population having received at least one dose by June 25, 2021. In turn, the second dose began to be administered on February 5th, and since then only 11.91\% of the population has been immunised (https://ourworldindata.org/covid-vaccinations). To achieve full coverage of people aged 18 and over by the end of 2021, Brazil needs an average of 1.5 million doses of vaccine administered per day\textsuperscript{15}. Currently, the population benefits from vaccines from Pfizer-BioNTech, Oxford-AstraZeneca, Janssen, and Sinovac (the latter two approved for emergency use up to the time of writing this paper).

As it is a country with continental dimensions, the epidemiological situation in some states is particularly worrisome, due to some preponderant factors such as the level of government intervention, investments in health, the pace of vaccination, and population mobility\textsuperscript{1,16,17}. Political polarisation and the spread of fake news also hamper the fight against COVID-19 and the adoption of non-pharmaceutical interventions\textsuperscript{18,19} (NPI). Rio de Janeiro is one of the most important states in Brazil (hereinafter...
referred to as Rio de Janeiro), in terms of demographic density and economic relevance. With an estimated population of approximately 17.3 million inhabitants in 2020 (https://www.ibge.gov.br/en/cities-and-states/rj.html), the state is more populous than countries like Belgium, Portugal, and Sweden. The first case reported in the state was that of a traveller returning from Italy and, since then, Rio de Janeiro has been one of the states in which the epidemic has grown the fastest, reaching a rate of contagion (in terms of the basic reproduction number) between 2.2 and 4.9\(^1\). The progress of vaccination in the state follows the slow pace of the rest of the country: 5.42 million people received the first dose (31.32% of the population) and 2.04 million people received the second dose (11.79% of the population) as of June 25, 2021 (https://www.gov.br/saude/pt-br/vacinacao). On average, approximately only 47,800 vaccines are administered per day since the start of the vaccination campaign in the state, on January 20, 2021.

Although Brazilians' tendency towards vaccination compliance is relatively high\(^2\), some factors were partly responsible for the slowness of the mass vaccination campaign. The country is paying a price for the slow pursuit of vaccines early on, especially regarding the federal government's rejection of vaccines from Pfizer in mid-2020\(^15,21\), in addition to the rebuke of the agreement signed with Sinovac\(^22\); millions of people are also missing their second dose, either because of excessive demand from the population concerning the national immunisation plan, where a number of doses may not have been reserved for this purpose, or because of misinformation, assuming that just one dose provides the expected immunity\(^23,24\); temporary interruptions of vaccination services, due to a lack of shots, logistical problems or absence of supplies (particularly active pharmaceutical ingredient)\(^25-27\); furthermore, there are on the one hand people who try to jump the queue to get vaccinated early\(^28\), and on the other hand those who choose not to get vaccinated, seemingly motivated by political ideology\(^29\).

All these events potentially affect the Brazilian population, since they delay vaccination and bring into disrepute the actions to help prevent the spread of COVID-19. Therefore, it is essential to investigate the likely consequences of such events and circumstances regarding the burden of the epidemic. For this purpose, we conduct this study aiming at investigating the following issues:

- What would be the influence of bringing forward or delaying the vaccination roll-out?
- How effective would a faster vaccination process be in mitigating the epidemic?
- How many deaths could have been averted if there had been more efforts to obtain and manage vaccines?
- How harmful is the choice of part of the population for not getting vaccinated?
- What is the effect of not taking the second dose of the vaccine on the population?

In this context, the objective of this work is to provide an analysis of scenarios related to the epidemic in Rio de Janeiro, in order to answer the issues raised employing computational simulations whose results can be compared to the current situation of the epidemic in the state.

**Results**

In this study, we consider that the target of individuals to be immunised in Rio de Janeiro is proportional to 80%, which also corresponds to the number of inhabitants aged 18 years or over (https://www.ibge.gov.br/apps/populacao/projeto/index.html). Since the vaccination process is carried out with four vaccines, the vaccination rates associated with each one of them is proportional to the number of doses granted to Rio de Janeiro by the Ministry of Health, as shown in Fig. 1a. The simulations are conducted considering three scenarios related to the overall vaccination rate: the base scenario is associated with the average vaccination rate at the time of writing this paper (considering the available data), that is, \( v = 0.275\% \) of the population vaccinated per day. This corresponds to approximately 47,500 vaccinated individuals per day, which agrees with the average of daily vaccinations. In two other hypothetical scenarios, we establish symmetric vaccination rates in relation to the base scenario, with \( v = 0.175\% \) and \( v = 0.375\% \) of the population vaccinated per day. In this setting, approximately 30,200 and 64,800 individuals are vaccinated per day, on average, respectively. Figure 1b shows the frequencies of vaccination rates taking into account both shots (single-dose vaccines count as second doses), given the cumulative number of individuals vaccinated per day, which in turn is shown in Fig. 1c. For the base vaccination rate, the target vaccination coverage for the first dose would be reached in approximately 290 days. This means that 80% of the population would have received at least the first dose by November 2021, as supported by the prediction shown in Fig. 1c. As for the second dose, the prediction indicates that the population would be immunised in the first months of 2022, respecting the interval between doses. For instance, adopting \( v = 0.275\% \) means that nearly 0.136% of the population is vaccinated daily with the Oxford-AstraZeneca vaccine, on average. Additionally, the attributes related to each vaccine’s efficacy and dosage (including the interval between doses) are listed in Table 1.
To perform the simulations, it is first necessary to infer the values of the free parameters of equation (3), whose model outcomes best fit the regularised training data. Figure 1e shows the posterior distributions of parameters $\beta_1, \ldots, \beta_4$, whose statistics are detailed in Table 2. Of note, the posterior distributions can reasonably be expressed by normal distributions and therefore the mean and MAP values (see Methods section) are quite similar. Figure 1d shows the behaviour of the function that describes the transmission rate, given by equation (3), using the MAP values from Table 2, for the time period over which the training data span over. In the early stage of the outbreak, with more frequent contact between people and in the absence of pharmaceutical interventions, the transmission rate was at a high level, gradually decreasing during the first wave of infections, approximately until the end of July 2020. A further increase in the transmission rate led to the second wave, which remained at a high level of transmission for months until its growth could be halted by the start of vaccination.

**Benefits and risks regarding the pace of vaccination** The influence of the pace of vaccination on the mitigation of the epidemic, in the matter of reducing the number of infected and dead individuals over time, is shown in Fig. 1f. The final time of the simulations varies according to the vaccination rate, respecting the expected vaccination coverage, as can be seen in the simulations of the cumulative number of vaccinated individuals. Note that the vaccination data agree with the simulations, even if they were not used to estimate the model parameters. The same goes for the cumulative data from infected and dead individuals, indicating that the choice of model parameters seems to correspond to the actual epidemic scenario in Rio de Janeiro. Such simulations indicate that if the vaccination process were faster, allowing to vaccinate approximately 17,300 more people per day compared to the amount vaccinated in the base scenario, on average, the number of cases could be reduced by 17.49%, from 947,209 (95% CI: 905,415–973,568) to 781,460 (95% CI: 755,341–794,967) cases, whereas the death toll would drop from 63,463 (95% CI: 60,662–65,229) to 52,357 (95% CI: 50,607–53,262). On the other hand, when the pace of vaccination is delayed by the same proportion, the adverse effect is disproportionately greater: the number of confirmed cases would rise to 1,785,228 (95% CI: 1,604,492–1,950,720), a meaningful increase of 46.94%, and deaths could reach 119,609 (95% CI: 107,500–130,696).

**How the timing of vaccination roll-out affects disease mitigation** Aiming to analyse how the epidemic would unfold in Rio de Janeiro if vaccination had been rolled out at another time, we propose to consider hypothetical scenarios in which the vaccination efforts get underway 10, 20 or 30 days before or after January 20, 2021. For each particular vaccination rate in this analysis, we simulate the model for all combinations of proposed scenarios, whose outcomes are shown in Fig. 2a, concerning the daily number of infected and dead individuals. In all results, left (←) and right (→) arrows denote anticipation or delay in the start of vaccination, corresponding to the number of days that accompany the symbol, respectively. The grey shaded area represents a six-month interval from the actual date the vaccination was started. For an arbitrary vaccination rate, visual inspection of such results makes it clear that starting the vaccination campaign a few days earlier is beneficial both in terms of “flattening the curves” and in terms of suppressing the epidemic. Take as an example the scenario in which $\nu = 0.275\%$. On April 15, 2021, when simulations show that the daily death toll would peak if vaccination had started 30 days late, there would have been 394 deaths (95% CI: 367–413). On the same day, had the start of vaccination been 30 days early, there could have been only 78 deaths (95% CI: 73–81). Note that in the latter case, deaths would peak on January 14, 2021, at 155 deaths (95% CI: 151–156).

