Modeling COVID Pandemics: Strengths and Weaknesses of Epidemic Models

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Abstract

We generally discuss modeling the present COVID pandemics. We argue that useful models have to be simple in the first case, yet their uncertainty has to be handled properly. In order to study circumstances of the upcoming wave of infection, we construct a simple stochastic model and present predictions it gives. We conclude that the autumn wave is most likely unavoidable and suggest concentrating to mitigation.

1 Introduction

Vast majority of epidemic models are derived from the seminal SIR model (Kermack and McKendrick, 1927). These models are all both *explainable* (opposed to black boxes, the mechanism of their predictions is understandable by humans) and *interpretable* (the assumed causes produce expected effects, coherent with common sense as well as scientific state of the art); as Rudin (2019) correctly points out, especially the latter property is important whenever the model takes part in decisions on "high-stake" matters, which a pandemic certainly is. Moreover, SIR-like models comply with the well known Hill's criteria of causation (Šmíd and Kuběna, 2022; Hill, 1965). Despite this, their application during the recent covid pandemics became subject of numerous controversies, mostly due to untreated or wrongly interpreted uncertainty, wider sense co-linearity, model risk and the models' normativeness, resulting e.g. in the prevention paradox.

Apparently, uncertainty is the most severe limiting factor of epidemic models as well as the most common source of misunderstanding. Uncertainty can be either about the characteristics of the disease and their variations, about human behavior, about efficiency of counter-epidemic measures, immunity waning, or the rate of reporting. Unfortunately, these uncertainties multiply in time, which brings problems especially to forecasting in the phase of the epidemic growth.

Moreover, parameters of the models often fail to be (in the statistical sense) identified. Unfortunately, often the parameters evaluating impacts of individual counter-epidemic measures suffer from this problem, so it is virtually impossible to quantify the measures' efficiency.

Further, there is a risk of omitted or a falsely considered factors in the models, called *model risk*. The omitted factors could be e.g. seasonality or the onset of a new virus variant. The false factor could, on the other hand, be an alleged effect of otherwise ineffective measure. Due to the multiplicative nature of the models, this can totally invalidate forecasts stemming from them.

Another problem is that epidemic models are potentially normative, meaning that people can act to prevent the predicted effects, e.g. when, in fear of the forecast, they impose measures and/or start behaving protectively, which consequently leads to damping of the epidemics contrary to the prediction; this effect is called the prevention paradox.

Yet these shortcomings are severe, they need not prevent the quantitative models from being used. If the uncertainty is correctly taken into account and the models are wisely formulated, then the models can give reasonable forecasts with a reasonable uncertainty. The co-linearity may be handled as well, yet for the price of not modeling all the influences individually. The model risk can be, to certain extent, guarded by means of suitable performance measure, which should, however, also evaluate the quantification of forecasts' uncertainty (see e.g. Bracher et al. (2021)). Finally, the normativeness of the models should be clearly communicated and, instead of unavoidable forecasts, the scenarios should be published, e.g. what would happen if no reaction takes place, what happens if a lockdown is imposed, etc.

In this slightly non-traditional, little informal paper, we demonstrate the ideas mentioned above by constructing a simple model predicting the autumn 2022 wave of Covid infection from the perspective of May 2022.

2 Simplicity First

After two years engagement in quantitative analysis of the COVID pandemic related data, I understood that one of the greatest virtues of successful models is simplicity. Together with Rudin (2019) I argue that added value of complex models in comparison to simple ones is sometimes negligible, especially when the overall uncertainty is high. Simple models, on the other hand, are sooner to be developed, easier to be maintained, easier to be explained, less time-consuming to be dealt with both by its author and the audience, and, most importantly, easier to be intuitively understood by the author, which fact brings him necessary confidence when using, presenting and justifying it.

Of course, there is always a trade-off between complexity and explainability of the model (Gilpin et al., 2018); however, benefits of simple models often prevail in my opinion, yet the price for the simplicity is the fact that we often have to create them ad-hoc for specific situations rather than trying to construct an universal reusable model. My experience can serve as an example: during the first year of pandemic, we developed a complex compartment stochastic SEIR model (Šmíd et al., 2021). Yet it appears to perform well, adjusting it so that it could answer a specific question always took substantial effort as well as time, both human and computational. Moreover, all the (possibly unrelated) parameters had to be always estimated, bringing additional uncertainty, and the evaluation and sensitivity analysis took so much time that it often could not be done. The simple model I am going to present here, on the other hand, has been created out of scratch within a single working day and is implemented using a OpenOffice spreadsheet[1] which means that any computation or parameter change is nearly immediate.