Figure 2b shows how delaying the start of vaccination combined with vaccination at a slow pace could be devastating to the population. In the worst-case scenario, with vaccination coverage increasing slowly ($\nu = 0.175\%$) and vaccination campaign starting 30 days after January 20, 2021, the number of infected individuals could have reached 3,553,280 (95% CI: 3,052,691–4,040,025), whereas there could have been 238,063 deaths (95% CI: 204,526–270,671). If we look at the opposite scenario, when more effort is put into a rapid vaccination ($\nu = 0.375\%$) that has started 30 days before the actual day, the number of cases and deaths would drop to 590,815 (95% CI: 575,842–596,880) and 39,584 (95% CI: 38,581–39,991), respectively. Simulations also show that delays in the roll-out of the vaccination campaign can cause harmful effects in the long term if the vaccine coverage rate plummets. Assuming that vaccination had followed at a rate equivalent to $\nu = 0.275\%$, there could have been 23,418 excess deaths (95% CI: 20,567–25,951) if compared to the scenario in which the vaccination rate is equal to $\nu = 0.375\%$, for the case where the start of vaccination is delayed by 30 days. But if we look into the possibility that mass vaccination campaign was launched 30 days in advance, the circumstantial comparison given the same vaccination rates would have resulted in 5,838 excess deaths (95% CI: 5,423–6,128), that is, a difference of more than 75% in relation to deaths that would have been averted.

We also sought to directly relate the number of vaccinated and dead individuals, aiming to analyse the likely hardship to the population when the start of vaccination is delayed, compared to the scenario in which vaccination had started earlier. Suppose vaccination had started on February 19, 2021, 30 days beyond the actual date, when 292 deaths (95% CI: 281–298) would have been confirmed, as shown in Fig. 2c. Based on the benchmark vaccination rate, the simulations show that the deaths would peak approximately in April 2021, at 394 deaths (95% CI: 367–413). At this time, about 2,431,489 people (95% CI: 2,430,402–2,432,739) could have been vaccinated (with both doses or with the single-dose vaccine), representing
show that deaths would peak at 182 (95% CI: 607–789). This means that, despite having been vaccinated nearly 72% more people, comparing both scenarios, a record-high daily death toll could have been reached, to a great extent driven by the late start of vaccination. On the flip side, if there had been efforts to get vaccination started around December 21, 2020, even with vaccination progressing at a slow pace (ν = 0.175%), the simulations in Fig. 2c show that deaths would peak at 182 (95% CI: 173–186) in March 2021. At that time, there would be about 2,134,722 vaccinated individuals (95% CI: 2,134,510–2,136,060).

Consider the transmissibility of SARS-CoV-2 in Rio de Janeiro in terms of the effective reproduction number, given by equation (2). According to the simulations, in 2020 the effective reproduction number was only below the threshold $R(t) = 1$ between the end of June and September, as shown in Fig. 2d. In spite of that, in this period the lowest value reached was $R(t) = 0.977$, at the end of July. Afterwards, the effective reproduction number was always above one, until the vaccination started to take effect. We are interested in analysing the effective reproduction number, given the scenarios considered in this work. So, at this point, assume that the vaccination had been brought forward by 30 days. On the same day as the start of vaccination, 2,148 new cases (95% CI: 2,105–2,155) would have been confirmed. Even maintaining a slow pace of immunisation (ν = 0.175%), the transmission potential of SARS-CoV-2 could have reached $R(t) = 1$ as early as February 2021 (approximately three months after the hypothetical start of vaccination), when Rio de Janeiro would have vaccinated 10.08% of the eligible portion of the population. In turn, when the start of vaccination is delayed, disease mitigation becomes much more challenging. If we now consider a 30-day delay in the roll-out of vaccination, access to vaccines would be opened when $R(t) = 1.116$ and, on this day, simulations indicate that 4,395 new cases (95% CI: 4,221–4,487) would have been confirmed in Rio de Janeiro. Under these circumstances, $R(t) = 1$ would only be reached at the end of June 2021, approximately four months after the start of vaccination, when there would already be 25.04% of the eligible population vaccinated.

**Potential aftermath of COVID-19 vaccine hesitancy** Despite the health benefits of immunisation, vaccine hesitancy raises concerns about the prevalence of the disease. Most public health experts admit that a herd immunity threshold is not attainable (at least not in the foreseeable future)\(^3\), but immunising 50 to 90 per cent of the population could be enough to curb the epidemic\(^3\). Aiming to analyse the adverse effects caused by people who are unwilling to be vaccinated, we simulate the model considering only 50% vaccination coverage, to the detriment of the 80% coverage that we used to adopt. In this scenario, Fig. 3a shows the model outcomes for the daily number of infected and dead individuals over time, given the three vaccination rates we have assumed, alongside the cumulative number of vaccinations. In these circumstances, the rate of vaccination also plays a key role in how the epidemic unfolds. Considering the benchmark vaccination rate, 50% vaccination coverage would be reached in the first half of September 2021, when simulations indicate that 250 cases (95% CI: 209–289) would be reported daily. In the same period, but assuming a slower vaccination rate, the daily number of confirmed cases would be 3,377 (95% CI: 2,793–3,942), when 34.51% of the population would be vaccinated. In addition, overall low vaccination coverage combined with a lethargic immunisation program could raise the possibility of a resurgence of cases (and hence deaths) as early as 2022. After experiencing a reduction in the number of cases, to a large extent due to vaccination, in May 2022 there would be the smallest number of infected individuals since the onset of the epidemic, 548 (95% CI: 320–826). However, in the following months, the incidence of cases could increase again, reaching 867 new cases (95% CI: 415–1,512) per day by mid-August 2022. Such an epidemiological situation would resemble that which occurred in early May 2020, which could eventually be indicative of a new outbreak.

Thousands of people have also been missing their second dose of vaccine in Rio de Janeiro, further complicating a campaign already marred by backwardness and supply shortages. To the best of our knowledge, there are still no studies that confirm the overall efficacy of all vaccines used in Rio de Janeiro when only one shot is provided (except for the Janssen vaccine), although some studies have already reported relevant results\(^3\). In the absence of such information, we assume two scenarios regarding vaccine efficacies (see Table 1) when only the first shot is given, that is, efficacies are weakened proportionally to $\mu = 25$% and $\mu = 50$%. Moreover, surveys show that around 14.5% of the Brazilian population somewhat disagree, strongly disagree or remain neutral regarding vaccination\(^3\). Within this frame of reference, we also consider scenarios with low ($\alpha = 20$%) and moderate ($\alpha = 10$%) demand for the second dose of vaccines (when applicable), as well as the best scenario in which $\alpha = 0$%.

Simulations for the number of dead individuals as of the actual day vaccination has started, combining factors associated with parameters $\mu$ and $\alpha$, are shown in Fig. 3d. Initially, assume that the first dose of vaccines would yield an efficacy proportional to $\mu = 25$% of the overall efficacy when both doses are given. In a scenario subject to slow vaccination, 50% of the eligible population would have been immunised in approximately 270 days. After this time frame, the number of daily deaths would be 289 (95% CI: 228–350) if 20% of the population eligible to be vaccinated missed their second dose. If the percentage of individuals who do not receive the second dose dropped to 10%, the death toll would be 218 (95% CI: 172–265) in the same period. In turn, if the efficacy of vaccines was weakened by $\mu = 50$% when the second dose is neglected, the number of dead individuals on the same day could be 240 (95% CI: 190–291) and 198 (95% CI: 156–241), bearing in mind the two scenarios
related to vaccination coverage with the second dose, respectively. By hypothesis, if the entire population vaccinated during this period had received both doses, simulations show that daily deaths could drop to 165 (95% CI: 130–200). Note that when vaccination progresses more quickly, the adverse effect of part of the population not receiving the second dose is mitigated.

**More ambitious vaccination targets and avertable deaths** All the aspects set out so far fall into the most dreadful scourge of a pandemic, the ensuing deaths. Tallying deaths that could quite possibly have been averted, had there been more efforts for an assertive vaccination campaign, means understanding the importance of having vaccines made available to the population as early as possible. We attempt to infer deaths that could have been averted simply by having vaccination started days earlier or if the daily rate of vaccination had been higher. Figure 3b shows the relationship between vaccinated individuals and cumulative deaths over time. We simulate the model using the benchmark vaccination rate \( \nu = 0.275\% \) and compare the outcomes in the context of a faster vaccination \( \nu = 0.375\% \), making allowance for different days for the start of vaccination from the day it actually started. We recall that the right \((\rightarrow)\) and left \((\leftarrow)\) arrows correspond to the days of delay and anticipation of the start of vaccination, respectively. In all simulations, the number of immunisations is the same, but the curves do not match, as the pace and day of the start of vaccination change the day on which a certain vaccination coverage is reached. Simulations show that presumably not-so-challenging measures, such as having anticipated the vaccination campaign roll-out by just ten days, combined with an average vaccination rate approximately 36% faster, could have averted 7,300 deaths (95% CI: 6,683–7,775), whereas if the start of vaccination had also been delayed by 10 days, under the same circumstances, there could have been 9,105 more deaths (95% CI: 8,268–9,803) in relation to the actual scenario; from a more optimistic, yet still realistic, perspective on the vaccination roll-out, consider a 30-day advance on the date on which the campaign actually started. In this framework, 18,041 deaths (95% CI: 16,659–19,110) could have been prevented, which represents 28.43% of the deaths (95% CI: 27.46%–29.30%) that would have occurred since vaccination was started, assuming a vaccination rate equal to \( \nu = 0.275\% \).

When vaccination became available in Rio de Janeiro, 490,821 cases and 28,215 deaths had already been reported (on that day, there were 4,015 new cases, with 189 deaths). Figure 3c shows that a hypothetical delay of 30 days in the start of vaccination, when there were already 569,184 confirmed cases and 32,045 deaths (aware that these data already encompass vaccination progresses more quickly, the adverse effect of part of the population not receiving the second dose is mitigated. One potential candidate is the mechanism of disease spread following a power-law distribution\(^{37,38}\), a behaviour that most epidemiology models can readily be modified to capture\(^39\).

**Discussion**

Until July 1, 2021, approximately 165 days since the roll-out of vaccination in Brazil, Rio de Janeiro was one of the states that had received the most doses per 100,000 inhabitants, about 70,540, only behind the states of Mato Grosso do Sul and Rio Grande do Sul, with 72,140 and 76,130 doses, respectively, as shown in Fig. 1a. Altogether, Brazil had about 63,980 doses per 100,000 inhabitants. In general, access to vaccines in Brazil is still limited, and this ends up affecting the pace of vaccination even in the states with the most supply of doses. This fact becomes clear when we place the situation in Brazil side by side with that of some other countries, such as Canada, in terms of access to vaccines. Vaccination was launched in Canada on December 14, 2020, nearly one month earlier than in Brazil. In the 165-day window since the launch of the vaccination in Canada, approximately 60,440 doses per 100,000 inhabitants had been administered (https://ourworldindata.org/covid-vaccinations), a pace similar to what had been performed in Brazil. However, as of July 1, 2021, Canada had reached around 100,220 vaccines administered per 100,000 inhabitants. Considering a seven-day rolling average of daily new deaths, at that time Canada had 0.42 deaths per million people, whereas Brazil had 7.36 deaths. Such statistics shed light on the importance of getting vaccinated as soon as possible.

From the information in Fig. 1f, we see that bringing forward the vaccination in Rio de Janeiro could have anticipated the epidemic peak, and also could have reduced the effective reproduction number to below the threshold \( R(t) = 1 \) on a date before the actual scenario. On the other hand, had the start of vaccination been delayed, the adverse consequences could have been disproportionately greater, as shown in Fig. 1f. The reason for this behaviour could be rationalised by an intrinsic feature of the transmission, which in turn was captured by the simulations. One potential candidate is the mechanism of disease spread
Although it is argued that power law is generally not appropriate for temporal spread\textsuperscript{38}, some authors have employed this theory to the spread of COVID-19 for both case and death data\textsuperscript{30-43}, all relying on the evidence that disease containment measures cause a sub-exponential increase of cases\textsuperscript{44}. Another point to be brought out is that, although we have used fixed values for the vaccine's efficacy, such values must be viewed with caution. Each efficacy is estimated considering different populations likely to be subject to different prevalent variants and therefore any variability must be taken into account\textsuperscript{45}. From a modelling point of view, this could be addressed in future studies through population stratification.

Spikes in the number of cases have also overwhelmed health services, largely due to a steep slowdown in vaccinations and relaxed public health protocols\textsuperscript{46}. Many municipalities in Rio de Janeiro are even worse off as they do not have ICU beds and patients eventually need to be admitted to nearby hospitals. Even after the start of vaccination, for more than two months the health care system continued to have an increase in the share of regular and ICU beds occupied, with peak occupancy in the first week of April (see Extended Data Fig. 3), with 91.2\% occupancy of ICUs and 80.9\% of regular beds. These data are in line with the simulations where the benchmark vaccination rate is adopted, which indicate the peak of daily infections on March 1, 2021 (see Fig. 1f). Shortage in vaccine supply also raises concern about the emergence of variants with potentially increased transmissibility, such as the case of the outbreak in the state of Manaus, which affected the whole of Brazil\textsuperscript{12}. The anticipation of the roll-out of mass vaccination, combined with a faster pace of vaccination, could also have played a role in reducing the demand for health services, as fewer people would contract the severe form of the disease\textsuperscript{6}. Our simulations show that 67.5\% of the eligible population in Rio de Janeiro could have been immunised within six months if just over 64,000 vaccines had been given daily ($v=0.375\%$), on average. Instead, only 50.33\% of the eligible population had received the first dose and 18.36\% had been immunised. The merits of an effective vaccination policy are clear when comparing the epidemiological curves within the grey boxes in Fig. 2a.

Social mobility and NPIs are also important factors when analysing the course of vaccination. The engagement of the Brazilian population in such measures has always been below expectations\textsuperscript{47}. A very relevant fact is that only 45.5\% of Brazilians say they wear a face mask outside the home\textsuperscript{48}. Our findings show that the possibility of an eventual resurgence of cases in 2022 should not be overlooked, even though the majority of the population has been vaccinated. This concern even brings up discussions about the need for extra doses\textsuperscript{49}, although vaccines may remain limited, especially in low-incoming countries\textsuperscript{50,51}, making NPIs essential even after achieving adequate vaccine coverage. By way of illustration, research shows that adopting non-pharmaceutical interventions in China for at least a year after vaccination has started would be the most efficient way to bring $R(t)$ below the epidemic threshold\textsuperscript{52}. There is also evidence that the resurgence of cases could be contained by moderate social distancing measures combined with vaccination, without the need for closure of most public venues, which gradual vaccination alone might not be able to achieve\textsuperscript{53}. In Rio de Janeiro, there was never a state-wide lockdown, but only partial closings and measures such as border restriction (with border health check), closure of educational institutions, and restrictions on public transport, airports, and individual movement. The population mobility trend reached its lowest levels days after the first cases were reported (see Extended Data Fig. 4a), with a reduction in the frequency of people at workplaces, transit stations and shops in general, while moving to be more often in residential environments. However, the population has always been resistant to most such measures, so much so that the number of people gathering indoors has practically always been increasing since then. If we look at mobility with regard to the municipalities (see Extended Data Fig. 4b), there seems to have been compliance with NPIs to some extent. At a time when there were 100,000 confirmed cases, there were still far fewer visits to workplaces than at the beginning of the year, before the epidemic swept the country. More recently, shortly after 1 million cases were confirmed (in mid-July 2021), vaccination has increasingly encouraged the return to face-to-face work. Such factors combined with a slow-paced vaccination may mean that the resurgence of cases and the emergence of new variants might not be so far on the horizon.