3 When the Next Wave Comes?

The question the intended model is supposed to answer is what will be the autumn COVID wave be like, and whether and how it could be influenced. As we cannot know how the virus will mutate, we shall assume that the currently variant Omicron will keep prevailing. For our analysis, we shall use a discretized and perturbed SIR model:

$$X_t = \rho s_{t-1} c_{t-2} I_{t-1} X_{t-1} + E_t, \qquad t \geq 1$$

where X_t is the number of reported cases of the Omicron variant, ρ is an estimated constant reflecting the infectiousness of the variant, I_t is the ratio of susceptible population, s_t is the seasonal factor, c_t is the risk contact reduction, and E_t is the error term. Two things are important here: the weekly time step and heteroskedasticity.

As for the former: Yet daily data are available, they show significant weekly seasonality with unpredictably changing pattern, modeling of which is a perfect example of an unnecessary complexity bringing unnecessary obstacles and little benefit (the estimate of ρ could be more precise only in case that we can handle the seasonality precisely).

The heteroskedasticity reflects the fact that variance of the errors scales with the cases numbers. In toy textbook models, the cases number would be Poisson, so the scale would be proportional to $\sqrt{X_t}$; in practice, however, the distribution is over-dispersed (Endo et al., 2020; Getz et al., 2006) so the error variance scales rather with X_t. As a consequence, we can reformulate the model as

$$D_t = \rho s_{t-1} c_{t-2} I_{t-1} + e_t, \qquad D_t = \frac{X_t}{X_{t-1}}, \qquad t \geq 1,$$

with e_t being white noise.

The seasonality term we assume to be

$$s_t = 1 + \kappa \cos(\phi + \psi t), \qquad t \geq 1,$$

where ϕ and ψ are such that the maximum of s happens in the middle of January each year. We set $\kappa = 0.18$, which is the value obtained by Šmíd (2022), roughly equal to the following from Gavenčiak et al. (2021).

The contact reduction is measured by the longitudinal study PAQ research (2021); the fact that the epidemic growth depends on c two weeks earlier is discussed in Šmíd and

[1] See `https://github.com/cyberklezmer/epidata/blob/main/autumn22.ods`.

Kuběna (2022); Šmíd (2022) as well as in Šmíd et al. (2021); it should be said, however, that, contrary to the previous years, only little or no contact reduction takes place this year and is not likely to happen in the future, so we keep c in the model only to be able to model potential crisis scenarios.

In line with Šmíd (2022), we further assume that

$$I_t = V_t J_t, \qquad V_t = 1 - \frac{Y_t}{p}, \qquad J_t = 1 - \frac{Z_t}{p}$$

where Y_t and Z_t are the numbers of individuals having the vaccine-induced immunity, post-infection immunity, respectively, and p is the total population of the Czech Republic. In determining Y_t and Z_t, we use quite precious estimates of vaccine effectiveness, post-infection protection and their waning, obtained by our recent work Šmíd et al. (2022). As for vaccination, we take

$$Y_t = Y_t^f + Y_t^b, \qquad Y_t^f = (1 - w_f)Y_{t-1}^f + e_f F_t - \gamma_f B_t, \qquad Y_t^b = (1 - w_b)Y_{t-1}^b + e_b B_t;$$

where F_t and B_t are numbers of newly fully vaccinated, having obtained the booster, respectively, $e_f = 0.45$ and $e_b = 0.61$ are the initial effectiveness of full vaccination, booster, respectively, $w_f = 0.056$ and $w_b = 0.082$ are the weekly rates of waning of the vaccination effectiveness, booster effectiveness, respectively, and γ_f is the rate of Y_t and its hypothetical counterpart with $e_f = 1$, $w_f = 0$.