The analysed scenarios reflect current knowledge about vaccination in Rio de Janeiro, from the perspective of available data. The persistence of such predictions depends to some extent on the confirmation of the hypotheses put forward. Particularly with regard to vaccine hesitancy (whether for both doses or just the second), the inaction of certain people depends a lot on facts that cannot be predicted. Despite this, social network posts can provide insight into attitudes and sentiments towards vaccination, for instance. From December 1, 2020 to March 31, 2021, a lexicon-based sentiment analysis of Twitter posts shows a steady trend in people's perception of Pfizer and Moderna vaccines, while hesitation over the Oxford-AstraZeneca vaccine appears to be increasing over time\textsuperscript{64}. Nevertheless, until July 1, 2021, Oxford-AstraZeneca vaccines supplied most of the Brazilian demand, with 49.5\% of all vaccines distributed so far (see Fig. 1a). This could be an indication that, even if the vaccine is available, popular sentiment may be volatile enough that eventually people would not return for the second dose, especially for vaccines where the interval between doses is high. In this context, social networks play a fundamental role in shaping the opinion of part of the population, since the sharing of narratives and personal opinions without scientific background comes to the knowledge of many people\textsuperscript{55,56}. In Brazil, the oscillations regarding the feelings analysed in the posts on social networks are due, in large part, to political actions\textsuperscript{57}. 


Methods

Model description We extend the well-known SIR (susceptible-infected-removed) model\(^5\), aiming to incorporate the effects of vaccination in the population. Initially, assume that \( \beta (t) \) is the transmission rate over time and \( \gamma \) is the removal rate. The gain in the infective class (\( I \)) is at a rate proportional to the product of the contact rates and transmission probability between infectives and susceptibles (\( S \)), that is, the rate of new incidences is given by \( \beta (t) S(t) I(t) / N \), where \( N \) is the population size.

In turn, the rate at which infected individuals move into the removed class (\( R \)) is given by \( \gamma I(t) \). Of note, we also compute the number of dead individuals, once infected, which are eventually moved into the dead class (\( D \)) at a rate of \( \rho I(t) \), where \( \rho \) is the death rate.

Assume that both susceptible and infected individuals can be vaccinated (the latter are able to be vaccinated as they may be asymptomatic). Considering that \( n \) vaccines can be administered in a population, individuals vaccinated with a given vaccine \( i \) are moved into the corresponding vaccinated class (\( V_i \)) at a rate equal to \( v_i (S(t) + I(t)) \), where \( v_i \) is the vaccination rate associated with vaccine \( i \), for \( i = 1, \ldots , n \). Individuals remain in compartment \( V_i \) for the period equivalent to the interval between doses (when applicable), which is given by \( 1 / \bar{\tau}_i \). After this period, vaccinated individuals are considered immune and therefore moved into the removed class taking into account the efficacy of the corresponding vaccine, \( \eta_i \). If immunity is not acquired with proper vaccination, vaccinated individuals may become susceptible again, whose class is fed back proportionally to \((1 - \eta_i)V_i\).

The model also covers two other aspects inherent to the vaccination process: first, part of the population eligible to be vaccinated can choose not to take both doses of the vaccine (when applicable). In terms of vaccine efficacy, such individuals have only partial protection, which we denote by \( \tilde{\eta}_i \), an impaired efficacy. In terms of the expected efficacy when both doses are given, \( \tilde{\eta}_i = \mu \eta_i \), where \( \mu \) is the parameter that modulated the drop in efficacy; second, a number of eligible individuals may decide not to get vaccinated. This portion of the population is denoted as \( \alpha \). Therefore, the rate of change of individuals who take both doses of the vaccine (or the single-dose vaccine) is represented by the amount \( \tau_i \tilde{\eta}_i (1 - \alpha) V_i(t) \), whereas for those who take only the first dose (when two are foreseen), or choose not to get vaccinated, are expressed by \( \tau_i \tilde{\eta}_i \alpha V_i(t) \).

The susceptible class is also fed back proportionally to the value of \( \alpha \). The general description of the model is provided in equation (1), the schematic representation is shown in Extended Data Fig. 1, and the summary of model parameters is given by Extended Data Table 1.

\[
\begin{align*}
\frac{dS(t)}{dt} &= -\beta(t) \frac{S(t) I(t)}{N} - \sum_{i=1}^{n} \left( v_i S(t) - \bar{\tau}_i ((1 - \eta_i)(1 - \alpha) + (1 - \tilde{\eta}_i) \alpha) V_i(t) \right) \\
\frac{dI(t)}{dt} &= \beta(t) \frac{S(t) I(t)}{N} - \left( \gamma + \rho + \sum_{i=1}^{n} v_i \right) I(t) \\
\frac{dV_i(t)}{dt} &= v_i (S(t) + I(t)) - \tau_i V_i \\
\frac{dR(t)}{dt} &= \gamma I(t) + \sum_{i=1}^{n} \bar{\tau}_i (\eta_i (1 - \alpha) + \tilde{\eta}_i \alpha) V_i(t) \\
\frac{dD(t)}{dt} &= \rho I(t)
\end{align*}
\]

Additionally, we employ the next-generation matrix method\(^5\)\(^9\)\(^,\)\(^6\)\(^0\) to derive the effective reproduction number expression, which is given by

\[
\mathcal{R}(t) = \frac{\beta(t) S(t)}{N \left( \gamma + \rho + \sum_{i=1}^{n} v_i \right)}.
\]

For detailed derivation, refer to Supplementary Notes 1.

Case incidence and vaccination data Daily data on confirmed cases and dead individuals due to COVID-19 in Rio de Janeiro are divided into two subsets, from before and during vaccination. In the former, which we call the training set, the data are in the range between March 10, 2020, the first day with at least five cases diagnosed, and January 19, 2021, the last day before the start of vaccination. These data subsets are denoted as \( \mathcal{D}^1 \) and \( \mathcal{D}^2 \), for infected and dead individuals prior to vaccination, respectively. The latter subset contains the data between January 20, the day the vaccination started, and June 29, 2021. Cumulative data on individuals vaccinated with the first dose and immunised (with both doses or with the single-dose vaccine) are also adopted from the same period. There is no distinction regarding the type of
GPRs have the ability to avoid simple parametric assumptions, that is, they do not require the data to follow a specific distribution. In these circumstances, the regularisation of data emerges as an alternative to reduce the noise level, without misrepresenting data behaviour, in order to streamline the task of fitting model responses to the data set. In particular, Gaussian Process (GP) models are a probabilistic approach to representing arbitrary functions by means of a probability distribution over all possible functions that fit a set of points. Gaussian Process Regression (GPR) differs from regular regression models in that distributions are defined over functions, rather than their parameters, not requiring the definition of a parametric model that would be able to fit a set of observable data. The strength of GPs in steering experiments is due to the fact that realisations correspond to random functions, such that priors for unknown regression functions are provided and updated with knowledge of observable data. GPs depend on defining covariance functions (also known as kernels) which are used to define a similarity measure of the inputs. Thus GPRs have the ability to avoid simple parametric assumptions, that is, because it is a non-parametric approach, while providing uncertainty quantification on the predictions.

More formally, let \( \mathbf{t} = (t_1, \ldots, t_p) \top \) denote the time training points associated to a set of \( p \)-dimensional observations \( \mathcal{D} = (\mathcal{D}_1, \ldots, \mathcal{D}_p) \top \). Recalling the regular regression problem, \( \mathcal{D} = f(t_i) + \epsilon \), the function \( f : \mathbb{R} \rightarrow \mathbb{R} \) maps a time training point into the data space (this is the GP we further expect to obtain), and \( \epsilon \sim \mathcal{N}(0, \sigma^2) \) is an additive independent and identically distributed Gaussian noise, where \( \sigma^2 \) is the noise variance. Assuming that \( t, t' \in \mathbf{t} \) are a pair of general input vectors, a process given by \( f(t) \), defined according to its mean \( m(t) = \mathbb{E}[f(t)] \) and a positive semi-definite kernel function \( k(t, t') = \mathbb{E}[(f(t) - m(t))(f(t') - m(t'))] \), is said to be a GP represented by

\[
f(t) \sim \mathcal{G} \mathcal{P} \left( m(t), k(t, t') \right).
\]

The mean is often assumed to be zero (since the observed outputs can always be centred in order to have a zero mean).