As for the post-infection immunity, we divide the infected into those, who were infected once by the Omicron variant, those infected once by the other variants, and those who were reinfected by the Omicron or the other variants:

$$Z_t = Z_t^o + Z_t^\delta + Z_t^{o+} + Z_t^{\delta+}.$$

Here,

$$Z_t^{O+} = Z_{t-1}^{O+} + O_t^+, \qquad Z_t^{\delta+} = Z_{t-1}^{\delta+} + \Delta_t^+$$

where O_t^+ and Δ_t^+ are the numbers of new reinfections of those, who were previously infected by the Omicron variant, other variants, respectively, and

$$Z_t^o = (1 - w_o)Z_{t-1}^o + O_t - \gamma_o O_t^+, \qquad Z_t^\delta = (1 - w_\delta)Z_{t-1}^\delta + \Delta_t - \gamma_\delta \Delta_t^+,$$

where O_t and Δ_t are newly coming infections by the Omicron variant, other variants, respectively, w_o and $w_\delta = 0.022$ are waning coefficients, and γ_o and γ_δ are analogous to γ_f. Note that we assume hundred percent initial post-infection immunity which does not wane if the individual has been infected twice. It should be stressed that w_o is still unknown as there is still a short time from the Omicron's emergence so relevant data is still not available. Thus we later perform our analysis for its various values. As not all infections are reported, we assume that

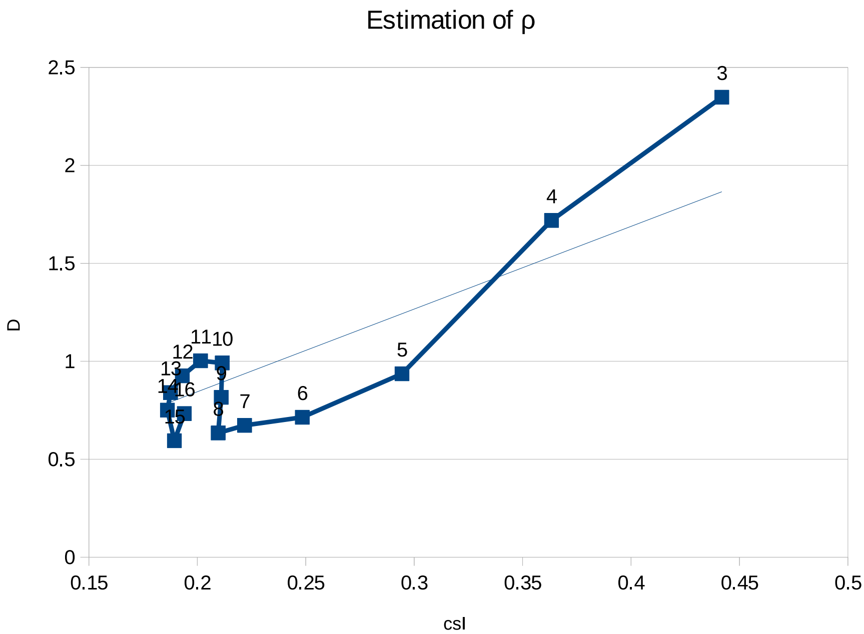
$$O_t = \frac{X_t}{\alpha},$$

where α is the ascertainment rate, i.e. the fraction of reported infections, and we compute Δ_t, O_t^+ and Δ_t^+ from their reported counterparts analogously. In line with Šmíd (2022), we put $\alpha = 0.4$.

4 Results

As inputs of our model, we used publicly available data ČR (2021) and an online variant proportion estimator.[2] For the estimation, we used data from week 2/2022 when the Omicron variant started to prevail, to week 16/2022 – two weeks before the model construction.

The following regression graph with the observation labeled by week numbers shows that the studied dependence may be regarded as linear; however, the onset of more infectious variant BA2 is suggested. We neglect this fact first and use the overall estimate, but we return to this issue later.