In a regression problem, the prior probability density of \( f(t) = (f(t_1), \ldots, f(t_p)) \top \) has joint multivariate Gaussian distribution \( f \sim \mathcal{N}(0, \mathbf{K}(t, t, \lambda)) \), such that \( \mathbf{K}(t, t, \lambda) \) is the covariance matrix (which is also noise-dependent), whose entries are \( (\mathbf{K}(t, t, \lambda))_{ij} = k(t_i, t_j, \lambda) + \sigma^2 \delta_{ij} \), for \( i, j = 1, \ldots, p \), where \( \lambda \) is the set of kernel hyper-parameters and \( \delta_{ij} \) is the Kronecker delta. Now consider new input time points, denoted by \( \mathbf{t'} \), and their associated output values \( \mathcal{D}' \), which we assume to be also normally distributed. The joint Gaussian distribution considering such points is given by

\[
\begin{bmatrix}
\mathcal{D} \\
\mathcal{D}'
\end{bmatrix} \sim \mathcal{N}
\left(0,
\begin{bmatrix}
\mathbf{K}(t, t, \lambda) + \sigma^2 \mathbf{I} & \mathbf{K}(t, t', \lambda) \\
\mathbf{K}(t', t, \lambda) & \mathbf{K}(t', t', \lambda)
\end{bmatrix}
\right),
\]

where \( \mathbf{I} \) is the \( p \times p \) identity matrix. Therefore, by deriving the conditional distribution, the posterior predictive equation is the multivariate Gaussian distribution

\[
p(\mathcal{D}' | \mathbf{t'}, \mathbf{t}, \mathcal{D}) = \mathcal{N}(\mathbf{\mu}^*, \Sigma^*),
\]

with mean

\[
\mathbf{\mu}^* = \mathbf{K}(t', t, \lambda)(\mathbf{K}(t, t, \lambda) + \sigma^2 \mathbf{I})^{-1}\mathcal{D}
\]

and covariance matrix

\[
\Sigma^* = \mathbf{K}(t', t', \lambda) - \mathbf{K}(t', t, \lambda)(\mathbf{K}(t, t, \lambda) + \sigma^2 \mathbf{I})^{-1}\mathbf{K}(t, t', \lambda).
\]

As new pairs \( (t', \mathcal{D}') \) are incorporated into the regression problem, the mean set \( \mathbf{\mu}^* \) is updated and adopted as the output of the GPR model, whereas \( \Sigma^* \) provides a measure of confidence in the estimate. In this work, we adopt the RBF (radial basis function) kernel,

\[
k(t, t', \lambda) = \exp\left(-\frac{|t - t'|^2}{2\lambda^2}\right),
\]

where \( \lambda = (\ell) \) is the length scale of the kernel. For the available training data, the optimal hyper-parameter values are \( \ell = 51.1 \) and \( \ell = 29.1 \) for the daily data of infected (\( \mathcal{D}^1 \)) and dead (\( \mathcal{D}^2 \)) individuals, respectively. Regularised data is shown in Extended Data Fig. 2.
Inference of model parameters  Model outcomes are fitted to the training set using Bayesian inference. As the training data is from the period prior to the start of vaccination, all model parameters that are associated with vaccination \((\alpha, \nu, \tau, \eta_i, \text{and} \, \bar{\eta}_i, \text{for} \, i = 1, \ldots, n)\) are set to zero at this point. In this setting, the model of equation (1) reduces to the SIR model (including the dead class). As for the remaining parameters, we take the removal rate and the death rate as biological parameters, which are equal to \(\gamma = 0.06^{67}\) and \(\rho = 0.06^{768}\) (a rate per day for both), respectively. In turn, regarding the transmission rate, we adopt the functional form given by
\[
\beta(t) = \beta_1 \exp(-\beta_2 t) + \beta_3 \exp(\beta_4 t). \quad (3)
\]
This specific choice is motivated by the fact that, in the particular time period over which the training data span over, there seems to be the incidence of two waves of infection. The contribution of the term associated with the negative exponential would be able to represent the infection rate at an early stage when few individuals are immune, and the contact rate between them leads to an increase in the incidence of cases until the peak of the first wave is reached. On the other hand, the contribution of the term associated with the positive exponential would be related to a new increase in the infection rate after the event of the first wave. Therefore, the parameters to be estimated are \(\theta = (\beta_1, \beta_2, \beta_3, \beta_4)\).

For Bayesian model updating, we employ the Transitional Markov Chain Monte Carlo \(\text{TMCMC}\) method. This sequential particle filter method combines aspects of simulated annealing optimisation \(\text{SAO}\) with Markov Chain Monte Carlo sampling. To infer the parameters \(\theta\), we initially obtain the set of estimators which generate the model outcomes that best fit the regularised training data, through least squares. Such values are denoted by \(\hat{\beta}_1, \ldots, \hat{\beta}_4\) and, in turn, are used to define the prior distribution \(p(\theta)\) of the corresponding parameters (our prior belief about the distribution of \(\theta\)), which we assume to be uniformly distributed,
\[
p(\hat{\beta}_j) \sim U \left(\hat{\beta}_j(1-\xi), \hat{\beta}_j(1+\xi)\right), \quad (4)
\]
where \(0 < \xi < 1\) is a relative displacement. In this particular application, the prior distribution of \(\beta_j\) is defined symmetrically around \(\hat{\beta}_j\), for \(j \in \{1, 2, 3, 4\}\), with \(\xi = 0.9\). This strategy aims to bypass parameter identification problems \(\text{ID}\).

The likelihood \(p(\mathcal{D} | \theta)\) expresses the plausibility of observing the data, given a specific \(\theta\). In this work, we assume that the likelihood follows a normal distribution,
\[
p(\mathcal{D}^q | \theta) \sim \mathcal{N} \left(\text{mean} = \mathcal{M}^q, \text{variance} = \sigma_q^2\right). \quad (5)
\]
Correspondingly to the data, the model responses \(\mathcal{M}^q\) represent the number of infected and dead individuals in equation (1), for \(q \in \{1, 2\}\), respectively. Of note, the model measures the cumulative number of dead individuals. Therefore, it is mandatory to differentiate the result obtained by the numerical approximation of equation (1), regarding compartment \(D\), so that \(\mathcal{M}^2\) is consistent with \(\mathcal{D}\). As the variance of the distribution is not known, it plays the role of a hyper-parameter and must therefore be estimated together with \(\theta\). In the sampling process, the solution of the system given by equation (1) is approximated using the Fehlberg method \(\text{F}\). For this purpose, the initial conditions adopted are \(I(0) = \mathcal{D}^1, D(0) = \mathcal{D}^2, R(0) = 0\) and, therefore,
\[
S(0) = N - I(0) - D(0) = \mathcal{D}^1. \quad (6)
\]
Since TMCMC gradually pushes the samples from the prior distribution to the posterior target distribution, the samples of the intermediate distributions are used to obtain an estimate of the evidence \(p(\mathcal{D})\). Therefore, the information from equations (4) and (5) are combined to compose the posterior distribution of the parameters,
\[
p(\theta | \mathcal{D}^q) \propto p(\mathcal{D}^q | \theta) p(\theta) .
\]

Information from observable data is employed to update the prior belief about the model’s parameters to a posterior belief, simultaneously considering data from infected and dead individuals. Posterior distributions are approximated using 6,000 samples. To compute the 95\% credible intervals (95\% CI), we adopt an equal-tailed interval, by computing the 2.5\% and 97.5\% percentiles of the posterior distribution \(p(\theta | \mathcal{D})\), that is, 2.5\% of the distribution on either side of its limits. In turn, the maximum a posterior (MAP) of each parameter is approximated by computing the maximum value of the probability density function estimated using the kernel density estimator \(\text{KDE}\).

References
1. Souza, W. M. et al. Epidemiological and clinical characteristics of the COVID-19 epidemic in Brazil. Nat. Hum. Behav. 4, 856–865, DOI: 10.1038/s41562-020-0928-4 (2020).
2. Castro, M. C. et al. Spatiotemporal pattern of COVID-19 spread in Brazil. Science 372, 821–826, DOI: 10.1126/science.abh1558 (2021).
3. Croda, J. et al. COVID-19 in Brazil: advantages of a socialized unified health system and preparation to contain cases. *J. Braz. Soc. Trop. Medicine* **53**, DOI: 10.1590/0037-8682-0167-2020 (2020).

4. Ponce, D. The impact of coronavirus in Brazil: politics and the pandemic. *Nat. Rev. Nephrol.* **16**, 483–483, DOI: 10.1038/s41581-020-03270-0 (2020).

5. Lopes, M. F. From denial to hope: Brazil deals with a prolonged COVID-19 epidemic course. *Nat. Immunol.* **22**, 256–257, DOI: 10.1038/s41590-021-00875-8 (2021).

6. Ranzani, O. T. et al. Characterisation of the first 250,000 hospital admissions for COVID-19 in Brazil: a retrospective analysis of nationwide data. *The Lancet Respir. Medicine* DOI: 10.1016/S2213-2600(20)30560-9 (2021).

7. Alves, L. Brazilian ICUs short of drugs and beds amid COVID-19 surge. *The Lancet* **397**, 1431–1432, DOI: 10.1016/S0140-6736(21)00836-9 (2021).

8. Mathieu, E. et al. A global database of COVID-19 vaccinations. *Nat. Hum. Behav.* DOI: 10.1038/s41598-021-92263-3 (2021).

9. Hallal, P. C. & Victora, C. G. Overcoming Brazil’s monumental COVID-19 failure: an urgent call to action. *Nature Medicine* DOI: 10.1038/s41591-021-01378-7 (2021).

10. Hallal, P. C. et al. Characterization of the first 250,000 hospital admissions for COVID-19 in Brazil: a retrospective analysis of nationwide data. *The Lancet Respir. Medicine* DOI: 10.1016/S2213-2600(20)30560-9 (2021).

11. Hallal, P. C. et al. SARS-CoV-2 antibody prevalence in Brazil: results from two successive nationwide serological household surveys. *The Lancet Glob. Heal.* 8, e1390–e1398, DOI: 10.1016/S2214-109X(20)30387-9 (2020).

12. Naveca, F. G. et al. COVID-19 in Amazonas, Brazil, was driven by the persistence of endemic lineages and P.1 emergence. *Nature Medicine* DOI: 10.1038/s41591-021-01738-7 (2021).

13. Mathieu, E. et al. A global database of COVID-19 vaccinations. *Nat. Hum. Behav.* DOI: 10.1038/s41591-021-01353-2 (2021).

14. Matos, C. C. S. A., Barbieri, C. L. A. & Couto, M. T. COVID-19 and its impact on immunization programs: reflections from Brazil. *J. Public Heal.* **54**, 114, DOI: 10.11606/s1518-8787.2020054003042 (2020).

15. Hallal, P. C. & Victora, C. G. Overcoming Brazil’s monumental COVID-19 failure: an urgent call to action. *Nature Medicine* **27**, 933–933, DOI: 10.1038/s41591-021-01353-2 (2021).

16. Barberi, L. G., Costa, S. F. & Sabino, E. C. Brazil needs a coordinated and cooperative approach to tackle COVID-19. *Nature Medicine* DOI: 10.1038/s41591-021-01423-5 (2021).

17. Almeida, G. B., Vilches, T. N., Ferreira, C. P. & Fortaleza, C. M. C. B. Addressing the COVID-19 transmission in inner Brazil by a mathematical model. *Sci. Reports* **11**, 10760, DOI: 10.1038/s41598-021-90118-5 (2021).

18. Gallotti, R., Valle, F., Castaldo, N., Sacco, P. & De Domenico, M. Assessing the risks of ‘infodemics’ in response to COVID-19 epidemics. *Nat. Hum. Behav.* 4, 1285–1293, DOI: 10.1038/s41562-020-09994-6 (2020).

19. Suryanarayanan, P. et al. AI-assisted tracking of worldwide non-pharmaceutical interventions for COVID-19. *Sci. Data* **8**, 94, DOI: 10.1038/s41597-021-00878-y (2021).

20. Lazarus, J. V. et al. A global survey of potential acceptance of a COVID-19 vaccine. *Nat. Medicine* **27**, 225–228, DOI: 10.1038/s41591-020-1124-9 (2021).

21. Londoño, E., Casado, L. & Lima, M. A Collapse Foretold: How Brazil’s Covid-19 Outbreak Overwhelmed Hospitals. *The New York Times* (March 27, 2021). https://www.nytimes.com/2021/03/27/world/americas/virus-brazil-bolsonaro.html.

22. Malta, M., Vettore, M. V., Silva, C. M. F. P., Silva, A. B. & Strathdee, S. A. Political neglect of COVID-19 and the public health consequences in Brazil: The high costs of science denial. *EClinicalMedicine* **35**, 100878, DOI: 10.1016/j.eclinm.2021.100878 (2021).

23. Fonseca, P. Brazil vaccination pace slows as production issues halt second doses. *Reuters* (June 1, 2021). https://www.reuters.com/world/americas/brazil-vaccination-pace-slows-production-issues-halt-second-doses-2021-06-01/.

24. Ionova, A. Millions in Brazil are missing their second vaccine dose, adding to the burden of a hard-hit nation. *The New York Times* (June 27, 2021). https://www.nytimes.com/2021/06/27/world/brazil-covid-vaccine.html.

25. Fonseca, P., Spring, J. & Reese, C. Brazil to pause production of AstraZeneca vaccine due to lack of ingredients. *Reuters* (May 13, 2021). https://www.reuters.com/world/brazil-pause-production-astrazeneca-vaccine-lack-ingredie...2021-05-13/.
26. Reuters Staff. Rio de Janeiro halts COVID-19 shots as vaccine supplies dry up. Reuters (February 15, 2021). https://www.reuters.com/article/health-coronavirus-rio-vaccines-idUSL1N2KL12Q.

27. Eisenhammer, S. A close-knit family’s vaccine hopes are shattered in Brazil. Reuters (June 25, 2021). https://www.reuters.com/investigates/special-report/health-coronavirus-brazil-family/.

28. Express Web Desk. Anger over Brazil’s rich trying to jump vaccine queue. The Indian Express (April 13, 2021). https://indianexpress.com/article/world/brazil-covid-19-vaccine-7271718/.

29. Phillips, T. ‘We’re being left behind’: anger and confusion in Brazil as vaccine program lags. The Guardian (December 31, 2020). https://www.theguardian.com/world/2020/dec/31/brazil-coronavirus-vaccine-jair-bolsonaro.

30. Aschwenenden, C. Five reasons why COVID herd immunity is probably impossible. Nature 591, 520–522, DOI: 10.1038/d41586-021-00728-2 (2021).

31. D’Souza, G. & Dowdy, D. What is Herd Immunity and How Can We Achieve It With COVID-19? Johns Hopkins Bloom. Sch. Public Heal. (April 6, 2021). https://www.jhsphs.edu/covid-19/articles/achieving-herd-immunity-with-covid19.html.

32. Vasileiou, E. et al. Interim findings from first-dose mass COVID-19 vaccination roll-out and COVID-19 hospital admissions in Scotland: a national prospective cohort study. The Lancet 397, 1646–1657, DOI: 10.1016/S0140-6736(21)00677-2 (2021).

33. Lopez Bernal, J. et al. Effectiveness of the Pfizer-BioNTech and Oxford-AstraZeneca vaccines on covid-19 related symptoms, hospital admissions, and mortality in older adults in England: test negative case-control study. BMJ n1088, DOI: 10.1136/bmj.n1088 (2021).

34. Chodick, G. et al. Assessment of Effectiveness of 1 Dose of BNT162b2 Vaccine for SARS-CoV-2 Infection 13 to 24 Days After Immunization. JAMA Netw. Open 4, e2115985, DOI: 10.1001/jamanetworkopen.2021.15985 (2021).