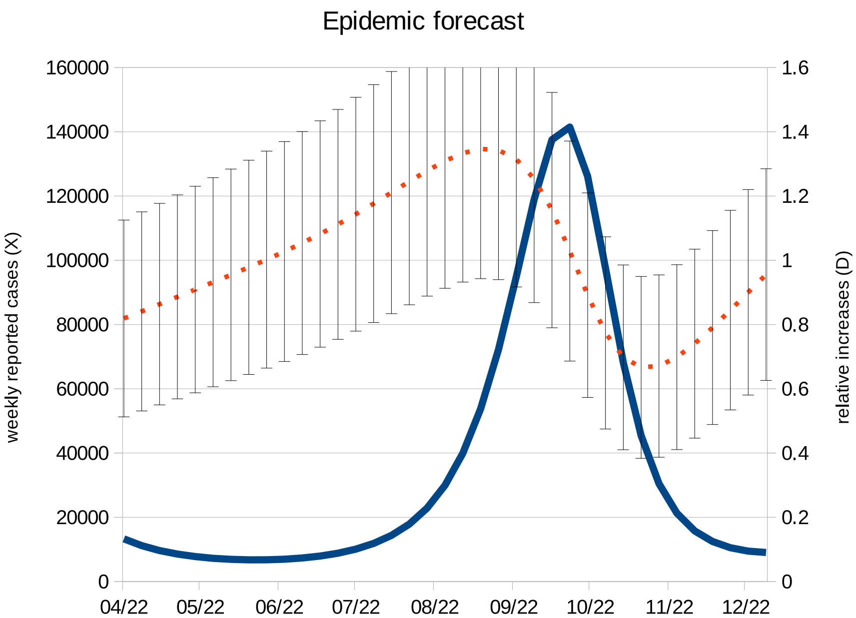


The estimated value of ρ is 4.22(0.25).

Before doing any forecast, we find important to realize that the future behavior of the pandemic depends on many parameters, some of which we are uncertain about, and, yet this additional uncertainty is often difficult to quantify, it has to be added up to the inherent uncertainty, represented by e_t and the estimation error of ρ. Maybe more important, however, is to realize that in systems depending on human behavior, which pandemic certainly is, not only the behavior can change in a reaction to the system (e.g. being careful when infection numbers are high), but it can change also in a reaction to our forecast.

[2] `https://covariants.org/`

The following graph shows a point forecasts of D and X given that (i) the contact reduction keeps unchanged, being equal to $c_t = 0.9$, (ii) the waning of the post-infection immunity after Omicron infection is the same as that after Delta $w_o = w_\delta$, and (iii) the vaccination rate will not change, i.e. there will be 2000 final doses and 10000 boosters a week:

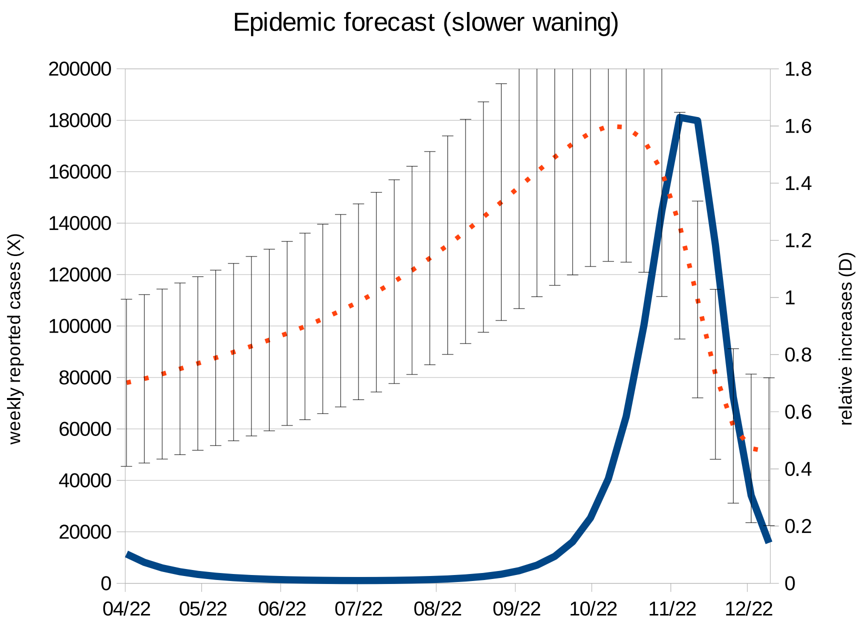


The solid line shows predicted numbers of observed cases X, the dotted line depicts the relative growths D together with a lower estimate of their standard forecast errors – we do not include the part of the uncertainty caused by the fact that I depends on D's, which could, in principle, be evaluated, but this is beyond the scope of this short paper – we only remark that, as the omitted errors would multiply, it is quite clear that the errors explode after the confidence interval for I starts to contain unity. The situation is even more serious for the predictions of X errors of which would start exploding immediately. Thus, taking these as well as the mentioned additional uncertainties into account, it is clear that such a forecast should be interpreted qualitatively rather than quantitatively.