35. Shroti, M. et al. Vaccine effectiveness of the first dose of ChAdOx1 nCoV-19 and BNT162b2 against SARS-CoV-2 infection in residents of long-term care facilities in England (VIVALDI): a prospective cohort study. The Lancet Infect. Dis. DOI: 10.1016/S1473-3099(21)00289-9 (2021).

36. Hyams, C. et al. Effectiveness of BNT162b2 and ChAdOx1 nCoV-19 COVID-19 vaccination at preventing hospitalisations in people aged at least 80 years: a test-negative, case-control study. The Lancet Infect. Dis. DOI: 10.1016/S1473-3099(21)00330-3 (2021).

37. Pinto, C. M., Mendes Lopes, A. & Machado, J. T. A review of power laws in real life phenomena. Commun. Nonlinear Sci. Numer. Simul. 17, 3558–3578, DOI: 10.1016/j.cnsns.2012.01.013 (2012).

38. Meyer, S. & Held, L. Power-law models for infectious disease spread. The Annals Appl. Stat. 8, DOI: 10.1214/14-AOAS743 (2014). 1308.5115.

39. Stroud, P. D. et al. Semi-empirical power-law scaling of new infection rate to model epidemic dynamics with inhomogeneous mixing. Math. Biosci. 203, 301–318, DOI: 10.1016/j.mbs.2006.01.007 (2006).

40. Vasconcelos, G. L. et al. Power law behaviour in the saturation regime of fatality curves of the COVID-19 pandemic. Sci. Reports DOI: 10.1038/s41598-021-84165-1 (2021).

41. Blasius, B. Power-law distribution in the number of confirmed COVID-19 cases. Chaos: An Interdiscip. J. Nonlinear Sci. 30, 093123, DOI: 10.1063/5.0013031 (2020). 2004.00940.

42. Singer, H. M. The COVID-19 pandemic: Growth patterns, power law scaling, and saturation. Phys. Biol. DOI: 10.1088/1478-3975/ab9fb5 (2020). 2004.03859.

43. Komarova, N. L., Schang, L. M. & Wodarz, D. Patterns of the COVID-19 pandemic spread around the world: exponential versus power laws. J. The Royal Soc. Interface 17, 20200518, DOI: 10.1098/rsif.2020.0518 (2020).

44. Maier, B. F. & Brockmann, D. Effective containment explains subexponential growth in recent confirmed COVID-19 cases in China. Science 368, 742–746, DOI: 10.1126/science.abb4557 (2020).

45. Lopez Bernal, J. et al. Effectiveness of Covid-19 Vaccines against the B.1.617.2 (Delta) Variant. New Engl. J. Medicine DOI: 10.1056/nejmoa2108891 (2021).

46. Requia, W. J., Kondo, E. K., Adams, M. D., Gold, D. R. & Struchiner, C. J. Risk of the Brazilian health care system over 5572 municipalities to exceed health care capacity due to the 2019 novel coronavirus (COVID-19). Sci. The Total. Environ. 730, 139144, DOI: 10.1016/j.scitotenv.2020.139144 (2020).

47. Dantas, R. C. C., de Campos, P. A., Rossi, I. & Ribas, R. M. Implications of social distancing in Brazil in the COVID-19 pandemic. Infect. Control. & Hosp. Epidemiol. 1–2, DOI: 10.1017/ice.2020.210 (2020).
1. Callaway, E. COVID vaccine boosters: the most important questions. Nature 596, 178–180, DOI: 10.1038/d41586-021-02158-1 (2021).
2. Paul, E., Steptoe, A. & Fancourt, D. Attitudes towards vaccines and intention to vaccinate against COVID-19: Implications for public health communications. The Lancet Reg. Heal. — Eur. 1, 100012, DOI: 10.1016/j.lanepe.2020.100012 (2021).
3. Garcia, K. & Berton, L. Topic detection and sentiment analysis in Twitter content related to COVID-19 from Brazil and the USA. Appl. Soft Comput. 100, 1–20, DOI: 10.1016/j.asoc.2020.107057 (2021).
4. Rasmussen, C. E. & Williams, C. K. I. Gaussian Processes for Machine Learning. Adaptive Computation and Machine Learning (MIT Press, Cambridge, 2006).
5. Noack, M. M. et al. Autonomous materials discovery driven by Gaussian process regression with inhomogeneous measurement noise and anisotropic kernels. Sci. Reports 10, 17663, DOI: 10.1038/s41598-020-74394-1 (2020).
6. Ren, J., Cai, J. & Li, J. High precision implicit function learning for forecasting supercapacitor state of health based on Gaussian process regression. Sci. Reports 11, 12112, DOI: 10.1038/s41598-021-91241-z (2021).
7. Werneck, G. L. et al. The incidence and geographical spread of SARS-CoV-2 in Rio de Janeiro, Brazil based on RT-PCR test results. J. Braz. Soc. Trop. Medicine 54, DOI: 10.1590/0037-8682-0779-2020 (2021).
8. Ching, J. & Chen, Y.-C. Transitional Markov Chain Monte Carlo method for Bayesian Model Updating, Model Class Selection, and Model Averaging. J. Eng. Mech. 133, 816–832, DOI: 10.1061/(ASCE)0733-9399(2007)133:7(816) (2007).
9. Kirkpatrick, S., Gelatt, C. D. & Vecchi, M. P. Optimization by Simulated Annealing. Science 220, 671–680, DOI: 10.1126/science.220.4598.671 (1983).
10. Massonis, G., Banga, J. R. & Villaverde, A. F. Structural identifiability and observability of compartmental models of the COVID-19 pandemic. Annu. Rev. Control. 51, 441–459, DOI: 10.1016/j.arcontrol.2020.12.001 (2021).
72. Dormand, J. & Prince, P. A family of embedded Runge-Kutta formulae. *J. Comput. Appl. Math.* 6, 19–26, DOI: 10.1016/0771-050X(80)90013-3 (1980).

73. Rosenblatt, M. Remarks on Some Nonparametric Estimates of a Density Function. *The Annals Math. Stat.* 27, 832–837, DOI: 10.1214/aoms/1177728190 (1956).

74. Parzen, E. On Estimation of a Probability Density Function and Mode. *The Annals Math. Stat.* 33, 1065–1076, DOI: 10.1214/aoms/1177704472 (1962).

75. Polack, F. P. *et al.* Safety and Efficacy of the BNT162b2 mRNA Covid-19 Vaccine. *New Engl. J. Medicine* 383, 2603–2615, DOI: 10.1056/NEJMoa2034577 (2020).

76. World Health Organization. Interim recommendations for use of the Pfizer-BioNTech COVID-19 vaccine, BNT162b2, under emergency use listing: interim guidance, first issued 8 January, 2021, updated 15 June, 2021. Technical documents, World Health Organization (2021). https://apps.who.int/iris/bitstream/handle/10665/341786/WHO-2019-nCoV-vaccines-SAGE-recommendation-BNT162b2-2021.2-eng.pdf?sequence=1&isAllowed=y.

77. WHO Strategic Advisory Group of Experts (SAGE) on Immunization. The Janssen Ad26.COV2.S COVID-19 vaccine: What you need to know. *World Heal. Organ.* (March 29, 2021). https://www.who.int/news-room/feature-stories/detail/the-j-j-covid-19-vaccine-what-you-need-to-know.

78. Voysey, M. *et al.* Single-dose administration and the influence of the timing of the booster dose on immunogenicity and efficacy of ChAdOx1 nCoV-19 (AZD1222) vaccine: a pooled analysis of four randomised trials. *The Lancet* 397, 881–891, DOI: 10.1016/S0140-6736(21)00432-3 (2021).

79. WHO Strategic Advisory Group of Experts (SAGE) on Immunization. The Sinovac COVID-19 vaccine: What you need to know. *World Heal. Organ.* (June 2, 2021). https://www.who.int/news-room/feature-stories/detail/the-sinovac-covid-19-vaccine-what-you-need-to-know.

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Author contribution statement
G.B.L., L.A., R.C.C.A., and S.M.C.M. conceived the study; G.B.L. collected the data; All authors analysed the data; G.B.L. designed the models and conducted computations; All authors analysed and discussed the results; G.B.L. wrote the manuscript, with input from all authors; G.B.L. prepared the figures and tables; L.A., R.C.C.A., S.M.C.M., and R.A.M. revised the content critically; R.C.C.A. and S.M.C.M. supervised the study; R.A.M. validated the study; All authors contributed to the final draft.