The great uncertainty of the forecast, however, does not mean that the model does not say anything. It is clear, for instance, that D will sooner or later reach unity, because their determinants V and I keep growing (the waning obviously overturns the effects of new vaccinations, new infections, respectively). In this sense, another wave seems unavoidable. Note also that, after the predicted October wave, the forecasts of D quickly approach unity again which means that another wave in the beginning of 2023 is likely.

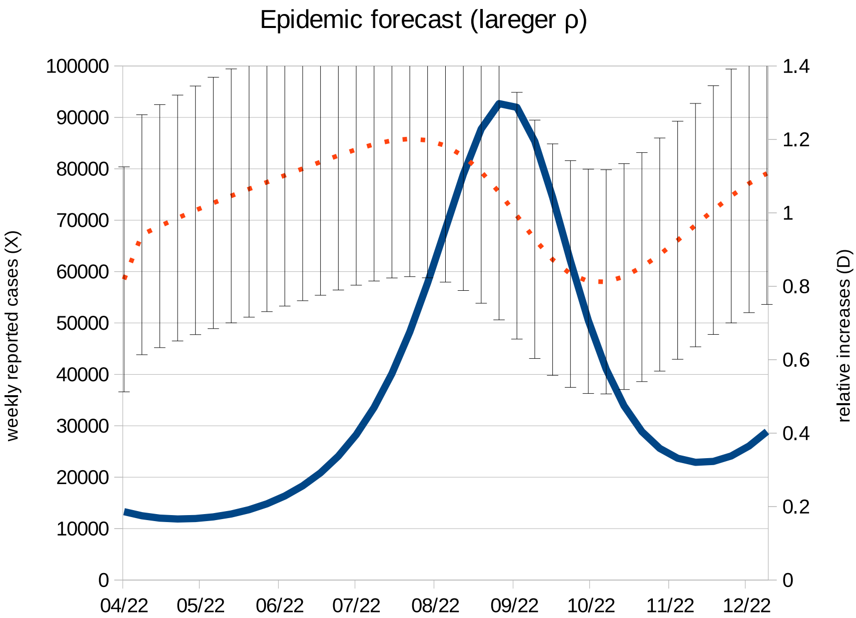
5 Sensitivity Analysis

As it has been already mentioned, two crucial parameters are subject of a great uncertainty. Most important it is the rate w_o of post-infection immunity waning given that the original infection was by Omicron. So far we assumed it to be equal to the same value 0.022 as if the original infection were by other variants. Newly we set it to the waning rate of the immunity against Delta after the Delta infection, i.e. $w_o = 0.003$. The result is following:



The fact that slowing the waning rate seven times only shifts the autumn wave one month later might seem surprising; however, it suffices to realize that there is still more people who were infected by older variants than those who underwent the Omicron infection and that the seasonal component grows in autumn.

The second highly uncertain parameter is ρ. Below is the forecast assuming that, from the time horizon (end of April), ρ starts to greater by 0.5, i.e. $\rho = 4.72$, perhaps due to the fact that a new variant of Omicron prevailed.



Not surprisingly, the expected wave came earlier. It is also less in its peak; however, this does not be a great victory as the numbers start to grow at the end of the year, obviously preparing for the next wave.

6 Discussion and Conclusion

We presented a simple model designed in order to study the circumstances of the expected autumn wave of the COVID infection. Having observed great uncertainty of the model's forecasts, we resorted to qualitative forecasts instead of quantitative ones. Still, however, we dare to conclude that another wave of infection is most likely unavoidable. Question arises, whether it can be averted or at least how it can be mitigated.

The answer to the first question is unfortunately no, the reason being the low effectiveness of the contemporary vaccines against Omicron infection. As we have no other acceptable means of preventing the infection spreading, it remains to take the upcoming wave as a fact and move to mitigation. As Šmíd et al. (2022) show, the existing vaccines are still rather effective against a severe course of the disease, so the most straightforward move is to vaccinate anyone who is or may be endangered. Moreover, still having time enough, it would be reasonable to discuss "logistic" aspects of the wave, namely to prepare measures which would prevent the wave from paralyzing daily life as it nearly happened during the recent wave when e.g. schools could hardly function due to strict quarantine rules.

The presented model, yet simple, can be improved too. As new data come, the waning and effectiveness parameters can be further refined, the impacts on hospitals can be studied and the uncertainty may be quantified more preciously.

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