Additional information
Code availability Code to replicate analysis and figures supporting the findings of the manuscript are available via the project GitHub repository at https://github.com/gustavolibotte/vaccines-COVID-19. The code is licensed under the MIT license.

Data availability Source data are provided with this paper and all data used in this study can be downloaded from the cited sources.

Competing interests The authors declare no competing interests.
Figure 1. Speed in vaccination and expectation of disease mitigation in Rio de Janeiro. a, Map of vaccine doses distributed in each Brazilian state per 100,000 inhabitants, and portion of each type of vaccine destined for Rio de Janeiro, until July 1, 2021. b, Frequency of vaccination rate for each shot, in terms of percentage of population per day. c, Perspective of coverage of the population eligible for vaccination for each shot. d, Time-dependent transmission rate, simulated with the maximum a posteriori of the inferred parameters. e, Posterior distribution of independent $\beta(t)$ parameters. f, Model simulation considering different vaccination rates, slow ($\nu = 0.175\%$), intermediate ($\nu = 0.275\%$), and fast ($\nu = 0.375\%$), taking into account the frequencies (b) and the proportion of vaccines of each type (a). The adopted transmission rate is given by (d, e). The model is simulated until reaching the same amount of vaccines administered in each scenario (see the lower right frame). The shaded areas represent the 95% credible interval according to (e). Note that the period of the end of vaccination in the scenario where an intermediate vaccination rate is adopted agrees with the prognosis in (c).
Figure 2. Importance of rolling out vaccination program as soon as possible. a, Simulations considering scenarios in which the start of vaccination is advanced or delayed by up to 30 days in relation to the actual start date. The grey shaded area represents the six-month interval from the start of vaccination, January 20, 2021. b, Cumulative number of dead and infected individuals when reaching 75% vaccination coverage, varying the day on which vaccination is started, as well as vaccination rates. The error bars are associated with the 95% credible interval of the simulations and the black dots refer to the simulations when the maximum a posterior of the inferred parameters are adopted. c, Relationship between the number of individuals vaccinated and dead over time, given a 30-day early or late start in vaccination in relation to the actual date. The vertical dashed lines express the approximate period at which deaths would peak, for each particular vaccination rate. d, Effective reproduction number, given the analysed scenarios.
**Figure 3. Flawed vaccination policy and excess deaths.**

**a,** Model simulation where part of the population eligible to be vaccinated does not receive any dose. **b,** Ratio between the number of deaths given potential scenarios in which the start of vaccination is ahead of the actual date. Scenarios where vaccination would be implemented 10, 20, and 30 days before January 20, 2021 are considered, as well as two vaccination rates ($\nu = 0.175\%$ and $\nu = 0.275\%$), and excess deaths are estimated. **c,** Variation in the cumulative number of deaths and the number of deaths at the peak of the epidemic curve (during vaccination) taking into account the start of vaccination on different days. The relative percentage amount of cumulative deaths is shown, as well as the month in which deaths would peak. **d,** Simulation considering that part of the population proportional to $\alpha$ does not take the second dose of the vaccine. Two scenarios are considered in which only the first dose of the vaccine has efficacy equivalent to $\mu \eta$, combined with two vaccination rates ($\nu = 0.175\%$ and $\nu = 0.275\%$).
Table 1. Characteristics of the vaccines used in the simulations, in terms of overall efficacy and interval between doses (when applicable). Of note, the recommended inter-dose interval for Pfizer-BioNTech vaccines is 21–28 days\(^75\). However, for countries that face a high incidence of COVID-19 cases and that have not yet achieved safe vaccination coverage rates, the World Health Organisation recommends that the interval between doses be extended to 12 weeks\(^76\), which has been adopted in all over Brazil.

| Vaccine         | Efficacy | Dosage                  | Source |
|-----------------|----------|-------------------------|--------|
| Janssen         | 66.9%    | Single-dose             | ref.\(^77\) |
| Oxford-AstraZeneca | 76%     | 2 doses, 12 weeks apart | ref.\(^78\) |
| Pfizer-BioNTech | 95%      | 2 doses, 12 weeks apart | ref.\(^75\) |
| Sinovac         | 50.34%   | 2 doses, 4 weeks apart  | ref.\(^79\) |

Table 2. Statistics of the posterior distribution of the free parameters that compose equation (3), inferred with respect to the regularised training data.

| Parameter | Mean       | Standard deviation | MAP      | 95% CI                |
|-----------|------------|--------------------|----------|-----------------------|
| \(\beta_1\) | 0.3067     | \(1.543 \times 10^{-3}\) | 0.3066   | (0.3036, 0.3096)     |
| \(\beta_2\) | 0.0334     | \(2.36 \times 10^{-4}\) | 0.0334   | (0.033, 0.0338)      |
| \(\beta_3\) | 0.109      | \(3.105 \times 10^{-4}\) | 0.1089   | (0.1083, 0.1096)     |
| \(\beta_4\) | \(7.71 \times 10^{-4}\) | \(1.307 \times 10^{-5}\) | \(7.73 \times 10^{-4}\) | (\(7.46 \times 10^{-4}\), 7.98 \times 10^{-4}) |
Extended data

Figure 1. Schematic representation of the model. The incidence of new cases is given by $\beta(t)S(t)I(t)/N$, where $N$ is the population size. Both susceptible and infected individuals are vaccinated at a rate proportional to $\nu$. Once infected, individuals are moved to the removed class at a rate proportional to $\gamma$, whereas the gain in the dead class is at a rate proportional to $\rho$. Vaccinated individuals can either be moved into the removed class or become susceptible again, respecting the interval between doses, $1/\tau$, when applicable. In the first case, immunised individuals are moved into the removed class proportionally to $\eta$, the overall vaccine efficacy. In the second case, the susceptible class is fed back proportionally to $(1-\eta)\alpha$. The portion of individuals who do not receive the second dose is equal to $\alpha$. In this case, an overall impaired efficacy is assumed, given by $\bar{\eta}$. In general, the model admits $n$ classes of vaccinated, depending on the types of vaccines used.

Table 1. Conceptual definition of model parameters. Association between symbols and their respective definitions, followed by measurement units.

| Symbol | Definition |
|--------|------------|
| $\beta$ | Transmission rate (per day) |
| $\rho$ | Death rate (per day) |
| $\gamma$ | Removal rate (per day) |
| $\nu$ | Vaccination rate (% of the population per day) |
| $1/\tau$ | Interval between doses (day) |
| $\eta$ | Overall vaccine efficacy (—) |
| $\bar{\eta}$ | Overall impaired efficacy (—) |
| $\alpha$ | Portion of people who have not received the second dose (—) |
Figure 2. Regularisation of training data. Daily data on infected \( (\mathcal{D}_1) \) and dead \( (\mathcal{D}_2) \) individuals are regularised through GPR. The predicted average for each data set is adopted as training data in the Bayesian inference process. The shaded areas represent the 95% CIs of the GPR. We also plot the equivalent results for cumulative data in order to show the agreement between original and regularised data.

Figure 3. Share of beds occupied in Rio de Janeiro. Data range from August 2, 2020 to July 3, 2021, and refer to the occupation of regular beds and intensive care units (ICU) throughout the state (https://painel.saude.rj.gov.br/monitoramento/covid19.html#).
Figure 4. Population mobility trends in Rio de Janeiro during the pandemic. a, 7-day rolling average of the population mobility trend obtained from aggregated, anonymised sets of data from Google users (https://www.google.com/covid19/mobility/). Data are broken down by location, represented by different colours according to the legend. Changes for each day are compared to a baseline value for that day of the week. The baseline is the median value, for the corresponding day of the week, over the 5-week period between January 3 and February 6, 2020 (before the epidemic). We have also included a timeline, with relevant events in the blue boxes, and the number of cumulative cases in the grey boxes. b, Maps of Rio de Janeiro with the trend of population mobility by municipality in relation to workplaces, for days corresponding to the events shown on each map. Municipalities whose area is hatched do not have consistent mobility data available.
Supplementary Files

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- supplementarynotes.pdf